A COMPUTATIONAL FRAMEWORK INCORPORATING HUMAN AND SOCIAL BEHAVIORS FOR OCCUPANT-CENTRIC EGRESS SIMULATION

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Abstract

Emergency evacuation (egress) is an important issue in safety design of large facilities and buildings. Studies of catastrophic incidents have highlighted the need to consider occupants' behaviors for better understanding of evacuation patterns. Although egress outcomes are influenced by human and social factors, quantifying these factors in design codes and standards is difficult because occupants' characteristics and emergency scenarios vary widely. As an alternative, computational egress simulation tools have been used to evaluate egress designs. However, most of current simulation tools focus on visual aesthetics and computational efficiency but they oversimplify the behavioral aspects of evacuees.

This thesis describes a flexible computational framework that incorporates human and social behaviors in simulations to aid occupant-centric egress design. To establish the theoretical underpinning of the computational framework, occupants' behaviors in emergencies are analyzed by conducting a thorough review of literature in social science and disaster studies. Based on the analysis, the design requirements of SAFEgress (**S**ocial **A**gents **F**or **Egress**), an agent-based simulation framework, are derived to model different occupants' behaviors in egress. Specifically, SAFEgress is implemented using a tiered decision-making process that allows the agents to exhibit individual, group, and crowd behaviors. Moreover, the representation of the egress environment and the occupants, as well as the algorithms that emulate human capabilities in perception and navigation are carefully designed, such that SAFEgress can simulate group dynamics and social interactions observed in real life egress situations. A series of validation tests has been conducted to verify the capability of the framework to model a wide range of behaviors. Different egress scenarios in a museum and a stadium are simulated using SAFEgress to demonstrate the

significance of human and social factors for egress analysis. The results show that considering group navigation could cause additional bottlenecks on egress routes, thus prolong evacuation. On the other hand, by strategically arranging stewards to control crowd flow, evacuation time can be significantly improved. By analyzing the results of different simulated evacuation, safety designs and evacuation strategies can be customized to account for specific emergency scenarios.

SAFEgress provides a means to systematically evaluate the effects of human and social factors on egress performance in buildings and facilities. Using the simulation results, facility managers and designers can develop occupant-centric solutions to crowd problems by addressing different scenarios and unique occupants' characteristics. Furthermore, the framework could be applied to support research in social science to investigate the collective behaviors of crowds in a built environment.

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Dedication

To my parents and siblings,

who give me strength and confidence I have needed.

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Chapter 1

Introduction

1.1 Motivation

Egress, the process of occupants exiting a building in both emergency and non-emergency situations, is an important design issue in buildings and facilities. To aid the design of a building's egress system, engineers and architects rely mainly on building codes and standards [1, 2, 3]. Although conventional egress design codes and standards specify some requirements on occupant and building elements (such as door widths and number of exits) to guarantee a certain level of occupancy safety in emergencies [3], recent studies of catastrophic incidents in buildings highlight the need to carefully consider occupants' characteristics and emergency scenarios [4, 5, 6, 7, 8]. For example, Aguirre et al. studied the 2003 Rhode Island Station Nightclub Fire and found that people in intimate groups, such as families and friendships, helped each other to escape even in extreme emergency situations [5]. Averill et al. also pointed out that individuals closely followed the instructions given by emergency responders during the 911 World Trade Center terror attacks [9]. Occupants' behaviors vary in different egress situations and directly govern the evacuation patterns and the casualties in emergencies [5, 10]. Despite the importance of the human and social factors in egress, quantifying these factors through equations and provisions in design codes is difficult because of the uniqueness of each emergency scenario and the wide variation of occupants' characteristics.

The need to incorporate social behaviors into current egress design practice has been echoed by the authorities in disaster management and social science [4, 11]. The use of computational models is an alternative way to examine the sufficiency of egress designs of buildings, particularly for large and complex facilities such as stadiums and airports [12, 13]. Although egress simulation tools are commercially available, most of the tools oversimplify occupants' behaviors in emergencies; for example, occupants are assumed to exit the building immediately and possess full knowledge of the exit routes [12, 14]. Crowd simulation research studies have started to explore and incorporate the behavioral aspect of crowds in simulations. However, most simulation models focus on modeling individual behaviors but oversimplify factors related to social groups and crowds, such as social relationship among occupants and the presence of authority. Researchers in the field of disaster management have concluded that there is a dire need to "improve the realism and accuracy of crowd behavior movement, in addition to improvising visual aesthetics [in existing commercial tools] [4]."

To predict evacuation patterns and outcome more accurately, egress simulation models need to incorporate the occupants' behaviors in a realistic manner [4, 5, 8, 11]. Existing social theories and case studies have established a rich set of factors and mechanisms that we can use to study evacuations [5, 7, 15, 16, 17, 18, 19]. However, incorporating these factors and mechanisms into egress simulations is not a straightforward task because these factors are usually qualitative and cannot be directly applied to evaluate building designs in a quantitative manner. To leverage the social science literature of human behaviors during emergencies, in this thesis, we design a computational framework to explicitly model the social characteristics of the evacuating crowd by following the principles in computational social science [20, 21]. The computational framework not only allows researchers to investigate human and social behaviors in emergencies but also aids building designers and facility managers in evaluating the performance of different egress designs or emergency response strategies in various emergency scenarios.

1.2 Scope of research

To contribute to the design of safe buildings, our research focuses on egress in emergency events in which most casualties occur. Moreover, we also study non-emergency situations that provide insights into the organizational factors (such as crowd control strategies) that are crucial in egress. We classify different egress scenarios according to the level of urgency and the threats presented to the occupants:

- **Egress triggered by emergency events**: this type of egress involves occupants who have a high level of urgency to escape as they perceive cues, such as alarms, fires, and booming sounds from explosions, that indicate potential threats [7, 22]. Studies of past incidents show that people in emergencies are likely to delay their evacuation upon perceiving the cues and exhibit social behaviors during evacuation. The delay and social behaviors of evacuees can cause additional congestions at critical junctions and further expose themselves to danger [5, 15]. Injuries or deaths are commonly reported in emergency egress when people are exposed to untenable conditions in the building as the threat develops.
- **Egress triggered by non-emergency events**: this type of egress involves occupants who have a low level of urgency to evacuate because they do not perceive the triggering events to be real threats to life safety; for instance, an audience exits the stadium after attending a sport event. Although the triggering events do not impose immediate threats to the occupants, casualties are occasionally reported in stampede accidents, such as the 1989 Hillsborough Stadium stampede in England [6] and the 2010 Love Parade Music Festival stampede in Germany [23]. In egress situations without life-threatening events, proper crowd control is critical to avoid overcrowding.

While we study both types of egress scenarios, our primary focus is human and social behaviors in emergency egress. Some common events that trigger the evacuation process, such as fire alarms and emergency announcements, are included in our study, but the modeling of smoke and fire propagation is not considered as the scope of this research. Nevertheless, understanding the importance to incorporate fire and smoke in egress analysis, we aim to design a modular framework to incorporate such threats in future extension.

1.3 Research goals and methodology

Our research aims to integrate social science knowledge on occupants' behaviors into egress analysis and thus to provide aid for the design of occupant-centric buildings. To achieve this overarching goal, we first synthesize the key factors affecting occupants' behaviors in egress. Then, we identify and design a computational framework to incorporate the key factors into egress analysis. The framework allows the assessment of egress designs and evacuation strategies considering different occupants characteristics and egress scenarios. The following list of questions serve as the points of departure for the research:

- What kind of actions do people take when they exit a building?
    - What are the factors (such as individual experience, social relationships, stimuli from the environment, or crowd influence) that trigger the actions?
    - How do people interact with others in the crowd?
    - How do their actions shape the emerging and collective pattern of the evacuation?
- How can we incorporate human and social factors in egress simulation?
    - What is the sufficient and appropriate framework to represent the complex egress process?
    - How can the diverse occupants' behaviors be simulated systematically?
    - How can the model be scaled to simulate large facilities where safe egress is critical?
- How can we improve safe egress design with the results?
    - How can we verify the model?
    - How do we assess and compare different egress designs?

Our research adopts a multi-disciplinary approach to answer the research questions, as summarized in Figure 1.1. The three main parts of our research methodology are as follows:

Multi-level analysis on social theories

Modeling human behaviors in emergencies is a complex task [5, 7, 11]. By reviewing the existing social theories and case studies, we deduce a theoretical framework that consists of individual, group, and crowd levels to classify different factors. The staged theoretical framework allows us to systematically study the effects of personal background, social relationships, and the influences of

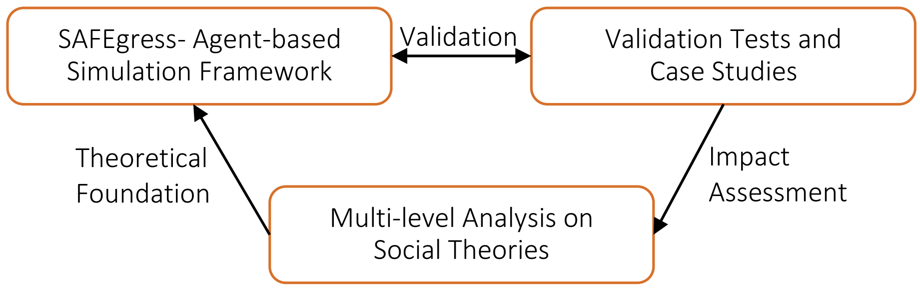


Figure 1.1: Overview of research methodology

crowds on the evacuating occupants. The analysis on the literature delineates the requirements in designing a simulation framework for modeling human behaviors in egress.

SAFEgress – Agent-based simulation framework for egress analysis

To incorporate human and social factors into egress simulation, we design an agent-based computational framework, named **S**ocial **A**gents **F**or **Egress** (**SAFEgress**), according to the theoretical analysis on social theories and empirical studies. Specifically, we first design the representations of the building environment, occupant population, and emergency cues to model an egress scenario. Second, we implement computational algorithms, such as visual sensing and navigation algorithms, to equip each agent with the capabilities to interact with the other agents (such as group members and surrounding crowds) and the environment. Third, to model different kinds of behaviors in simulation, we design a multi-stage agent behavioral model that follows the studies on human behavioral process in emergencies. To facilitate the modeling of large crowds, the algorithms have been carefully designed to enhance computational efficiency.

Validation tests and case studies

To verify the accuracy of the fundamental assumptions in SAFEgress, we first compare the simulation results to the expected outcomes in validation tests and demonstrate the range of occupants' behaviors that can be captured by SAFEgress. Moreover, we develop a set of quantitative measures (such as crowd density) and statistics (such as delay time, overall egress time, and exit usage) to describe the simulation results such that we can compare different egress scenarios. Finally, in our case studies of a museum and a stadium, we apply SAFEgress to mimic real life egress situations and to illustrate the potential use of the framework to assess the human and social factors in egress designs.

The development of the computational framework, SAFEgress, is based on detailed analysis on human and social behaviors in real-life emergencies from the perspectives of social science and disaster management. Upon validation, SAFEgress can be a useful platform to study realistic human and social behaviors in egress and is applicable to related fields of research such as safety engineering, emergency planning, crowd management, social science, and many others.

1.4 Organization of the thesis

The thesis is organized into eight chapters, including this introductory chapter.

Chapter 2 identifies research gaps from the existing literature of various fields. Firstly, standards and code for egress design are studied to understand how design specifications address behavioral factors. Secondly, social theories related to crowds and empirical studies of past accidents are surveyed to understand human and social behaviors during emergency evacuations. Lastly, existing egress and crowd simulation models are reviewed to identify the steps necessary to incorporate occupants' behaviors into egress simulations.

Chapter 3 presents a multi-level (individuals, groups, and crowds) theoretical framework to systematically study existing and prevalent social theories. We organize and analyze the social theories and case studies to examine the key factors and mechanisms underlying the behavioral outcomes. This theoretical framework lays the foundation for designing comprehensive computer models for egress simulation.

Chapter 4 describes the SAFEgress computational framework, an agent-based model designed to simulate individual, social, and emerging crowd behaviors during evacuations. We present an overview of the framework and discuss the representation of the egress environment and the occupant population (the agents). We also describe the perception and navigation capabilities that equip the agents to allow each of them to interact with the virtual environment and other agents.

Chapter 5 focuses on the simulation process, which is a multi-stage agent behavioral cycle to determine the individual and social behaviors of agents during egress simulations. Moreover, we demonstrate several individual, group, and crowd behaviors that are designed according to findings in past emergency studies and observations in real-life.

Chapter 6 first discusses the rationales of each of the different stages of validation tests (component testing, qualitative validation, functional verification, and case studies). Then, component testing and qualitative validation are presented to verify the basic assumptions and the behavioral capabilities that are built into the model. A series of tests on the agent attributes are presented as functional verification to show the range of behaviors that SAFEgress can capture.

Chapter 7 demonstrates the potential use of the SAFEgress framework in real-world applications. We use the current SAFEgress prototype to evaluate the egress performance of a museum and a stadium with realistic assumptions on the occupant population and the evacuation scenarios.

Chapter 8 summarizes the contributions of the dissertation and discusses potential directions for future research.

Chapter 2

Background

In this chapter, we study relevant literature in safety engineering, social science and crowd simulation to identify the research gaps in incorporating human and social behaviors into egress simulations. Firstly, we review the design codes and standards that specify the key design criteria of egress for buildings. We then provide a comprehensive account of different social theories on crowd behaviors in emergencies and evacuations. Lastly, we review the existing models that focus on modeling human behaviors during egress and in crowds.

We pose the following questions when reviewing the codes, theories, and models:

- How do the egress design guidelines and standards incorporate human and social factors?
- What are the prevalent concepts in explaining human and social behaviors? How do people make decisions in emergencies?
- What is the state-of-the-art of egress and crowd simulation? What are the gaps between simulation models and actual human behaviors during egress?

The answers to these questions set the groundwork of our research on building a robust framework to analyze human and social behaviors in egress.

2.1 Egress design guidelines

In practice, designers and engineers refer to egress design standards and codes to evaluate the level of life safety for buildings [2, 3, 24]. The key rationale for design codes is to provide continuous and unobstructed means of egress to building occupants in case of emergencies. The design codes describe the specifications regarding the occupant loads and the important components of egress design. For example, the *2012 International Building Code* limits the occupant load based on the function of the space and specifies the required width of the egress pathway on a per occupant basis [2]. The *Life Safety Code* by the National Fire Protection Association (NFPA) and the design handbook by the Society of Fire Protection and Engineering (SFPE) also provide egress specifications on other egress features, such as sprinkler systems, alarms, and emergency lighting, for different types of buildings [3, 21, 24]. Although the codes and standards provide detailed prescriptive guidelines to provide certain level of life safety for the building occupants, the actual performance of the egress system is not explicitly defined and quantified [25]. In addition, various human factors, such as intervention of emergency personnel and occupants' preference to evacuate, may change the use of exit routes of people and cause additional congestions that are not considered in design [5, 15].

In the last decade, egress design assessments, particularly for large facilities, have shifted to performance-based analysis, which evaluates the egress design in terms of egress time under the assumed egress scenarios. Examples of the assessment guidelines are the *ISO/TR 16738:2009* technical guideline [26] and the *Engineering Guide to Human Behavior in Fire* by SFPE [27]. In a performance-based analysis, the two key quantitative measures are the time lapse when the building becomes untenable to the occupants after the start of the emergencies (i.e., Available Safe Escape Time—ASET) and the time required for the building occupant to escape (i.e., Required Safe Escape Time—RSET) [28]. The value of ASET is determined based on the assumed fire scenarios and the physical properties and dispersion of the toxic fire effluents under different fire conditions [29]. On the other hand, the value of RSET depends upon a series of processes consisting of time for the occupants to detect the threat, delay time in starting evacuation, pre-movement time, and the actual travel time during evacuation. By comparing the ASET and RSET values, safety engineers and building designers assess whether all occupants would be able to escape from a building under specific fire scenarios.

Unlike other aspects of building design, such as structural design or wind engineering, building egress performance depends very much on the occupants' behaviors and their interactions during the emergency events. Because human behaviors are difficult to evaluate and specified quantitatively, the performance-based design approach provides a means to gauge the realistic outcome of an egress scenario [1, 25, 26, 28]. For example, SFPE provides some methods to estimate the values of RSET, depending on the factors (such as congestion or the occupants' delay) that govern the overall egress time [3]. Nevertheless, in order to estimate a reasonable range of values for the egress times in various scenarios, the governing physical phenomena, such as merging flows and high density crowd, and more importantly, the human and social factors, such as helping behaviors and presence of emergency personnel, must be incorporated into the evaluation of egress design.

2.2 Human and social behaviors in egress

To understand occupants' behaviors during egress, we first examine three classic theories, namely, bounded rationality, reward-maximizing, and place scripts, to understand how people make decisions in an individual setting [30, 31, 32, 33]. Then, we study the social theories that are developed through empirical studies of past accidents. These social theories explain people's decision making processes within a social context, which is complementary to the individual-based decision-making theories.

2.2.1 Theories on individual processes and factors

Some early individual-based decision-making theories suggest that people go through a rational evaluative process to determine their final choices [30, 31, 32, 33]. The first example, bounded rationality, suggests that people first use their perceived information and heuristics to limit alternatives to problems [31]. People then choose one solution by comparing the outcomes of the alternatives to some criteria or targets. The decision is said to be bounded because not all of the alternatives are evaluated and the outcome of the choice may not be optimal. Moreover, when a good-enough solution is found, people tend not to deviate until the solution is not viable. The second example is reward-maximizing theory proposed by Mintz [30, 32]. According to reward-maximizing theory, a person makes decisions that maximize his/her reward. The expected reward is calculated based on the reward structure, which is shaped by the behaviors and reactions of the crowd. In an egress scenario, people are motivated by the chance of exiting safely. When the crowd is exiting orderly, people show cooperative behaviors; however, as soon as pushing occurs, they exhibit non-adaptive behaviors because they react to the disturbance in order to restore the chances of exiting safely.

While bounded rationality and reward-maximizing theories adopt different mechanisms to explain people's decision-making process, they both suggest that individuals remain rational in making decision in emerging situations. Nevertheless, these two theories does not address the situational factors of the specific emergency scenario. In an emergency situation, an individual also responds based on the context of the place and the role of the individual in the place. For instance, in a shopping mall evacuation, the response of a visitor will be different from that of a staff because they are motivated by different goals. Therefore, we also examine the place script theory that emphasizes the context and the functional role of the individuals in guiding individual behaviors.

According to Tong and Canter, the reactions of people are governed by their social role and the place rules, which together form the "place scripts" [33]. Organizational and place-related roles and social structures tend to be maintained throughout emergencies. In an emergency situation, people may follow the place scripts they learnt prior to the event because the scripts allow the place to function in normal circumstances. For example, in the King's Cross Underground Station fire in 1987, researchers found that some people continued to use the route they were familiar with to evacuate, instead of using the most direct exits [15]. One explanation of this behavior is that people have developed a routine to exit the station in the past and expect that routine to continue working in new situations. Also, in a rapidly developing emergency event, people are unlikely to develop a script that assists them in recognizing the emergency situation, unless they have previous appropriate training or applicable experiences. Failure to break from the normal script can result in delay and inappropriate actions.

Studies of past emergencies and accidents show that individuals do not just make decision based on rationality, but also their functional roles in the emergency situation. These factors explain why people exhibit different individual behaviors even when facing the same threats in emergencies.

2.2.2 Theories on social processes and factors

In an emergency situation, people rarely evacuate on their own; instead, they are often accompanied by others when exiting the building. As highlighted by many studies of past emergency events and evacuation drills, the presence of others motivate evacuees to exhibit different kinds of social behaviors, such as following authority's instructions and helping people who are in need. The social behaviors cannot be explained by the individual-based processes and factors alone. In the following, we describe several prevalent social theories that highlight the interactions and influence among occupants in crowds to guide people's social behaviors:

- **Group mind theory**: LeBon's group mind theory suggest that in being part of a large gathering under emergencies, individuals lose all sense of self-responsibility, gain the sentiment of invincible power by being a part of the crowd, become subject to contagion, and exhibit extraordinary behaviors [34]. Individuals become a part of the crowd with anonymity and share group emotion. This transformation makes individuals feel, think and act in a manner different from in the state of isolation. Park and Blumer further argued that crowd behaviors are developed in five stages: an exciting event (such as social unrest), milling (i.e., discussion of the events among the crowd), emergence of a common object of attention, collective excitement through social contagion, and the resulting collective behaviors [16].
- **Predispositionist theory**: Allport, Millar, and Dollard viewed the crowd as a collection of individuals who have learning abilities and are inclined to react in a way that comply with the emerging majority [16]. Through the process of social facilitation, i.e., observing others and responding in kind, individuals reciprocally stimulate each other and heighten the level of group activities. According to the theory, crowd behaviors are the result of each individual's predisposed behaviors and non-adaptive behaviors arise when individuals face opposing drive [19].

The early crowd theories, such as group mind and predispositionist theories, assume that individuals in the crowd undergo some transformative, contagious processes and become a part of the homogenous crowd. They do not make recourse to the social structure of the crowd or the effect of pre-existing social relationship among individuals in the crowd. Recent theories, on the other hand, emphasize the sociality of the crowd in explaining the occupants' reactions. This alternative explanation divulges a new realm of theories resting at the social and group level. Some significant examples of these social theories are as follows:

- **Normative theory**: The emergent norm theory, proposed by Turner and Killian, has three fundamental concepts: (1) normative orders which guide behaviors when facing routine problems, (2) the social structure (the existence of social relationships) that specifies the expectation of behaviors of each member in relations to other members, and (3) the communication channel in which social interaction takes place [5, 19, 35]. Milling and keynoting are the two key processes in the normative theory [16, 35]. Milling is the social process that takes place among participants in a crisis setting as they attempt to define the uncertain situation, propose and adopt new, appropriate norms for behavior, and seek coordinated, collective action to find a solution to a shared problem. Keynoting is the convergence of predispositions shared by a significant portion and advocated by a keynoter.
- **Affiliative theory**: This theory suggests that people's motivation to move to a particular direction is based on place and people affiliation. Based on analysis of the Summerland fire disaster in 1973, Sime found that the occupants' route choices were largely influenced by their role, the presence of social ties to individuals located elsewhere in the building, and the proximity of exits [36]. Mawson further classified emergency responses based on (1) the severity of the environmental conditions and (2) people's proximity with their groups and familiar place [18]. According to Mawson's classification, affiliative behavior is expected when individuals are close to their groups and perceive mild environmental threats. When flight occurs, individuals tend to move with social group, thus maintaining proximity with their groups. If an individual is alone, even mild environmental threats will cause his/her flight action to travel to his/her familiar place.
- **Social identity**: Tajfel and Turner suggested that people tend to categorize themselves into one or more "in-groups," building a part of their "social identity" on the basis of membership of that group and enforcing boundaries with other groups [37]. The intensity and kind of identity used to represent self and other vary with one's motives, values and expectations, background knowledge and theories, and the social context within which comparison take place. For example, in their study of historical emergency events, Drury et al. found that increasing threat had a significant correlation to increasing sense of "we-ness," i.e., viewing themselves as one collective of individuals [6, 37]. Moreover, the level of "we-ness" also positively correlate to

the number of occurrences of mutual assistance among the evacuees [6]. When people identify others as a part of the psychological crowd, the share identity leads to higher degree of concern toward others and enhances co-ordination and mutual assistance.

The normative, affiliative, and social identity theories emphasize that social behaviors are emerging, rather than pre-defined, results of occupants' interactions. The interactions are mediated by existing social structures, affiliations, and norms. Although each of the social theories proposes different mechanisms in explaining the emerging social behaviors, we do not weigh one theory over another because there is no unified theory which fully explains human behavior in different emergency situations. In fact, some of these theories are complementary to each other. For example, social identity theory helps to explain the collective behavior and altruistic behavior among strangers and achieve large group unity in emergency situations in a short period of time, which cannot be explained by the normative and affiliative approach.

Broadly speaking, individuals, as a part of the crowd, retain their rationality and sociality and behave in a socially structured manner. The social and psychological theories bridge the missing gap between the individual actions and the collective outcomes of the large gathering. Nevertheless, these theories have diverse origins and use different units of analysis to explain the outcomes under specific conditions. To further apply these theories to study human behaviors in egress, a theoretical framework is needed to systematically organize the key factors and concepts.

2.3 Current simulation approaches

Depending on the purpose of the simulation models, researchers and software developers adopt different modeling approaches to simulate crowd in evacuation scenarios. We describe three main approaches in the simulation practice:

- The first example of these modeling approaches is particle-based, which models the motions of each occupant driven by forces or potential fields. This approach is commonly used to simulate the mass movements of high-density crowds. One well-known example of this approach is the social force model, which represents evacuees' movement based on repulsive and attractive forces due to external factors and internal motivations [38, 39]. The particle-based approach, despite being fast and computational efficient, lacks realism in modeling the micro behaviors of individuals and groups in the larger crowd [11, 40].

- The second modeling approach, cellular automata, represents the space as a uniform grid of cells and models people's movement as a series of transitions from one cell to another. This approach is commonly adopted by commercially available egress simulation tools, such as STEPS and EXODUS [13, 41]. While the cellular automata approach provides computational efficiency to model the building space and occupants' movements, it tends to generate unnatural trajectories because the movements are discrete and restricted to adjacent cells [40]. Moreover, such model may not be capable of modeling congestions as the simulated crowd density is limited by the assumption of the maximum number of occupants in one cell [42].
- Thirdly, the agent-based models (ABMs) simulate individuals as virtual agents that possess customized characteristics and capabilities to model human-like activities, such as perception and navigation. As a result of interactions of virtual agents, ABMs can often capture some emergent phenomena, such as herding and formation of queues [40, 43]. In recent years, many egress models have adopted the agent-based approach due to its flexibility in modeling both individual and collective behaviors. Examples of these models are MASSEgress [44], HiDAC model [40] and ViCrowd [43]. Other models, which are originally developed based on other approaches like cellular automata, also begin to adopt the concept of 'agent" by including occupant characteristics in the models to simulate some commonly observed behaviors [45].

In the following, we review models that adopt the agent-based approach in modeling crowd in egress. In particular, we focus on how the different models represent occupants and simulate occupants' movements in egress.

2.3.1 Representation of occupants

Many ABMs have different levels of sophistication in modeling the individual aspects of the occupants. The first example, SIMULEX, allows users to assign values to a fixed set of attributes that describe the individual characteristics of the occupants, including movement speed, body dimensions, gender and age, and delay time to respond to alarm [12]. Second, EXIT89 specifies individual traits and some egress related parameters, such as threshold of smoke level, to model more complicated behaviors like changing evacuation path [14]. The third example, EXODUS, apart from demographic and mobility information, allows users to define also the agent's degree of familiarity with the building and the tasks performed prior to evacuation action [11, 13]. In most ABMs, the fundamental assumptions of crowd movements (such as maintaining personal space and the flow-density relationship [20, 21]) are also incorporated in the model assumptions to model individual agent's movements in a crowd.

Although early ABMs model the individual aspects of the occupants in a relatively comprehensive manner, they often ignore the effects of group and crowd behaviors on evacuation [4, 5]. Only recently have efforts been attempted to incorporate social behaviors into egress simulations. For example, MASSEgress is one of the first egress simulation models that considers social behaviors, such as leader-follower behaviors in groups and competing and queuing behaviors in crowds [44]. Tsai et al. have included in their implementation exit knowledge, families, and emotional contagion on evacuation and studied the impacts of emotional and informational interactions between agents [42]. Similarly, Aguirre et al. have described an agent-based model that attempts to implement the pro social model in simulating emergency evacuations [5]. Features, such as leaders and followers within a group, have been implemented both to simulate population at a group level and to investigate emergent patterns as a result of social relationships. Other ABMs that are developed based on individual assumptions have also developed extra functionalities or sub-modules that address the needs to consider social behaviors in predicting egress outcomes. For example, Mossauid et al. have extended the social force model to simulate the group walking pattern by considering ease of communication as a "physical force" that affects an agent's motion [39]. In addition, EXODUS models a mechanism to represent the social hierarchy that exists prior to the evacuation, and the inclusion of this social factor can change the agent's response time and evacuation routes [45].

While recent research efforts in simulation models have started to consider the social aspects of the occupants during egress, most of these models implement a subset of social attributes sufficient to demonstrate specific social behaviors. To model the diverse occupant behaviors in egress, a comprehensive representation scheme to model the occupants is needed. Nevertheless, the huge variability of human behaviors in different egress situations presents a challenge to design such a representation scheme. We conjecture that the prevalent social theories and empirical evidence could provide us some insights to design a meaningful occupant representation scheme.

2.3.2 Modeling of occupants' movements

Since human movements aggregate to form the collective crowd flow, egress simulations need to model properly the individual agent navigation decision in order to predict the overall egress performance. We first describe some important concepts in field of environmental psychology that are relevant to occupants' movements in egress. Then we review the methodologies adopted by ABMs in modeling agent's navigation.

Studies in environmental psychology have proposed some elementary concepts to explain how people move in a place [46, 47, 48, 49]. As pointed out by Gärling et al., humans, instead of moving randomly, tend to perform wayfinding when navigating the environment [47]. During the wayfinding process, they examine the surrounding layout and perceive (visual or audio) sensory information, and then move toward a direction based on their purpose of navigation, destinations, and knowledge of the space [47, 48]. The wayfinding process, unlike the motion of molecules or particles that are determined by interaction with their immediate neighbors, depends on both the short-term, nearby information and the long-term goal. Broadly speaking, the wayfinding capability of a person depends on several key components: (1) the perceptive capability of the person to detect the environment, (2) voluntary or involuntary attention switch to direct attention on objects that are relevant to the context, and (3) the spatial network that is built based on people's knowledge of the space and perceived information. For egress simulation, the wayfinding process is an important consideration because evacuees typically decide their route dynamically in real time and may not have complete knowledge of the space, particularly during emergencies in an unfamiliar environment.

To emulate the wayfinding process of human in simulations, an egress simulation model needs to incorporate the notion of spatial connectivity for agents' navigation. The spatial connectivity is often represented as a navigation graph or a roadmap in the fields of robotics and motion planning [50, 51]. A variety of techniques have been developed to create a navigation graph from a given building geometry, such as Voronoi decomposition and probabilistic roadmap [51, 52]. Approaches that are capable of more accurately modeling human perception and spatial cognition are based on visibility graphs [51, 53]. A visibility graph consists of nodes defined by the physical geometry of the building, its special features, and the destinations of the agents. An edge is added to link two nodes if they are in the line of sight. Although most of these techniques are commonly used for steering robots, they need to be modified for egress simulation to mimic human-like cognition and navigation, following the principles derived from the research in environmental psychology and spatial cognition [48, 49].

In most ABMs, the agent navigation routes are usually pre-defined by specifying explicitly the origins and destinations of the occupants [14, 13, 54]. Optimal routes (usually defined in terms of travel time or distance) are obtained by assuming that the agents possess good, often perfect, knowledge of the environment. Examples are the wayfinding model in EXODUS and the simulation model proposed by Kneidl et al. [13, 54]. On the other hand, some ABMs model agents' navigation decisions as the outcomes of decision-making processes, rather than pre-defined or optimized routes. One example is ViCrowd [43]. ViCrowd is a crowd simulation tool in which an agent's route can be determined by a set of dynamic behavioral rules using events and reactions. Another example is the exosomatic visual architecture (EVA) [48]. EVA implements a more sophisticated spatial representation of the environment to guide the agent's movements without the need to assign the agent with extra information about the location of a destination and an escape route. These two models consider agents' behaviors as a perceptive and dynamic process subjected to external changes.

Modeling crowds is a formidable task that has been studied in the fields of robotics and crowd simulation. Despite its challenging nature, emulating human movements is fundamental to egress simulation. Agent's navigation algorithms, such as wayfinding and collision avoidance, should be carefully designed to emulate realistic human movements, thus establishing confidence in using simulation results to improve egress designs.

Chapter 3

Theoretical Framework

In recent years, the study of crowd behaviors, especially during emergencies, has shifted from assuming individuals as identical entities acting irrationally to viewing individuals as heterogeneous actors who respond to the changes in a socially driven and collective manner [4, 5, 6, 15, 18]. The theory of mass panic has eroded as the empirical studies of past emergency accidents show little evidence of people becoming irrational and behaving ruthlessly. Evacuees continue to be concerned for other people and exhibit social behaviors, such as helping each other and even putting themselves in danger in search for missing ones [5, 6, 18]. In addition, evacuees often communicate and interact with other people to interpret the emergency situation and make evacuation decisions. The evacuation of occupants from building emergencies, as evidenced by numerous studies in disaster management and social science, is a socially driven and collective process.

Existing social theories and case studies have established a rich set of factors and social mechanisms that we can use to study evacuations; however, while each developed theory can be used to explain some egress situations, none can explain all situations. Developing a unified theory that can fully explain occupants' behaviors and reactions in different situations is difficult because of the apparently unlimited set of factors that may influence occupants' behaviors. In our work, instead of creating a new theory, we have chosen to extract and organize the critical factors and the individual and social processes from the past studies. In this chapter, we aim to (1) identify an integrated framework to study existing and prevalent social theories systematically, (2) organize and analyze the theories and case studies to examine the key factors and mechanisms underlying the behavioral outcomes, and (3) lay the foundation for designing comprehensive computer models for egress simulation.

3.1 Multi-level analysis of behaviors in egress

Human behaviors in emergencies are an instance of collective behaviors that displays emergent characteristics that cannot be reduced back to the level of individual decisions and beliefs [5, 15, 55, 56]. Although all social processes proceed from individual persons, the analysis of human behaviors in emergencies is not restricted to the individual level [57, 58]. Empirical studies of past accidents show that individual's affiliation with pre-existing groups and participation in the crowd directly impacts people's behaviors and, consequently, movement patterns [4, 59]. To explain the behaviors of the evacuees, we need to refer to the aggregated and collective characteristics of the individuals, such as group size and authority hierarchy. Our investigation focuses not only on the factors and mechanisms that are based at the individual actors, but also on the characteristics and behaviors of the aggregate and more macroscopic social structure, such as groups and crowds.

As depicted in Figure 3.1, we propose to classify the factors and the mechanisms that affect the behaviors of the occupants at three levels: the individual, social group, and crowd. The rationale to model the social group and crowd separately is that the two aggregated units have different emergent properties. Groups are underpinned by the pre-existing relationships among group members, whereas such kind of relationship is absent in a crowd. Therefore, the social influence on group members is more structured and is guided by pre-existing group norms, and the crowd influence on participants largely depends on the ad hoc interactions among the individuals. Both the concepts of groups and crowds are important to explain the emergent social behaviors exhibited by the individual occupants in emergencies, as highlighted by the links shown in Figure 3.1. At the individual level, we focus on the individual traits that shape the behaviors and the psychological and cognitive processes of the evacuees in emergencies. The group level consists of the characteristics of pre-existing group relationships and the intra-group process such as negotiation within group and leadership. Finally, the crowd level focuses on the compositions of the heterogeneous crowd and the crowd-level processes, such as emotion contagion.

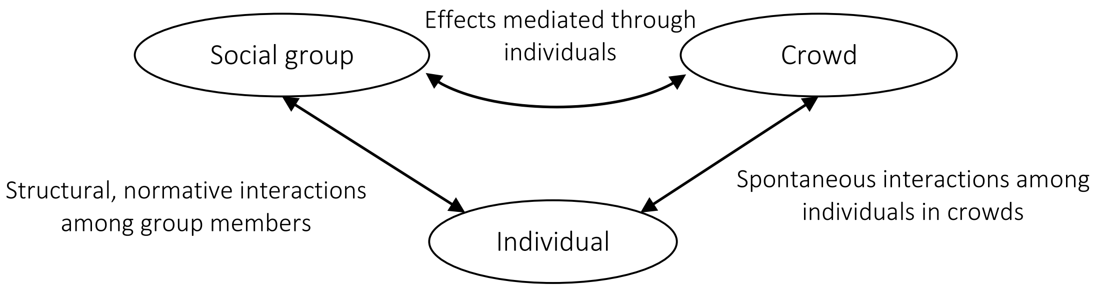


Figure 3.1: Levels of analysis of human behaviors in egress: individual, group, and crowd

3.1.1 Individual

Understanding individual behaviors is the first important step to study emerging behaviors in the groups and crowds, because social behaviors observed in emergencies arise from individual behaviors and interactions among individuals. We consider occupants as heterogeneous actors in a crowd because each actor has different individual qualities and background (such as demographics and knowledge and experience of emergencies) that lead to different interpretations and actions of the individuals, even when they perceive the same cues in emergency situations [8, 22, 15]. We investigate different aspects of individual qualities that shape the evacuees' behaviors during a rapidly developing emergency situation.

Convention and context of the place

Occupants' emergency behaviors are often shaped by the convention of the place learned by the occupants over time [15, 33]. These conventions include the type of building in which the emergency event occurs, the role an occupant undertakes in that place, and the way in which a place is used under normal circumstances. These factors collectively define the "place scripts." Through learning the place scripts, the occupants establish the cognitive structures to process and react to changes in the environment. The place scripts not only guide the behaviors of the occupants in normal situation, but also affect occupants' initial reactions to emergency situations. When encountering a new, emerging emergency situation, the occupants recall their previous "place scripts" to decide their behaviors such that they do not need to establish new rules to interpret the situation and make decisions. As reported in many studies, occupants tend to follow their prior plans (such as continuing their original intended route to exit the building) and assume that previous actions are applicable responses to the immediate emergencies [36, 18].

Prior to detecting any emergency cues that trigger evacuations, the occupants are often engaged in the goal- or place-related activities prior to the emergency, such as traveling to a particular exit in a transit station or working in the office. Different levels of engagement in previous activities can take up the cognitive capacity of the occupants to process information and render the occupants to be less sensitive to external cues; the pre-occupation of activities and events thus lead to what termed "selective attention" by the individual [44, 46]. For example, studies of residential fires show that people who are asleep are less sensitive to noises from fires and might respond to an emergency situation after a longer delay, resulting in longer cue recognition time for night evacuations than for day-time evacuations [10, 22].

Knowledge of emergency cues and emergency experiences

Emergency cues are often ambiguous in nature and vary in intensity [8, 22, 29, 60]. Ambiguity and cues of low intensity often lead occupants to recall prior experience and knowledge to help them to make sense of the situation. For example, in the 911 World Trade Center (WTC) study, an occupant who had smelled jet fuel before recognized that the smell of the smoke was from a plane rather than a regular fire [7]. With knowledge of the fuel smell, the occupant concluded that the situation was abnormal and informed others. On the contrary, other occupants who had no experience in dangerous situations did not recognize the smell of fuel, leading to longer delay in evacuation actions until they perceived obvious emergency cues that indicated the need to start evacuation. In cases when the emergency cues are consistent and intensive (such as multiple announcements of consistent messages or seeing the ignition of explosion), occupants often recognize the threats according to their instinct and initiate timely evacuation [7, 61].

Emergency evacuation experiences affect individuals' risk perception and their responses to potential risks. People who survive life-threatening experiences are likely to recall memories of negative experiences from previous emergencies. These people are more perceptive to slight emergency cues. Anchoring upon memories of negative past experiences, they envision negative consequences in response to the perceived cues [61, 62, 63]. While relevant past emergency experiences can guide the occupants to react in a suitable manner, however, experiences that do not resemble the current situation can lead to adverse consequence as the occupants recall their past experiences and actions until the situation is noticeably different from their past experiences [8]. For example, the study of the 911 WTC attack has pointed out that many survivors of the 1993 bombing were likely to interpret the booming sounds as explosions from a bombing attack and started evacuation action promptly [7, 9]. Other occupants who were not present in the 1993 bombing accident associated the loud booming sounds to previous accidental explosions in the building, such as construction or building equipment maintenance accidents, which did not lead to immediate evacuation actions. These occupants who were not involved in the 1993 bombing accident later also realized the bombing attack, but after a longer delay [7]. The extent of occupants following their past experience depends on (1) the level of confidence the occupants have in their past experience, (2) the cues perceived by the occupants, and (3) the development of the emergency situation.

Empirical evidence shows that people are poor at judging the nature and growth speed of emergency situation from ambiguous cues, such as smoke and alarm [7, 22, 64]. Emergency drills can be used as opportunities for establishing the appropriate rules about roles and responsibilities through direct experience. For example, in an office building, such drills and trainings can assign some office occupants to take the role of evacuation wardens, or perform rescue or medical duties in emergency situations [15]. By learning a particular script in response to emergencies, occupants switch promptly to appropriate behaviors in response to the emergency cues.

Knowledge of the environment

People's knowledge of the space influences their risk perceptions of the emergency event. Mawson suggested that people tend to attach to familiarity (both places and people) in emergencies and will show flight behavior only under severe danger [18]. The attachment model suggests that individuals who are familiar with the building are over-confident in their abilities to withstand danger thus lowering their perception to risk. These overconfident individuals are likely to anchor upon these perceptions when an emergency actually occurs. Attachment to familiarity can lead to prolonged delay to start evacuation. The normalcy bias is also consistent with the behaviors proposed by the attachment model. The normalcy bias suggests that occupants receiving slight and ambiguous environmental cues or lacking previous evacuation experience are predisposed to interpret the situation as if nothing is wrong [65, 66]. Because people operate under this normalcy bias, they will assume they are not at risk and might even censor conflicting cues in order to fit what is happening into the bias they anchor in [7, 44].

Moreover, people's choice of evacuation routes is affected by their familiarity with the particular place. As pointed out by Mawson and Sime, people tend to choose routes that lead to their familiar places in emergencies [18, 36]. Attachment to familiarity can lead to congestion at major exits. In a study of the 1987 King's Cross underground fire in London, Donald and Canter also suggest that people tend to use familiar exits or follow their original routes when they do not perceived immediate threats that urge them to escape [15].

In summary, facing emergencies, an occupant does not simply react to external cues; they also refer to their prior experience and learnt conventions to determine their behaviors. The wide array of individual factors relating to past experiences, knowledge, and convention explains the diverse individual behaviors in emergencies. Although the individual factors discussed do not fully represent all the possible factors affecting individual behaviors (which can be an infinite set of properties), the individual factors discussed are deemed most relevant in the context of egress and have significant effects on the behaviors of the more complex and macro-level of social entities, such as social groups and crowds.

3.1.2 Social groups

The second unit of analysis is social groups. The investigation of groups is important, as individuals often participate in mass gatherings with their social groups. We define groups as a collection of individuals who have pre-existing social relations. Some examples of social groups are families, couples, and groups of friends. Occupants affiliated with a social group often behave differently than when facing emergencies alone. They continue to be concerned for their groups and exhibit social behaviors in emergencies, such as holding discussions among group members and moving to the exits considering other group members [5, 15, 64]. Even in a rapidly developing emergency situation, people put themselves at risk while searching for others who are dear to them [4, 5, 67]. In the following sections, we discuss the characteristics of groups that influence the interaction among the occupants in their social groups.

Group size

The size of a group has significant effects on its members. To examine the effects of group sizes on group intimacy, it is useful to distinguish smaller groups, such as dyads and triads, from larger groups [68, 69]. In a dyad, each member is interdependent and largely irreplaceable to the other. When one member withdraws, the dyad relationship dissolves, whereas the relationship continues to exist for larger groups. According to Simmel, the personal interdependence between two persons in a dyad is often signified by the intimate character of the relationship, which defines the extent of how each member recognizes, and is recognized by, the others [68]. Adding one more person to a dyad to form a triad fundamentally changes the feature of interdependence and irreplaceability. In a triad, each member operates as an intermediary between the other two. The introduction of one or more members to a dyad, creating a triad or larger group, increases the formation of an objective, macro-level group structure that ties the members together. Members in a triad or larger group tend to refer to the objective, collective membership as defined in the macrostructure, rather than interact directly with the individual members. As the group becomes larger, the more easily it forms an objective collective unit up and above its members. In doing so, it becomes less intimate [68].

Additionally, the size of a group is also an important determinant in the development of group consensus via communication, which in turn determines the timing of the evacuation of the whole group. Through milling and keynoting, the key social processes suggested by emergent norm theory (ENT), people in a group create a new, emergent normative structure that guides their behaviors [19, 35]. During the milling process, individuals communicate with one another in order to collectively define the situation. During keynoting, emerging leaders suggest interpretations of the event or propose actions to be taken by the whole group. An empirical study of the 2003 Rhode Island Nightclub fire accident demonstrates that when the members in a group know others well, and the group size is large (meaning more than 20 individuals), the group is more cooperative in searching for shared meaning and it is likely to have a longer milling process [5]. Larger group size also typically requires a longer time to share information among the group members, thus leading to longer time for the group to interpret the urgency of the situation as urgent. Generally speaking, the bigger the group, the longer it takes for the group to decide to evacuate as the natural response to a crisis.

Types of relationships

According to Simmel's seminal study on social groups, there are several different kinds of relationships between individuals; these are interest groups, acquaintances, discretions, friendships and love relationships, and marriage unions [68]. Members of different types of social relationships have different degrees of reciprocal knowledge regarding members. For example, in an interest group, the members are associated with one another based on a particular interest; the interaction and the pursuit of common purpose does not depend on people's psychological knowledge of the others in the group, whereas in personal relationships, like friendship and marriage, the connection is built upon knowledge of another in their totality, rather than mutual interest, and therefore there is a greater amount of reciprocal knowledge.

Members, with different risk perceptions on the emerging situation, interact to reach a consensus and define new group norms [19, 35, 69]. The intensity of the social interactions to arrive at consensus depends on the kind of social relationship the evacuees belong to. Empirical research shows that enduring social relationships can facilitate the process of recognizing threats and initiate early evacuation, as group members are able to ascertain the situation more quickly, and then utilize available resources more effectively [55]. Moreover, facing emerging, emergency situations, a group with greater diversity of knowledge and experience might face more conflicts in risk perception among its members, thus requiring more interactions among the members to reach a consensus for collective actions, potentially prolonging the group evacuation process.

Mutual helping among members, as a resulting of strong pre-existing relationships, is commonly observed during evacuations [4, 5, 17, 65]. Members of groups cooperate with each other, engaging in behaviors such as helping one another in difficult situations and searching for missing members; these exhibited behaviors are not only the result of maximizing personal benefits but also the result of showing concern for others. The social behaviors are also supported by affiliative theory, which states that individuals' flight behaviors are motivated by individuals' desires to stay close with their familiar objects (e.g., attempts to escape with other group members with close psychological ties) [18].

Leadership

Group leadership has an effect on both the interpretation of the event (milling) and the decision-making process (keynoting). Emergent norm theory (ENT) hypothesizes that, for groups with clear leadership, meaning a predefined leader role, members are likely to have a more effective milling process because group members tend to observe group norms and follow group leaders [19, 48]. However, for a group without a clear leader, milling can be slower, or even ineffective [55]. Nevertheless, during keynoting, new leaders may emerge, proposing interpretations of the situation or providing suggestions on what to do next [19]. People who become emergent leaders might not be the one who conform to the norms of the group, nor the predefined leaders in the group [16, 19, 35]. More likely, in these situations, the member of the group who becomes the leader is the one who "proposes an innovative solution to the current situation that is judged plausible and credible [by the others] [11]." An individual with relevant experience and knowledge on evacuations also has a greater chance to emerge as the leader because others perceive them as more certain about the situation. For example, in the case of the 2001 World Trade Center terrorist attack, survivors reported that some non-management individuals emerged as leaders and used authoritative voices to issue clear directives [7].

Group level characteristics, group size, the type of pre-existing relationships, and leadership affect the collective behaviors and the outcomes of the groups. Motivated and mediated by their past and present group relationships, individuals interact with each other to exchange information, interpret the situation, and arrive consensus collectively in response to the emerging emergency situation. Members in social groups not only influence each other's individual evacuation behaviors, such as speeding up or delaying evacuation, or choosing a particular egress route, but they also foster different social and altruistic behaviors, such as helping or even putting oneself at risk for the dear ones, which have been widely reported in disasters and emergencies. Group behaviors in emergencies have unique characteristics that cannot be reduced back to the individual level, nor can they be generated from the interactions of isolated individuals. The aggregated and macroscopic social structures have to be considered in order to explain different group behaviors.

3.1.3 Crowd

Mass-gathering events, such as concerts and sports games, are typically composed of a number of small groups and non-socially bonded individuals. Even without any prior connections, as a participant of a larger crowd, an individual will interact with their surrounding crowd during an emergency. Studies of past incidents have shown that people exhibit certain social behaviors during a crisis, such as following the majority to escape a situation or helping people who have no prior social ties [4, 6, 33, 70]. In the following sections, we investigate the dynamics of the crowd and its participants.

Role extension and authority

People with special roles in normal situations, such as managers or staff members, often extend their roles and assume certain responsibilities in emergency events in order to serve others. These people with special roles define their responsibilities and expected functionalities by referring to their previous functional roles and the place convention learned over time [15, 33]. In places and facilities with transient populations, such as restaurants and theaters, it is unlikely that evacuation training with the occupant population would have taken place. In these situations, occupants would likely rely on the instructions given by the staff to define their actions. For example, in the Beverly Hills Supper Club Fire in 1977, staff and security personnel reported that they facilitated the evacuation, instructing the patrons to escape [17]. Similar role extension behaviors were observed during the Rhode Island Nightclub Fire in 2003, where the staff prevented patrons from exiting through special passages used by performers, and directed the crowd to the main entrance instead [5].

Symbols of authority, such as uniforms, suggest potential leaders among the crowd. These authoritative personnel (such as building managers or emergency responders) serve as social control agents who regulate the actions of the individuals in the crowd. Studies have shown that people rely heavily on the instructions given by the authorities to guide their evacuation decision because they consider the information provided by the authority in emergencies as an important and credible source of information. For example, in the 2003 Rhode Island Nightclub Fire, staff prohibited patrons to exit through the special passage that was used by special personnel only, and the patron in the nightclub followed the instructions and used exits that were farther away even in emerging danger [5]. Although individuals in crowds comply with instructions and information given by authorities in most cases, when the messages are inconsistent with the majority of the crowd's belief, advocators with innovative ideas or specific knowledge of the situation may take the role to initiate a collective movement. In this situation, the role of leaders can shift [35] – "[keynoting] is an interactive and not a unidirectional process; official directives are often ignored because of inaccurate understanding by the authorities of the priorities and needs of people [11]."

Emotions of the crowd

Different types of crowds have different purposes, activities, and overall emotions. For example, there are ambulatory crowds, in which individuals walk in the space in a relaxed manner; spectator crowd, consisting of people gathering for a particular event with excitement and cheer; or there can be violent crowds, that can exhibit hostility or fear. The types of crowd predetermine the overall state of emotions of the crowd, and some crowds are more susceptible to heightened tensions and intensified states of emotions [34, 19].

Even in non-emergency situations, the occurrence of events that trigger emotional arousal among a crowd, such as a false alarm or a severe confrontation between two groups, can change the emotional state of the people who are in the group. Further, emotional arousal among a local crowd can be contagious [34, 37]. The process of emotion contagion is explained by different social theories using various mechanisms. For example, social comparison theory suggests that individuals update their perception and urgency to escape an event in comparison with others who are facing the same situation [42]. Furthermore, contagious theory assumes that an individual becomes a member of the crowd with anonymity and becomes emotionally identical to the others in the crowd. Influenced by the crowd, a person would feel, think, and act in a different manner than if the person is isolated from the crowd [34]. Generally speaking, individuals, as participants in a crowd, both overtly and implicitly perceive the energy of the crowd, and thus their perception and state of emotion are influenced by the crowd's behavior.

Convergence of majority behaviors

Individuals in a crowd observe each other and mimic one another's actions, particular in uncertain and unfamiliar situations [38, 71]. Over a period of time, preferences and behaviors converge, and a herding phenomenon may result. The herding phenomenon is indeed commonly observed in pedestrian movements. Herding behaviors are important behaviors to be considered in emergencies because they can lead to serious congestion and uneven usage of available exits, hence prolonging the evacuation process.

Herding in crowd movement during an emergency is dynamic in nature, and it can even dissolve as an emergency situation is dynamically changing. For example, in the 2003 Rhode Island Nightclub Fire, people initially attempted to escape through the main entrance because it was the familiar exit, and most people were moving in that direction. When the main entrance became too congested, some individuals withdrew from the crowd and broke the windows to exit the building. Others observed the new alternative method of escape via the windows and followed. As a result, about one-third of the survivors escaped from these unconventional egress outlets [5]. Unlike herding in the context of social migration and polarization, which are presumably irreversible processes [72], herding phenomena in crowd movement are transient and are subjected to changes in the dynamic emergency environment.

Emergence of social relationships

Individuals in a particular crowd often share some common interests and have a similar purpose for being in the gathering; for example, an audience in a stadium might be there to attend a sport game or concert-goers to see a musical performance. According to Simmel, the association based on a particular interest constitutes the most basic and causal form of a social relationship—the interest group [68]. Interest groups form the foundation for emergent, collective and social behaviors among a particular crowd that consists of individuals with no prior social ties. Different crowd theories have developed to study the social processes that lead to emergent groups and identities among heterogeneous actors in a crowd, such as self-categorization theory and emergent norm theory (ENT) [6, 35].

As suggested by self-categorization theory, individuals in an evacuating crowd tend to categorize themselves not only with their personal identity “I” but also with the social identity “we,” grouped by common emotions and perceived fates [6, 17]. Increasing environmental threats strengthen the “we-ness” (i.e., crowd identity) and intensify emotions. According to self-categorization theory, an emerging collective identity motivates people’s social and altruistic behavior, such as mutual assistance among strangers. Moreover, the notion of groups described in ENT can be extended more broadly to include emerging groups within a crowd. ENT emphasizes that social behaviors, such as following a leader and helping others, can be explained using group relationships. In emergencies, emerging psychological groups are formed through interactions; once these groups are developed and consolidated, members are likely to interact with one another to exchange information, come up with new norms and expectations, advocate for actions, and show concern for others [16, 35].

Personal space and crowd density

People typically seek interaction with others in their surroundings, while trying to avoid intruding others' personal space and defend intrusions [73, 74]. The preferences for personal space vary depending on different individual and sociological factors, such as cultures and genders. Nevertheless, people tend to follow social norms except under atypical situations such as overcrowding and emergencies [75]. Maintaining personal space clearly has an impact on the movement speed of the individuals because individuals are constrained by not only their physical mobility, but also the social rules that resist them to move freely based on their decisions. Several studies have conducted to explore the relationships of crowd densities and movement speed of the people, such as the crowd flow diagrams developed by Fruin and the Green Guide [20, 59]. When crowd density reaches a certain magnitude, such as the safety limit of 4 people per square feet suggested by Still, maintaining personal space may become practically impossible [59].

The greater the crowd density, the more likely it is that comfort is diminished and risk to individuals is increased [21]. In extreme high crowd densities, the pushing force of the surrounding crowd forms a "supra force," which is transferred among the individuals in a crowd, moving the crowd without individual self-control [5]. Often, trampling and stampedes are not caused by people's ruthless intentions to harm others, but are rather the unintended events caused by the uncontrolled overcrowding conditions [17, 23]. For this reason, the interior design of buildings and facilities needs to address the potential occurrence of overcrowding by identifying high congestion areas along critical egress routes.

The evacuating crowd has both structured qualities and emergent qualities. The structured qualities are often determined by previously established social norms regarding authority and personal space. The emergent qualities result from the interactions of individuals who are not socially bonded prior to an emergency event. Through the interactions of the individuals in the crowd, emotions spread, identities are formed, and groups emerge. The social interactions among a crowd are transient and less structured when compared to groups, which result in different emerging phenomena in the case of a mass evacuation.

3.1.4 Summary

Based on a multi-level analysis of human behaviors during an emergency exit, we conclude that occupants' movements are neither random nor irrational; instead, they are the results of individuals' decisions and social interactions, and are mediated by different individual and social factors. Figure 3.2 summarizes the factors at each level and the influences between the different levels. It shows the important characteristics affecting behaviors in emergencies, which describe the individual, group, and crowd; the latter two have characteristics that are essential and are irreducible back to the individual level.

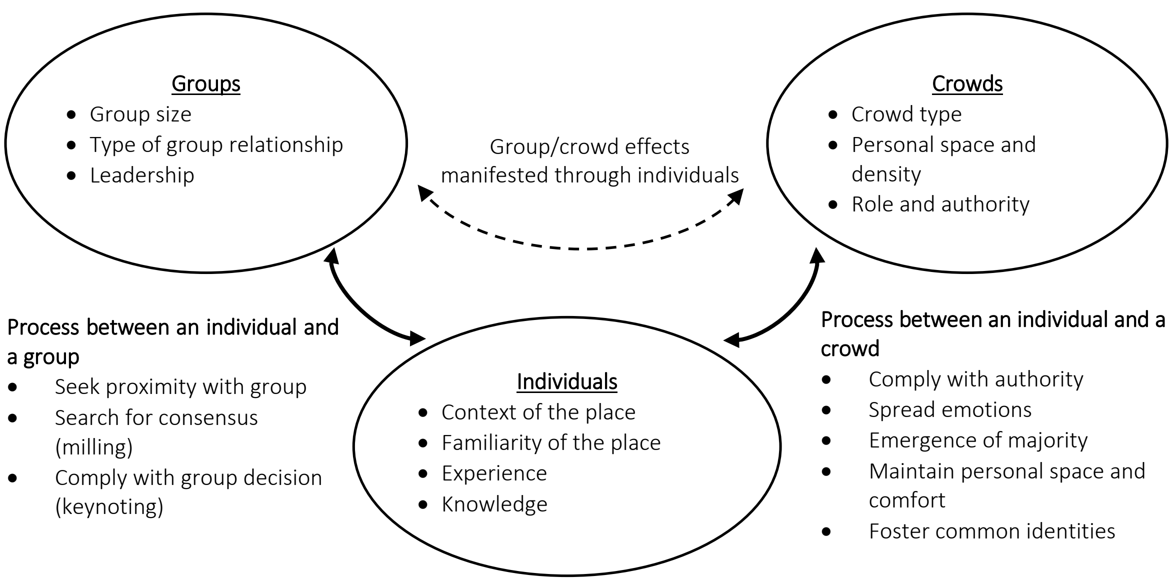


Figure 3.2: Individual, group, and crowd level factors and processes

The micro-to-macro connections between the individual and his/her social group, as well as the connections between the individual and his/her surrounding crowd, are important and relevant in the context of egress because the characteristics at one level directly affect the other through the connections. The macro-to-macro link between the group and the crowd, however, is less direct. The effects of crowds on group, and the vice versa, have not been fully explored, such as whether a pre-existing group relation would strengthen or weaken in a crowd with heightened mood. We conjecture that the macro-to-macro pathway is mediated through individuals. For example, a member in the group (i.e., an individual) is influenced by the crowd to choose a particular route; and his/her decision in turn affects other members in the pre-existing groups.

3.2 Implications for modeling egress behaviors

To reproduce the human behaviors in emergency evacuation, an egress simulation model needs to capture the important factors that influence the occupants. Based on the analysis, we conclude that the representation of evacuees in simulation model needs to address the behavioral characteristics at the individual, groups, and crowd levels. An entity mimicking an occupant in the simulation model should be considered not only as an individual entity, but also as a member of the social groups and a part of the crowd. Such simulation model needs to replicate not only the physical mobility of the occupants but also, more importantly, the behavioral aspects and social characteristics of the occupants.

In choosing the modeling unit to represent the evacuating population, there are three possible choices as informed by our analysis: individual, group, and crowd. We choose to keep the agency at individual level because it is methodologically hard and theoretically difficult to attribute agency to a group or a crowd directly. Nevertheless, we emphasize the need to define individual agents as a part of the group and crowd. Among the different prevalent modeling paradigms for crowd simulation (reviewed in Section 2.3), we adopt the agent-based simulation paradigm to represent the building occupants and model the occupants' behaviors in egress. We summarize the important requirements in designing a simulation framework for modeling human behaviors in egress:

Representing occupants as the agents embedded in groups and crowds

- Define agents with past history, including individual physical traits, experience of emergency, knowledge of the building, and their routines and roles in the building; consider the effects of the "past" in agents' behaviors.
- Model the sociality of the agents not only with individual psychological variables, such as emotions and personality, but also the agents' affiliation and position in the macro-level structures, such as social groups and the crowd.
- Define the collective structure with background and "history," such as the size and the type of relationship of the social groups, the nature of the crowds and role of authority within the crowd, because these qualities set the initial conditions of the social interactions and cannot be generated or emerged during the emergency events.

Modeling agent's capability to interact with others and the environment

- Model the perceptive and cognitive capability of the agent to dynamically perceive and interpret emergency cues such that agents' evacuation action is perceptive (i.e., initiated based on perception) rather than prescriptive (i.e., predefined actions).
- Assume certain communicative abilities of the agents and social influence mechanisms to account for the agents' interaction and influencing process.
- Consider the social interactions and processes among the agents that are motivated by the pre-existing social relationships (i.e., the social groups) and the social interactions with other agents (i.e., the crowds).

Considering ecology and context of the event and the egress environment

- Define the initial spatial distribution of agent population in the building space, which affects whether the agent population can perceive emergency cues that are triggered by local events.
- Consider the initial separation of group members that determines the visual presence of members to each other – the prerequisite to initiate the group interaction and the absence of group members can lead to other group behaviors.
- Model the context of the emergency situation, such as the triggering events and the occupants' activities during the time of events, because these factors have direct impacts on the agents' risk perception and urgency to evacuate.

- Represent the physical geometry and the safety designs unique to each building, in which the agents perceive and move around.

Providing a flexible and modular framework to test diverse human behaviors in egress

- Ground the simulated behaviors on the empirical evidence and observations in real-life situations and past incidents, rather than oversimplifying or generalizing the human behaviors with simple rules.
- Design a highly flexible and modular modeling platform that can capture and model a wide array of human and social behaviors that simulate the diverse human behaviors observed in real life egress situations.

Based on the requirements derived based on the analysis of social theories and historical studies, we design a computational simulation framework that incorporates individual, group, and crowd level behaviors to study different individual and social factors in egress.

Chapter 4

SAFEgress Framework

SAFEgress (**S**ocial **A**gents **F**or **Egress**) is an agent-based model designed to simulate individual, social, and emerging crowd behaviors during evacuations. Three key egress components are modeled in SAFEgress: building environment, occupant population, and emergency cues. The representations of these components are designed to allow agents to interact with other agents and perceive the environment. The SAFEgress framework is described over two chapters. In this chapter (Chapter 4), we provide an overview of the framework and discuss the representation of the egress environment and the occupant population (i.e., the agents). In Chapter 5, we will focus on the simulation process and the agent behavioral cycle, which determines the individual and social behaviors of agents during simulations.

In the following sections, we first describe the major modules in the SAFEgress framework. Then, we explain the model of the building environment, which is also called virtual environment, and the representation of the building occupants by autonomous agents. Last but not least, we describe the agents' perception and navigation capabilities, which allow agents to interact with each other and with the virtual environment.

4.1 SAFEgress architecture

Figure 4.1 depicts the system architecture of SAFEgress. The three key modules are the Global Database, Crowd Simulation Engine, and Agent Behavior Models Database:

- The Global Database stores all the information about the agent population, the geometry of the building, and the emergency cues. It also maintains the state of the agents (such as mental states and behavioral decisions) and the status of the cues during simulations. The Global Database is supported by the Population Generator, the Geometry Engine, and the Situation Data Input, which will be discussed in Sections 4.2-4.4 of this chapter.
- The Crowd Simulation Engine is responsible for performing time-step simulation by iterating a loop that models an interval of the simulated time. The main algorithmic steps of the Crowd Simulation Engine are described in Figure 4.2. At each simulation step, the Crowd Simulation Engine updates the emergency events (also called cue objects) and the behavior of each agent. It also tracks the number of active agents and ends the simulation when all agents have exited the building. The perception and navigation of the agents are modeled in the Perception and the Navigation sub-modules, which will be described in Section 4.4.2 and Section 4.4.3, respectively. At the end of each step, the Crowd Simulation Engine stores the results in the Global Database and the Result Recorder, and graphically displays the simulation through the Visualizer.

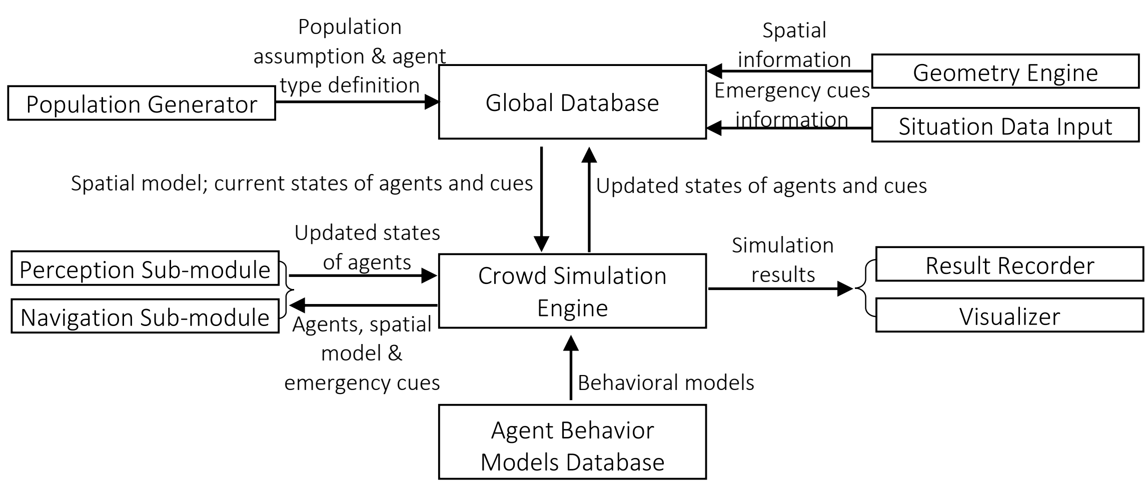


Figure 4.1: Architecture of SAFEgress

```
Procedure: Crowd Simulation Engine
Create the virtual environment by calling the Geometry Engine
Initialize cue objects by calling the Situation Data Input
Instantiate agents by calling the Population Generator
UNTIL all agents are evacuated,
    Check status of emergency cues
    FOR each agent (picked in random order),
        Compute agent's action over a time interval
    END FOR;
    Call Visualizer to generate graphic output;
    Record results in the Result Recorder;
END UNTIL;
```

Figure 4.2: Algorithmic steps of Crowd Simulation Engine

- The Agent Behavior Models Database contains the individual, group, and crowd behavioral models. These models are used to define agent's behaviors during the simulation. In additional to the default behavioral models implemented in the framework, users may create new models to investigate a wide range of behaviors that are observed during evacuations.

SAFEgress decouples the definition of agents and environments from the simulation logic. Information about the three key egress components (occupant population, building environment, and emergency cues) is provided by the users through specific sub-modules (the Population Generator, the Geometry Engine, and Situation Data Input, respectively). The logic and procedures to update the states of the agents and the cues are specified in the Crowd Simulation Engine. Decoupling the representation of the egress components and the simulation logic allows the users to (1) easily generate and test different crowd population by specifying different population distributions in the Population Generator module, (2) model multiple building environments and emergency cues that describe different egress scenarios by providing different inputs to the Geometry Engine and Situation Data Input respectively, and (3) incorporate different updating functions by modifying the logic and procedures in the Crowd Simulation Engine.

4.2 Virtual environment

Building geometry and locations of certain building features (such as doors) have major impact on the occupants' choice of egress routes [48, 76]. In SAFEgress, a spatial model called virtual environment is set up from the users' inputs to the Geometry Engine. The virtual environment represents the geometry of the building layout and the locations of navigation features (see Figure 4.3). With the information from the virtual environment, an agent can avoid collision with obstacles, detect navigation features, and determine navigation directions during simulation.

The geometry of the building is modeled by a 2D collection of rectangles representing projections of obstacles (e.g., walls and furniture) on the horizontal floor. The information of the obstacles is used during the simulation to perform (1) visibility tests to determine which subset of the virtual environment is visible to an agent and (2) collision tests to determine the separating distance between an agent and the nearby obstacles. In the current version of SAFEgress, all obstacles are both navigation and view obstructing. In other words, no obstacle is only navigation obstructing (e.g., a glass wall) or only view obstructing (e.g., a curtain).

In emergency evacuation, people often use building features (such as doors and exit signs) to guide their navigation across the building [76]. SAFEgress represents such features as navigation objects, each defined by its type, location, orientation, and, in some cases, directional information. The characteristics of the navigation objects are provided by the user. Figure 4.4 shows instances of navigation objects. In the current SAFEgress, three types of navigation objects are implemented:

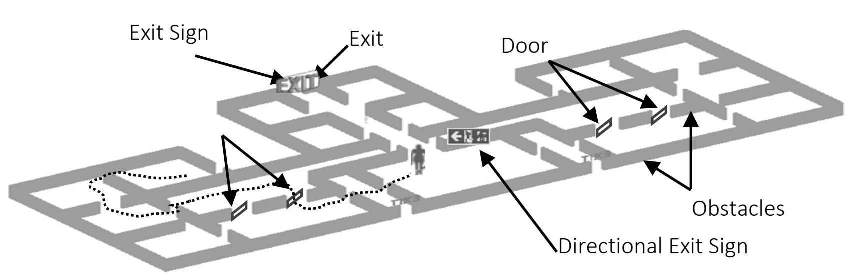


Figure 4.3: Illustration of virtual environment

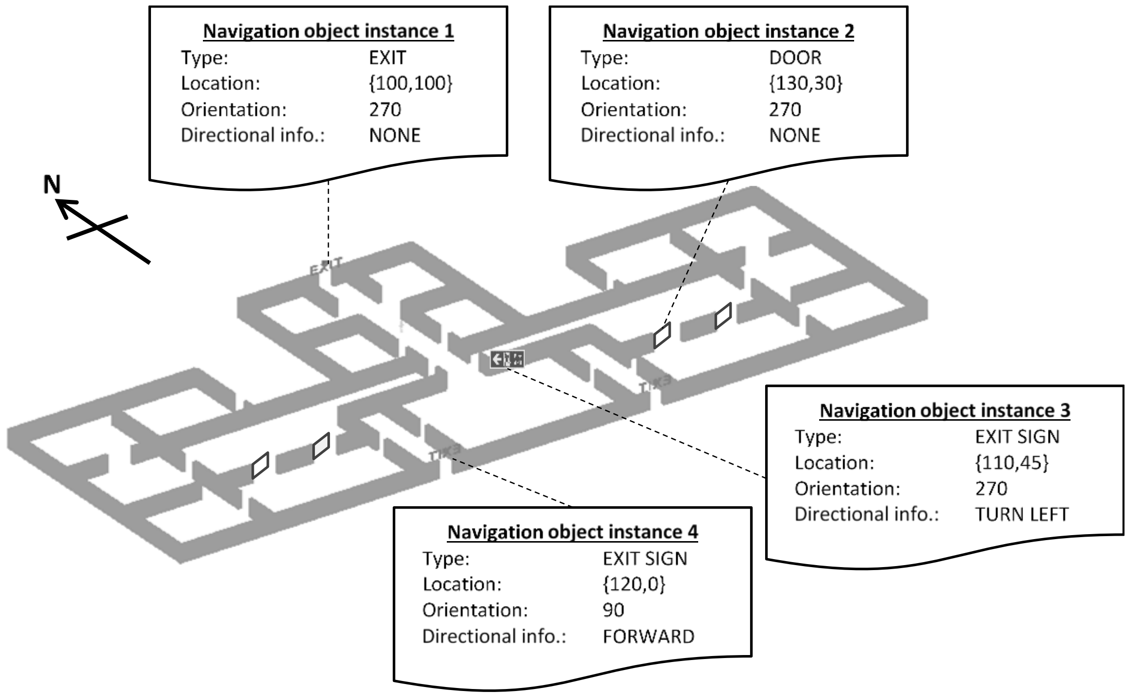


Figure 4.4: Instances of navigation objects

- Exit objects: each exit object represents an outlet of the building. If an agent decides to escape through a specific exit, it navigates toward the location recorded in the exit object. When the agent reaches the exit, it is removed from the building. For example, "navigation object instance 1" in Figure 4.4 represents an exit outlet that leads agents to the outside of the virtual environment.
- Door objects: a door object is similar to an exit object. However, upon arrival to a door, an agent is not removed from the building. For example, "navigation object instance 2" shown in Figure 4.4 represents a south-facing door that leads agents from one room to another.
- Exit sign objects: an exit sign object serves as an attraction point for the agents. It may also provide navigation instruction. For example, in Figure 4.4, "navigation object instance 3" represents an exit sign with directional information "turn left" and "navigation object instance 4" represents another exit sign with directional information "forward."

Although exits, doors, and exit signs do not represent all possible building safety features, they are the most salient features in egress design and provide key information to guide people's evacuation routes. The representation of navigation objects in SAFEgress is designed to accommodate additional types of navigation objects.

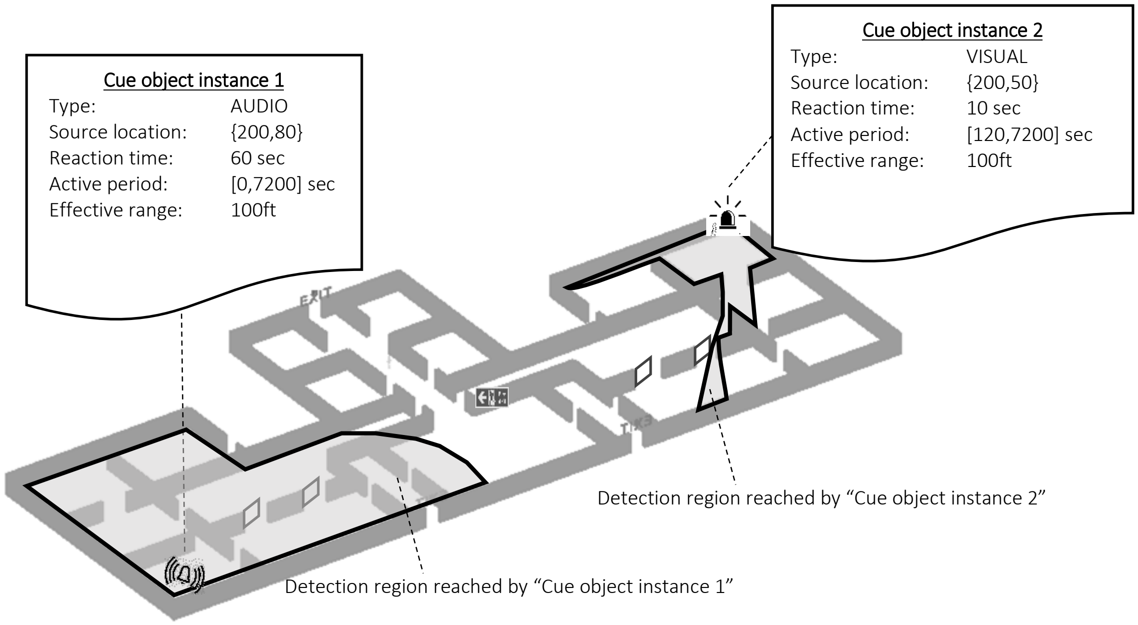


Figure 4.5: Instances of cue objects

4.3 Representation of emergency cues

During emergencies, occupants are frequently presented with cues that trigger evacuation actions [8, 60]. Some common emergency cues are alarms, flashlight, and fire [10]. We model such cues using cue objects, which are defined by the type, source location, effective range, active period during the simulation, and reaction time. The reaction time specifies the expected time lag of an occupant to initiate a new evacuation action after perceiving the cue assuming that the occupant has no prior experience of the cue. The characteristics of the cue objects are provided by the users through the Situation Data Input. The current SAFEgress implements two types of cue objects:

- Audio cue: It refers to an announcement or an alarm. An agent can detect the audio cue when the agent is located within the effective range of the cue object. For example, as shown in Figure 4.5, "cue object instance 1" represents an alarm cue that is active throughout the simulation (by defining a long active period from time = 0 to time = 7,200 seconds, i.e., 2 hours) and affects all the agents that are within 100 ft. from the source location.

- Visual cue: Visual emergency cues, such as flashlight or fire, are detectable by an agent's vision capability. An agent detects a visual cue when (1) the agent is within the effective range of the cue object and (2) the line of sight between the agent and the location of the cue object is not obstructed by any obstacles. In Figure 4.5, "cue object instance 2" represents a flashlight that could be detected by the agents within an effective range of 100 ft. of the object.

Occupants perceiving ambiguous cues often take longer time to assess the emergency situation and trigger evacuation actions after a longer delay, while unambiguous cues with high intensity (such as fire or explosion) cause the affected population to react quickly [22, 61, 8]. For example, from the studies of past residential fire, Proulx found that, after perceiving an alarm, the evacuees started evacuation after 3 minutes to 20 minutes; whereas in the situation when an announcement was used, the average delay time was within one minute [60]. In SAFEgress, each detected cue object has an effect on the agent's urge to start evacuation or modify its current evacuation actions. Emergency cues with different effects on agent's urgency can be modeled by varying the reaction time associated with the cue. For example, in Figure 4.5, "cue object instance 2" has a shorter reaction time than "cue object instance 1"; therefore, the agents perceiving "cue object instance 2" typically start evacuation sooner than those perceiving "cue object instance 1."

4.4 Agent

Each occupant is represented as an autonomous agent with a set of static attributes[1] describing its individual and social characteristics. In the following, we first describe the agent's attributes; then, we present the perception and navigation capabilities of the agents.

4.4.1 Agent attributes

Attributes specify the agent's physical traits, experience profile, affiliation with social group, and social traits. We select the agent attributes based on our analysis discussed in Chapter 3. This choice

[1] The values of static attributes of the agents are defined by users prior to simulation. The dynamic attributes of the agents, which will be introduced in Chapter 5, are updated during simulations. In this thesis, the term "attribute" refers to static attribute unless otherwise specified.

is crucial because the attributes implicitly define the spectrum of the agent types that users can specify and test with SAFEgress. So, we must define attributes for not only individual behaviors, but also group and crowd behaviors. We categorize the agent attributes, listed in Table 4.1, into three levels – individual, group, and crowd – as described below (attributes are shown **in bold** characters).

- Individual level: each agent is assigned to a **physical profile** that specifies its demographics, body size, and movement speed (see Table 4.2) [12]. Furthermore, the agent's decision to evacuate depends on its previous experience with emergencies and familiarity with the building [7, 15, 33, 18]. The agent's emergency experience is quantified using a set of **cue awareness factors**. Each factor describes the level of threat perceived by the agent upon detecting the cue object during simulations. The agent's familiarity with the building is defined by a set of **known exits**, the locations of which are known by the agent.
- Group level: each agent can be affiliated with one predefined **social group**. Each social group consists of a group of agents. An agent with a group affiliation does not systematically exhibit group behaviors; instead, the agent is likely to exhibit group behaviors only when it has a high compliance with the group, which is defined using the attribute **group compliance**. To model the relationships within a group, each social group is characterized by the attributes **group influence**, **time to reach group consensus,** and **group separation tolerance** (see Table 4.3). The group influence describes the agent's influence on other members in the same group — the higher the value of an agent's group influence, the more influential the agent is among its

Table 4.1: Agent static attributes

Level	Static attributes	Range of values
Individual	Physical profile Cue awareness factors Known exits	see Table 4.2 array of non-zero positive numbers of size equal to no. of cue object instances array of exit objects
Group	Group compliance Social group	high/low social group index*
Crowd	Crowd compliance Crowd-following time lag Social order Assigned tasks	high/low non-zero positive integer non-zero positive integer between 1 and 10 (inclusive) 2D coordinates of duty location; 1 exit object as exit instruction

* Each social group is characterized by the attribute group influence, time to reach group consensus, and group separation tolerance (see Table 4.3)

group members. Group members also tend to start evacuation as a group [5, 55], and the time needed for the group to collectively decide evacuation is specified by the time to reach group consensus. Moreover, the agent uses the group separation tolerance to detect whether it is too far from the group (i.e., if the average separation from other visible members is larger than the group separation tolerance). By instantiating group level attributes with different values, different kinds of group relationships can be defined. For example, a family group can be defined with a shorter time to reach group consensus because the group members know each other's skills and can utilize the resources more efficiently as compared to a loosely related group [55].

- Crowd level: agent's **crowd compliance** describes whether the agent will be influenced by the surrounding crowd [15, 38]. Under the crowd influence, the agent adopts the risk perception of its neighbors after certain amount of time, which is specified by the **crowd-following time lag** attribute. The agent's social position is defined by the **social order** that reflects the likelihood of the agent to influence other agents [17]. Special agents, such as authority figures and safety personnel, are typically defined with high social order so that these agents can influence the risk perception and evacuation decisions of other agents. The special agents with **assigned tasks** are responsible for providing the neighboring agents with the instructions to exit [5, 15]. An assigned task specifies both (1) the location where the special agent must perform the task and (2) the exit that the neighboring agents should evacuate from.

Table 4.2: Agent physical profiles [12]

Population type	Radius of whole body circle (in.)	Radius of torso circle (in.)	Radius of shoulder circle (in.)	Walking velocity (in./sec.)
Adult Male	10.6	6.3	3.9	53.2
Adult Female	9.4	5.5	3.5	45.3
Child	8.3	4.7	2.8	35.4
Elderly	9.8	5.9	3.5	31.5

Table 4.3: Agent static attributes at group level

Group attributes	Range of values
Time to reach group consensus	non-zero positive integer
Group separation tolerance	non-zero positive integer
Group influence	array of non-zero positive float between 0 and 1 of size equals to the group size

In additional to the individual, group, and crowd attributes that describe the characteristics of an agent, a **behavioral profile** is also assigned to each agent. It specifies the pre-evacuation behavior (initial behavior at the start of the simulation), as well as the individual, group, and crowd behaviors to be invoked when the agent decides to evacuate. The behavioral models in the Agent Behavioral Models Database can be used to instantiate the behavioral profile. Details of behavior modeling of the agent will be described in Chapter 5.

Users can create different types of agents by assigning different values to the attributes of the agents. For example, a "frequent visitor" agent can be defined by assigning all exit objects to the attribute **known exits**, whereas a "first-time visitor" agent has no **known exits**. Furthermore, users can specify the distribution of different agent types within the population (such as a 50/50 distribution of frequent visitors and first-time visitors). Both the definitions of the agent types and the population distribution over different agent types are inputted through the Population Generator.

4.4.2 Perception

Building occupants receive emergency cues that make them aware of emergency situations. Moreover, the occupants observe their group members and the nearby crowd to obtain information on the situation and discuss the appropriate course of actions [4, 65]. In SAFEgress, each agent is able to perceive the virtual environment, the emergency cues, and other agents through the perception sub-module of the Crowd Simulation Engine.

4.4.2.1 Detecting visible objects by point tests

Agent's visibility of a particular object in the space is implemented using a point test [44]. The algorithm takes the location (point P) of a particular object and determines that the object is visible if: (1) P lies within the cone of vision of the agent, (2) P is within the perception distance of the agent, and (3) the line segment between the agent and P does not intersect with any obstacles[2].

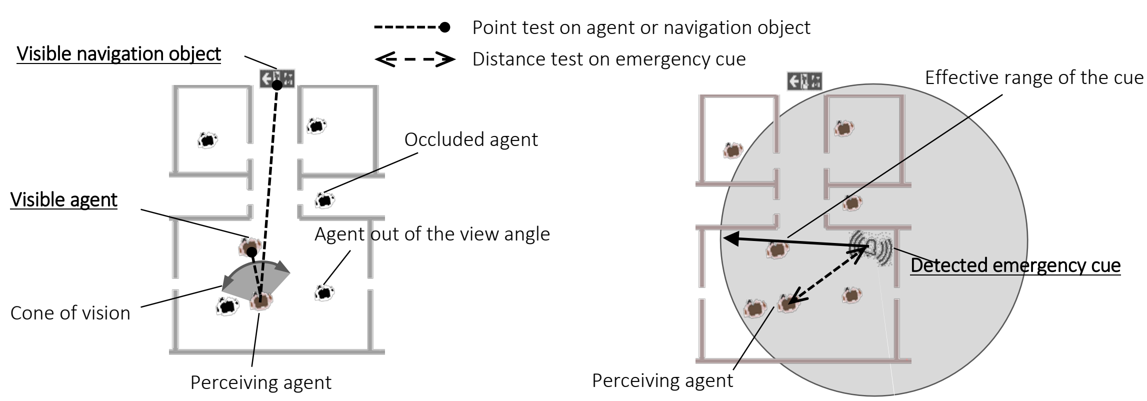
[2] We assume that an agent's line of sight is not obstructed by other agents. This assumption is deemed reasonable because the crowd blocks an agent's vision only temporarily as the agents are constantly moving during simulation.

During simulation, the agent detects visual cues, building safety features, and other agents to guide their evacuation decisions. As illustrated in Figure 4.6a, the agent invokes a point test to determine whether an object is visible. Different perception ranges can be defined for different objects in order to better mimic human perception [46]. For example, an agent's perception range to detect nearby agents is typically shorter than the perception range to detect an exit sign because, during evacuation, a person is more likely to direct his/her attention toward signage that provides guidance to egress routes, instead of observing the crowd that is far apart.

4.4.2.2 Detecting audio objects by distance tests

An agent's ability to detect an audio object, such as an alarm cue, is implemented by a distance test. If the agent is located within the effective range of the audio object, then the agent is able to detect the object.

During simulation, various cue objects may become active at different times and last for specific periods of time. At each simulation step, each agent determines whether it can detect any audio objects by performing distance tests with detect the active audio objects (Figure 4.6b). The detected audio cues are recorded and used by the agents to adjust their behaviors.



(a) Point test to determine if an agent or an object is visible

(b) Distance test to detect an emergency cue

Figure 4.6: Agent perception tests

4.4.2.3 Locating neighboring agents with grid method

During simulation, each agent detects other agents in its vicinity to assess its urge to evacuate and to avoid collisions with them. Different algorithms to efficiently detect neighboring agents for collision avoidance have been explored in crowd simulation research [77]. The grid method is an efficient algorithm for proximity and collision tests within a large crowd [44]. SAFEgress implements and extends the grid method to track the agents using a 2-D grid and to allow an agent to retrieve its neighboring agents.

In a pre-computation phase prior to simulation, a 2-D grid of uniformly sized square cells is casted over the virtual environment. Each cell of the grid maintains the subset of agents that reside in the cell. In the current implementation, the cell size is 60 inches by 60 inches, which can accommodate approximately 25 -30 agents in extreme crowd density.

During simulation, the movement of an agent across two cells triggers an update that removes the agent from the previous cell and then registers the agent in the new cell. Figure 4.7 illustrates the process of retrieving the list of neighbors of an agent. When the agent needs to locate the agents in its vicinity, it queries the grid with its current location and obtains a list of neighboring agents that are residing in its cell and the 8 adjacent cells (Figure 4.7b). The agent can then perform point tests to detect the visible agents from the list (Figure 4.7c). The grid method to retrieve neighbors of an agent has constant time complexity because the number of neighbors is bounded by the number of agents residing in the 8 adjacent cells and the agent's cell.

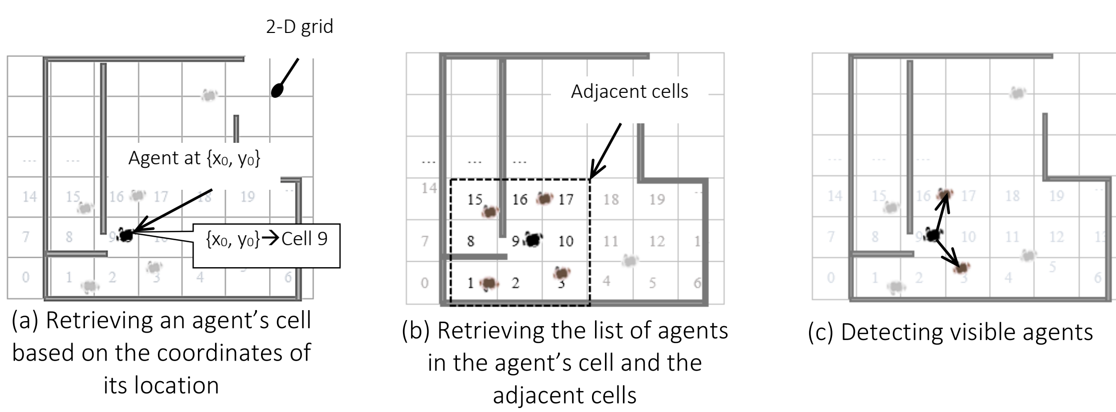


Figure 4.7: Grid method to locate an agent's visible neighbors

4.4.3 Navigation

During evacuation, building occupants choose evacuation paths and navigate to the exit. We design the navigation sub-module following studies in the fields of environmental psychology [48, 47] and robotic motion planning [77, 53, 50]. Each agent is equipped with abilities to perform (1) high-level wayfinding to explore the environment and travel to their navigation goals and (2) low-level locomotion to move toward the navigation target.

4.4.3.1 High-level wayfinding

Humans move naturally in a direction that allows them to explore the environment further [48, 49]. This navigation strategy is similar to the next-best view method used by a robot when constructing the map of an unknown environment [53]. At each step, the robot maximizes the expected amount of new spatial information it will obtain at its next position. In SAFEgress, we employ the concept of visibility map in motion planning to represent the space. In a pre-computation phase prior to simulation, we compute navigation points (denoted as “NP”) and create a navigation map (i.e., a network of NPs). The NPs and the navigation map are used during simulation to allow agents to make navigation decisions efficiently.

NPs are points in the virtual environment where visibility is locally maximal area-wise. The NPs are computed as follows:

- The continuous space is first discretized into a uniform grid of square cells. Then, for each cell, the visible region of the cell is calculated as the region that can be seen without any obstruction from the center of the cell (Figure 4.8a).
- If the area of the visible region of a cell is greater than the area of the visible region of every adjacent cell, then the center of the cell is marked as an NP.
- The centers of all the cells containing the navigation objects (namely, exits, doors, and exit signs) are also marked as NPs.

The navigation map is constructed by adding edges to link pairs of NPs that are visible to each other; thus an agent can navigate between them without collision with obstacles. The edges represent the connectivity of the accessible space and building features (Figure 4.8b). If the

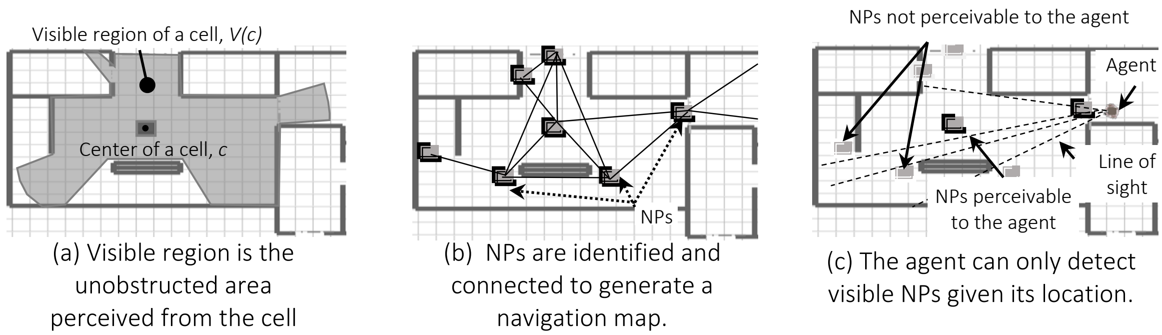
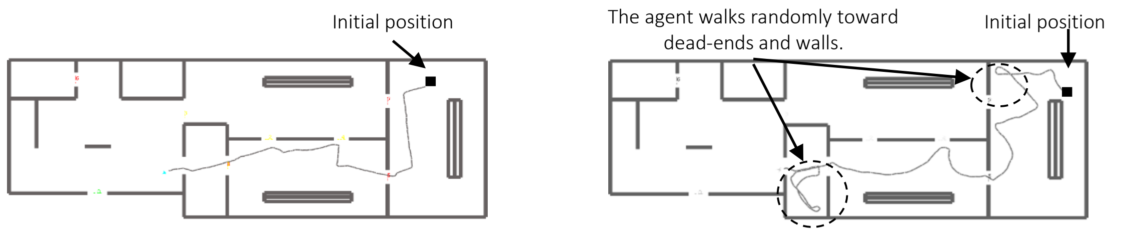


Figure 4.8: Illustration of navigation points and navigation map

obtained graph contains more than one connected component, additional NPs are iteratively introduced. These additional NPs are introduced either at random locations or in regions where NPs are sparse. For computational efficiency, the NPs and the navigation map are pre-computed and re-used throughout a simulation unless events cause changes in the building layout that trigger an update. The time schedule of the triggering events and the post-event geometries are user inputs. When a new event becomes active during simulation, the Crowd Simulation Engine updates the virtual environment and computes a new navigation map using the new geometry. We consider that using a discrete time schedule to model changes in the virtual environment is a reasonable assumption because the building geometry is relatively static during evacuation.

When perceiving the environment, each agent can determine the NPs that are visible from its current location (Figure 4.8c). This agent's perception capability is consistent with human visual capability of seeing only their obstacle-free surroundings. With the navigation map, an agent can perform navigation that mimics human movements in a real environment:

- Exploring the floor: Just as humans can only see their local surroundings, the agents can only access the "visible" portion of the navigation map to decide their movements. An agent queries the navigation map to determine the NPs that are visible from the agent's current position. Figure 4.9 shows two simulated trajectories of an agent: one obtained with the navigation map and the other relying only on local collision avoidance. In the second trajectory illustrated in Figure 4.9b, the agent performs unnatural movements, such as walking toward a wall or into a small dead-end. Using the navigation map, the agent avoids erratic movements and mimics better human navigation, as shown in Figure 4.9a.



(a) Trajectory with navigation map

(b) Trajectory without navigation map (relying on local collision avoidance)

Figure 4.9: Agent's trajectories with and without a navigation map

- Traveling to a known destination: When an agent does not have a goal destination, it chooses randomly one of the NPs to explore the virtual environment. Otherwise, it selects the next NP to navigate to according to its current knowledge of the virtual environment. For example, an agent knowing a particular exit would choose the visible NP that is nearest to the exit. As illustrated in Figure 4.10, the agent, with knowledge of the main entrance as its familiar exit, would choose among the five visible NPs the NP labeled "1" in order to move closer to the main entrance. In contrast, an agent with no knowledge of the exits would weigh all the options equally and would navigate to a randomly selected NP, unless the agent is influenced by other information, such as others' instructions.

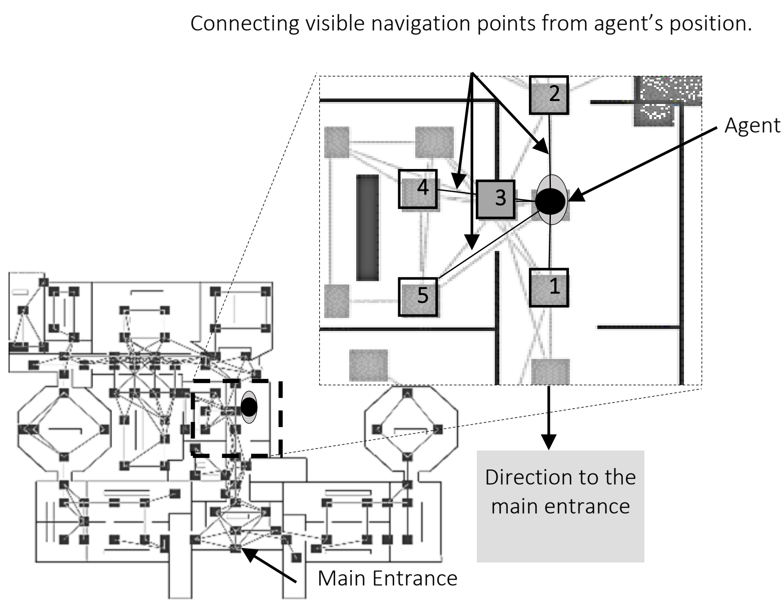
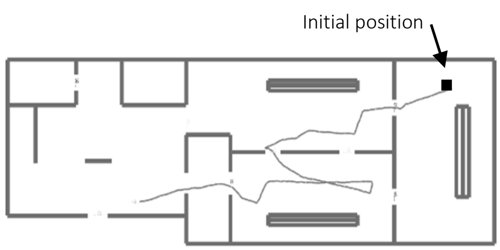


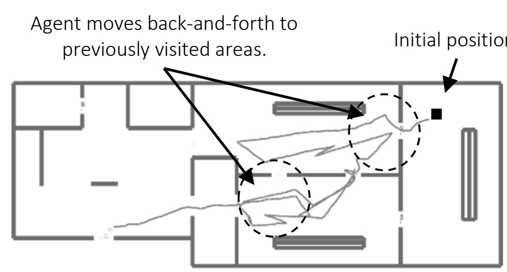
Figure 4.10: Illustration of agent's visible NPs

- Memorizing visited space: During simulation, an agent can remember the areas it has visited by recording the attained NPs[3]. When the agent chooses an NP to navigate, it gives a smaller weight to the visible NPs that it has been visited before. By doing so, the agent can avoid visiting the same area repeatedly. This simulated cognitive ability is essential for generating natural navigation trajectories in a situation where an agent has no prior knowledge of the virtual environment and therefore must explore the environment to evacuate. Figure 4.11 shows the agent's trajectories: one with the memory of the visited NPs and the other without. As shown in Figure 4.11a, the agent with memory tends to explore new areas with little backtracking. In contrast, as depicted in Figure 4.11b, the agent without memory moves repeatedly back-and-forth to the same areas.

In summary, using a navigation map, an agent in SAFEgress can (1) explore the virtual environment by navigating to open areas instead of relying on local collision avoidance, (2) travel to a known destination (e.g., a familiar exit) that is not directly visible by traversing through intermediate NPs, and (3) keep a record of the visited space to avoid moving around the same area.



(a) Trajectories with "memory"



(b) Trajectories without "memory"

Figure 4.11: Agent's trajectories with and without memory of previously visited areas

[3] In our current implementation, an agent is considered to have attained an NP when the agent has reached the cell containing the NP. This modeling assumption is made so that multiple agents targeting the same NP do not have to reach the exact cell (i.e., the NP) before traveling to the next NP. This assumption results in more natural trajectories.

4.4.3.2 Low-level locomotion

Upon determining a visible navigation target (such as an exit, an NP, or a leader agent), an agent aims to move toward that target while avoiding collisions with neighboring agents and obstacles. Multi-agent motion planning has been studied in robotics and crowd simulations [53, 50]. Here, we describe the locomotion algorithm to emulate a step of an agent, which is partly inspired by the concepts of repulsive and attractive forces in the social force model [23]. During one simulation step, the Crowd Simulation Engine performs the locomotion algorithm on all the agents in a random order. Figure 4.12 summarizes the key steps of the algorithm. As depicted in Figure 4.12, the selected agent determines a valid move by iterating the direction of movement. At each iteration, the agent calculates the direction of movement based on (1) the navigation target, (2) the nearby obstacles, and (3) the neighboring agents. The agent then anticipates a new position to move into and checks if the position is free of collisions with obstacles and neighboring agents. If the step is collision-free, the agent executes the move and stops the iteration; otherwise, it continues to adjust its direction of movement by increasing the repulsive effects due to obstacles and neighboring agents. The number of iterations is limited to some pre-defined constant such that if the agent fails to find a collision-free position after a certain number of attempts, it stays in the same position.

```
Procedure: Determining locomotion of an agent in a simulation step
Assign a random number between 10 and 50 (inclusively) as the max. number of trials
For i = 1…max. number of trials
    Calculate new  movement direction
    Calculate new speed
    Compute the expected position at the end of the simulation step
    IF the position is collision-free
       THEN RETURN  movement direction and speed
       ELSE if the position collides with an obstacle
                THEN increase effects from obstacle repulsion
                ELSE increase effects from neighbor repulsion
END FOR
Return current position of the agent
```

Figure 4.12: Algorithmic steps to determine an agent’s movement at a simulation step

At each iteration, the direction of movement of the agent, $\vec{u}_m$, is defined as:

$$\vec{u}_m = \frac{\vec{u}_{target} + \alpha\varepsilon\vec{u}_{obst} + \beta\varepsilon\vec{u}_{neighbors}}{1 + \alpha\varepsilon + \beta\varepsilon} \tag{4.1}$$

where $\vec{u}_{target}$ is the unit attractive vector due to the navigation target, $\vec{u}_{obst}$ is the unit vector of the repulsive vector due to nearby obstacles (described in Equation 4.2), $\vec{u}_{neighbors}$ is the unit vector of the repulsive vector due to neighboring agents (described in Equation 4.3), ε is the increment constant, and α and β are the weights assigned to the two vectors $\vec{u}_{obst}$ and $\vec{u}_{neighbors}$ respectively. At the beginning of the iterative cycle, both α and β are initialized as zero, i.e., the direction of movement aligns with the direction to the navigation target.

The unit repulsive vector due to nearby obstacles, $\vec{u}_{obst}$, is defined as:

$$\vec{u}_{obst} = \frac{\sum_{\theta} f(d_\theta)\vec{u}_\theta}{\sum_{\theta} f(d_\theta)} \tag{4.2}$$

where $\vec{u}_\theta$ is the unit repulsive vector on the agent due to the obstacle θ, d_θ is the distance between the location of the agent and the obstacle, and $f(d_\theta)$ is a function that describes the intensity of the repulsion based on the distance d_θ. In the current implementation, $f(d_\theta)$ is assumed to be $\frac{1}{{d_\theta}^2}$. Following this function, the obstacles that are in the close vicinity of the agent (i.e., the value of d_θ is small) will impose a higher repulsion on the agent, such that the agent tends to navigate away from these obstacles.

The unit repulsive vector due to the presence of the neighboring agents, $\vec{u}_{neighbors}$, is defined as:

$$\vec{u}_{neighbors} = \frac{\sum_{\gamma \in neighbors} I(\gamma)h(d_\gamma)\vec{u}_\gamma}{\sum_{\gamma \in neighbors} I(\gamma)h(d_\gamma)} \tag{4.3}$$

where $\vec{u}_\gamma$ is the unit repulsion vector due to the neighboring agent γ, d_γ is the distance between the agent and the neighboring agent γ, $h(d_\gamma)$ is a function that describes the intensity of the repulsion based on the distance d_γ, and $I(\gamma)$ is the indicator function that returns 1 if the neighboring agent γ is moving toward the agent and 0 otherwise. In the current implementation, $h(d_\gamma)$ is chosen to be $\frac{1}{{d_\gamma}^2}$ such that the neighbors who are closer to the agent (value of d_γ is small) will impose a greater repulsive effect on the agent.

During the collision checks with the neighboring agents of an agent, if the neighbor has already determined its new position at the current simulation step (i.e., the neighbor is selected to perform locomotion before the agent), the new position of the neighbor is used for the collision test; otherwise, the position of the neighbor from the previous simulation step is used.

In the current implementation, only the new position is checked against collisions, while collision checks are omitted for the intermediate positions along the trajectory from the agent's previous position to its new position. Although testing every intermediate position can guarantee collision-free paths, the collision checks are computationally expensive and will significantly increase the computation time. We specify the lapse time of a simulation step as 1/6-th of a second, such that the maximum distance of a step does not exceed the agent's body radius. Therefore, checking collisions for the ending position of the step approximates the potential collisions along the short trajectory. Nevertheless, when the lapse time of a simulation step is increased, collision checks for intermediate positions may be necessary to simulate collision-free trajectories of the agents. Further study can be conducted to investigate the trade-offs between the computational time and the accuracy of the simulated trajectories, such as tracking the number of collisions due to an increase of simulation time lapse.

4.5 Summary

SAFEgress consists of three key modules: Global Database, Crowd Simulation Engine, and Agent Behavior Models Database. These modules are supported by seven sub-modules: Geometry Engine, Situation Data Input, Population Generator, Navigation Module, Perception Module, Result Recorder, and Visualizer. This modular framework is intended to provide flexibility in modifying existing and adding new functionalities. For example, the fire and smoke information can be stored in a separate module and synchronized with the egress simulation. Moreover, the locomotion algorithm could be modified to model the actual pressure or force on persons due to pushing in high-density crowds. The details for future extension of the SAFEgress framework are discussed further in Chapter 8.

SAFEgress models the three essential elements in egress – virtual environment, cue objects, and agents – to facilitate the modeling human and social behaviors. Each agent is defined at individual, group, and crowd levels, and is equipped with perception and navigation capabilities. In Chapter 5, we will demonstrate how the agents interact with the virtual environment and other agents to exhibit individual, group, and crowd behaviors during simulation.

Chapter 5

Individual and Social Behaviors in SAFEgress

In Chapter 4, we have described the representation of the virtual environment, the emergency cues, and the autonomous agents mimicking occupants in egress. An agent is defined by a set of attributes at three levels– individual, group, and crowd – and is capable of perceiving its surroundings and navigating in a virtual environment.

In this chapter, we focus on the Crowd Simulation Engine. At each simulation step, the Crowd Simulation Engine selects each agent in random order to update its behavior through the agent behavioral cycle. We first provide an overview of the agent behavioral cycle, followed by a detailed explanation of the interpretation and decision-making stages of the cycle. One of our main goals in designing these two stages is to make it possible for the user to flexibly model different agent behaviors. Finally, we illustrate several individual, group, and crowd behaviors motivated by real-life human behaviors observed during evacuations.

5.1 Agent's behavioral cycle

Occupants in emergencies do not act randomly or react automatically in response to events; instead, their behaviors are the result of complex processes. Accordingly, in SAFEgress, the agents' reactions are modeled through a multi-stage behavioral cycle (perception – interpretation – decision-making – execution), shown in Figure 5.1. The agent behavioral cycle is designed after the study of human behaviors in evacuations and emergencies [7, 8, 61]. During one simulation time step, each agent perceives the surroundings in the virtual environment, interprets the cues, and makes decisions to determine its behavior and action. The dynamic attributes of the agent (shown in **bold** below and listed in Table 5.1) are updated at different stages of the behavioral cycle:

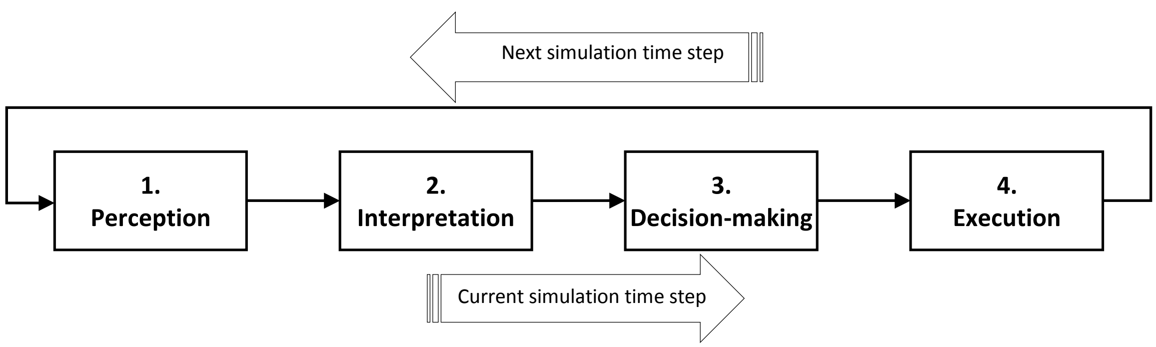


Figure 5.1: Agent behavioral cycle

Table 5.1: Agent dynamic attributes

Stage	Dynamic attributes	Possible attribute values
Perception	Visible navigation objects Visible group members Neighboring agents Detected cues	array of visible navigation objects array of agents in the same social group} array of visible gents array of detected cue objects
Interpretation	Urge	number between 0 and 1 (inclusively)
Decision-making	Selected behavior Navigation goal Navigation target	pre-evacuation/individual/group/crowd a navigation object or agent(s) a NP or agent(s)
Execution	Spatial position Spatial knowledge	2D coordinates a map with key-value pair as <NP, no. of times visited>

- At the perception stage, an agent tracks and perceives four kinds of information: (1) **visible navigation objects**, (2) **visible group members**, (3) **neighboring agents**, and (4) **detected cues**. Figure 5.2 illustrates the objects and agents detected by the agent at the perception stage. Using the perceptive capabilities of an agent as described in Section 4.4.2, an agent (1) performs point tests to detect navigation objects, group members, and visual cues (Figure 5.2a), (2) uses the grid method to retrieve neighboring agents (Figure 5.2b), and (3) employs distance tests to identify audio cues (Figure 5.2c).
- At the interpretation stage, based on the perceived cue objects and the urges of its social group and the neighboring crowd, the agent updates its internal **urge**. The urge level, which has a value ranging from 0 (low urge) to 1 (high urge), measures the agent's urgency to undertake or modify the evacuation actions. Details of the interpretation stage will be described in Section 5.2.1.
- At the decision-making stage, the agent first determines its default individual behavior and then reasons through the group and the crowd level to determine whether it would exhibit group or crowd behavior. At the end of the decision-making stage, the agent updates its **selected behavior**, **navigation goal**, and **navigation target**. Details of the decision-making stage will be described in Section 5.2.2.
- At the execution stage, based on its navigation target, the agent performs low-level locomotion to update its **spatial position** using the navigation sub-module as described in Section 4.4.3. As the agent navigates, it keeps track of the areas previously visited (i.e., **spatial knowledge**).

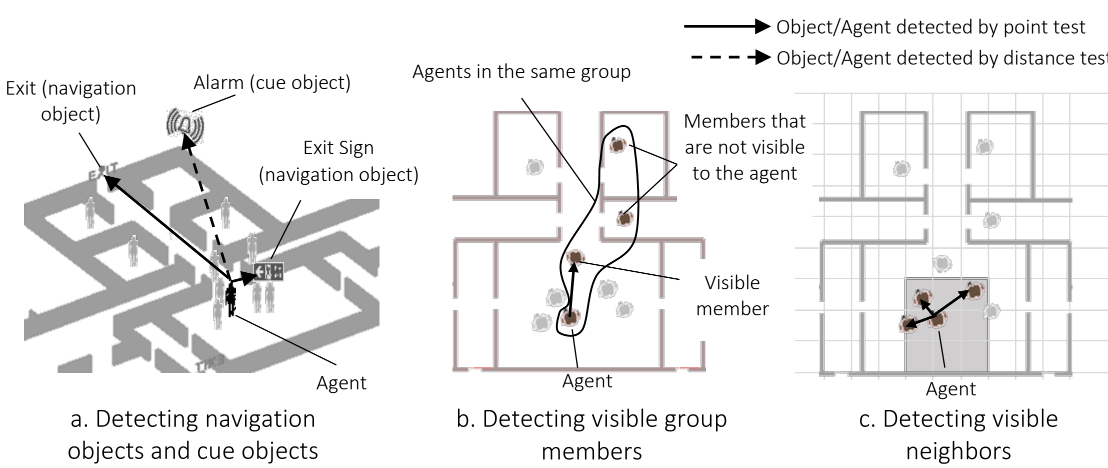


Figure 5.2: Information tracked by agents at perception stage

5.2 Behavior modeling

As observed in past accidents and emergency incidents, people may behave in different ways even when they perceive the same emergency cues [22, 46, 65]. Their reactions depend on both the perceived information and their individual and social backgrounds [7, 9, 61, 78, 79]. In SAFEgress, the agent behavioral cycle is designed to accommodate a broad spectrum of agent behaviors. In the following, we describe how an agent updates (1) its internal urge at the interpretation stage, and (2) its behavior at the decision-making stage.

5.2.1 Interpretation stage

Each agent tracks its urgency level to decide on evacuation actions based on the value of its urge, a dynamic agent attribute. At the start of the simulation, the agent's urge is set to zero. The value of urge, ranging from 0 (low urge) to 1 (high urge), is updated during simulation. At a simulation step, the urge of an agent, U_{t+1}, is updated as:

$$U_{t+1} = U_t + \Delta U_t \tag{5.1}$$

where U_t is the current urge and ΔU_t is the change of urge at the current simulation step.

When an agent reaches the high urge, it triggers evacuation behavior. At each simulation step, the change of the urge, ΔU_t, is computed as:

$$\Delta U_t = \Delta U_{cue} + \Delta U_{group} + \Delta U_{crowd} \tag{5.2}$$

where ΔU_{cue} is the change of urge due to perceived cues, ΔU_{group} is the change of urge due to the influence of social group, and ΔU_{crowd} is the change of urge due to the influence by the surrounding crowd. The change of urges due to perceived cues, group and crowd influences are described in the following sub-sections.

Effect of cue objects on urge

When an agent first detects a cue object, the agent evaluates the delay time to start evacuation. The evacuation delay time depends on (1) the agent's reaction time of the detected cue object, denoted as T_i and (2) the agent's cue awareness factor of the cue object i, denoted as β_i (a static attribute described in Section 4.4.1 that is assigned to the agent for the cue object). When the agent has no experience with the detected cue, the value of β_i is set to 1. If the agent associates a high level of threats with the detected cue, the value of β_i is set to be lower than 1. Otherwise, if the agent associates a low risk with the detected cue, the value of β_i is set to be higher than 1. Mathematically, ΔU_{cue}, the change of the agent's urge due to detected cues, is defined as follows:

$$\Delta U_{cue} = \Delta t \times \sum_{i \in detected\ cues} \frac{1}{T_i \times \beta_i} \tag{5.3}$$

where Δt is the duration of the step (in seconds), T_i is the reaction time (in seconds) associated with the cue object i, and β_i is the agent's cue awareness factor of the cue object i. When the agent has no experience with the detected cue (i.e., β_i equals to 1), the agent reaches a high urge to evacuate after T_i. On the other hand, if the agent has a high emergency awareness toward the cue (i.e., β_i is lower than 1), the agent's reaction time (i.e., $T_i \times \beta_i$) will be shorter than the reaction time specified by the cue objects (i.e., T_i). In our current implementation, the effects of multiple cues are additive. Different equations to model the combined effects of multiple cues can be further explored [62, 80, 81].

Effect of social group on urge

The visual presence of a social group can also affect an agent's urge during the simulation. The effect of the social group on an agent's urge depends on (1) the difference between the group's urge and the individual's urge, and (2) the time needed for the members to reach a consensus [5, 55, 68, 69]. Mathematically, ΔU_{group}, the change of the agent's urge due to its social group is expressed as:

$$\Delta U_{group} = \frac{\Delta t \times (U_{group} - U_t)}{T_{group}} \tag{5.4}$$

where Δt is the time in seconds of each behavioral cycle, U_{group} is the maximum urge among all the visible group members, U_t is the urge level of the agent at the current simulation step, and T_{group} is time needed for a group to arrive at a consensus. T_{group} is defined based on the group intimacy level, which is a group level attribute of the agent (see Section 4.4.1). A group with close relationships (such as a group of close friends or family) tends to arrive at a consensus sooner than a group with a loose relationship (such as a group of co-workers). The value of T_{group} is smaller for groups with a high intimacy level than that of groups with a low intimacy level. Following Equation 5.4, ΔU_{group} increases as T_{group} decreases; therefore, a high intimacy group has greater social influence on the agent's urge to evacuate.

Effect of crowd on urge

The surrounding crowd also has an impact on the agent's urge to evacuate. The effect of the crowd on an agent's urge depends on (1) the difference between the urge of the neighbors and its urge, and (2) the time needed for the agent to follow its neighbors and adopt their risk perception. Mathematically, the change of the agent's urge due to the crowd is expressed as:

$$\Delta U_{crowd} = \frac{\Delta t \times (U_{crowd} - U_t)}{T_{crowd}} \tag{5.5}$$

where Δt is the time in seconds of each behavioral cycle, U_{crowd} is the maximum urge among the neighboring agents, U_t is the urge level of the agent at the current simulation step, and T_{crowd} is the time needed for an agent to adopt the risk perception of its neighbors.

T_{crowd} is defined based on the crowd-following time lag, which is an agent attribute. The value assignment of this attribute can also be related to the agent's familiarity with the building [18, 36]. Agents with a low level of familiarity with the building, such as first-time visitors, tend to follow others in emergency situations. On the other hand, agents who are familiar with the building follow their risk perception of the situation and take longer time to conform to the crowd [6, 82]. As a result, T_{crowd} is shorter for agents with low level of familiarity with the building than that of agents who are familiar with the building or with knowledge of the cues. Following Equation 5.5, ΔU_{crowd} increases as T_{crowd} decreases; therefore an agent with a lower familiarity with the building is more receptive to the crowd.

After updating its internal urge at the interpretation stage, the agent proceeds to the decision-making stage to determine the navigation goal and the navigation target using the perceived information.

5.2.2 Decision-making stage

At the decision-making stage, the agent decides the actions to undertake based on the information gathered and processed at the perception and interpretation stages. First, the agent evaluates the need to exhibit evacuation actions by assessing its urge to evacuate. If the agent has a low urge to evacuate (urge is less than 1), it then exhibits the pre-evacuation behavior, such as exploring the environment randomly; if the agent has a high urge to evacuate (urge equal to 1), the agent then invokes a three-level (individual, group, and crowd) reasoning process to determine the final behaviors.

Figure 5.3 shows the three-level reasoning process to determine the final evacuation behavior of an agent during a simulation step:

1. The agent determines its individual behavior, which is the default behavior.
2. If the conditions to invoke group behavior are satisfied, the agent will select the group behavior, which could override the individual behavior. The default condition for an agent to exhibit group behaviors is having high compliance with the group.
3. The agent then checks the conditions to invoke crowd behaviors, which can also override the individual or group behaviors. The default condition for an agent to exhibit crowd behaviors is having high compliance with the crowd.

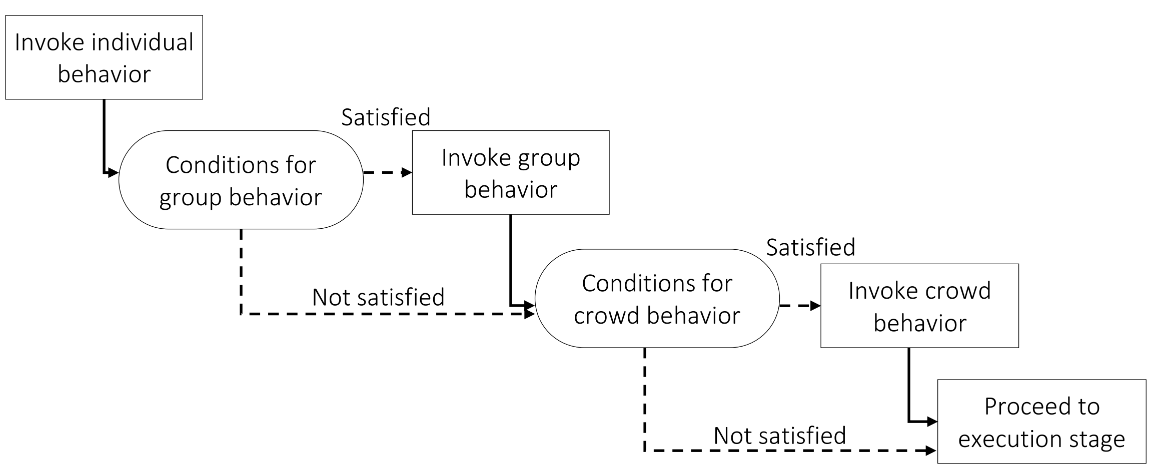


Figure 5.3: Three-level reasoning process to determine evacuation behavior

With the default settings, the assignments of the group compliance and crowd compliance attributes directly determine the range of behaviors an agent can exhibit. Other conditions to invoke group or crowd behaviors can be added to simulate more complex group and crowd dynamics.

When invoking a specific behavior, the agent retrieves and reasons through the behavioral model specified in the behavioral profile to determine a behavior routine (such as going to a specific exit or following an agent). By calling the behavior routine, the agent updates its navigation goal and navigation target, which are then passed to the execution stage to guide its locomotion.

5.2.2.1 Behavioral model

The behavioral models are implemented using decision trees, each describing one kind of behavior to be exhibited by the agent. The behavioral rules are defined in the decision nodes, the outcome of the reasoning is described in the termination nodes, and the operations on the agents' attributes are defined in the operator nodes. Figure 5.4 illustrates an example of a decision tree that describes the group leader-following behavior.

Decision node

Each decision node consists of a collection of conditions, which are constructed using the agent attributes and are combined using logical operators (such as "AND" and "OR"). Based on the result of the decision node, the agent proceeds to check the corresponding sub-trees until a termination node is reached.

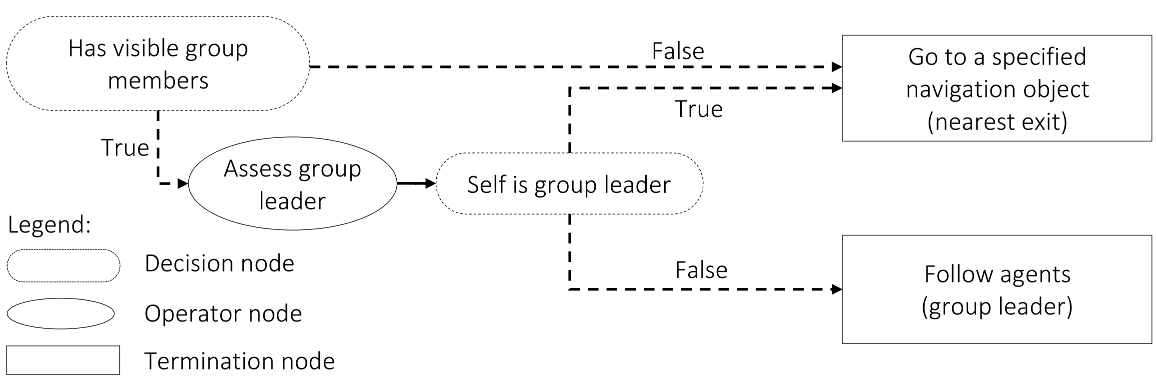


Figure 5.4: Example of a decision tree

Operator node

An agent can perform operations on its static and dynamic attributes to determine an intermediate result that can be used in the condition checks. For example, as shown in Figure 5.4, an agent can assess whether it is the leader or the follower based on the visible group members (a dynamic attribute) and the group influence (a static attribute). The result of the operation can be used to generate more complex behaviors, such as leader-follower behavior and crowd following behavior (which will be discussed later in Section 5.3).

Termination node

The final outcome of the decision tree is described in the termination nodes. Each termination node specifies a behavioral routine that updates the agent's navigation goal and navigation target, which are both agent's dynamic attributes. The key difference between the navigation goal and the navigation target is that the navigation goal may not be in the agent's line of sight as it is a high-level description of the agent's desired destination (such as an exit that the agent prefers), whereas the navigation target is visible to the agent (such as a visible navigation point on the shortest route to the preferred exit). Moreover, the navigation target determines the intended direction of movement of the agent at the execution stage. In the current SAFEgress prototype, four implemented behavioral routines are described as follows:

- ***Go to a specified navigation object***: This routine takes a navigation object as an input argument. When the routine is invoked, the agent updates its navigation goal and navigation target to the specified navigation object. If the specified object is not in the line of sight of the agent, the agent performs wayfinding and reset the navigation target to an intermediate navigation point (NP) visible to the agent (as described in Section 4.4.3.1).
- ***Follow agents***: This routine takes a list of agents as an input argument. When the routine is invoked, the agent first calculates the centroid position of the group of specified agents. The agent then sets the centroid position as its navigation goal and navigation target. In the case where the agent is following only one agent (such as the group leader), the agent moves toward the leader's location.
- ***Follow navigation object***: This routine takes a list of navigation objects the agent perceives at the perception stage as an input argument. An agent may perceive multiple navigation objects

at its location, and some types of navigation objects are perceived to be more important than the others. For example, people normally prefer going to the exit outlet than following the exit sign because the exit outlet is a direct line of safety. Accordingly, the agent ranks the visible navigation objects based on three criteria (in order of importance):

1. object types: exits are preferred over exit signs; exit signs are preferred over doors
2. number of prior visits: objects which have been visited the fewest times are preferred
3. distance from the objects: nearer objects are preferred

For example, when the agent sees more than one sign but no exit, the agent chooses the sign that has been explored the fewest times. If both of the locations of the signs have been visited once by the agent, the agent prefers the nearer sign over the farther. After prioritizing, the agent chooses one navigation object and set the navigation object as the navigation goal. Then the agent sets the navigation target as the NP that is consistent with the directional information of the navigation object. For example, if the exit sign indicates that the agent should move toward the left, the agent will search for a visible NP that is on the left of the exit sign and set the NP as the navigation target.

- ***Explore space***: This routine does not take any input argument. Upon invoking this routine, the agent first determines the nearby open areas (which are represented by NPs) and navigates toward the NP that has been explored the fewest times (as described in Section 4.4.3.1).

Each behavioral model – consisting of decision nodes, operator nodes, and termination nodes – defines one kind of agent behavior. At the end of the decision-making stage, the agent updates its navigation goal and navigation target. Moreover, the agent's movement speed can be modified to reflect a different level of urgency to perform an action.

The behavioral models are defined prior to the simulation and are stored in the Agent Behavior Models Database, such that they can be easily reused to instantiate different agent types. Moreover, by decoupling the behavioral logic (represented in the behavioral model) from the definition of an agent's characteristics (defined by the agent attributes), users can modify the existing behavioral models without changing the values of agent attributes and the population distribution. New behavioral models could be added to the Agent Behavioral Models Database to verify new behaviors. In the following sections, we illustrate different agent behavioral models that mimic some commonly observed evacuation behaviors in real life situations.

5.3 Demonstrations of different agent behaviors

We illustrate the flexibility of SAFEgress to model different individual, group, and crowd behaviors. In each behavior demonstration, we describe the behavioral model (as well as the behavioral rules), followed by a simple simulation example. We also highlight the static attributes and dynamic attributes (both shown in **bold** characters) used to define the behavioral models. Lastly, to compare and contrast the evacuation patterns as a result of different behavioral models, we adopt the same virtual environment in which the agents interact and navigate, as shown in Figure 5.5. The simulated floor space is 130 ft. long by 72 ft. wide, with two exits (Exit 1 and Exit 2) and 5 doors (Door A to E).

5.3.1 Following perception to evacuate

The floor geometry and the spatial arrangement of building safety features (such as signage and exits) directly affect the evacuation routes of the occupants [47, 49]. In SAFEgress, agents can perceive the navigation objects in the virtual environment to guide their evacuation. We define the behavioral model "following perception to evacuate" to simulate the process of searching for exits following the guidance from the virtual environment.

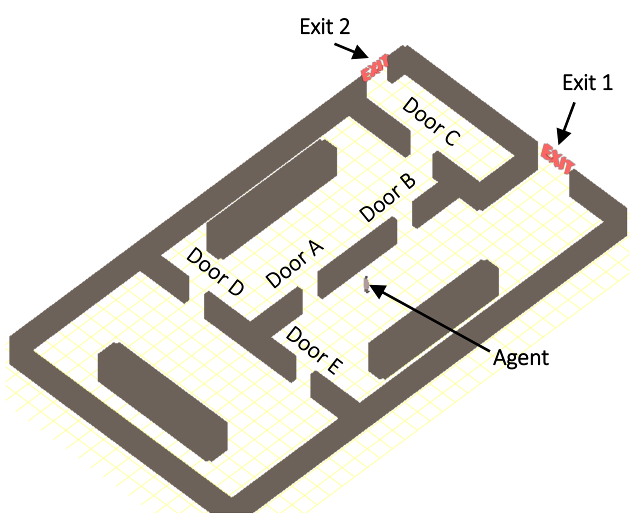


Figure 5.5: Virtual environment for demonstrating different behaviors

Behavioral rules and decision tree

The behavioral rule of "following perception to evacuate" is straightforward: if the agent can see any navigation object, then it follows cues from its visible navigation objects; otherwise, it explores the virtual environment.

The decision tree encoding the behavioral rule is shown in Figure 5.6. When reasoning through the decision tree, the agent assesses the dynamic attribute **visible navigation objects** during the simulation to determine the final behavioral routine.

Demonstration of usage

Figure 5.7 demonstrates the behavior of an agent adopting the "following perception to evacuate" behavioral model. In Figure 5.7a, because the agent cannot detect any visible navigation object, it then invokes the "explore space" routine to explore the virtual environment. In Figure 5.7b, as the agent navigates around the obstacle, it perceives two navigation objects, Door D and Door E. Since the agent detects the visible navigation objects, it invokes the "follow navigation object" routine. Because both objects are door objects that the agent has not visited, the agent navigates toward the nearest object, Door D. As the agent navigates, it continues to detect the navigation objects and to update the visible navigation objects. As shown in Figure 5.7c, when Door A becomes visible to the agent, the agent chooses to navigate toward Door A, because Door A has not been explored before and is the nearest navigation object among the unexplored objects (i.e., Doors A, B, C). After arriving at Door A, the agent detects a new navigation object, Exit 1, as shown in Figure 5.7d. Because the agent preferred exit objects to door objects, it navigates toward Exit 1 (Figure 5.7d).

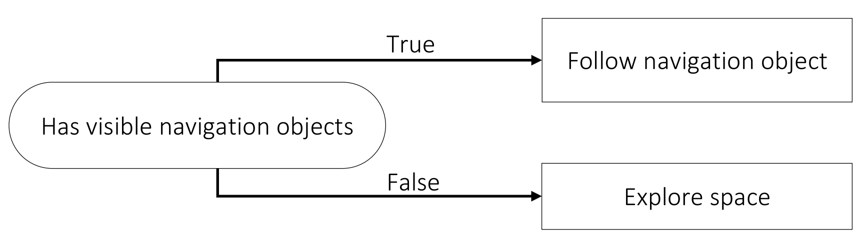


Figure 5.6: Decision tree for "following perception to evacuate"

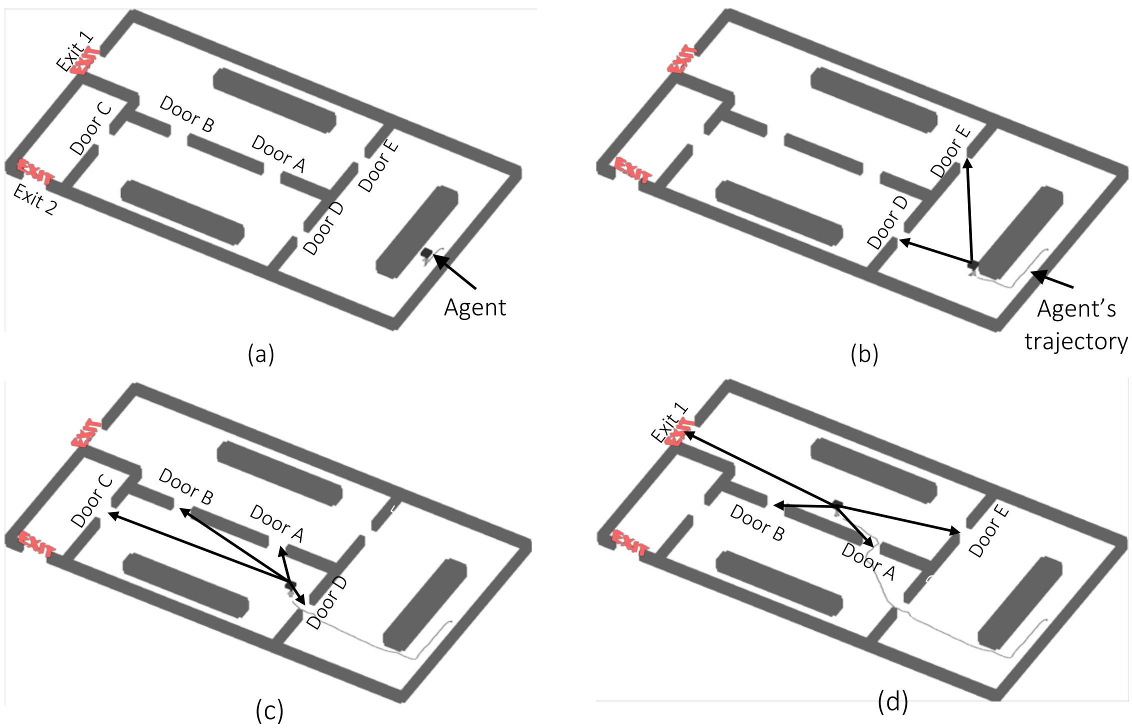


Figure 5.7: Behavior modeling for "following perception to evacuate"

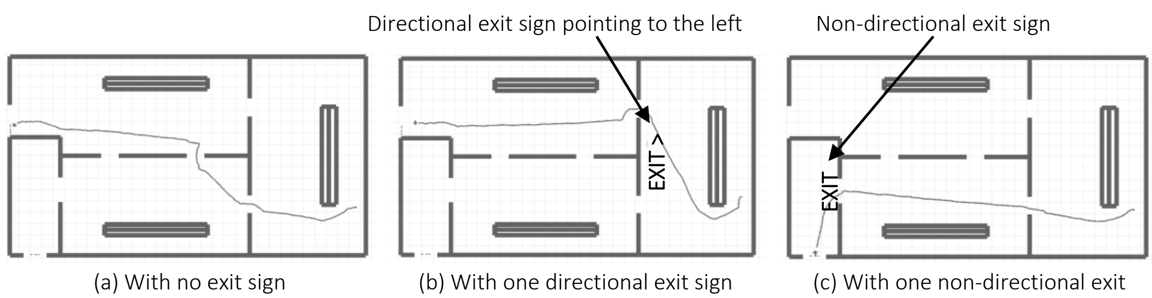


Figure 5.8: Agent's trajectories with different signage arrangements

Exit signage provides markings of exits and escape routes in buildings and are designed to assist the occupants in evacuating from the buildings. The "following perception to evacuate" behavioral model simulates occupants that are unfamiliar with the environment and follow the signage to search for an exit. Figure 5.8 shows the evacuation patterns under different signage arrangements. In Figure 5.8a where there is no signage, the agent navigates through doors to reach the exit. In both Figure 5.8b and Figure 5.8c, one exit sign is defined in each case. In these cases, upon perceiving the sign, the agent follows the guidance from the sign and adjusts its trajectories accordingly. Moreover, as illustrated in Figure 5.8b, directional information displayed on the sign impacts the agent's navigation route. The presence of exit signs, the arrangement of signs, and the information displayed on the signs provides guidance to the occupants of the locations of exits. Upon implementing the appropriate behavioral rules that encode information from the environment (such as the "following perception to evacuate" model), SAFEgress can be used to assess the effectiveness of different egress designs.

5.3.2 Following knowledge to evacuate

When making evacuation decisions, people often refer to their emergency experience and knowledge of the place [15, 33]. Occupants who visit the building regularly may have learned their preferred exits over time, or they have knowledge of the nearest exits. The occupants may also recall evacuation drill experience, from which they learn the evacuation routes in case of emergency. We define the behavioral model "following knowledge to evacuate" to simulate the behaviors of exiting via familiar routes.

Behavioral rules and decision tree

The decision tree encoding the rules of "following knowledge to evacuate" is shown in Figure 5.9. When reasoning through the decision tree "following knowledge to evacuate," the agent assesses its static attribute, **known exits**, and the dynamic attribute **visible navigation objects** during the simulation to invoke a behavioral routine.

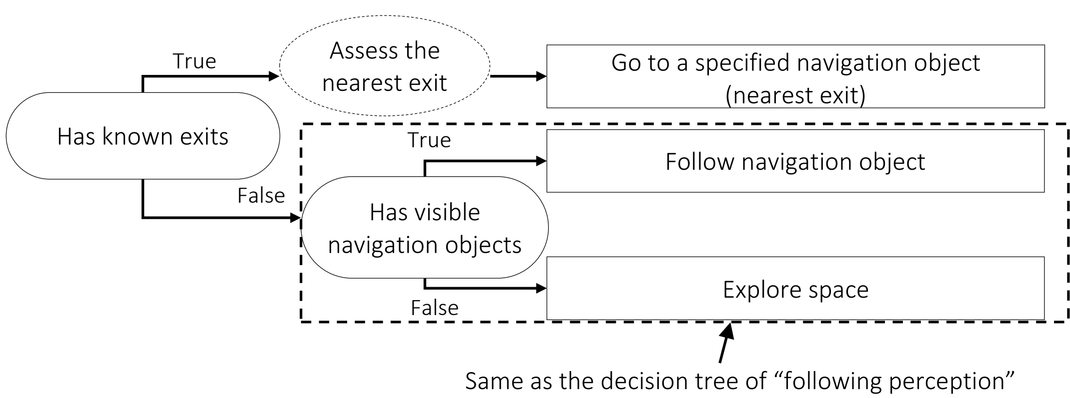


Figure 5.9: Decision tree for "following knowledge to evacuate"

The behavioral rules of following knowledge to evacuate are defined by the following steps:

1. If the agent has any known exits, then it moves toward the known exit; otherwise, it checks the next condition.
2. If the agent can see any navigation object, then it follows a navigation object; otherwise, it explores the virtual environment.

Demonstration of usage

Figure 5.10 illustrates the behavior of an agent adopting the "following knowledge to evacuate" behavioral model. Prior to the simulation, the agent is assumed to have knowledge of all exits. In this example, the known exits of the agent are Exit 1 and Exit 2. As shown in Figure 5.10a, during the simulation, because the agent possesses exit knowledge, it invokes the behavioral routine "go to a specified navigation object" and proceeds to the nearest exit among its known exits (i.e., Exit 2). Following the "go to a specified navigation object" routine, the agent calculates the shortest path to reach Exit 2 and navigates via the visible NPs along the shortest path. In Figure 5.10b, as the agent travels, it resets the navigation target to be the visible NP that is closer to the navigation goal. As shown in Figure 5.10c, the agent continues the trajectory until it reaches Exit 2, the navigation goal.

On the contrary, if the agent does not possess any exit knowledge, the agent then assesses whether there are any visible navigation objects and performs either the behavioral routines "explore space" or "follow navigation object." In this case, the evacuation pattern of the agent would be similar to the one shown in Figure 5.7.

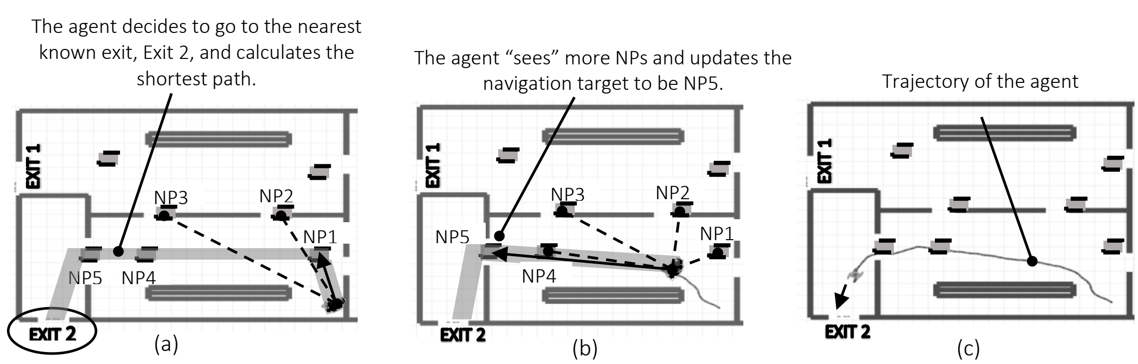


Figure 5.10: Behavior modeling for "following knowledge to evacuate"

The "following knowledge to evacuate" model illustrates the "nesting" property of the decision trees to generate more complex, aggregated behavioral models. As highlighted by the dotted line box in Figure 5.9, the behavioral model "following knowledge" is developed based on the behavioral model "following perception" because the sub-tree of the "following knowledge" model is the same as the decision tree of the "following perception" model. By nesting the decision trees, more complex decision trees can be defined to represent complicated behaviors.

5.3.3 Navigating with group members

During evacuation, members belonging to a group, such as families, often maintain proximity with their social group when moving toward the exit [5, 18]. In SAFEgress, each agent can be affiliated with a social group, which is characterized by the group level attributes, group influence and group intimacy level. We define a behavioral model "navigating with group members" that makes use of the group affiliation to model the group walking behaviors.

Behavioral rules and decision tree

Figure 5.11 shows the decision tree of "following group leadership." When reasoning through the decision tree, the agent assesses the static attribute related to its **social group** (**group influence** and **group separation tolerance**) and the dynamic attribute **visible group members** to determine the final behavioral routine.

The behavioral rules of navigating with group members are defined by the following steps:

1. The agent determines if it is a group leader based on the agent's group influence among the visible group members. If the agent is a follower, it follows the leader among the visible group members; otherwise, the leader agent checks the next condition.
2. The leader agent calculates the average separation distance between itself and the visible group members. If the group is dispersed (i.e., the group separation is larger than the separation tolerance), the leader will navigate toward the group; otherwise, it checks the next condition.
3. If the visible group is walking too slowly (i.e., the group separation distance is increasing), the leader agent will slow down to wait for the group members; otherwise, it will exhibit individual behavior, such as following knowledge, to exit the building.

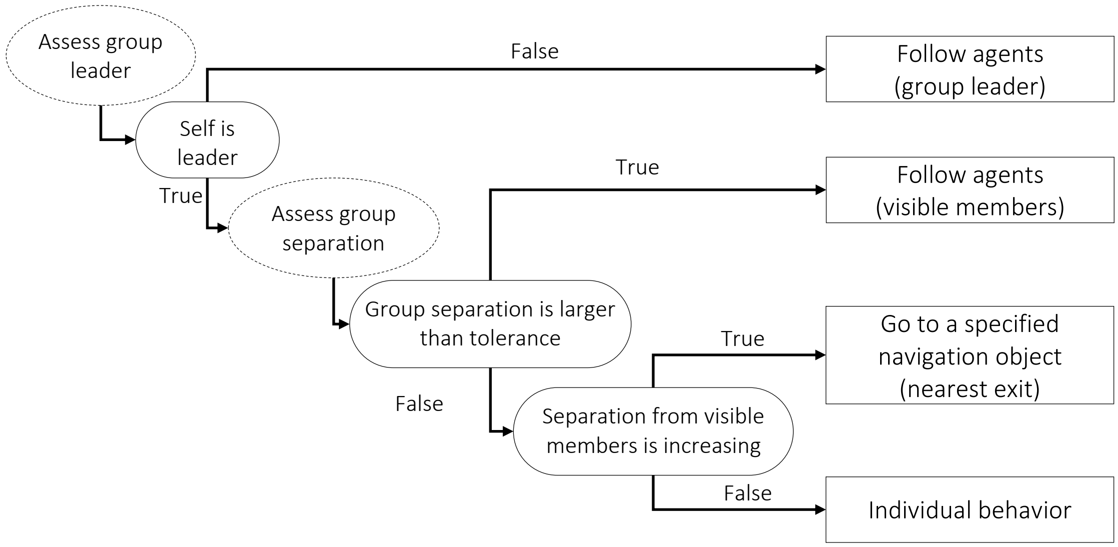


Figure 5.11: Decision tree for “navigating with group members”

Demonstration of usage

Figure 5.12 illustrates the process of a group of agents assuming the behavioral model “navigating with group members.” The group consists of six members who are initially separated into two sub-groups. In Figure 5.12a, each sub-group leader leads the followers to the exit until they “see” other group members. Then, as shown in Figure 5.12b, the leader of the merged group moves closer to the group centroid because the group is dispersed. Finally, in Figure 5.12c, the leader navigates to the exit only when it sees all the group members are nearby.

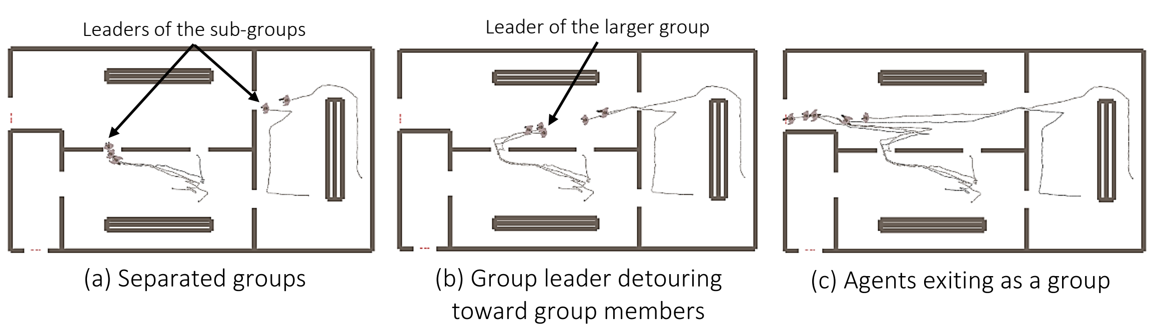


Figure 5.12: Behavior modeling for “navigating with group members”

5.3.4 Navigating with entire social group

During evacuation, members of social groups (such as families and close friends) are concerned about the safety of other members. Even when evacuation is urgent, people often look for and evacuate with the entire group [65, 17]. In SAFEgress, this group seeking behavior can be defined so that the leader among the visible group members assesses whether all the group members are visible and possibly triggers the action to search for the members who are missing.

Behavioral rules and decision tree

Figure 5.13 shows the decision tree of "navigating with entire social group." During the reasoning process, the agent assesses the group level static attributes, **group influence**, **group separation tolerance,** and **social group** size, as well as the dynamic attribute, **visible group members**.

The behavioral rules of navigating with the entire social group are defined by the following steps:

1. The agent determines if it is a group leader based on the agent's group influence among the visible group members. If the agent is a follower, it follows the leader among the visible group members; otherwise, the leader agent checks the next condition.
2. The leader calculates the average separation distance between itself and the visible group members. If the group is dispersed (i.e., the group separation is larger than the separation tolerance), the leader will navigate toward the group; otherwise, it checks the next condition.
3. If the visible group is walking too slowly (i.e., the group separation is constantly increasing), the leader will slow down to wait for the group members; otherwise, it checks the next condition.
4. The leader checks if there are any group members missing (by comparing the number of visible group members to the group size). If there are members missing, the leader agent will explore the virtual environment to search for the missing members; otherwise, the leader agent will exhibit individual behavior to exit the building.

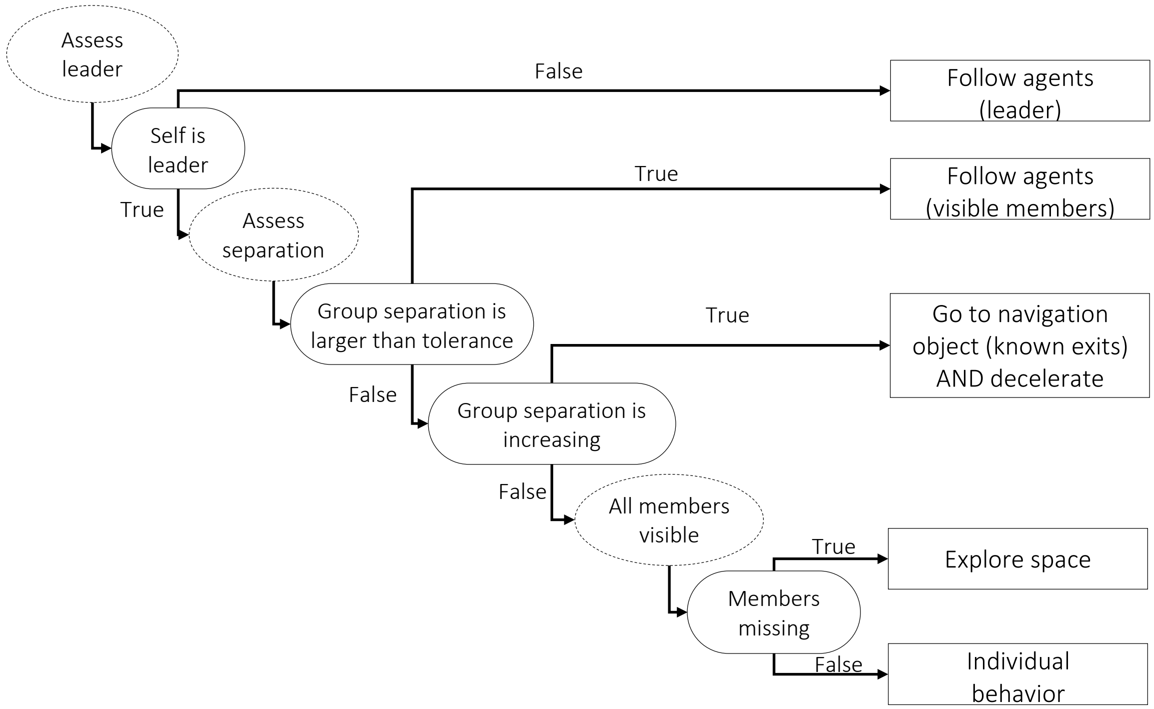


Figure 5.13: Decision tree for "navigating with entire social group"

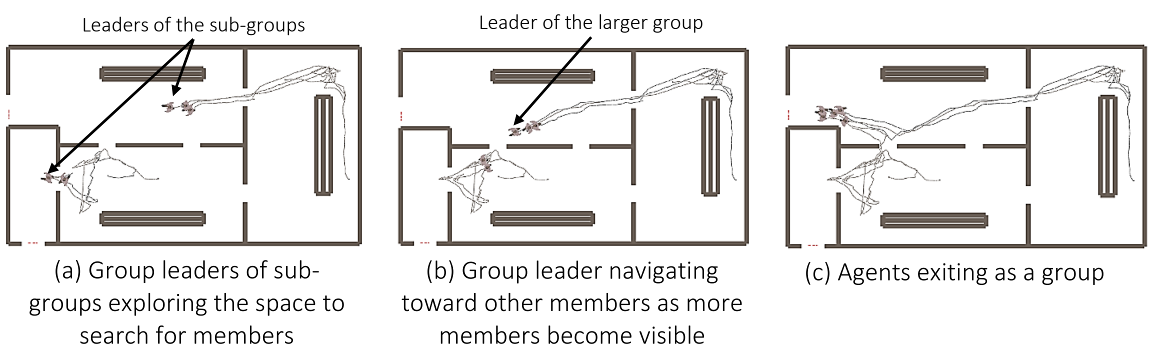


Figure 5.14: Behavior modeling for "navigating with entire social group"

Demonstration of usage

Figure 5.14 illustrates the process of a group of agents assuming the behavioral model "navigating with entire social group." The group consists of five members who are separated into two sub-groups initially. Each sub-group leader leads the followers to search for the members who are missing. Instead of going directly to the exit, the agents make detours and explore the space, leading to the irregular agents' trajectories shown in Figure 5.14a. Once the leaders of the two sub-groups "see" each other, one of the leaders becomes the follower of the leader of the larger group. The leader of the merged group moves closer to the group centroid because the group is dispersed, while at the same time, the followers travel to maintain proximity to the leader (Figure 5.14b). The leader navigates to the exit only when all the group members are visible and nearby (Figure 5.14c).

The "navigating with entire social group" behavioral model simulates the behaviors of people who are in a group of high intimacy. As evidenced by the empirical studies of past accidents, the members of a high intimacy group continue to be concerned about the safety of other members, even in emergencies [5, 6, 17]. For example, in the 1973 Summerland fire in the UK, parents searched for their children before evacuating the building, and some people even re-entered the building to search for the members who were missing [36]. Their group behaviors are not only guided by the visual presence of group members, but also the social relationships that are established before an emergency event. Because different types of groups have different social dynamics, SAFEgress accommodates the diverse social behaviors by providing a flexible framework to test different behavioral assumptions.

5.3.5 Following the crowd to evacuate

As the first sign of an emergency threat is often ambiguous, people may spend time to investigate and interact with one another before deciding their responses [70, 78, 79]. The movement of some evacuees toward different exits also hints at the availability of alternative exits to safety, and people often choose the exits preferred by the majority of the crowd in ambiguous situations [38]. We define the "following the crowd" behavioral model to simulate the herding phenomena when people follow the crowd to exit a building.

Behavioral rules and decision tree

Figure 5.15 shows the decision tree of "following the crowd to evacuate." During the reasoning process, the agent assesses the dynamic attributes **visible navigation objects**, **neighboring agents**, and **selected behavior** (of previous simulation step) to determine the final behavioral routine.

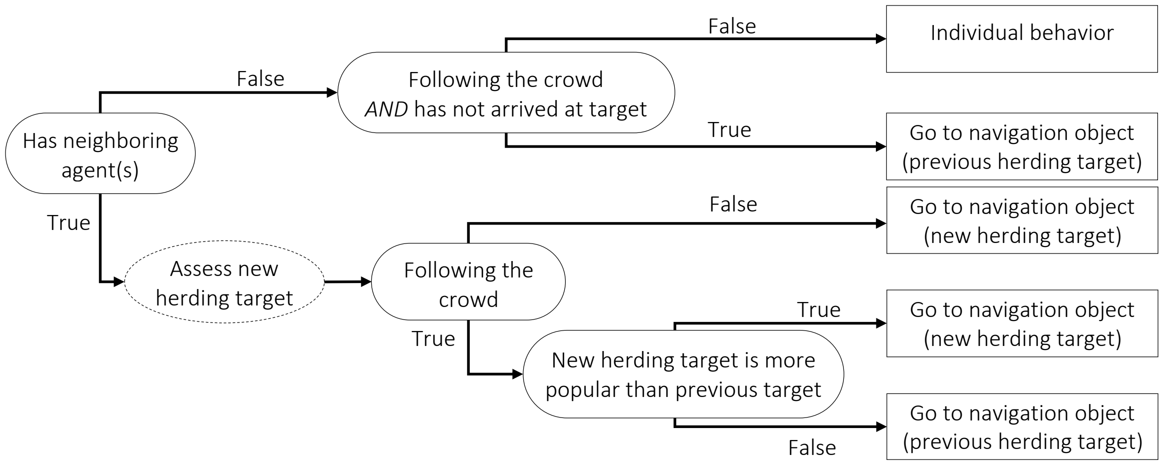


Figure 5.15: Decision tree for "following the crowd to evacuate"

The behavioral rules of "following the crowd" are defined by the following process:

1. If the agent perceives neighboring agents, it checks the following conditions:
    a. The agent determines the new herding target by assessing the navigation object that attracts the most neighboring agents. If the agent is not following the crowd (i.e. its previous selected behavior is not "following the crowd to evacuate"), the agent will go to the new herding target; otherwise, it checks the next condition.
    b. If the new herding target is more popular than the previous herding target (i.e. more agents move toward the new target than the previous target), the agent will go to the new herding target; otherwise, it will continue to proceed to the previous herding target.

2. If the agent does not perceive any neighboring agents, it checks the following condition:
    a. If the agent is following the crowd (i.e. its previous selected behavior is "following the crowd to evacuate"), and it has not arrived at its previous herding target, it will continue to go to the previous herding target; otherwise, it adopts individual behavior, such as following perception.

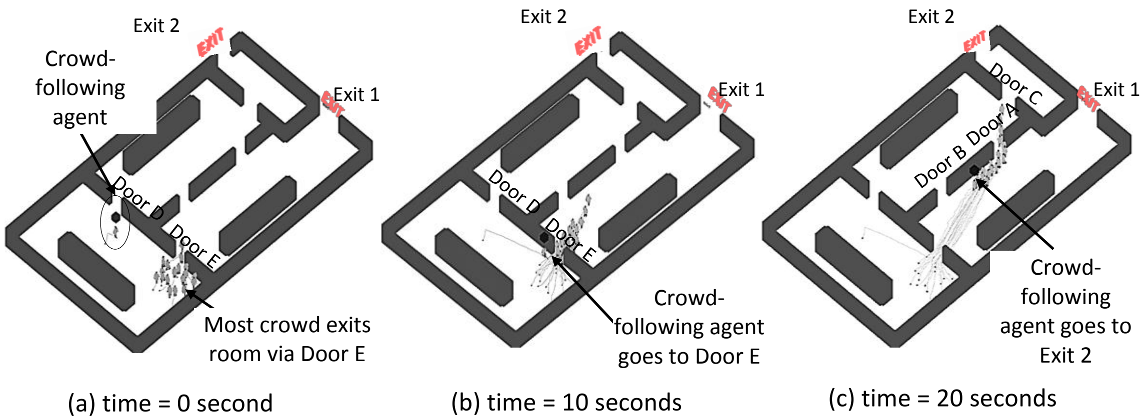


Figure 5.16: Behavior modeling for "following the crowd"

Figure 5.16 illustrates the crowd-following agent (circled in Figure 5.16a). All other agents prefer exiting through Exit 2. In Figure 5.16a, the crowd-following agent assesses the number of agents who are traveling toward Door D and Door E. All other agents are heading to Door E but none through Door D. In Figure 5.16b, because more agents are leaving the room via Door E, the crowd-following agent then follows the crowd and navigates towards Door E, despite that Door D is closer to the agent. As shown in Figure 5.16c, the agent continues to assess visible navigation objects and follows the crowd to exit from Exit 2 via Door A and Door C.

5.3.6 Following authority's instruction

In an emergency situation, there are often emergency responders who are responsible for certain assigned tasks during the evacuation, such as providing evacuees the directions to exit [17]. People who receive the instructions from emergency responders tend to follow the instructions because they perceive the information as reliable and authoritative [7, 9]. To mimic the interactions between the emergency responders and the crowd, we implemented a crowd behavior "following authority's instruction" by assigning some agents as the authoritative agents that can be detected by the crowds.

Behavioral rules and decision tree

Figure 5.17 shows the decision tree of "following authority's instruction." When an agent invokes this behavior, it assesses the static attribute **assigned task**, and the dynamic attributes **neighboring agents** and **selected behavior** (of previous simulation step) to decide final behavioral routine.

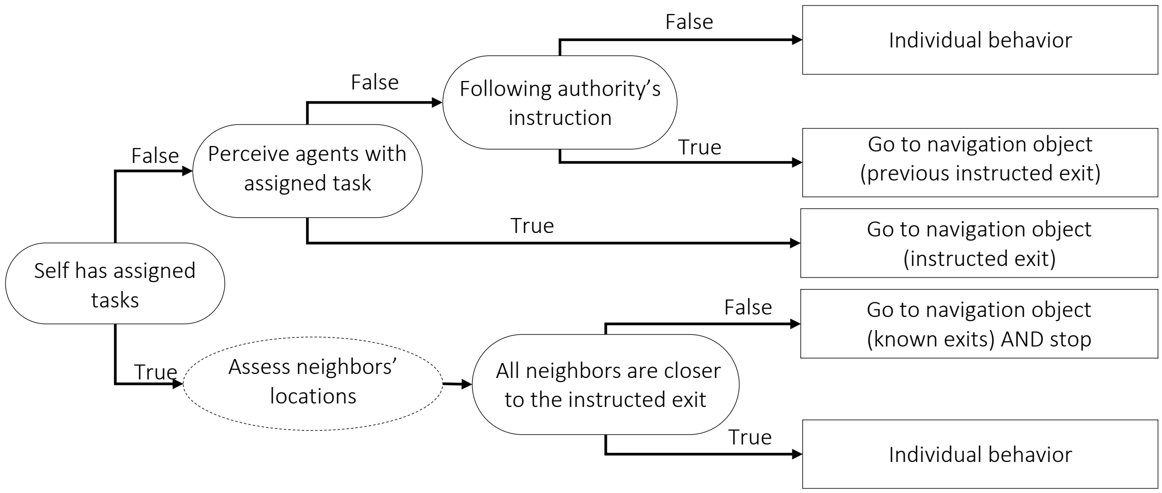


Figure 5.17: Decision tree for "following authority's instruction"

The behavioral rules of the behavior "following authority's instructions" are defined as follows:

1. If the agent has assigned a task (i.e. an authoritative agent), it assesses if all of its neighbors are closer to the instructed exit than itself. If all neighbors are closer to the instructed exit, the authoritative agent adopts individual behaviors, such as following knowledge to evacuate; otherwise, it remains stationary at the duty location.
2. If the agent does not have any assigned tasks, it checks the following conditions:
    a. If the agent perceives any agents with assigned tasks (i.e., the authoritative agent), it follows the instruction given by the authoritative agent; otherwise, it checks the next condition.
    b. If the agent has been following the instruction from an authoritative agent (i.e., its previously selected behavior is "following authority's instruction"), the agent continues to go to the instructed exit; otherwise, it adopts individual behavior, such as following knowledge, to evacuate the building.

Demonstration of usage

Figure 5.18 illustrates the behaviors of a group of agents that are instructed by an authoritative agent. In this simulation, the authoritative agent (circled in Figure 5.18a) has an assigned task to instruct agents to go to Exit 2, whereas other ordinary agents do not have assigned tasks and prefer to exit through Exit 1. In Figure 5.18a, the agents with no assigned tasks (i.e., the ordinary agents) follow their knowledge and navigate toward Exit 1. As shown in Figure 5.18b, when the ordinary

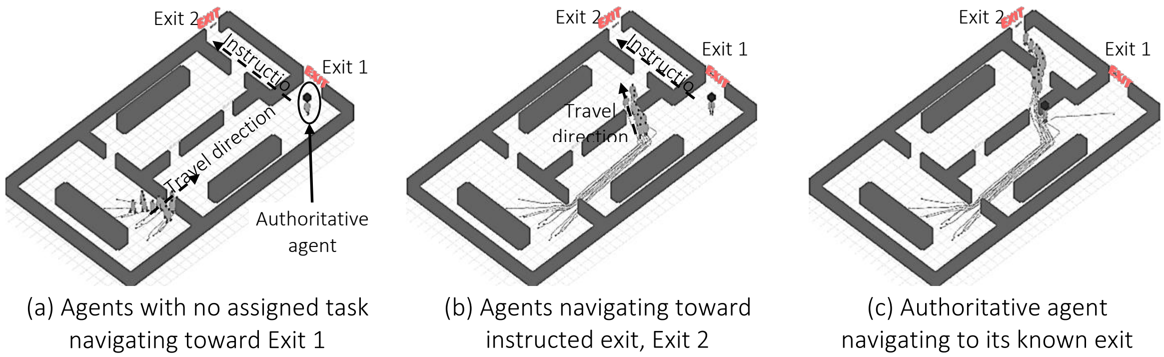


Figure 5.18: Behavior modeling for "following authority's instruction"

agents perceive the authoritative agent, the ordinary agents then follow the instruction from the authoritative agent and go to the instructed exit, Exit 2. Meanwhile, the authoritative agent assesses the locations of its neighbors and determines to stay at the duty location. In Figure 5.18c, the ordinary agents continue to go to the previously instructed exit, while the authoritative agent starts navigating toward Exit 2 when all its neighbors are closer to the instructed exit than it does.

To show the importance of authoritative agent arrangement, we increase the number of agents to 40 in the illustrative simulations. Figure 5.19 compares the evacuation patterns with different arrangements of the authoritative agent. In Figure 5.19a, without assuming any authoritative agents, congestion occurs at the opening where agents encounter each other when moving to their preferred exit. In Figure 5.19b, an authoritative agent is positioned to instruct the ordinary agents to exit through Exit 2 effectively; as a result, counter flow at the opening is avoided. In Figure 5.19c, the authoritative agent is positioned at a less visible location to the agents who are traveling to Exit 1. The agents traveling to Exit 1 perceive the authoritative agent only after passing through the opening and have to backtrack as they follow the exit instruction. As highlighted in Figure 5.19c, positioning the authoritative agent ineffectively can even cause a higher level of congestion in some critical areas. The simulations illustrate that the presence of authoritative agents, as well as the arrangement of these agents, can significantly affect the congestion patterns.

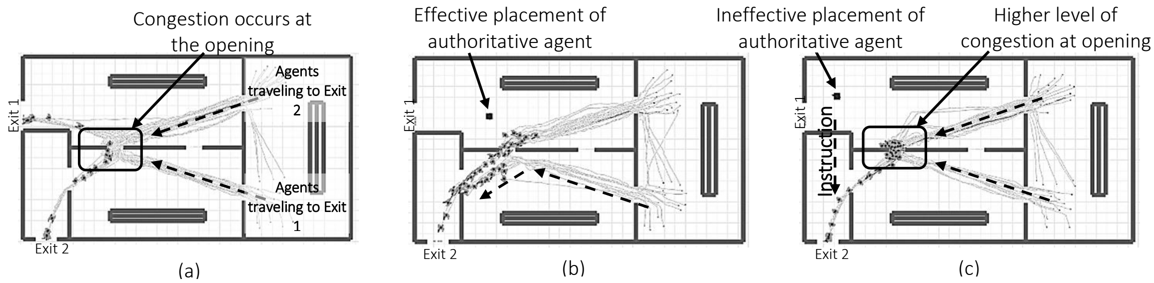


Figure 5.19: Evacuation patterns with different arrangements of authoritative agents

5.3.7 Summary

During a simulation step, each agent perceives the environment, interprets the urge to evacuate, decides a behavior through a tiered reasoning process, and executes the action. Each of the individual and social behaviors is represented as a separate decision tree. We have illustrated six behavioral models, namely, following perception, following knowledge, navigating with members, navigating with entire social group, following the crowd, and following authority's instruction. These behavioral models demonstrate the flexibility of the framework to incorporate different individual, social group, and crowd behaviors. As shown in Figure 5.20, different behavioral assumptions lead to various movement trajectories and evacuation times. When an agent exhibits group or crowd behaviors, it tends to adopt a longer route and take more time to exits the building. The routes and egress times change because the agents also prefer to maintain proximity with their group members and the surrounding crowd while exiting the building. By modeling the individual agents as a part of the social group and crowd, SAFEgress allows users to test different behavioral models and assess the effects of individual and social factors on egress performance.

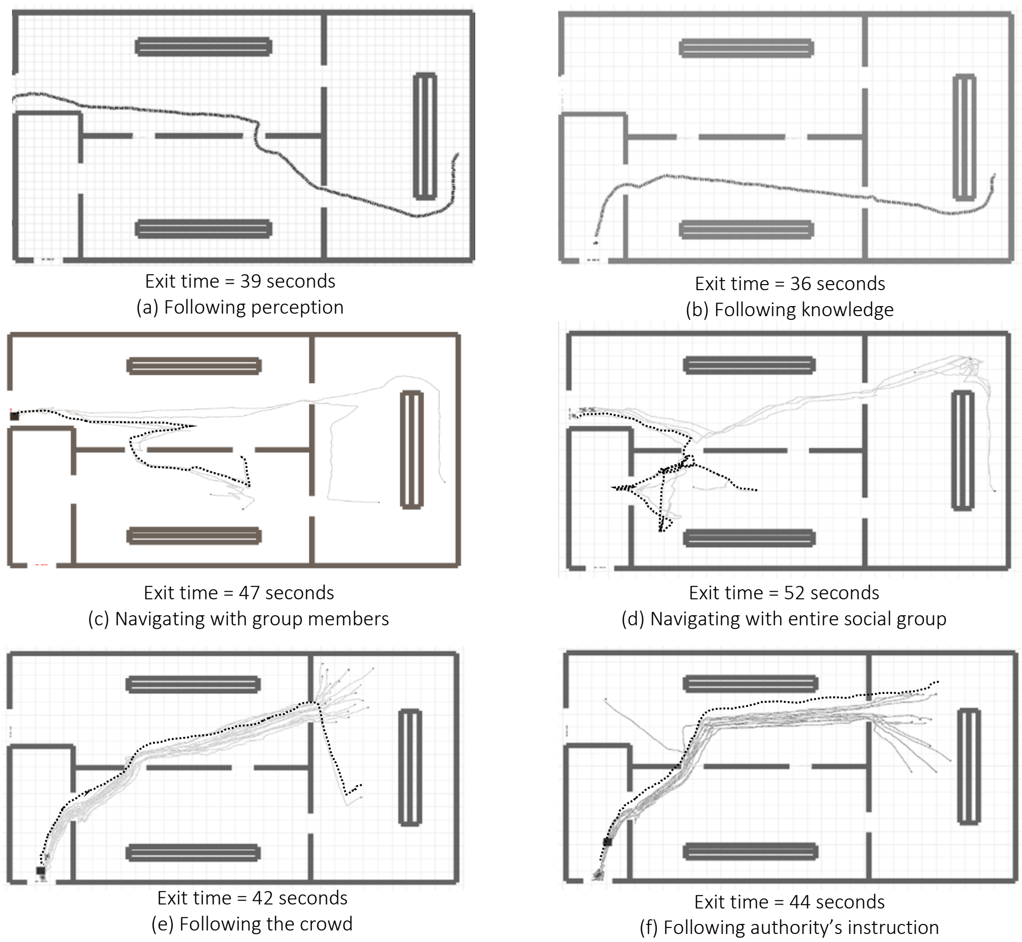


Figure 5.20: Comparison of agent trajectories and exit times with different behavioral models

In summary, the design of SAFEgress aims to provide a flexible way to model the effects of groups and crowds in egress:

- First, by defining an agent with group and crowd level characteristics, users can model group behaviors governed by pre-existing social relationships, as well as emergent crowd behaviors as a result of the dynamic crowd situation. Upon further study, additional attributes can be added to each of the levels (individual, group, and crowd) to enrich the representation of an agent and allow the modeling of more complex agent behaviors.
- Second, the multi-stage behavioral cycle (perception – interpretation – decision-making – execution) is designed to mimic the behavioral process of an occupant in an emergency situation [8, 61]. Each stage is modeled separately, such that existing functionalities at one stage can be modified easily. For example, new updating function modeling the effect of

conflicting emergency cues can be implemented at the interpretation stage without interfering with the succeeding decision-making stage.

- Third, the design of an agent's decision-making process decouples the behavioral logic (represented in a behavioral model) from the definition of the agent's characteristics (defined by the agent attributes). This design pattern aims to allow the re-use of behavioral models to generate different aggregated behavioral profile. Moreover, new behavioral models could be added to represent a new kind of behaviors observed in egress. For example, helping behavior toward the elderly can be modeled as a new behavioral model, in which the helping agent maintains a close distance with an elderly agent, while the elderly agent follows the helping agent.

Human and social behaviors, particularly in emergencies, are complex in nature. The implemented urge updating functions and the behavioral models are demonstrations of how SAFEgress can systematically incorporate individual preferences and knowledge, group relationships, and crowds in simulations. By designing a systematic representation of egress based on the studies pertaining to human behaviors in emergencies, we aim to facilitate the investigation of different human and social factors in a complex egress situation.

Chapter 6

Validation

This chapter discusses the rationales and tests conducted to validate the SAFEgress simulation framework. Model validation is an on-going and important task for simulation research. Due to the unpredictability of egress scenarios and variability in human behaviors, model validation cannot guarantee that simulated egress results resemble precisely egress outcomes in real-life situations. Nevertheless, extensive validation can establish confidence in simulation results and verify the intended functionalities of the simulation model. We adopt a bottom-up approach to validate different aspects of SAFEgress [83]. The tests are classified into four categories:

- Component testing: Component tests are carried out to verify the basic functionalities of an agent, such as walking at assigned speed and avoiding collisions with obstacles.
- Qualitative validation: This form of validation tests qualitatively the model's capabilities to produce expected outcomes when simulation inputs are modified, such as reducing the number of exits, which should increase the evacuation time.
- Functional verification: Functional verification is specific to simulation models as the model capabilities and inherent assumptions of each simulation model are different. We carry out a series of tests on the attributes and the decision-making process of the agents to show the range of behaviors that SAFEgress can capture.

- Case studies: Case studies demonstrate the real-world application of the SAFEgress framework. We use the current SAFEgress prototype to evaluate the egress performance of a museum and a stadium. These studies employ realistic assumptions of the occupant populations and evacuation scenarios.

This chapter provides details on component tests, qualitative validation, and functional verification. The museum and stadium case studies will be described in Chapter 7.

6.1 Component testing and qualitative validation

Component tests and qualitative validation are tests that are designed to verify the underlying assumptions and the behavioral capabilities built into the model. The accuracy of these tests is fundamental to producing correct results of more complex simulations. We consider five test cases, which are adopted from the Interim Guidelines for Evacuation Analyses for New and Existing Passenger Ships by International Maritime Organization (a.k.a. IMO guidelines) and handbooks on pedestrian design [20, 84].

6.1.1 Test 1: Moving at assigned movement speed

The first test is adapted from IMO guidelines [84]. The test validates the walking speed assumptions in the agent physical profile. As shown in Figure 6.1, we model a 2 m wide and 40 m long corridor and assume an exit at the far-right end of the corridor. One agent is populated at the other end of the corridor and has a walking speed of 1 m/s. The expected outcome of the test is that the agent will walk along the corridor from one end to the other in about 40 seconds. Over ten simulation runs, the average simulated time for the agents to arrive at the exit is 41.2 seconds and the standard deviation of 1.5 seconds.

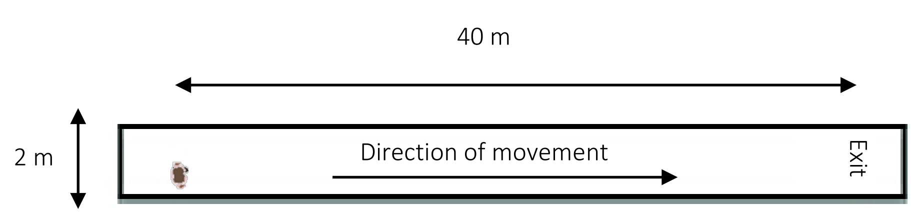


Figure 6.1: Setup of Test 1 (plan view)

6.1.2 Test 2: Measuring flow rate through exit outlet

The second test is adapted from IMO guidelines to validate the expected flow rate of the agents passing through a 1-m exit door [84]. As shown in Figure 6.2, we model an 8 m by 5 m room with a 1-m exit located centrally on the 5-m side. 100 agents of "Adult Male" type are assigned to evacuate from the room via the exit once the simulation has started (i.e., no delay time). The expected outcomes of the test are (1) the flow rate at exit should not exceed 1.33 persons/second and (2) agents do not overlap with each other at any time. Over ten simulation runs, the average simulated time for evacuation was 76.5 seconds (with a standard deviation of 2.5 seconds). Figure 6.3 shows the rate of evacuation of a typical simulation run. The average flow rate is 1.32 persons/second, which does not exceed the expected maximum flow rate specified in IMO guidelines [84].

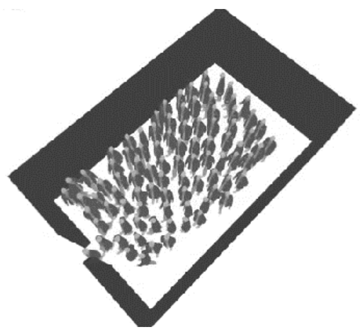


Figure 6.2: Setup of Test 2 (isometric view)

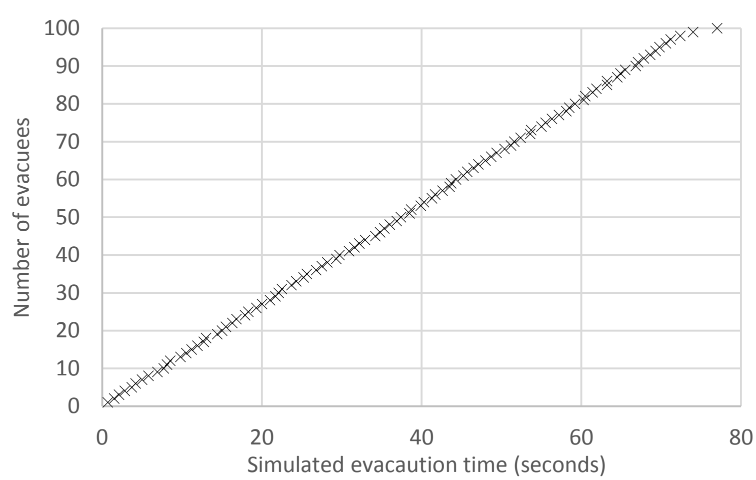


Figure 6.3: Rate of evacuation of a typical simulation run in Test 2

6.1.3 Test 3: Navigating considering physical obstacles

The third test, also extracted from the IMO guidelines [84], validates the agents' ability to navigate around a corner without penetrating the boundaries. As shown in Figure 6.4, we model a 2 m wide corridor with a left-hand turn. 20 agents of "Adult Male" type (described in Chapter 4) are initialized at the spawning area. During the simulation, the agents travel to the specified destination around the corner. The expected outcomes of the test are (1) the agents navigate around the corner without penetrating the boundaries and (2) agents do not overlap with each other at any time. Figure 6.5 shows the screenshots of a typical simulation run, which demonstrates that all agents successfully navigate around the corner without penetrating the boundaries.

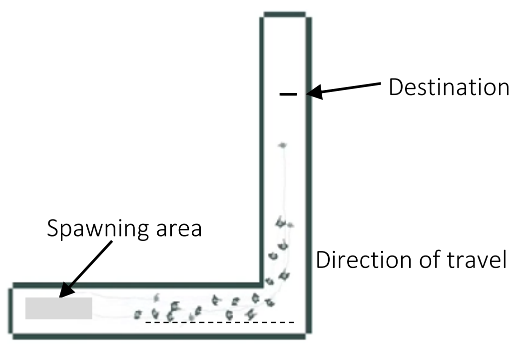


Figure 6.4: Setup of Test 3 (plan view)

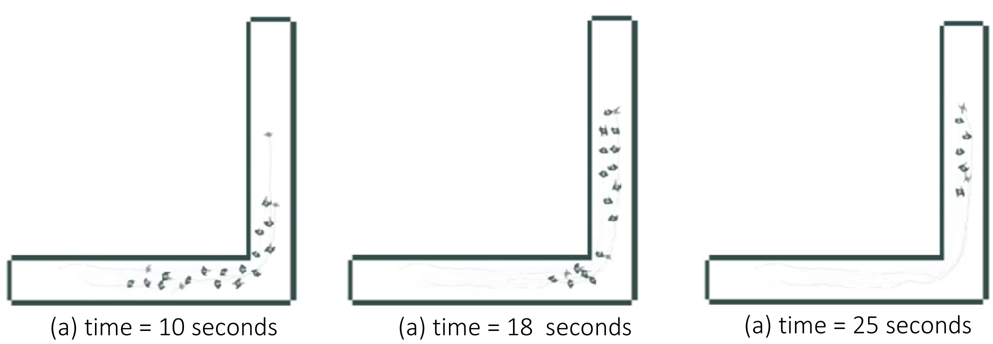


Figure 6.5: Simulation screenshots of Test 3

6.1.4 Test 4: Relationship between exit time and number of exits

The fourth test is adapted from IMO guidelines to validate the lengthening of evacuation time due to a reduction in exits [84]. Figure 6.6 shows the test setup that specifies a 30m by 20m room with four 1-m wide exits. Figure 6.7 shows the SAFEgress model that follows the specifications. 1,000 agents of "Adult Male" type are uniformly distributed in the room. Once the simulation has started, all the agents leave via the nearest exits (i.e., no delay time). Two cases are simulated: (1) evacuation through all 4 doors and (2) evacuation using only Door 3 and Door 4. Over ten simulation runs, the average simulated time for the first case is 210 seconds, and the results for the second case is 424 seconds. The result is consistent with the predicted test outcome stated in IMO guideline – when the number of exits is reduced by half, the total evacuation time is doubled [84].

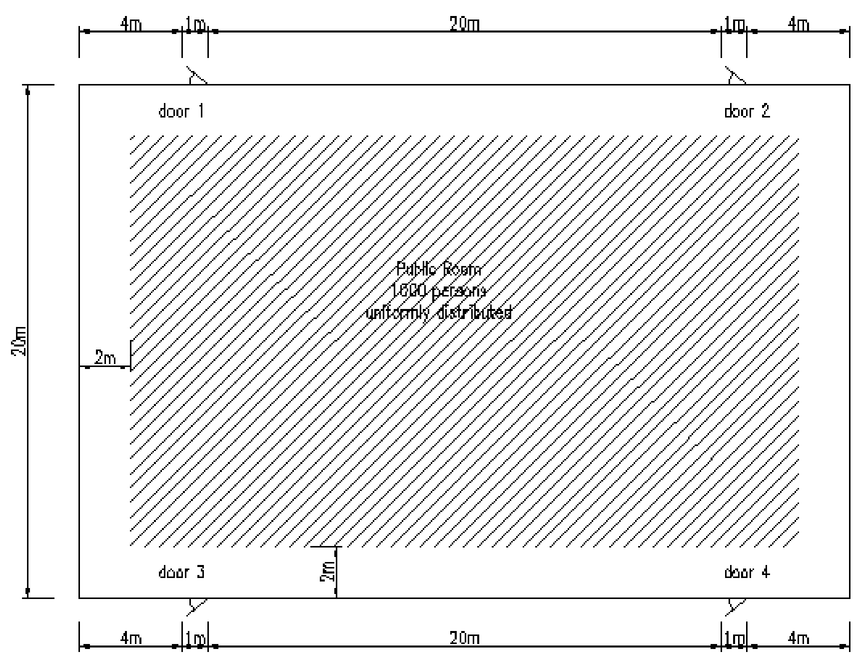


Figure 6.6: Exit flow from a large public room (adopted from [84])

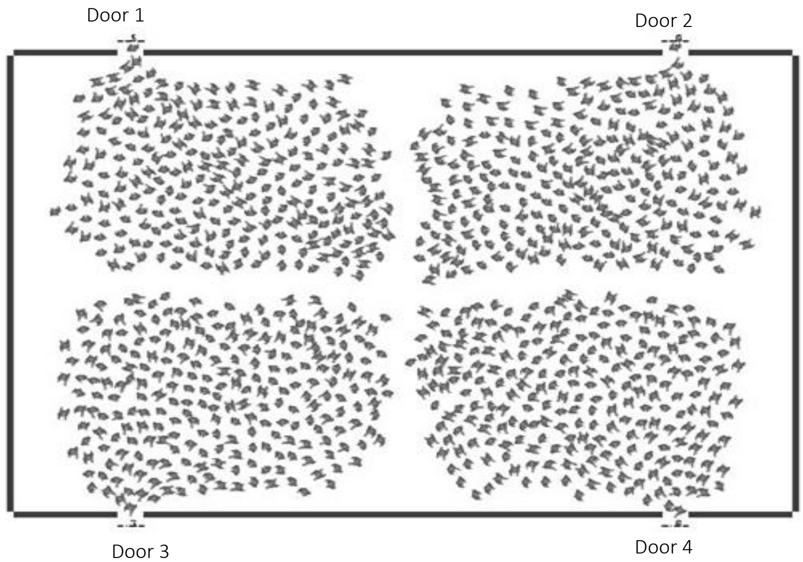


Figure 6.7: Setup of Test 4 (plan view)

6.1.5 Test 5: Replicating fundamental diagram

The fifth test validates the specific flow through a corridor at different crowd densities [20]. Specific flow is defined as the number of people passing a one-meter wide cross section per second (the unit of measure is persons/m/second). Several pedestrian studies have proposed different, but similar, formula to describe the relationship between the specific flow and crowd density [3, 20]. In this test, we adopt the formulas suggested in Society of Fire Protection Engineers (SFPE) to evaluate the specific flow measurements in SAFEgress simulations [85, 86].

As shown in Figure 6.8, a corridor of 3-m wide and 50-m long is modeled to obtain the flow measurements. We assign a continuous influx of agents of "Adult Male" type at a rate of 3

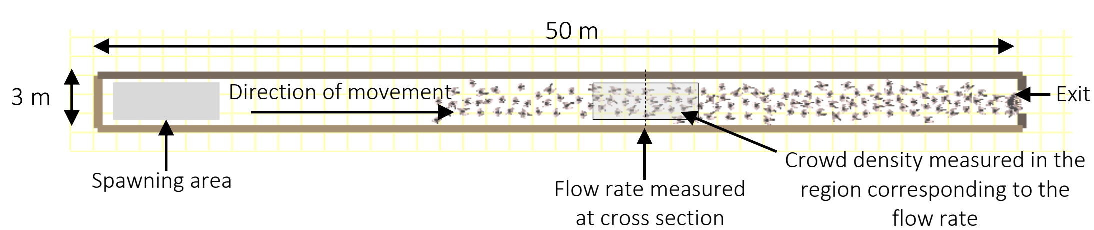


Figure 6.8: Setup of Test 5 (plan view)

persons/second in the spawning area, and these agents travel along the corridor to arrive at the exit. In different sections of the corridor, we measure the average specific flow rate in a 5-second interval and record the corresponding crowd densities in the section. The measurements of 10 simulation runs are collected and are compared to the formula suggested in SFPE [85, 86].

Figure 6.9 shows the SAFEgress measurements and the SFPE formula that describes the relationship between the crowd density and the flow rate. Overall, the SAFEgress flow measurements are consistent with the SPFE predictions. In extremely high crowd density (i.e., personal space is less than 0.3 m^2/person), the agents' movements are impeded by the lack of space, therefore, the flow rate is low (less than 50 persons/m/min.). As the congestion alleviates and the agents attain more space to perform locomotions, the flow rate increases and peaks at around 0.5 m^2/person. Nevertheless, as agents acquire more space for navigation (i.e., crowd density decreases), the flow rate decreases. The decrease in flow rate is because, when the crowd density is low, the flow rate is bounded by the number of agents traveling in the area.

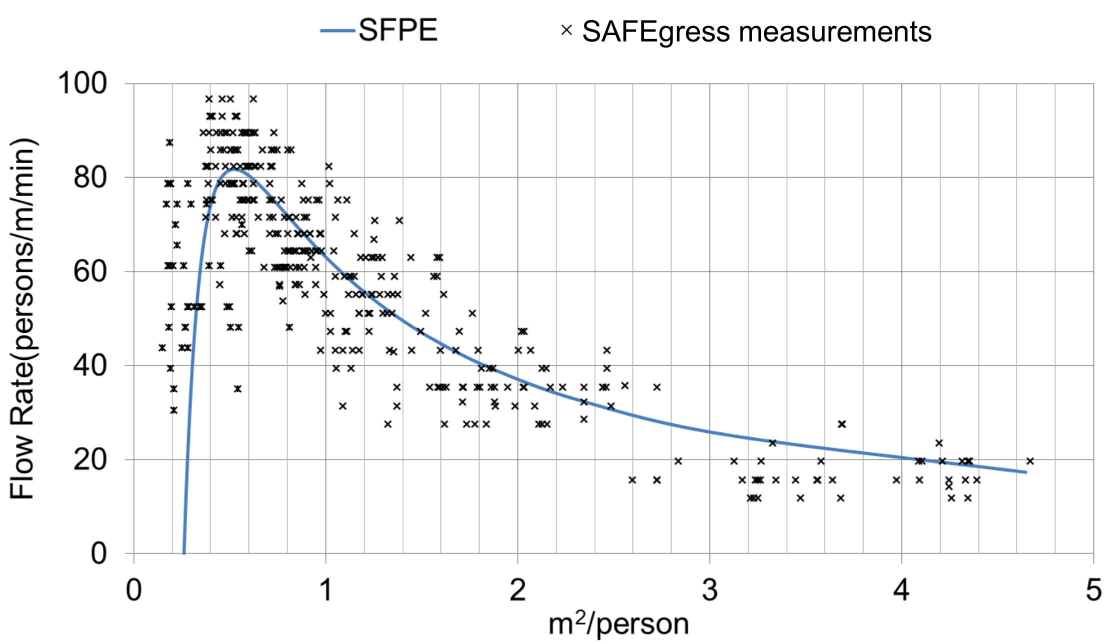


Figure 6.9: Plot of specific flow rate against personal space

6.2 Functional verification

In SAFEgress, the occupant population is modeled as agents with individual, group, and crowd level attributes. Group compliance and crowd compliance are the two important agent attributes that determine the range of behaviors that an agent can exhibit. Both of these compliances can be assigned as either low or high. By assigning different values to the group compliance and the crowd compliance, we can broadly define four kinds of agents that exhibit different ranges of behaviors:

- **Individualistic agent (default agent)**: An agent with low compliance with both the group and the crowd can only exhibit individual behaviors.
- **Agent considering its social group:** An agent with high group compliance but low crowd compliance can exhibit both individual and group behaviors.
- **Agent considering the crowd:** An agent with high crowd but low group compliance can exhibit both individual and crowd behaviors.
- **Agent considering both its social group and the crowd:** An agent with high compliance with both the group and the crowd can exhibit individual, group, and crowd behaviors.

Using the first three kinds of agents, we illustrate the range of individual, group, and crowd behaviors captured by SAFEgress. Furthermore, using the fourth agent type, we show the capability of an agent to reason through individual, group, and crowd behaviors during the simulation.

In the following tests, we adopt the same floor configuration shown in Figure 6.10 for easy comparison of the results. The simulated floor space has two main exits (Exit A and Exit B) and two emergency exits (Exit C and Exit D), as well as four exit signs. An alarm cue is assumed to become active at simulation time = 0 second to trigger the evacuation process. The effective range of the alarm is the entire floor. We further assume that the average reaction time to start evacuation is 30 seconds for an occupant with no prior emergency experience associated with an alarm cue (i.e., agent's cue awareness factor equals to 1).

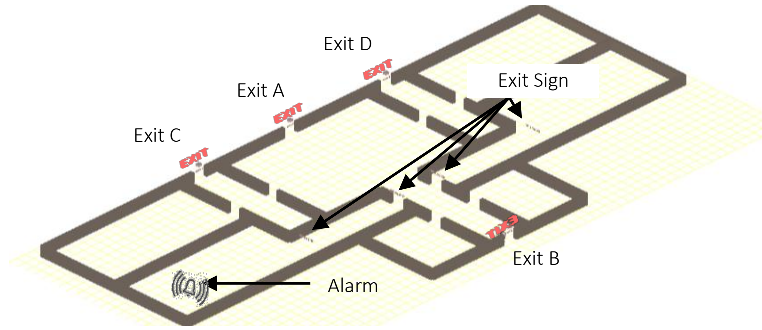


Figure 6.10: Virtual environment for demonstrating different behaviors

6.2.1 Individual

At the individual level, each agent is defined by the physical profile, cue awareness, and knowledge of the building. Physical profile is mainly related to the walking speed and physical size of the agent, which have been discussed in the component tests. In this section (Section 6.2.1), we focus on the use of cue awareness and knowledge of the building to model different individual behaviors. Because both tests focus on the individual attributes of the agents, we ignore the group and crowd level attributes in the following two tests.

6.2.1.1 Cue awareness

Test set-up: An agent's cue awareness can change the agent's reaction time to initiate evacuation upon perceiving an emergency cue. We design two types of agents: (A1) agents with high awareness of an alarm cue, and (A2) agents with no or low awareness of an alarm cue. We simulate 10 agents of Type A1 (high awareness) and 10 agents of Type A2 (low awareness). Table 6.1 shows the values of the attributes of each agent type. The difference between the two agent types is the value of the cue awareness factor (β) – when an agent is more vigilant, the value of β is smaller. The values of cue awareness factor are randomly assigned to the agent within the range specified in Table 6.1. The cue awareness factor directly affects an agent's delay times to start evacuation, as described in the interpretation stage in Section 5.2.1. The expected outcome is that the high awareness agents have shorter delay time than the low awareness agents.

Results: Agents with different cue awareness levels experience different pre-evacuation delays. Figure 6.11 shows the delay time of each agent in the simulation. The average delay time for the agents with high cue awareness is 14.8 seconds, whereas the agents having low cue awareness have an average delay of 29.8 seconds. Consistent with our expectation, the agents with high cue awareness initiate evacuation sooner than those with low cue awareness. Figure 6.12 shows the trajectories of the agents during the simulation. At time = 30 seconds, only agents with high cue awareness have started evacuation, whereas the low awareness agents remain in the room. At time = 50 seconds, all agents have started evacuation, and the agents with high cue awareness are closer to the exit as they have started evacuation earlier than those with low cue awareness.

Table 6.1: Attribute values of agent types in cue awareness test

Agent type	**(A1) High awareness agents**	**(A2) Low awareness agent**
Physical profile	Adult male	Adult male
Known exits	None	Non
Cue awareness factor* (β)	**0.25-0.75**	**0.75-1.2**
Pre-evacuation behavior	Explore space	Explore space
Individual behavior	Follow perception to evacuate	Follow perception to evacuate

*randomly assigned to agents with a uniform distribution of the specified range

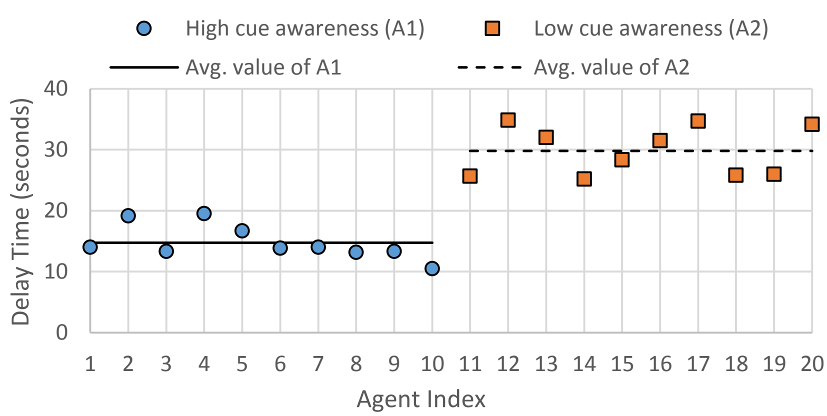


Figure 6.11: Delay times to initiate evacuation with different levels of cue awareness

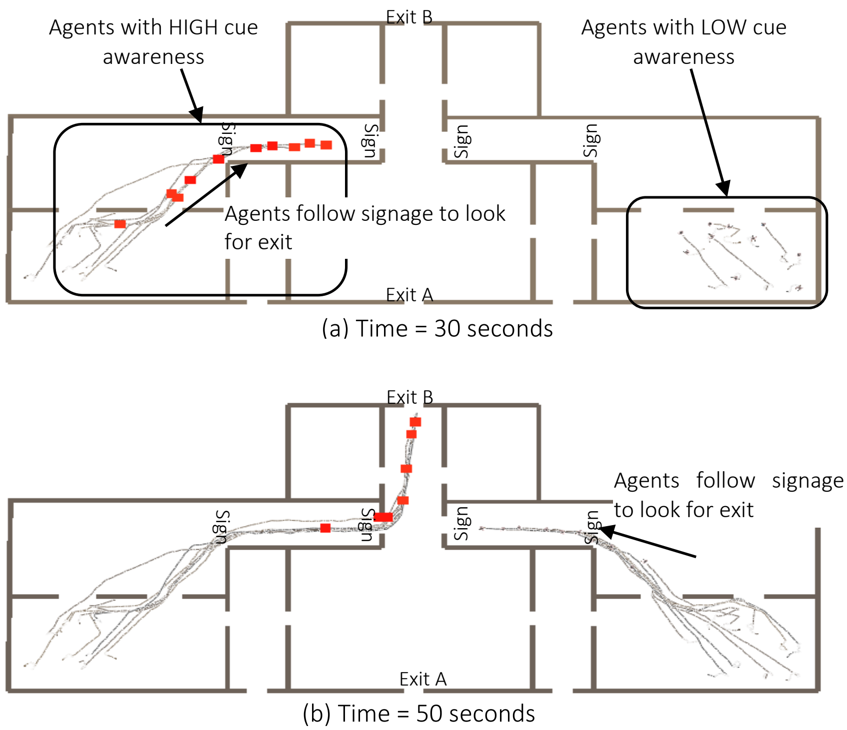


Figure 6.12: Agents' trajectories with low and high levels of cue awareness

6.2.1.2 Building familiarity

Test set-up: An agent's familiarity with the building is modeled using the attribute "known exits." We design two types of agents, which are defined by the attributes shown in Table 6.2. Type F1 agents are familiar with the building and possess knowledge of all exits and Type F2 agents are not familiar with the building and possess no exit knowledge. When an agent possesses knowledge of an exit, the agent can travel to the exit via the shortest routes using its wayfinding capability

Table 6.2: Attribute values of agent types in familiarity test

Agent type	(F1) High familiarity agents	(F2) Low familiarity agents
Physical profile	Adult male	Adult male
Known exits	**All four exits**	**None**
Cue awareness factor*	0.25-0.75	0.25-0.75
Pre-evacuation behavior	Explore space	Explore space
Individual behavior	Follow knowledge to evacuate	Follow knowledge to evacuate

*randomly assigned to agents with a uniform distribution of the specified range

(described in Section 4.4.3.1), even if the exit is not in their line of sight. We assume 10 agents of Type F1 (high familiarity) and 10 agents of Type F2 (low familiarity) in the simulations.

Result: Agents with different knowledge of the building exit using different evacuation routes, which in turn affects the overall evacuation times. Figure 6.13 shows the evacuation time of each agent. The average evacuation time for the agents with high familiarity is 36.4 seconds, whereas that of agents with low familiarity is 54.5 seconds. The familiar agents exit the building faster than the unfamiliar ones because the familiar agents choose a shorter evacuation route. Figure 6.14 shows the agents' trajectories during simulation. The agents with high familiarity know the nearest exit, Exit C, (since they possess knowledge of all exits) and evacuate within a shorter period of time. On the other hand, the agents without any knowledge of the exits follow the exit signs, which lead them to exit through Exit B.

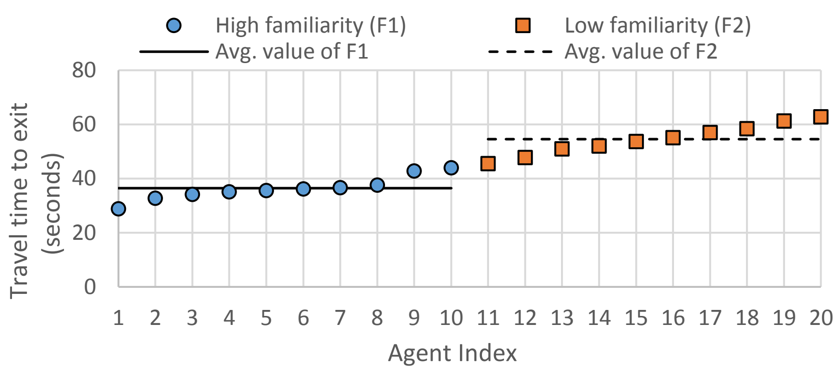


Figure 6.13: Delay times with different levels of familiarity

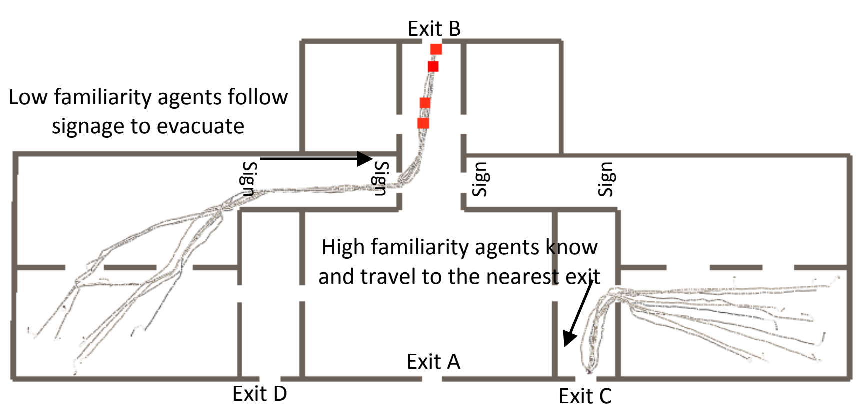


Figure 6.14: Agents' trajectories with and without exit knowledge

Summary of individual behavior modeling

Both the emergency experience and prior knowledge of the building directly affect occupant's behaviors in egress. In SAFEgress, an individual's emergency experience is modeled by cue awareness factors, whereas the individual's familiarity of the building is modeled by known exits. With different value assignments to these two parameters, users can create different agent types to model occupants who have different levels of sensitivity to an emergency cue and egress routines that are learned prior to the events.

6.2.2 Social groups

At group level, each agent can be affiliated with a social group, and the strength of the social affiliation is defined by the agent's group compliance attribute. The group influence and the intimacy level describe the characteristics of the social group. In our current implementation, one member is randomly selected to be the leader and has the highest influence among all the members.

We first define three types of agents that are the members of the social groups. Table 6.3 shows the attribute definitions of the three agent types. The key differences among these three agent types are the cue awareness and the group compliance. Agents of Type G1 comply with the group, whereas those of Type G2 do not follow their group. Agents of Type G3 are highly aware of the cues (defined by small value of cue awareness factor), and they also comply with the groups.

Table 6.3: Attribute values of agent types in social group tests

Agent type	**(G1) High group compliance**	**(G2) Low group compliance**	**(G3) High awareness & group compliance**
Physical profile	100%"adult male"	100%"adult male"	100%"adult male"
Known exits	Exit B	Exit B	Exit B
Cue awareness factors*	**0.25-0.75**	**0.25-0.75**	**0.01**
Pre-evacuation behavior	Explore space	Explore space	Explore space
Individual behavior	Follow knowledge	Follow knowledge	Follow knowledge
Group compliance	**High**	**Low**	**High**
Group behaviors	Navigating with group members	Navigating with group members	Navigating with group members

*randomly assigned to agents with a uniform distribution of the specified range

6.2.2.1 Group compliance

Test set-up: An agent with group affiliation does not systematically exhibit group behaviors; instead, the agent shows group behaviors only when the agent has a high group compliance. To test the effect of group compliance, we conduct two kinds of simulations: (1) all groups consisting of agents that have high group compliance (i.e. all members are of Type G1 in Table 6.3) and (2) all groups consisting of agents that have low group compliance (i.e. all members are of Type G2 in Table 6.3). In both simulations, we employ 10 groups of agents, and each group has four members.

Results: Compliance with groups affects agents' movement patterns, and thus the evacuation times. Table 6.4 reports the evacuation time for the two simulations, one assuming high group compliance and the other one assuming low group compliance. The agents with high group compliance take a longer time to evacuate because they also attempt to maintain proximity with other members when escaping. Figure 6.15 are simulation screenshots showing how the agents travel in the two simulations. For the agents with high group compliance, they navigate with their group members in cluster form (Figure 6.15a), whereas members with low group compliance do not attempt to maintain proximity with their group members, and travel to the exit as if they were not affiliated with any social groups (Figure 6.15b).

Table 6.4: Delay and evacuation times of groups with high and low compliances

Simulation run	(1) Groups with high compliance members (G1)	(2) Groups with low compliance members (G2)
Average delay time (seconds)	12.6	12.6
Total evacuation time (seconds)	71.5	58.2

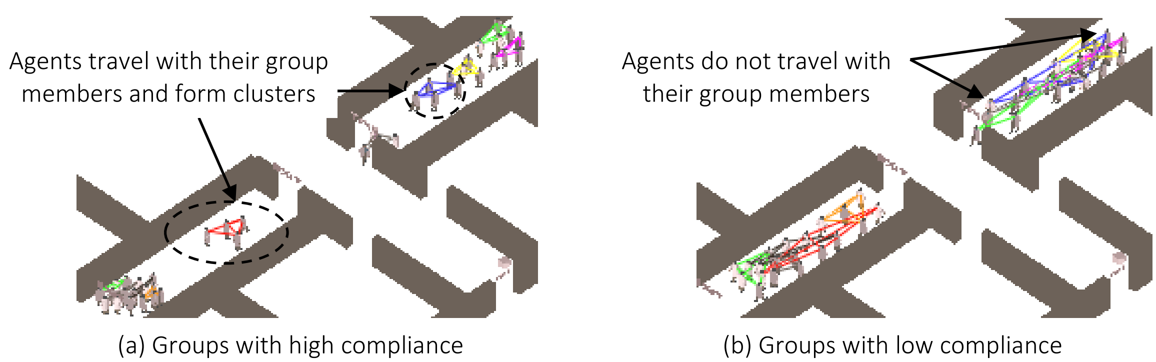


Figure 6.15: Simulation screenshots of the two simulations in group compliance test

6.2.2.2 Group size

Test set-up: Several empirical studies have highlighted the effects of group size on group navigation [39, 75]. In general, group size has an inversely proportional effect on walking speed. From our observations of movements of groups in normal egress, we also realized that larger groups tend to stop more frequently to wait for other members in order to maintain proximity to the group. In order to test the effect of group sizes, we vary the group size distribution when populating agents. Assuming 48 agents in the simulation, we change the size of groups in each simulation. Specifically, we test group with sizes of 1 (i.e., individual agents), 2, 4, and 6. To eliminate the effect of delay time, we assume all agents start evacuation action promptly (Type G3 in Table 6.3).

Results: The simulation result suggests that larger groups take longer time to evacuate compared to smaller groups. Figure 6.16 shows the overall evacuation time with different assumptions on the group sizes. With increasing group sizes, the total evacuation time increases nonlinearly. The increase in evacuation time is because, with more members in the groups, the members tend to make detours to maintain closeness with the others. Figure 6.17 shows the trajectories of the agents during the simulation. When the group size is large, a higher level of congestion in the corridor and irregular trajectories are observed because the agents tend to wait for other members.

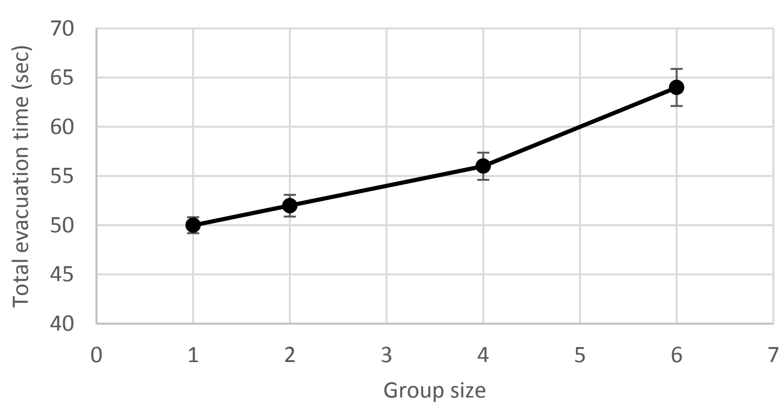


Figure 6.16: Total evacuation times with different group sizes

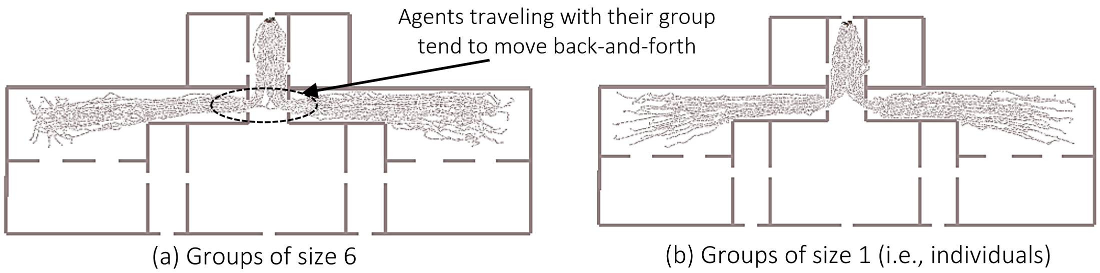


Figure 6.17: Agents' trajectories with and without groups

6.2.2.3 Group intimacy

Test set-up: The intimacy level describes the closeness of the group relationships, e.g., a family group has a high intimacy level. In SAFEgress, users can define groups with different intimacy levels (low, medium, and high) by specifying the separation tolerance and the time to reach group consensus. To test the effect of group intimacy, we conduct three simulations assuming groups of (1) high (2) medium, and (3) low intimacy, and the corresponding assumptions on separation tolerance and the time to reach group consensus are listed in Table 6.5. In each simulation, we employ 10 groups with four members in each group, and all agents have high group compliance (i.e., Type G1 in Table 6.3). The group influence on agent's urge to start evacuation has been described in the interpretation stage in Section 5.2.1. The expected outcome is that, with a higher level of group intimacy, the members tend to start evacuation sooner.

Results: Groups of different types reach consensus at various rates (see Table 6.5), thus have different delays to start evacuation. Figure 6.18 shows the agents' average delay to start evacuate assuming they are affiliated with groups with high, medium, and low intimacy level (12.6 seconds, 14.2 seconds, and 14.8 second, respectively). First, groups with higher levels of intimacy have shorter average delays than the groups with lower levels of intimacy. This is because closely related

Table 6.5: Characteristics of groups with different group intimacy levels

Group intimacy level	Group separation tolerance (in.)	Time to reach group consensus (sec.)
High	50	10
Medium	60	30
Low	70	50

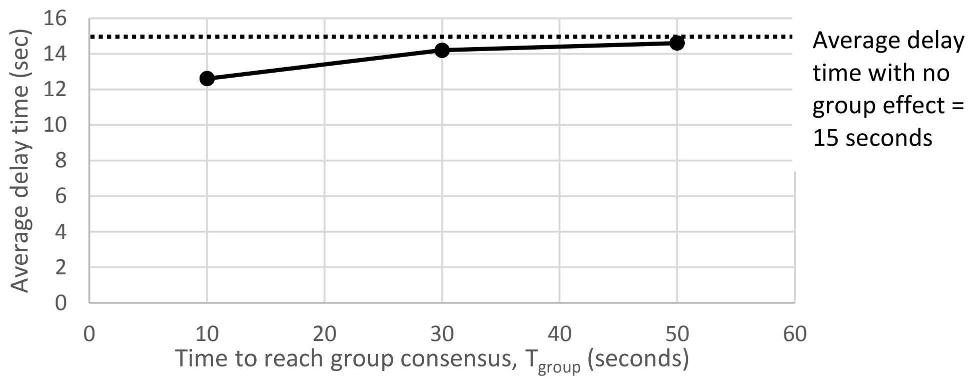


Figure 6.18: Delay times with different times to reach group consensus

groups are assumed to have a shorter time to arrive at group consent (as shown in Table 6.5), therefore, the time needed to determine the evacuation is shorter. Second, in all three cases that assume agents are affiliated with groups, the delay times are shorter than the simulation assuming all individuals[4]. It is because when an agent is affiliated with a social group, the agent attempts to adopt the highest urge among its visible group members, and the increase in urge makes the agent evacuate sooner compared to when the agent is alone.

Summary of group behavior modeling

SAFEgress incorporates the notion of social groups by incorporating group-level characteristics and processes. An agent can be assigned to one social group, which is characterized by group intimacy level and group influence. The modeling of groups is motivated by the social theories and empirical studies of past accidents. As a part of the social group, people continue to be concerned about the safety and whereabouts of other members while navigating toward their destinations. The separation and visual presence of group members determine the movements of the group members. Therefore, in SAFEgress, a high group compliance agent determines its group behaviors based on the dynamic states of other group members. Our tests illustrate the capability of SAFEgress to model some of these important group behaviors in emergencies.

[4] The average individual delay, 15 seconds, is estimated by multiplying the expected value of the cue awareness factors (i.e., 0.5) of all 40 agents of Type G1 with the reaction time of an alarm (i.e., 30 seconds).

6.2.3 Crowd

At the crowd level, each agent can be affected by the neighboring agents, depending on its crowd compliance. If the agent has high crowd compliance, the agent is likely to adopt the behaviors of the crowd. Moreover, the agent's urge to evacuate can be affected by the crowd, and the degree of crowd influence is described by the time needed for the agent to adopt the crowd's risk perception (defined as crowd-following time lag). In the following, we focus on testing the crowd compliance and the time lag to follow crowd perception.

6.2.3.1 Crowd compliance

Test set-up: In order to test the effect of crowd compliance, we design four agent types, which are summarized in Table 6.6. Types C1, C2, and C3 agents all have a low compliance with the crowd, but they have knowledge about different exits: agents of Type C1 prefer Exit A, those of Type C2 prefer Exit B, and those of Type C3 have no knowledge of the exit. On the other hand, agents of Type C4 have a high compliance with the crowd and have no knowledge of the exits. Two scenarios are designed to illustrate the effect of crowd behaviors on the exit usages:

- **Scenario 1- all individualistic agents without crowd-following agents:** the population consists of 20 agents exiting from Exit A (Type C1), 10 agents exiting from Exit B (Type C2), and 20 agents following perception to evacuate (Type C3);

Table 6.6: Attribute values of agent types in crowd level tests

Agent type	C1	C2	C3	C4
Physical profile	adult male	adult male	adult male	adult male
Known exits	**Exit A**	**Exit B**	**None**	**None**
Cue awareness factors*	0.25-0.75	0.25-0.75	0.25-0.75	0.25-0.75
Individual behavior	Follow knowledge	Follow knowledge	Follow perception	Follow perception
Crowd compliance	**Low**	**Low**	**Low**	**High**
Crowd-following time lag	20	20	20	20
Crowd behaviors	Follow crowd	Follow crowd	Follow crowd	Follow crowd

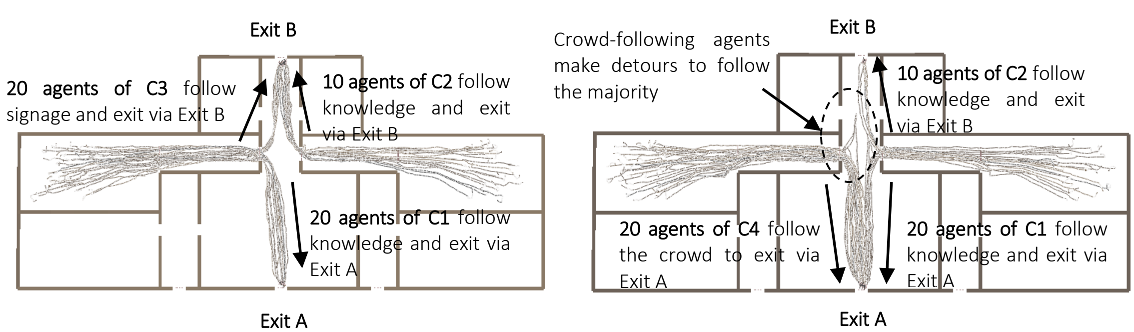
*randomly assigned to agents with a uniform distribution of the specified range

- **Scenario 2- individualistic agents with 20 crowd-following agents:** the population consists of 20 agents exiting from Exit A (Type C1) and 10 agents exiting from Exit B (Type C2). However, different from Scenario 1, 20 crowd-following agents (Type C4) are assumed in this scenario instead of perception-following agents (Type C3).

Results: Table 6.7 shows the exit usage in the two scenarios. The usage of the two exits is more even in Scenario 1 compared to Scenario 2. The agents' trajectories, as shown in Figure 6.19, are examined to understand the outcomes in the two scenarios. In Scenario 1 (Figure 6.19a), 20 agents prefer Exit A (Type C1); 10 agents prefer Exit B (Type C2); the remaining 20 agents (Type C3) follow their perception to evacuate. For those agents who follow perception, because Exit B is the nearest exit, all of them choose to evacuate through Exit B. Therefore, the usage of Exit B is higher than Exit A in Scenario 1. In Scenario 2 (Figure 6.19b), because more agents prefer Exit A (20 agents of C1) than Exit B (10 agents of C2), the crowd-following agents follow the majority to exit through Exit A, despite that Exit B is the nearest exit. Moreover, the crowd-following agents make detours to follow the majority. As highlighted in Figure 6.19b, some crowd-following agents initially choose to exit through Exit B. As the crowd-following agents continuously assess the exit preference of the crowd, they switch to Exit A from their initial exit choice.

Table 6.7: Exit usage of two scenarios in crowd compliance test

	Scenario 1 (all agents with low crowd compliance)	Scenario 2 (20 agents with high crowd compliance)
Exit A	20	40
Exit B	30	10



(a) Scenario 1 (all agents with low crowd compliance) (b) Scenario 2 (20 agents with high crowd compliance)

Figure 6.19: Agents' trajectories during simulations in crowd compliance test

6.2.3.2 Crowd influence on urge

Test set-up: The surrounding crowd has influence on an agent's urge to evacuate. Some agents may comply with the crowd sooner than the others, depending on its crowd-following time lag (T_{crowd}). To test the effect of crowd influence on urge, we assign 50 agents with T_{crowd} value of 2, 20, and 40 seconds in three simulations. The value of T_{crowd} directly affects the delay time, as described in the interpretation stage in Section 5.2.1.

Results: Figure 6.20 shows the average delay times and total evacuation times of the simulations assuming agents with different values of T_{crowd}. First, the average delay time with crowd effects is lower than the average delay time assuming no crowd effects (i.e., 15 seconds). It is because when an agent considers its neighbors with updating its urge, the agent conforms to the crowd by adopting the highest urge among the neighbor. Hence, the crowd has a positive effect in reducing the delay time of the agent. Second, as an agent takes a longer time to adopt the crowd urge (i.e., larger value of T_{crowd}), the crowd effect to reduce agent's delay diminishes. As shown in Figure 6.20, when T_{crowd} is 40 seconds, the average delay time is similar to that without crowd effects.

Summary of crowd behavior modeling

Even without prior connections, as a participant in the larger crowd, individuals interact with the surrounding neighbors in emergencies. SAFEgress incorporates the notion of crowds by modeling the agent with the capability to detect the neighbors by simulated vision during the simulation. The

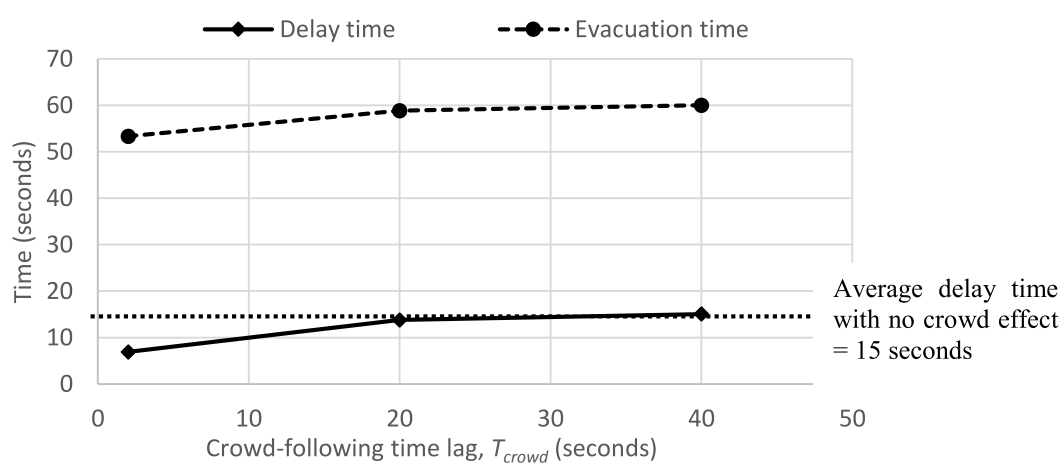


Figure 6.20: Delay times with different crowd-following time lags

agents can exhibit emergent crowd behaviors, such as herding toward one exit or following instructions from authority, depending on the state of the surrounding crowd.

6.2.4 Tiered decision-making process modeling different behaviors

During simulation, an agent invokes a three-level (individual, group, and crowd) reasoning process to determine final behaviors. Figure 6.21 shows an example of the decision-making process of an agent that has "following knowledge to evacuate" as its individual behavior, navigating with group members as its group behavior, and following crowd to evacuate as its crowd behavior. The implementations of these behavioral models are detailed in Chapter 5; here, we illustrate how an agent can switch between behaviors at different levels.

First, we define four types of agents with different knowledge of the exits and different levels of group compliance and crowd compliance (Table 6.8). These agent types are used to define the leader and members in social groups that follow the decision-making process shown in Figure 6.21.

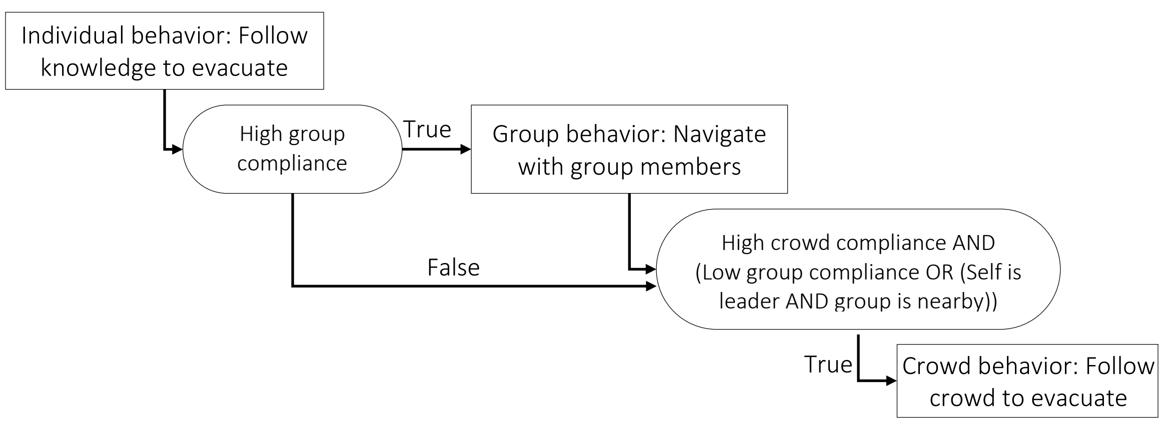


Figure 6.21: Example of agent's decision-making process

Table 6.8: Attribute values of agent types in tiered decision-making test

Agent Type	T1	T2	T3	T4
Known exit	Exit B	Exit B	Exit B	Exit A
Group compliance	High	Low	High	Low
Crowd compliance	High	Low	Low	Low

Next, we create two kinds of groups that consist of different leaders and members:

- Weak leadership: Leader has high compliance with both group and crowd (Type T1) and members have low compliance with both group and crowd (Type T2). Therefore, during simulation, the leader tends to maintain proximity with the members while following the crowd, while the members adopt individual behaviors and do not following the leader.
- Strong leadership: Leader has high compliance with both group and crowd (Type T1) and members comply with the group but not with the crowd (Type T3). Therefore, the leader tends to maintain proximity with the members while following the crowd, and the members follow the leader.

We employ two simple simulations to illustrate the behaviors of the groups under different kinds of leadership. In the first simulation, we employ 10 individualistic agents (Type T4), who will evacuate through Exit A. A weak leadership group consisting of four agents is also assumed in the simulation. Figure 6.22 shows the evacuation process of a group with weak leadership. In Figure 6.22a, because the leader perceives the proximity of other group members, its crowd conditions to exhibit crowd level behavior are satisfied, thus the leader follows the crowd to the exit. Other group members also move toward the sign as they follow their knowledge to evacuate from the building via Exit B; the members do not follow the leader because they have low group compliance and thus disregard group level behavior. Figure 6.22b shows the leader maintaining a short distance from the members and exhibiting crowd behaviors to follow the crowd and travel to Exit A. Other members continue to exhibit individual behaviors and travel to Exit B. In Figure 6.22c, when the leader detects that the group is dispersed, the leader no longer exhibits crowd behavior. The leader changes its direction of travel to be near the group members, while the members continue to navigate toward Exit B. In Figure 6.22d, the members leave via Exit B. As the leader continues to maintain proximity to the group, the leader also moves toward and leaves from Exit B.

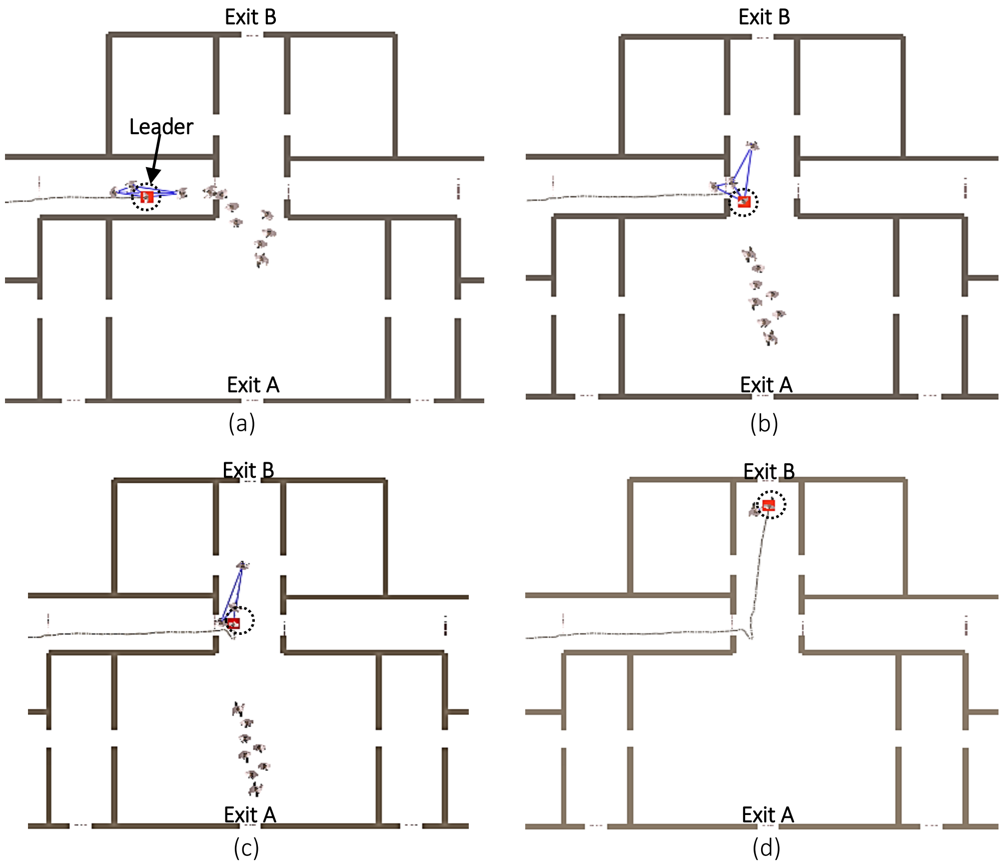


Figure 6.22: Evacuation process of a group with weak leadership

In the second simulation, we employ 10 individualistic agents (Type T4 in Table 6.8) and one strong leadership group consisting of four agents. Figure 6.23 shows the evacuation process of a group with strong leadership. In Figure 6.23a, as the group members are far apart, the leader travels toward the center of the group and omits crowd behavior. Other members, with high group compliance, navigate toward the leader. As shown in Figure 6.23b, when the leader maintains close proximity to the members, it exhibits crowd behaviors to follow the crowd and move to the door of the room, while other members continue to follow the leader. The group travels in cluster form. In Figure 6.23c, after arriving at the door, the leader, continues to follow the crowd to travel to Exit A, while the members continue to follow the leader. As illustrated in Figure 6.23d, the leader continues to travel to Exit A, and the rest of the group follows.

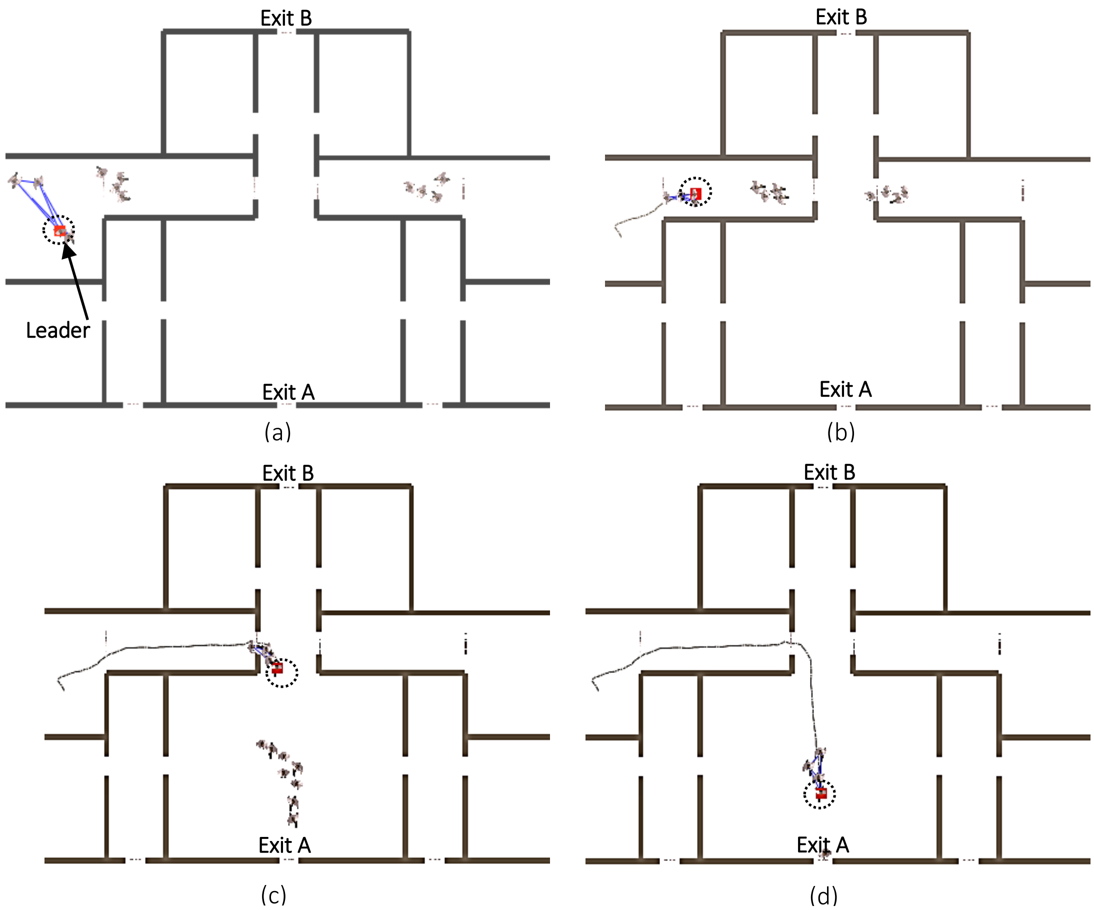


Figure 6.23: Evacuation process of a group with strong leadership

The simple simulations above highlight the capability of agents to switch their guiding behaviors from one level to another during simulation:

- Leader: In both illustrations, the leaders have high compliance with both group and crowd, thus may exhibit both group and crowd behaviors. The selected behavior depends on the locations of other group members. When the group is dispersed, the crowd conditions to invoke crowd behavior are not satisfied; so the leader exhibits group behavior instead, which overrides individual behavior. When the leader detects the proximity of other members, the leader's high crowd compliance invokes crowd behavior, which overrides the group behavior.
- Members: In the weak leadership group, the members have low group and crowd compliance, so they ignore group and crowd behaviors and exhibit only individual behavior to go to the known exit. On the other hand, in the strong leadership group, as the members have high

compliance with the group, they invoke group behaviors to follow the leader, overriding their original individual behaviors.

Following the two simple illustrations, we design three scenarios to test the effects of group and crowd dynamic on egress time and exit usage. We assume 20 groups, each composed of four agents. The agent assumptions of the three scenarios are as follows:

1. All agents are individualistic agents that evacuate through Exit A (Type T4).
2. 10 groups are individualistic agents and the other 10 groups have weak leadership in which the members tend to exit from Exit B and do not follow the leader.
3. 10 groups are individualistic agents and the other 10 groups have strong leadership in which the members tend to exit from Exit B and also follow the leader.

Table 6.9 lists the evacuation times and exit usages of the simulations assuming different kinds of group relationships. Scenario 3 (strong leadership) has the slowest evacuation, whereas Scenario 2 (weak leadership) has the fastest evacuation. The results show that strong leadership does not necessary lead to better outcomes, at least in this particular egress situation. We examine the evacuation pattern to understand the effects of leaderships on the overall evacuation. Figure 6.24 illustrates the trajectories of the agents in all three scenarios. In Scenario 1 where all agents exit the building using individual behaviors, all agents directly travel to their known exit, Exit A (Figure 6.24a). By comparing Scenario 1 to the two that assume group leadership (Scenarios 2 and 3), we observe two noteworthy outcomes:

Table 6.9: Evacuation time and exit usage assuming different group structures

Scenario		1. All individuals	2. Individuals + weak leadership	3. Individuals + strong leadership
Total evacuation time (seconds)		46	42	67
Exit usage (no. of agents)	Exit A	80	40	80
	Exit B	0	40	0

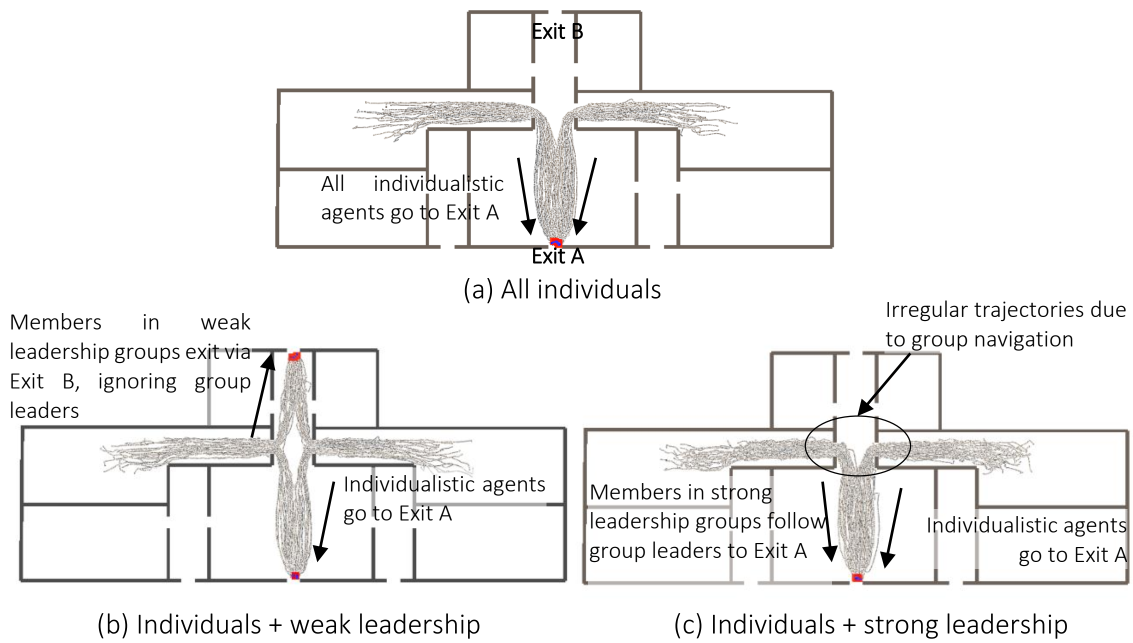


Figure 6.24: Simulation screenshots assuming weak leadership

- First, in Scenario 2, the members of the weak leadership groups evacuate from their familiar exit (Exit B), and the leaders follow the members. As shown in Figure 6.24a and Figure 6.24b, the exit usage is more even in Scenario 2 than in that in Scenario 1, resulting in faster evacuation.
- Second, although the strong leadership scenario (Scenario 3, Figure 6.24a) has a similar exit usage as the individualistic scenario (Scenario 1, Figure 6.24a), the underlying mechanism of Scenario 3 is different from Scenario 1. In Scenario 3, the members of the strong leadership groups follow the group leader, and the leaders follow the crowd to evacuate through Exit A. The biased usage of Exit A is driven by the agents' leader-following behaviors in Scenario 3, whereas in Scenario 1, the usage of Exit A is driven by the agents' individual preferences. Moreover, the evacuation time is increased by 46% in the strong leadership scenario (Scenario 3), as compared to the individualistic scenario (Scenario 1), because 50% of the agents in Scenario 3 navigate with their social groups. As shown in Figure 6.24c, the trajectories of the agents are irregular compared to the individual agents Figure 6.24a) because they travel back and forth to maintain proximity to the group.

By allowing agents to switch behavior from one level to another level during the simulation, we can model an agent's behavior governed by its individual preferences (such as following knowledge), by its group relationships (such as following leader), or by the crowd influences (such as following the crowd). Moreover, we can also simulate emerging patterns that are mediated through the agent's group relationship. For example, in the strong leadership group, even when a member does not follow the crowd, yet, as mediated by its group relationship, the member navigates to the most crowded exit because the member is influenced by its leader who follows the crowd. With the tiered design of the agent's decision-making process, SAFEgress allows users to define the underlying social mechanisms to generate emerging patterns that involve interactions at all three individual, group, and crowd levels.

6.2.5 Summary

In SAFEgress, building occupants are represented with individual, group, and crowd attributes. This tiered representation provides a systematic way to investigate different human and social behaviors as a result of individual preference and experience, social relationships, and crowd influence. In this chapter, we illustrate the range of behaviors that an agent in SAFEgress can exhibit. Understanding that social behaviors cannot be modeled in an exhaustive manner, we aim to design a meaningful representation of the overall egress situation and the behaviors of evacuating occupants to allow the investigation of different factors in a complex situation. Based on our current implementation, we also highlight the possible extension at each level to include more complicated behaviors in simulation.

Chapter 7

Case Studies

In this chapter, we illustrate the application of SAFEgress to evaluate the egress performance of a museum and a stadium. For each of these case studies, we first describe the physical layout and the egress features of the building, and then discuss the simulation assumptions of the baseline scenario, including the emergency cues, as well as the definition and distribution of agent types. Based on the results of the baseline scenario, we simulate additional scenarios to assess the effects of human and social factors on egress performance and the effectiveness of different evacuation strategies.

Several measures are used to evaluate egress simulation results:

- Evacuation time: Evacuation time provides a quantitative measure of the egress performance of a building. SAFEgress tracks the individual evacuation time for each agent, as well as the total time needed to evacuate all agents.
- Delay time: Pre-evacuation delay is another important measure of egress performance because delays prolong the overall evacuation time [22, 65]. SAFEgress records the timestamp when the agents begin evacuation. The delay time of individual agent is then calculated as the time lapse between the start of the simulation and the beginning of the agent's evacuation action.

- Crowd density: By measuring the peak crowd density, we compare the crowd patterns with some standard measurements, such as the Level-of-Service scale [20]. We also adopt the Gaussian Mixtures Model clustering technique to analyze the spatial distributions of agents. By analyzing the agents' movement patterns, bottleneck areas with high crowd density can be identified.
- Exit usage: Exits are the key components of egress designs because they are the outlets leading to the building exterior. Nevertheless, the geometry of the exit doors often constrains the flow rate of evacuees, thus governing the overall evacuation time. By tracking the trajectories of the agents, we can analyze the usage of exits and identify any inefficient use of the egress system.

The evacuation time, delay time, crowd density, and exit usage are useful metrics that allows us to both quantitatively and qualitatively assess the egress performance under particular scenarios. By comparing the results across different scenarios, we can evaluate the efficacy of alternative evacuation strategies and egress designs.

7.1 Egress performance of a museum

Our first case study is a museum building that consists of several exhibition halls. We conduct egress simulations for the first floor, where most exhibition halls are located. Figure 7.1 shows the virtual environment of the museum and the locations of the exits and signage. There are five main exits, including the main entrance, the left and right atrium exits, the garden exit, and the café exit.

From the information provided by the museum's facility management, we assume that the visitors to the museum have the following characteristics:

- About 240 visitors enter the museum in a single one-hour interval during the weekdays, and about 350 visitors enter the museum in a one-hour interval on the weekends.
- About 50% of the guests are first-time visitors; 30% are occasional visitors who have visited at least once before, and 20% are frequent visitors.

An alarm cue is assumed to become active at time = 0 second to trigger the evacuation process. The effective range of the alarm is the entire floor. We further assume that the average reaction time to start evacuation is 30 seconds for an occupant with no prior emergency experience associated with an alarm cue.

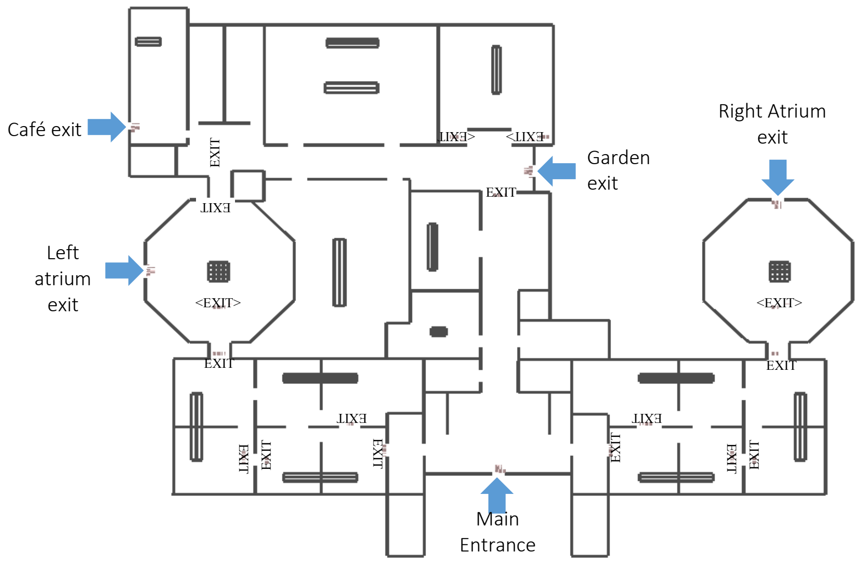


Figure 7.1: Virtual environment of the museum

In the following, we first present a baseline scenario that models egress under normal occupancy load (350 agents). Then, we present the results of three comparison scenarios and analyze the effects of group behaviors and delay times. In the first comparison scenario, we increase the occupancy load (550 agents) simulating the visitor crowds during peak hours. Then, in the second scenario, we test the group effects by assuming agents in social groups. Finally, in the third scenario, we simulate and assess different emergency evacuation measures to reduce pre-evacuation delay time.

7.1.1 Baseline scenario

A total of 350 agents are employed in the baseline scenario. There are three types of agents—frequent visitors, occasional visitors, and first-time visitors (20%, 30%, and 50% respectively). Table 7.1 describes the three agent types. The three agent types have the following key differences:

- Knowledge about exit routes: The frequent visitors are familiar with all the museum exits, whereas the occasional and first-time visitors have limited knowledge about the exit locations.

- Emergency awareness: The frequent visitors, understanding the urgency to evacuate upon hearing the alarm, initiate evacuation promptly, whereas the occasional and first-time visitors, who have little awareness of the emergency of an alarm cue, react more slowly. The personalized delay time is calculated as the normal reaction time of an alarm (i.e., T_{cue} = 30 seconds in this case) factored by the individual cue awareness factor (β_{cue}).
- Perception toward the crowd: The frequent visitors take a longer time to follow the crowd, whereas the occasional and first-time visitors take a shorter time to adopt the urge of the surrounding crowd as they are unfamiliar with the environment. The time needed for an agent to comply with the crowd is specified by crowd-following time lag (T_{crowd}).

Furthermore, for the baseline scenario, the agents are assumed to have no social group affiliation, equal social order, and no assigned tasks.

Table 7.2 summarizes the agent behavior during both pre-evacuation period and evacuation. As the alarm becomes active at the start of the simulation, the agents update their urges for evacuation as described in the interpretation stage in Section 5.2.1. Before the agents trigger evacuation behaviors, they exhibit pre-evacuation behavior to explore the space by invoking behavioral routine “explore space” at ambulatory walking speed. When the agent reaches a high urge to evacuate, the agent adopts different behaviors to evacuate the building, depending on the agent types (as shown in Table 7.2):

- Frequent visitors, having knowledge of all the exits, exit via the nearest exits.
- Occasional visitors exit via the main entrance, which is the only exit they know of.
- First-time visitors follow the route taken by the majority of neighboring agents; if there are no visible neighboring agents, the first-time visitors follow guidance from navigation objects to evacuate.

Table 7.1: Attribute values of agent types in Museum baseline scenario

Type of agents	**First-time visitors**	**Occasional visitors**	**Frequent visitor**
Distribution	50%	30%	20%
Physical profile	Adult male/female	Adult male/female	Adult male/female
Exit knowledge	No exit knowledge	Main entrance	All exits
Cue awareness factor, β_{cue}	0.8-2.0	0.8-2.0	0.4 - 0.6
Crowd compliance	High	Medium	Low
Crowd-following time lag, T_{crowd}	10 seconds	20 second	120 seconds

Table 7.2: Behaviors profile of different agent types in Museum baseline scenario

Type of agents	First-time visitors	Regular visitors	Frequent visitor
Pre-evacuation behaviors	Explore space randomly at 50% normal walking speed		
Individual behavior	Following navigation objects to evacuate	Following knowledge to evacuate	Following knowledge to evacuate
Crowd behavior	Following crowd to evacuate	No assumed crowd behavior	No assumed crowd behavior

Our simulation results suggest that the evacuation of the baseline scenario is governed by the delay time of the agents, instead of congestion at exits. Figure 7.2 illustrates the cumulative number of evacuees in the baseline scenario. As shown in Figure 7.2, the rate of evacuation slows down significantly after time = 85 seconds. To understand the slow evacuation rate during the last phase of the evacuation, we study the crowd density patterns throughout the process. Figure 7.3 shows the distribution of crowd density in the last 40 seconds of the evacuation. As shown in Figure 7.3a to Figure 7.3c, congestion starts to develop and continues to persist at both the main entrance and the garden exit. However, as shown in Figure 7.3d, the crowd at the exits dissolves at time = 80 seconds, and there are some observed crowd movements toward the major exits. The development of congestion at the exits temporarily obstructs the flow, but it does not critically delay the overall evacuation time. Instead, the prolonged delay time and travel time of the last few agents exiting the building dominate the total evacuation time.

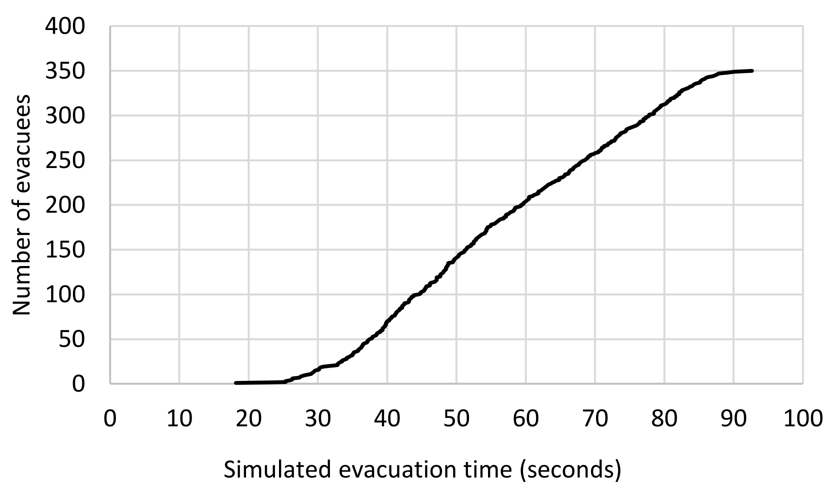


Figure 7.2: Cumulative number of evacuees of Museum baseline scenario

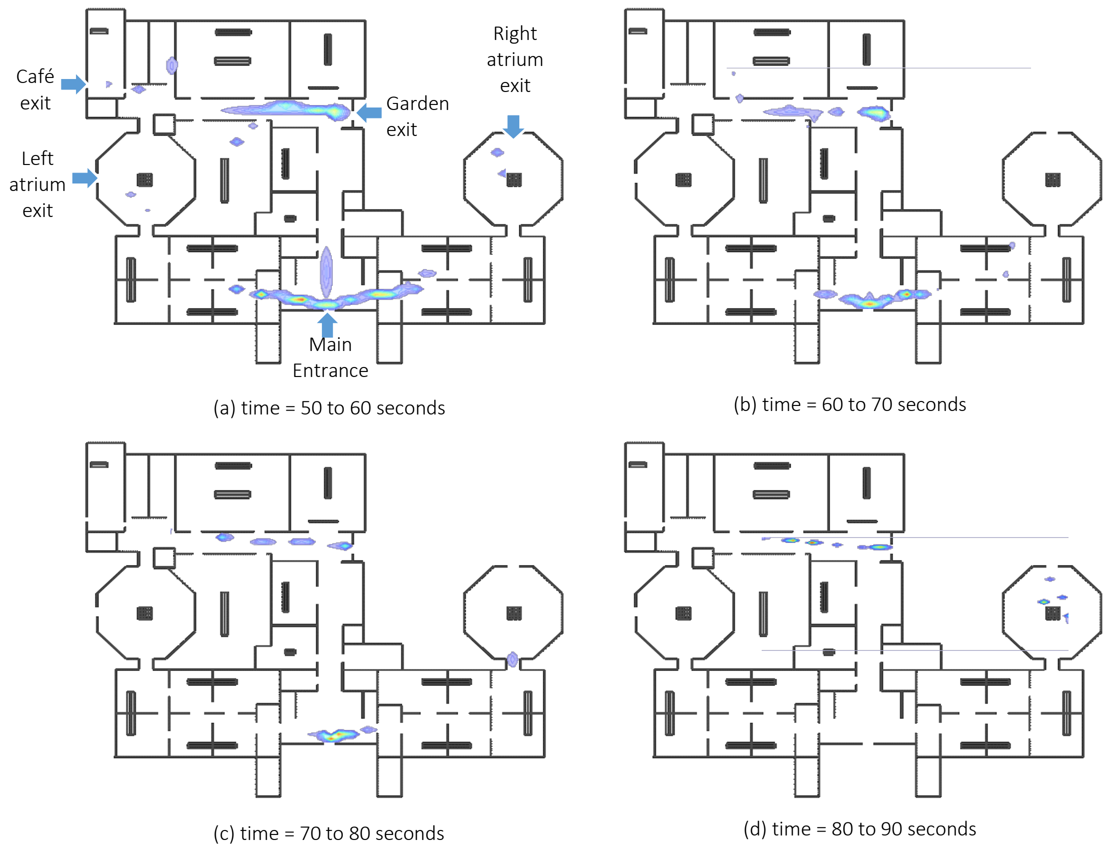


Figure 7.3: Distribution of crowd density of Museum baseline scenario

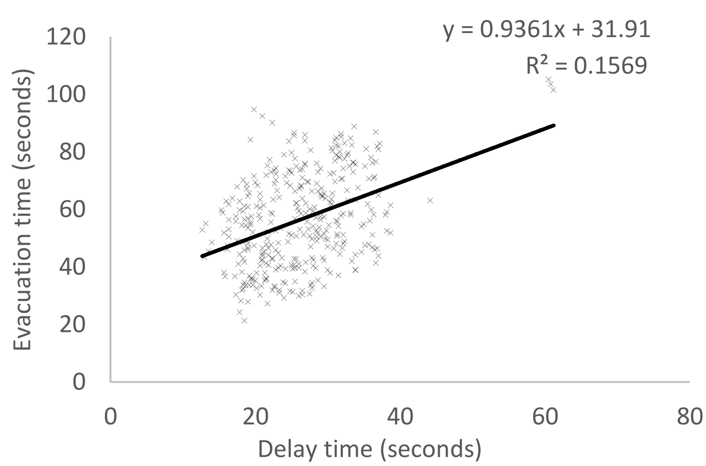


Figure 7.4: Relationship between delay and evacuation times of Museum baseline scenario

Pre-evacuation delays of the agents significantly prolong the overall evacuation, as shown from our analysis of the delay and evacuation times of individual agents. Figure 7.4 illustrates the relationship between delay time (x-axis) and the evacuation time (y-axis) in a typical simulation run. The graph confirms that the delay time is positively correlated to the evacuation time (Pearson's coefficient is 0.3961). On average, the agents wait for 22 seconds before they initiate an evacuation action. The result suggests that the overall evacuation time can be improved by minimizing the delay time.

The agents tend to exit through either the main entrance or garden exit, leading to uneven usage of the exits. Table 7.3 lists the statistics of exit usage and egress time of 350 agents over ten simulation runs. More than 70% of the crowd evacuate from the main entrance and the garden exit, which are the two most accessible exits among all. These two major exits are mainly used by the occasional visitors and the first-time visitors, who have limited knowledge of the nearest exits and perceive these two exits as the most viable routes to leave the building. The biased exit usage is also confirmed by the crowd density pattern shown in Figure 7.5, which shows that congestion occurs mainly on the exit route to the main entrance and the garden exit. Moreover, because the first-time visitors lack knowledge of the exits, they need extra time to explore the building before following others to evacuate. The simulation result suggests that the evacuation time can be improved by providing the visitors better guidance about alternate exit locations.

Table 7.3: Egress performance of Museum baseline scenario

Average delay time	25.8 ± 1.1 seconds	
Total evacuation time	96.9 ± 7.1 seconds	
Exit usage	Main entrance	40.7%
	Café exit	12.0%
	Right atrium exit	9.7%
	Garden exit	33.3%
	Left atrium exit	4.3%

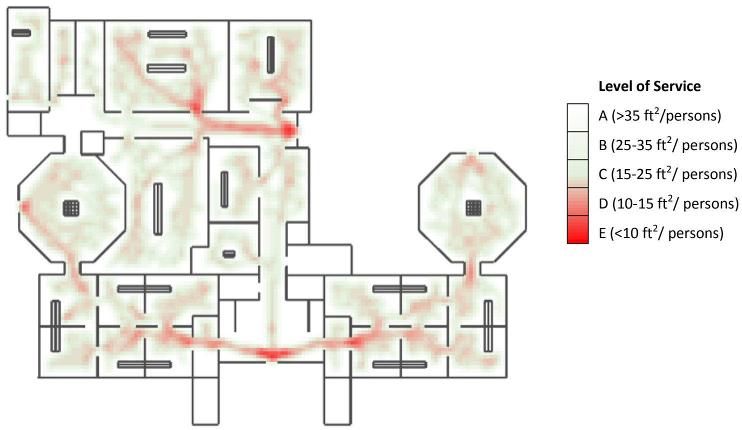


Figure 7.5: Overall congestion pattern of Museum baseline scenario

The simulation results show that the egress time is governed by the pre-evacuation delays and the long travel time of the last few evacuees to arrive at the exits. Based on the results of the baseline scenario, several questions can be posed:

1. How will the egress results change if the maximum occupancy of the floor is employed in the simulations? Would congestion be the governing factor in this case?
2. As the visitors often come to the museum in social groups, how would the group behaviors affect the egress results?
3. The average delay time is 30% of the overall evacuation time. Is it possible to reduce the delay time and, thereby the evacuation time?

In the following, we address each of the questions by simulating three different scenarios and comparing the results from the new scenarios with those of the baseline simulation.

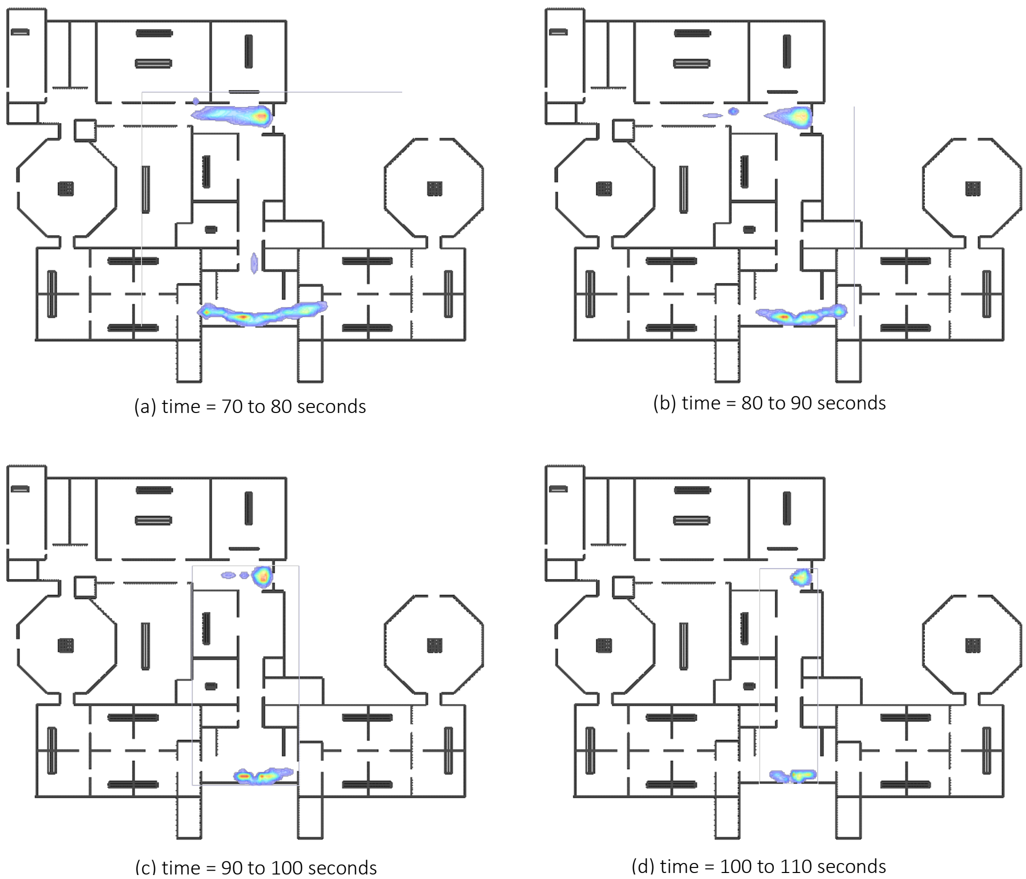
7.1.2 Scenario 1: Increased occupancy load

In the first scenario, we assume an increase of occupancy load in the museum by modeling 550 agents in the simulation runs (15ft^2 per occupant in the 8,250-ft^2 exhibition areas [2]). Similar to the baseline scenario, the definitions and distributions of the frequent visitors, occasional visitors, and first-time visitors are the same as the baseline scenario (Table 7.1).

The simulation results of increased occupancy show that, the overall evacuation time is not linearly proportional to the number of evacuees. Table 7.4 summarizes the delay time, the total evacuation time, and the exit usage assuming baseline scenario and increased occupancy (Scenario 1). In Scenario 1, the overall evacuation time is only 15% longer than the baseline scenario, despite the number of occupants being increased by 57%. We study the evacuation pattern and rate to understand the nonlinear relationship between evacuation time and occupancy load. Figure 7.6 shows the distribution of crowd density in the last 40 seconds of the evacuation in Scenario 1. As indicated in Figure 7.6a, congestions start to build up at the major exits (the main entrance and the garden exit). The congestions at the major exits persist and continue to obstruct the exit flow throughout the evacuation (Figure 7.6b to Figure 7.6d). Figure 7.7 illustrates the cumulative number of evacuees in the baseline scenario (normal occupancy) and Scenario 1 (increased occupancy). The graph of Scenario 1 in Figure 7.7 shows that the evacuation rate remains constant throughout the evacuation. The constant evacuation rate indicates that, when the occupancy load is increased, the flow rates at the major exits governs the overall evacuation time.

Table 7.4: Egress performance of Musuem baseline scenario and Scenario 1

		Baseline Scenario	Scenario 1 (increased occupancy)
Average delay time		25.8 ± 1.1 seconds	23.0 ± 1.5 seconds
Total evacuation time		96.9 ± 7.1 seconds	112.1 ± 3.1 seconds
Exit usage	**Main entrance**	40.7%	33.3%
	Café exit	12.0%	16.8%
	Right Atrium exit	9.7%	13.9%
	Garden exit	33.3%	28.9%
	Left Atrium exit	4.3%	7.1%



(a) time = 70 to 80 seconds (b) time = 80 to 90 seconds

(c) time = 90 to 100 seconds (d) time = 100 to 110 seconds

Figure 7.6: Distribution of crowd density of Museum Scenario 1

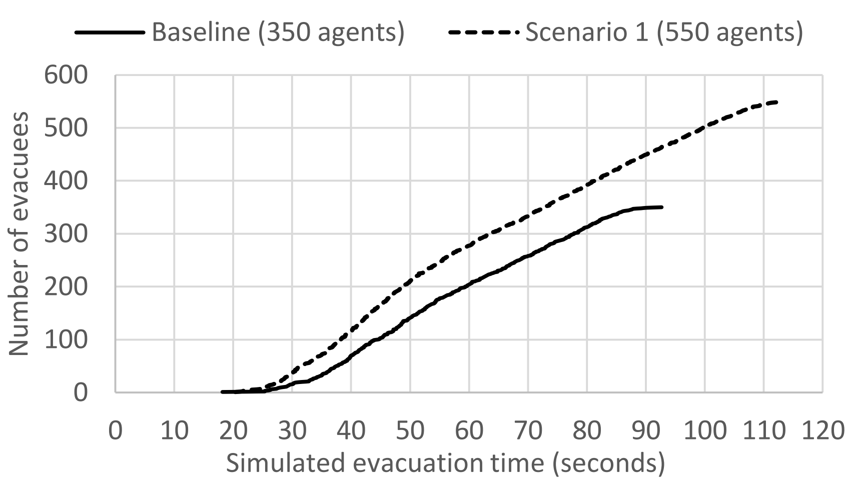


Figure 7.7: Cumulative number of evacuees of Museum baseline scenario and Scenario 1

The museum evacuations are governed by different factors (pre-evacuation delay or congestion) when various levels of occupancy loads are assumed. Due to the changes in the governing mechanisms in different scenarios, various intervention measures should be considered to improving the egress time. When the evacuation occurs during normal business hours (e.g., on weekdays), minimizing the delay time of the visitors is the key to improving evacuation time. If the emergency incident happens at the time when the museum has maximum occupancy load (e.g., on event days), alleviating the congestions at the major exits is the most critical consideration. In this case, museum staff can re-direct the crowd flow to other outlets to reduce the traffic at the major exits. Depending on the occupancy of the museum at the time of emergency events, the safety personnel can adopt different strategies to evacuate the building effectively.

7.1.3 Scenario 2: Visitors in social groups

From our observation and discussion with the facility managers, most museum guests visit the facility as groups. In Scenario 2, we investigate the effect of the social group on evacuation by assigning each agent an affiliation with a social group. The distribution of the group sizes is shown in Table 7.5. We assume that the museum visitors continue to maintain proximity with their groups and navigate with the group when evacuating the building. Therefore, we assign the "navigating with group members" behaviors to the agents as their group behaviors.

The group behaviors slow down the overall evacuation process. Table 7.6 summarizes the delay time, the total evacuation time, and the exit usage in the baseline scenario and Scenario 2. The delay time and the usage of the exits in Scenario 2 (with group behaviors) are similar to the baseline simulation (without group behaviors), whereas the overall evacuation is increased by 15%. To examine the reasons for the increase in evacuation time and the slowing in evacuation process, we examine the congestion pattern of the evacuation. Figure 7.8 shows the comparison of the crowd density pattern in the baseline scenario (assuming individual behaviors) and Scenario 2 (assuming group behaviors). As shown in Figure 7.8a, congestions occur at the major exits when agents exit

Table 7.5: Distribution of group sizes in Museum Scenario 2

Group size	1	2	3	4
Proportion	10%	20%	30%	40%
Number of agents	55	110	165	220

individually, whereas in Figure 7.8b, high crowd densities are observed at the intersections of corridors and at the locations connecting the exhibition halls to the corridor. The additional congestions and lengthened evacuation are due to the fact that the agents in groups may wait or take a detour to stay close with the group as they leave the exhibition halls, therefore causing congestion at the corridors and at the intersections.

The simulation results assuming group behaviors show that group navigation causes additional congestions along the egress routes, hence leading to prolonged evacuation time. The congestion pattern also indicates some potential improvements on the layout of the exhibition halls to facilitate safe egress. For example, widening the opening in the right and left atriums could facilitate group navigation by providing better visibility. Instead of assuming visitors as unconnected individuals, facilities managers and designers should anticipate additional congestions due to group navigation when considering indoor egress design.

Table 7.6: Egress performance of Msueum baseline scenario and Scenario 2

		Baseline Scenario	Scenario 2 (group behaviors)
Average delay time		25.8 ± 1.1 seconds	25.8 ± 0.4 seconds
Total evacuation time		96.9 ± 7.1 seconds	114.9 ± 7.5 seconds
Exit usage	**Main entrance**	40.7%	41.2%
	Café exit	12.0%	11.7%
	Right Atrium exit	9.7%	9.8%
	Garden exit	33.3%	33.3%
	Left Atrium exit	4.3%	4.0%

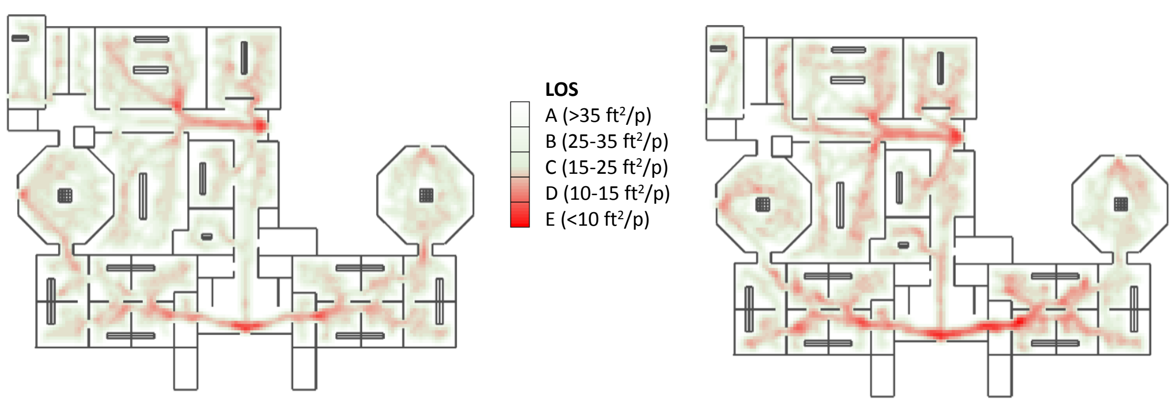


Figure 7.8: Overall congestion patterns of Museum baseline scenario and Scenario 2

7.1.4 Scenario 3: Improvement in pre-evacuation delays

Our baseline results show that the pre-evacuation delay time of visitors has a significant effect on the total evacuation time. In Scenario 3, we explore the effectiveness of two different means to reduce pre-evacuation delay of the evacuees:

- Scenario 3A: Due to better publicity of evacuation in case of emergencies, the frequent visitors have a higher awareness toward an alarm (cue awareness factors is 0 to 0.2 for the frequent visitors).
- Scenario 3B: A clear, unambiguous message is deployed to inform all visitors to evacuate. The reaction time of the announcement cue is assumed to be 5 seconds (i.e, one-sixth of an alarm).

Table 7.7 shows the individual delay times of different types of agent under difference scenarios. In Scenario 3A, the pre-evacuation delays of the frequent visitors are improved due to the publicity of immediate evacuation, whereas the occasional and first-time visitors have the same individual delay times. In Scenario 3B, the clear and unambiguous evacuation announcement is characterized by a shorter nominal reaction time (i.e., 5 seconds). Perceiving the announcement cue, all agents start evacuation within a short period.

Table 7.7: Range of delay times in Museum baseline scenario and Scenario 3

	First time and occasional visitors	Frequent visitors
Baseline scenario	24 – 60 seconds	12 – 18 seconds
Scenario 3a (improving frequent visitors' awareness)	24 – 60 seconds	0 – 6 seconds
Scenario 3b (providing a clear emergency message)	4 – 10 seconds	2 – 3 seconds

Table 7.8: Egress performance of Musuem baseline scenario and Scenario 3

		Baseline Scenario	Scenario 3A - Frequent visitors' awareness	Scenario 3B – Clear message
Average delay time		25.8 ± 1.1 seconds	21.4 ± 0.5 seconds	6.1 ± 0.1 seconds
Total evacuation time		96.9 ± 7.1 seconds	92.1 ± 5.0 seconds	79.7 ± 5.1 seconds
Exit usage	**Main entrance**	40.7%	41.1%	42.3%
	Café exit	12.0%	11.8%	11.5%
	Right Atrium exit	9.7%	9.1%	9.2%
	Garden exit	33.3%	34.1%	32.9%
	Left Atrium exit	4.3%	3.9%	4.1%

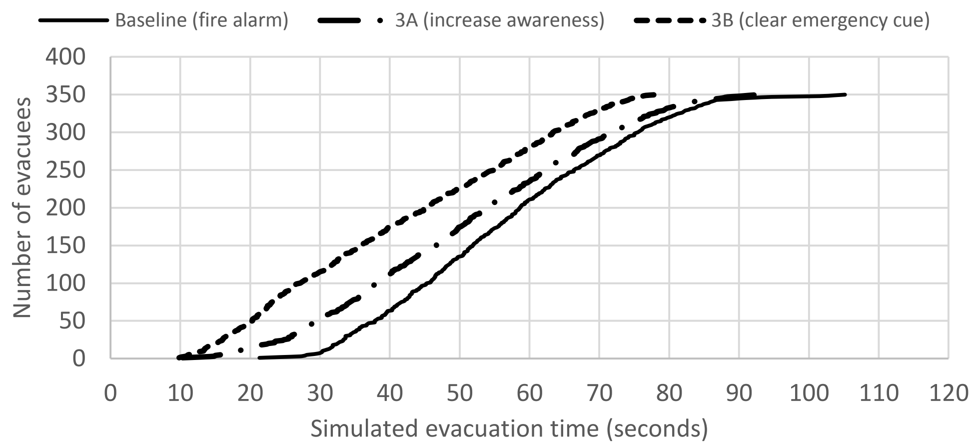


Figure 7.9: Cumulative number of evacuees of Museum baseline scenario and Scenario 3

Our simulation results show that increasing evacuation awareness among frequent visitors (Scenario 3A) is less effective than adopting a clear notification system in improving the overall evacuation time (Scenario 3B). Table 7.8 summarizes the average delay time, the total evacuation time, and the exit usage of 350 agents in Scenario 3. In Scenario 3A, where the frequent visitors understand the alarm cue and initiate evacuation sooner, they influence other visitors to react sooner as well. Therefore, the overall delay time is improved by 3.4 seconds, and the evacuation time is improved by 4 seconds, as compared to the baseline scenario. Shortening the delay time of the frequent visitors can improve the egress time; however, the improvement is not hugely significant because the number of frequent visitors have a limited effect on the overall visitor population. In Scenario 3b, where the announcement is unambiguous, all the visitors initiate the evacuation promptly (the average delay time is 6 seconds, which is improved by 19 seconds) and the overall egress time is significantly improved (the egress time is reduced by 17 seconds, a 26% reduction).

Adopting an unambiguous notification also leads to more efficient evacuation. Figure 7.9 compares the cumulative number of agents exiting the building in the baseline scenario and Scenarios 3A and 3B. As shown in Figure 7.9, with the unambiguous announcement, the rate of evacuation reaches maximum at the early stage of the evacuation (starting at time = 10 seconds). The rate maintains throughout the evacuation, indicating that the evacuation is governed by flow rate at the exits, rather than the delay and travel time of the last few evacuees. By comparing the results from the two different ways to improve pre-evacuation delays, we find that adopting different strategies can result in various levels of improvements in overall egress performance.

7.1.5 Summary of Museum case study

SAFEgress is applied to study the evacuation process of the museum under different assumptions regarding the visitors and the notification system. Using an Intel Core i5-650 machine, the average computation time for each simulation run is approximately 3 minutes. Table 7.9 summarizes the egress times and governing factors of the tests conducted in this case study. In our baseline scenario, with the assumption of an average volume of museum visitors, the evacuation is governed by the delay and travel time of the last few evacuees rather than congestions at the major exits. In subsequent scenarios where we assume an increased occupancy load (Scenario 1), group behaviors (Scenario 2), and two different strategies to minimize delays (Scenario 3), the egress governing factors vary and lead to different evacuation times.

The museum case study shows that the volume of visitors, the pre-evacuation delay, and the prolonged travel time due to visitors' social groups all have a direct impact on the overall egress performance. More importantly, these factors affect the evacuation through different mechanisms. Scrutinizing the evacuation patterns and outcomes from simulations, facility managers and evacuation responders could identify the governing factors in specific scenarios and customize safety designs and evacuation strategies to facilitate effective evacuations.

Table 7.9: Egress times and governing factors in Museum case study

	Baseline	Scenario 1: Max. Occupancy	Scenario 2: Group	Scenario 3: Reduce delay time	
				(a) Frequent visitors' awareness	(b) Clear message
Delay time (s)	25.8 ± 1.1	23.0 ± 1.5	25.8 ± 0.4	21.4 ± 0.5	6.1 ± 0.1
Egress time (s)	96.9 ± 7.1	112.1 ± 3.1	114.9 ± 7.5	92.1 ± 5.0	79.7 ± 5.1
Governing factor	Pre-evacuation delay	Congestion at exits	Congestion at intersections	Pre-evacuation delay	Congestion at exits

7.2 Egress performance of a stadium

In the second case study, we investigate the egress performance of the stadium located at the campus of Stanford University, which has an occupant capacity of 50,000. Figure 7.10 shows the overview of the stadium. The stadium can be divided into upper bowl and lower bowl where approximately 60% of seats are located in the upper bowl and 40% are located in the lower bowl. The mezzanine level is situated in between the two levels of seating and is accessible to guests from both levels.

We model the physical setting of the mezzanine level of the stadium and the guest population in SAFEgress. Figure 7.11 shows the virtual environment of the mezzanine level model, including the locations of the tunnels, the location of signage, and the staircases where the agents are discharged. We assume that the agents arrive at the mezzanine level via the staircases at the rate of 1 person/second and navigate in the mezzanine level to exit the stadium. Over the course of 5 minutes, 13,200 agents (corresponding to about 70% of the total seating capacity at the lower bowl) enter the mezzanine level via the 44 staircases and exit through the tunnel. From the information provided by the Stanford Department of Athletics, we assume the guests can be classified into two types: regular guests (70%) and new guests (30%). We simulate the evacuation process triggered by an emergency public announcement. The clear emergency cue triggers instantaneous evacuation behavior of the agent population (i.e., no delay time).

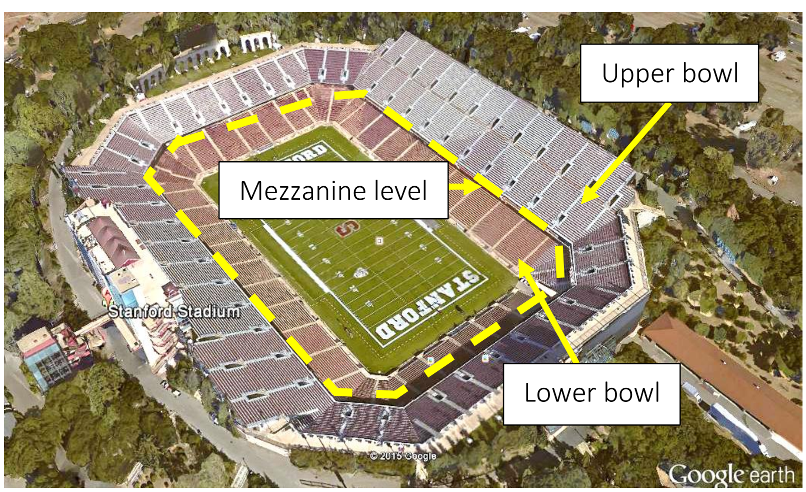


Figure 7.10: Overview of Stanford Stadium

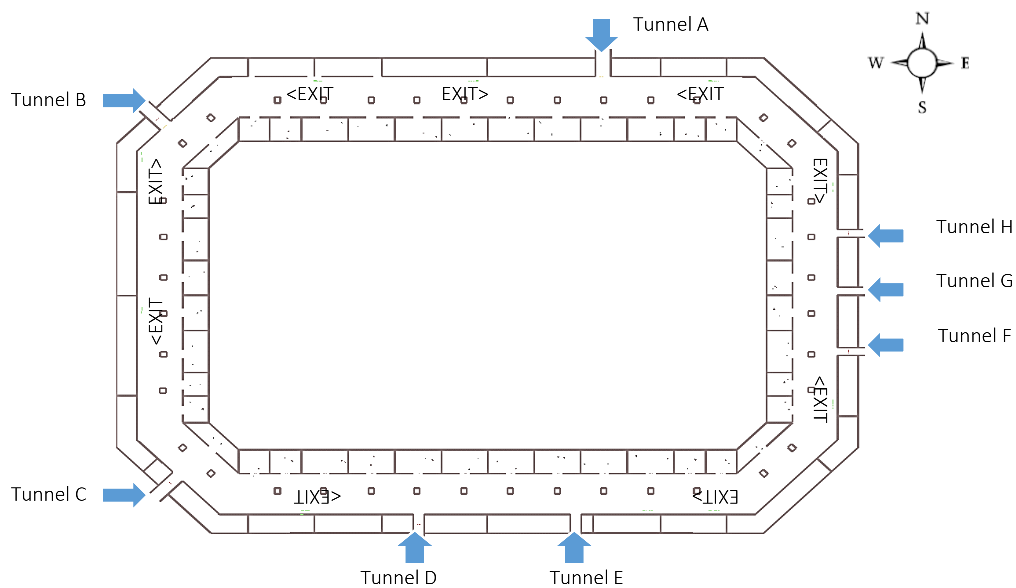


Figure 7.11: Virtual environment of mezzanine level model

In the following, we first present a baseline scenario that simulates non-emergency egress situation assuming the guests follow signage and familiar routes to exit the stadium as they perceive no urge to escape. Then, we present the results of two emergency egress scenarios when (1) all guests exit from the nearest tunnels, and (2) effective stewarding to control the crowd flow is incorporated.

7.2.1 Baseline scenario

In the baseline scenario, we employ two types of agents, namely, regular guests (70%) and new guests (30%). Table 7.11 summarizes the assumptions of the different agent types, which differ in exit knowledge and evacuation behaviors. Regular guests have learned the exit routes prior to the events and can choose to exit through either the nearest tunnel exit or the tunnels that they used to enter the stadium. From our discussion with the Stanford stadium management, we assume that most of the regular guests preferred exiting through Tunnel D and Tunnel E, which connect to the entrance gates and the parking spaces. New guests, on the other hand, have little knowledge about the stadium and follow the signage to look for an exit. Furthermore, all agents are assumed to have no social group affiliation, and they have no assigned tasks in the baseline scenario.

Table 7.10: Attribute values of agent types in Stadium study

Type of agents	Regular guests	New guests
Distribution	70%	30%
Physical profile	Adult male/female	Adult male/female
Exit knowledge	Tunnel D, Tunnel E, and the nearest exit	No exit knowledge
Individual behavior	Either following knowledge to evacuate (50%) or following perception to evacuate (50%)	Following perception to evacuate

The baseline scenario assumes that the regular guests evacuate through either the nearest exits or their familiar exits, and the new guests follow the signage to search for an exit. The average evacuation time over 5 simulation runs is 14 minutes 45 seconds. Figure 7.12 illustrates the exit usage in a typical simulation run of the baseline scenario, and Figure 7.13 shows the rate of evacuation at the mezzanine level. Because the baseline scenario is used to benchmark with the later tests, we first check the reliability of the simulation results.

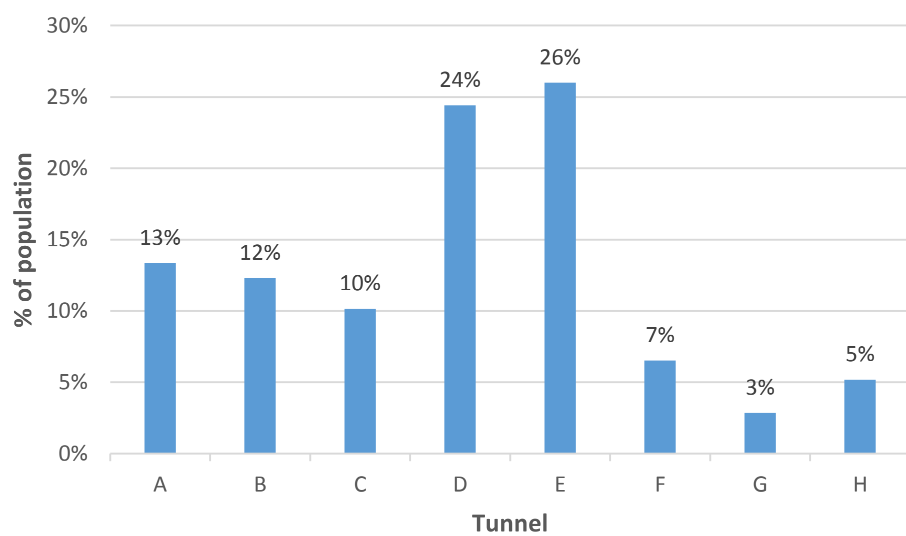


Figure 7.12: Exit usage of Stadium baseline scenario

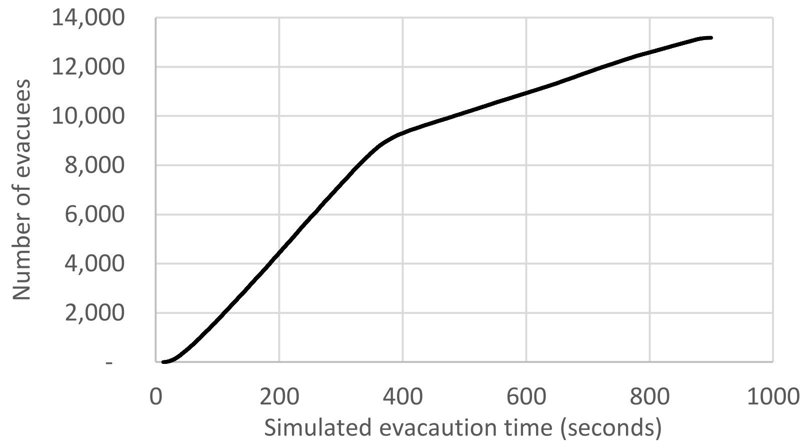


Figure 7.13: Cumulative number of evacuees of Stadium baseline scenario

Table 7.11: Calculation of flow time at Stadium tunnels

Tunnel	Width (m)	(ft.)	Maximum flow rate* (persons/sec.)	Number of agents received^	Time needed to exit via the tunnel (sec.)
A	4.2	13.8	5.61	1,761	314
B	3.9	12.7	5.61	1,623	315
C	3.9	12.7	5.15	1,340	260
D	3.0	9.8	5.15	3,222	813
E	3.0	9.8	3.96	3,336	842
F	2.4	7.8	3.96	859	271
G	2.4	7.8	3.17	377	119
H	2.4	7.8	3.17	682	215

* Assume a maximum specific flow rate of 1.3 persons/m/sec [85].
^ Calculated based on the simulated exit usage, refer to Figure 7.12

To assess the validity of the egress time, we estimate the time for the assumed population to evacuate through the tunnels using basic flow calculation. Table 7.12 lists the time for the crowd to exit from the tunnels assuming maximum flow rate at each tunnel. The overall evacuation time of the simulation is governed by flow at Tunnel E, where approximately 26% of the agent population exit from. The calculated flow time is 842 seconds, i.e., 14 minutes 2 seconds, which closely matches the simulated egress time (885 seconds, i.e., 14 minutes 45 seconds).

As shown in Figure 7.13, the rate of evacuation slows down after 400 seconds and remains constant afterward. The decrease in evacuation rate is because most of the regular guests prefer to exit through Tunnels D and E, and other tunnels receive relatively less incoming flow. The uneven use of exits not only causes a decrease in evacuation rate but also lengthens the overall egress time. Figure 7.14 illustrates the distribution of crowd density from time = 200 seconds to time = 500 seconds of the evacuation in the baseline scenario. As shown in Figure 7.14a and Figure 7.14b, there is a continuous crowd flow from the north side of the stadium to Tunnels D and E. Congestions build up at the two tunnel exits and become the bottlenecks of the evacuation time (Figure 7.14c and Figure 7.14d). Further, as highlighted in Figure 7.14d, cross flow is formed as the regular guests travel to the Tunnel E. This results in local congestions at the heavy traffic area near Tunnel F.

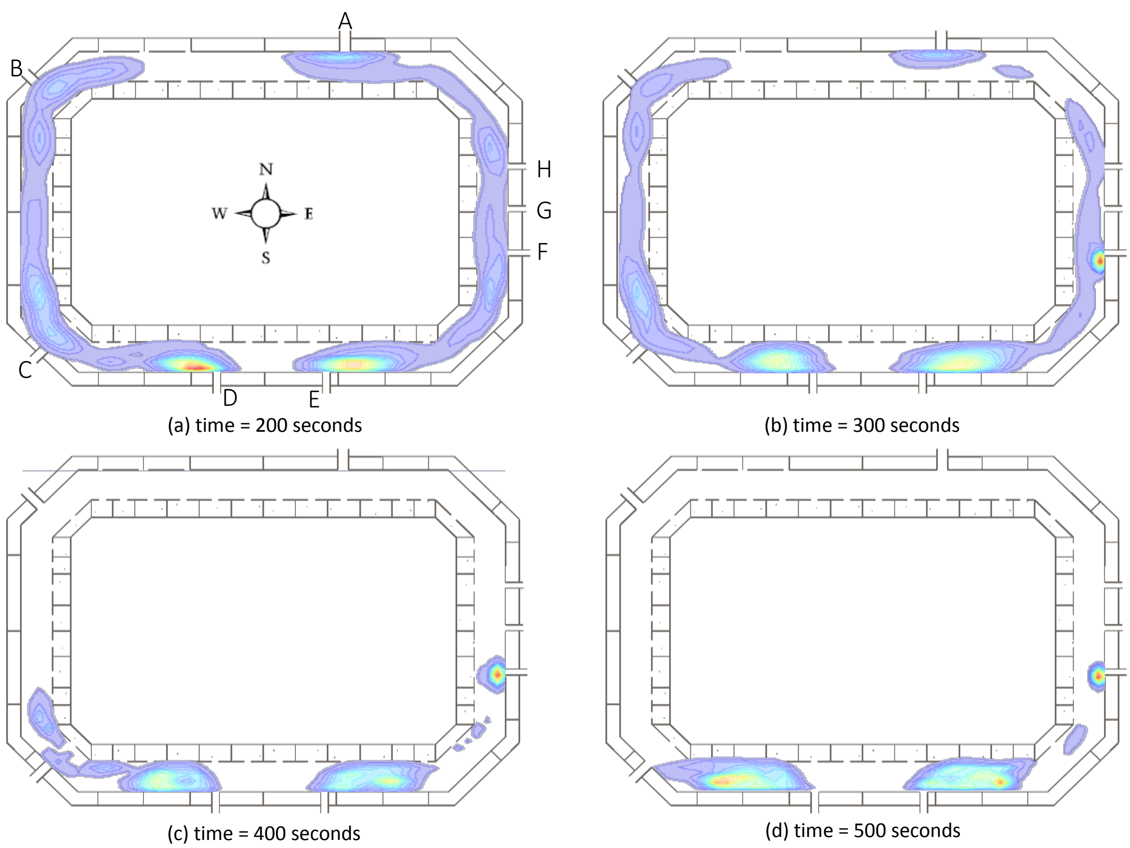


Figure 7.14: Distribution of crowd density of Stadium baseline scenario

Our baseline results show that the exit usage plays a significant role in the overall egress time. The regular guests prefer exiting from their familiar tunnels and cause serious congestion at certain tunnel exits, which, in turn, govern the overall egress time. Based on the baseline scenario results, we pose the following questions:

1. How long is the evacuation if we can facilitate a more evenly distributed exit usage? How would the congestion pattern change in this particular case?
2. During emergencies, event stewards or staffs are often present to facilitate the evacuation. How will the role of stewards affect the egress results? Is it possible to arrange the locations of stewards strategically to achieve optimal egress results?

In the following, we simulate and compare different scenarios to address these questions.

7.2.2 Scenario 1: Exiting from nearest tunnels

In this scenario, we examine the egress time achieved by balancing out the usage across different exits. We first assume the same number of agents and the distribution of the agent types as the baseline scenario. Then, we assign new exit preference to the regular guests, such that all regular guests exit the stadium via their nearest exits, instead of Tunnel D and Tunnel E. Under the new exit preference assumptions, the evacuation time reduces to 8 minutes 51 seconds averaged over five simulation runs.

Figure 7.15 shows the exit usage. In Scenario 1, the crowd flow is more evenly distributed across different tunnel exits—the most-used tunnel in Scenario 1 (i.e., Tunnel B) received 20% of the agent population, whereas the one in baseline simulation (i.e., Tunnel E) is 26%. Furthermore, Tunnels A, B, and C, the larger tunnels of the stadium, all receive more agents than the other smaller tunnels. These tunnels are capable of handling a higher outflow because they are wider than the other tunnels. The combined effects of (1) even exit usage and (2) more agents exiting through the wider tunnels reduce the egress time significantly by 40% to 8 minutes and 51 seconds.

From the simulation results, we observe that different parts of the mezzanine level have different congestion patterns—the east and south sides have less congestion compared to the north and west sides. Figure 7.16 illustrates the crowd density patterns throughout the evacuation. As shown in Figure 7.16a, congestions are observed at all the tunnel exits at time = 200 seconds. However, at time = 300 seconds, the congestions on the east side of the stadium start to ease (Figure 7.16b).

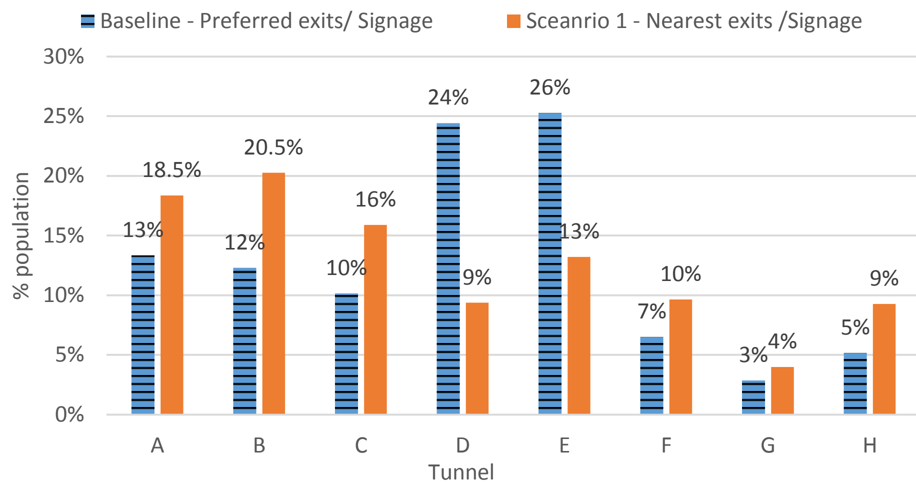


Figure 7.15: Exit usage of Stadium baseline simulation and Scenario 1

Figure 7.16c and Figure 7.16d clearly show that the evacuation on the east side is more effective than the west side of the stadium. The differences in congestion pattern at different parts of the mezzanine level can be explained by the asymmetric arrangement of the tunnel exits. First, as more exits (Tunnels F, G, and H) are located on the east side of the mezzanine level, the crowd on the east side is distributed to more exits, therefore yielding less load per exit at Tunnels F, G, and H. On the other hand, there are only two tunnels, B and C, servicing the west side of the mezzanine level. As a result, more guests exit through each of these tunnels and cause heavy congestions at these tunnel exits.

Redirecting the crowd to exit through the nearest exits decreases the egress time by 40% compared to the baseline scenario in which most regular guests exit through the tunnels they are familiar with. Moreover, the asymmetric arrangement of the tunnels poses a challenge for even, effective utilization of all the tunnels for fast evacuation. To achieve better egress time, stewards or stadium staff can be mobilized to direct crowd flow to the under-utilized exits. In the next scenario, we explore the effectiveness of stewarding to facilitate evacuation.

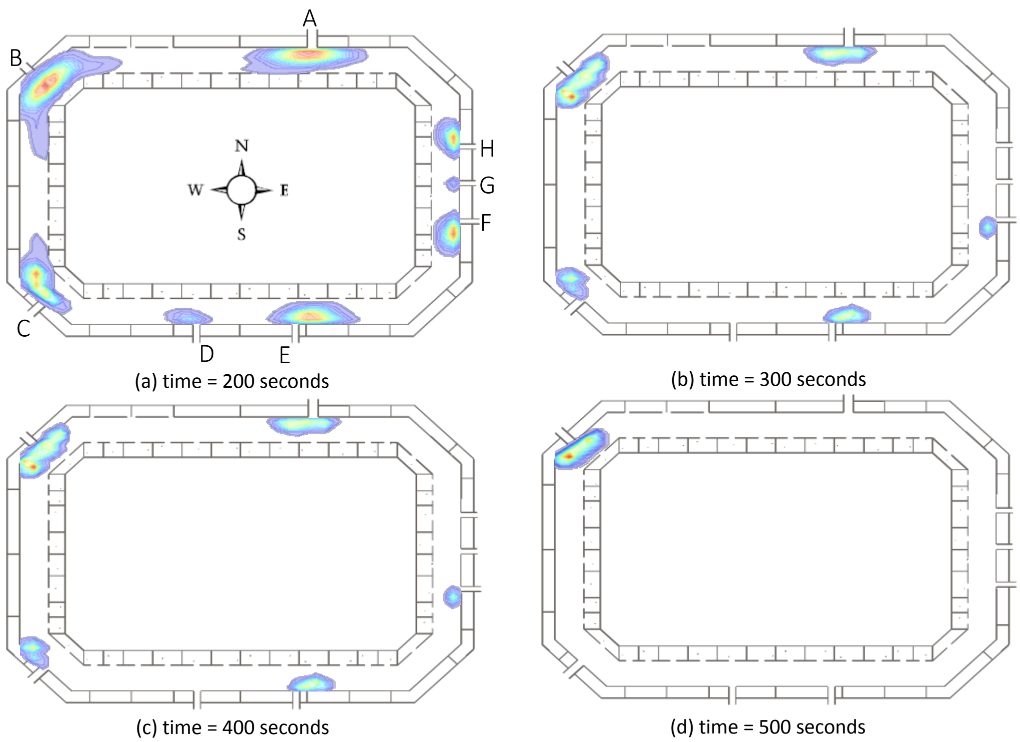


Figure 7.16: Distribution of crowd density of Stadium Scenario 1

7.2.3 Scenario 2: Evacuation facilitated by stewards

Prior to large-scale events in the stadium, the facility management and security personnel often establish plans to ensure the crowd safety during the events. Stewarding is one of the most important parts of event management because it provides ease of ingress and egress. During an emergency evacuation, the primary role of the stewards is to disperse the crowd in order to prevent overcrowding and facilitate evacuation. In this scenario, we assume a new type of agent to model as the stewards who have the pre-assigned task to provide exit instructions to the crowd. In this scenario, all agents assume the “following authority’s instructions” as their crowd behaviors. In the “following authority’s instructions” model, if a guest agent perceives a steward agent within a range of 40 ft., the guest agent will follow the exit instruction given by the steward agent. Otherwise, if the guest agent cannot perceive any steward agents, it navigates to the exit following their individual behaviors (i.e., following knowledge or signage). We assign the positions and the tasks of the steward agents based on the insights derived from the baseline scenario and Scenario 1:

- Redirecting regular guests to the nearest exits such that the crowd flow is distributed more evenly across different exits.
- Redirecting the crowd to the east and south sides of the mezzanine level to reduce the load on Tunnels A, B, and C.

Figure 7.17 shows the locations and exit instructions of 11 steward agents assumed in the simulation. The simulation result of Scenario 2 shows that effective stewarding has a significant effect on the egress performance. The average evacuation time over 5 simulation runs is 8 minutes and 30 seconds. This egress outcome represents an improvement of 41% compared to the baseline scenario and a 7% decrease compared to Scenario 1 (exiting from the nearest tunnels). Figure 7.18 compares the rate of evacuation in Scenarios 1 and 2. As shown in Figure 7.18, the maximum evacuation rate with stewarding is similar to that of Scenario 1 where all agents exit via the nearest exits. The fast evacuation rate indicates that a proper stewarding strategy can direct the crowd flow to achieve a better exit usage and egress time.

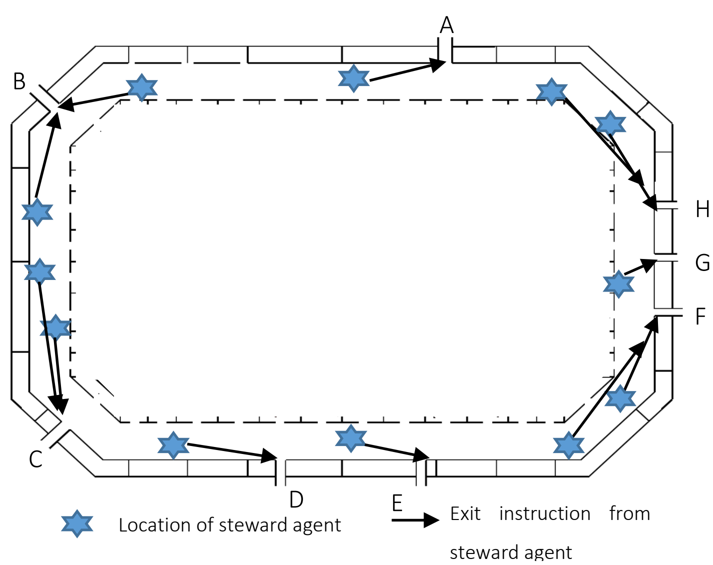


Figure 7.17: Locations of steward agents and exit instructions

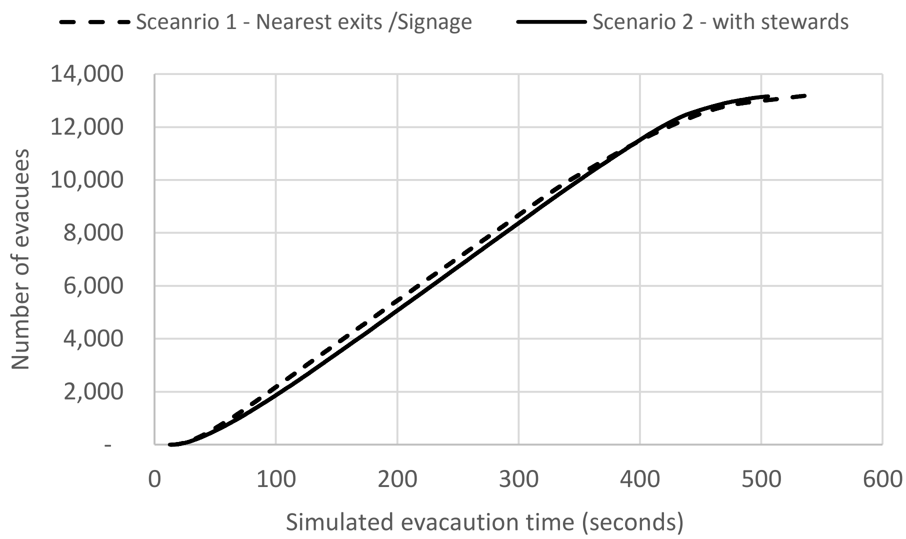


Figure 7.18: Cumulative number of evacuees of Stadium Scenario 1 and Scenario 2

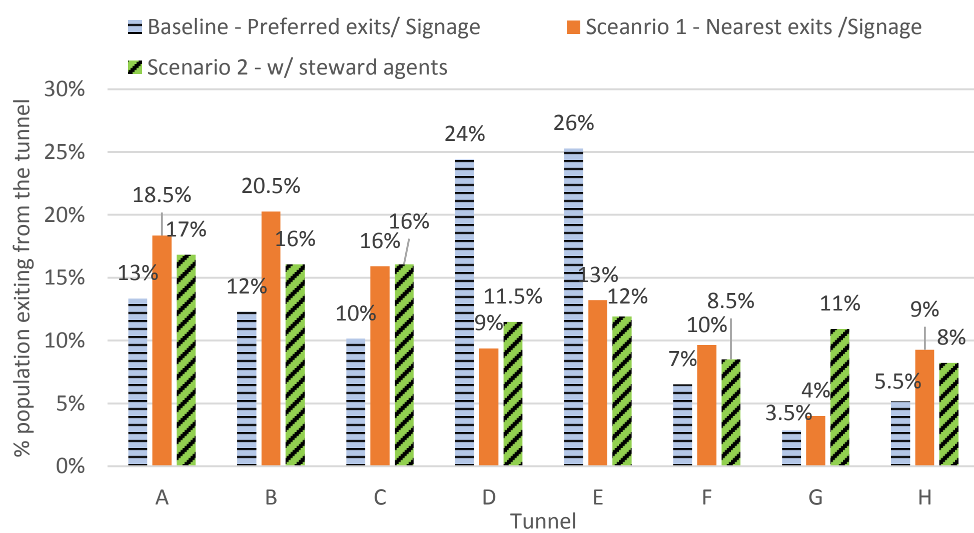


Figure 7.19: Exit usage in all Stadium scenarios

Figure 7.19 compares the exit usage in all three scenarios. In fact, the distribution of crowd flow to different exits is even more balanced in this scenario (assuming steward agents) as compared to Scenario 1 (exiting via the nearest tunnels). This also explains the slight improvement in egress time in this scenario. Figure 7.20 shows crowd density patterns during the evacuation with stewarding agents. As shown in Figure 7.20, the evacuating crowd is distributed evenly to different tunnel exits, resulting in congestion situations that are similar across different sides of the mezzanine level. The congestion patterns throughout the simulation suggest that the instructions from the steward agents are effective in facilitating optimal exit usage. Moreover, stewarding also alleviates the congestions due to cross flow as a result of agents encountering each other when moving to their preferred exit. The simulation results from Scenario 2 conclude that effective crowd control by the stewards can greatly affect the egress pattern and hence improve the overall evacuation time.

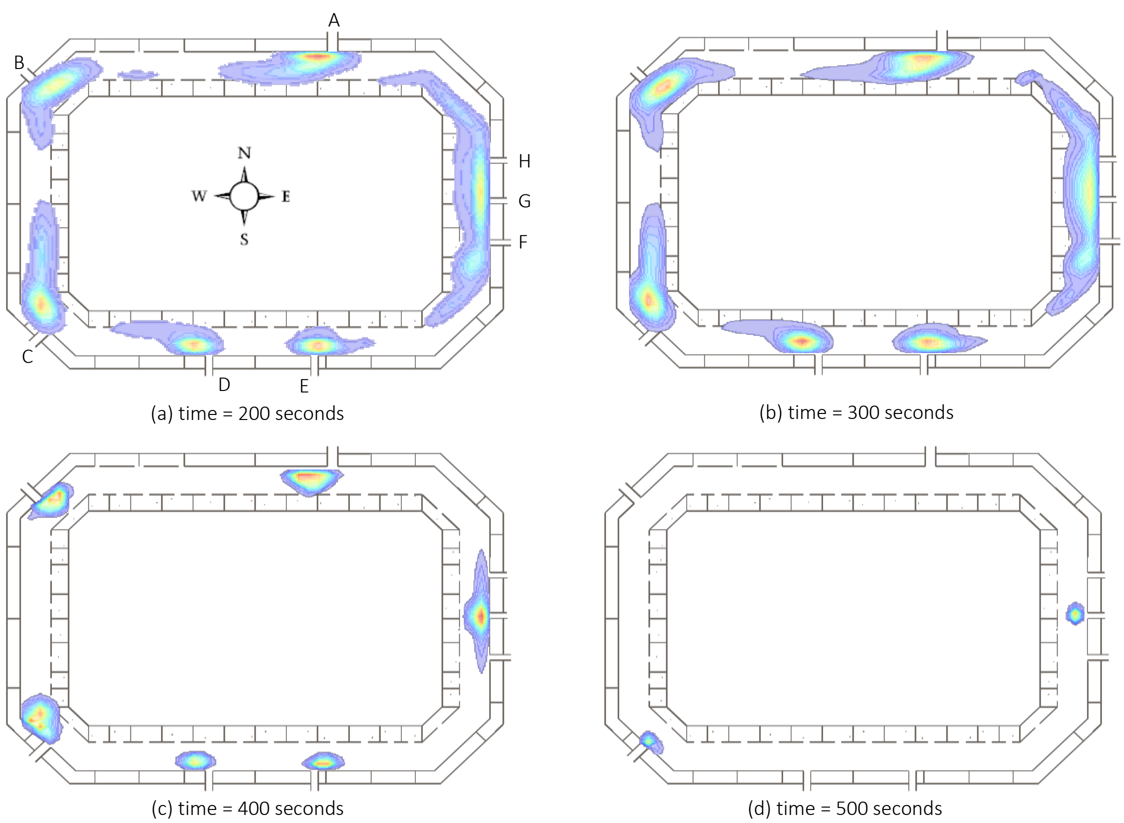


Figure 7.20: Distribution of crowd density of Stadium Scenario 2

7.2.4 Summary of Stadium case study

Using the floor plan of the Stadium mezzanine level, SAFEgress is applied to simulate three different egress scenarios: guests with knowledge of the stadium following their familiarity to exit (baseline scenario); guests exiting via the nearest exits (Scenario 1); and stewards directing the crowd flow (Scenario 2). The average evacuation times are 14 minutes 45 seconds, 8 minutes 51 seconds, and 8 minutes and 30 seconds respectively. Using an Intel Core i5-650 machine at 3.2 GHz, the average computation time for one simulation run is around 5 hours and 30 minutes.

The stadium case study has two important implications for evacuation planning in the Stadium. First, the balanced use of exits is the key to improving evacuation times, as reflected by the significant improvement in evacuation time in Scenario 1 (exiting via the nearest exits) compared to the baseline scenario (following familiarity to exit). Second, by strategically arranging stewards for crowd control can further improve the egress time, as shown in Scenario 2 (stewarding). By testing and comparing different egress scenarios with different occupant behaviors, we highlight the importance to consider the unique egress design of the venue (such as exit arrangement and signage) and the exit preference of the participants when planning emergency egress strategies.

Chapter 8

Conclusions and Future Work

Understanding occupant behaviors is a fundamental step in designing egress systems that can safeguard people's lives and properties in emergencies. Despite the importance of the human and social factors, quantifying these factors is difficult because of the huge variability in scenarios and occupants' characteristics. This thesis presents the development of a computational simulation framework, SAFEgress, which addresses the need to incorporate human and social behaviors to aid occupant-centric egress design. In the following, we provide a summary of the thesis, discuss the main contributions of the research, and propose some future research directions.

8.1 Summary

As evidenced by empirical studies of past emergencies, the outdated view of mass panic in emergencies and homogenous crowd should be abandoned [4, 5, 8, 65]. Instead, people's responses are shaped by their individual backgrounds and social relationships with others in the crowd [33, 19, 6]. This has been shown in real-life incidents, as evacuees continue to be concerned about other people and exhibit different forms of social behaviors, such as helping each other and even putting themselves in danger in search for others. However, the current practice in egress analysis largely ignore the uniqueness of each emergency scenario and the wide variation of occupants' characteristics [11, 22, 65, 87]. Thus, there is a need for incorporating the underlying human and social behaviors into the variables used in safe egress analysis. In this thesis, we have proposed and developed a flexible computational framework, SAFEgress, emphasizing the factors and mechanisms that govern human behaviors in emergencies.

Based on an extensive review of pertinent literature on human behaviors in crowds and emergencies, we adopt a multi-level framework to classify and study different related social theories and empirical studies. We conclude that occupants' movements are clearly neither random nor irrational. Instead, they are the results of individuals' decisions and social interactions, and are mediated by different factors at the individual, group, and crowd levels. More specifically:

- At the individual level, occupants do not just react to external cues; they also refer to their prior experience and learned conventions to determine their behaviors.
- At the group level, members' interactions are motivated and mediated by their pre-existing relationships. In emergencies, groups have unique characteristics that cannot be reduced to the individual level, nor can they be generated from the interactions of isolated individuals.
- At the crowd level, the evacuating crowd has both structured qualities (such as respecting personal space) and emergent qualities (i.e., spontaneous interactions among individuals). The social interactions within the crowd are more transient and less structured when compared to groups, which results in different crowd patterns in mass evacuation contexts.

Building upon the multi-level analysis of social studies on crowds and emergencies, we propose a computational framework, SAFEgress, to model the egress situations. We adopt an agent-based simulation paradigm to simulate occupant movements in evacuations. We emphasize the need to define individual agents as a part of the social group and crowd. The key features in SAFEgress that address the diversity in occupant behaviors are summarized as follows:

- An agent mimicking an occupant is defined using individual, group, and crowd level attributes. Additional attributes can be added to each of the levels to enrich the representation of an agent.
- A multi-stage behavioral cycle (perception – interpretation – decision-making – execution) is implemented to mimic the behavioral process of an occupant in an emergency situation [8, 61]. Each stage of the behavioral cycle is modeled separately to allow easy modifications to existing functionalities.

- The behavioral logic (represented in the behavioral model) is decoupled from the agent model (defined by the agent attributes and simulated capabilities). This design pattern aims to facilitate the re-use of behavioral models. The existing behavioral model can be modified easily, whereby new behavioral models can be added to represent the diverse behaviors observed in real life.

Last but not least, we adopt a bottom-up approach to validate SAFEgress. Our validation tests illustrate a wide range of behaviors that SAFEgress can capture. Using SAFEgress to study the museum floor plan, we investigate the impacts of the volume of visitors, pre-evacuation delays, and prolonged travel time due to visitors' social affiliations on egress performance. In the stadium case study, we illustrate the importance of considering the unique egress design of the venue (such as exit arrangement and signage) and the exit preference of the participants when planning emergency egress strategies. Supported by the analysis of diverse simulation scenarios, practitioners can customize safety designs and evacuation strategies to account for particular characteristics of the occupants and emergency conditions.

8.2 Contributions

The development of SAFEgress presents a multidisciplinary effort in bridging the gap between social science knowledge on human behaviors and the real-world crowd problems in emergencies. Our research directly contributes to civil engineering, particularly to the area of safety engineering, by establishing a better understanding of occupant behaviors in emergencies and providing a tool for the design of safer, occupant-centric egress systems. In the following, we highlight the key areas of contributions of this research:

- **Multi-level theoretical framework to systematically analyze complex human and social behaviors in egress:** although social science studies have established a rich set of factors and social mechanisms that explain the evacuation outcome, there is no single unified theory that can adequately explain occupants' behaviors in different situations. A theoretical framework consisting of three levels–individuals, social groups, and crowds–is developed to study human and social behaviors systematically. Using this framework, relevant factors and processes developed by different social theories and case studies can be extracted to represent occupants' behaviors in egress. This theoretical framework lays the foundation for further research in egress modeling.

- **A new representation of modeling occupants that considers not only individual preference and experience, but also social relationships:** A flexible representation scheme of the building occupants is developed such that not only individual, but also social group and crowd level characteristics and behaviors can be explicitly described and modeled in the computational simulation. The modeling of occupants emphasizes the pre-existing social relationships and backgrounds to explain emerging phenomena. Such a modeling effort is among the very first in egress and crowd simulations, which traditionally focus on the visual aesthetics and computational efficiency of simulations and oversimplify the social behaviors of the individuals in the crowd.
- **A flexible computational framework that is capable of modeling diverse occupants' behaviors:** We have designed a flexible computational framework that decouples the logic of behaviors (such as searching for the group and following crowds) from the modeling of occupants (i.e. the agents). This design pattern increases the usability of the framework because users can conveniently define different agent types by pairing different behavioral models to each agent definition. Moreover, new behaviors can be tested by adding new behavioral models or modifying existing behavioral models.
- **A means to apply social science knowledge to real world engineering problems:** Through the case studies, we have demonstrated that groups and crowds have different effects on egress performance under different emergency scenarios. Applying social theories to investigate egress of buildings is an example of using social science knowledge to enhance engineering designs and provide insights to real world problems. The framework also offers a means to test different social theories by translating the theories into logic that govern the agents' behaviors in the simulations.
- **A set of performance metrics to assess human and social factors in egress:** Conventionally, egress performance of a building is evaluated based on timings (such as required and available evacuation times). To analyze a broad range of egress scenarios, we have designed and employed a richer set of performance metrics, such as crowd density maps, crowd patterns, and statistics of exit usage and delay time. The set of evaluation metrics presents new analytical means to explore performance-based simulation results.

- **Efficient computational algorithms to simulate human-like capabilities in agents and to allow the modeling of a large crowd:** Specifically, the computational methods implemented in SAFEgress include the following:
    - Constructing a navigation map to represent the connectivity of the accessible areas (Section 4.4.3.1). Agents in SAFEgress can query the navigation map using their knowledge of the building to guide their motion.
    - Adopting point tests and distance tests to mimic the visual and audio sensing capability for agents in SAFEgress (Section 4.4.2).
    - Using decision trees to model agent decision-making processes (Section 5.2.2).
    - Extending the grid method to aid the agent in locating its neighboring agents among a large number of agents [44] (Section 4.4.2.3);
    - Implementing a motion control algorithm to determine the locomotion of all agents sequentially (Section 4.4.3.2).

8.3 Future work

The development of SAFEgress represents a step forward in incorporating human and social factors into occupant-centric design and crowd safety. This section describes five main research directions. The first four areas are related to the limitations and the possible extensions of the current SAFEgress system: (1) more precise modeling of the egress environment; (2) improving agent's capabilities to mimic evacuees; (3) incorporating other salient group and crowd effects; and (4) enhancing model scalability. Finally, we discuss how the potential integration of crowd movement data in SAFEgress can both validate the model and implement crowd control measures and adaptive emergency systems.

8.3.1 Enhancing the modeling of egress environment

Incorporating smoke propagation

Incorporating the fire and smoke model in SAFEgress is important because fire effluents directly and rapidly affect human behaviors in emergencies. While the current implementation does not include fire and smoke modeling, simulation results from a fire and smoke propagation model could be integrated into the SAFEgress simulation through the Crowd Simulation Engine. For example, in the pre-simulation phase, smoke propagation could be analyzed using existing fire simulation software programs [88, 89]. The smoke simulation results could be stored with timestamps that are synchronized with the SAFEgress simulation, so that the Crowd Simulation Engine could retrieve the smoke simulation results as it updates each simulation step. Moreover, the 2-D grid that is designed to efficiently locate neighboring agents could be re-used to store smoke information, such as the concentration of toxic gases and visibility reductions, so that the agents residing in the cell could assess the local smoke condition efficiently.

Modeling multistory building

The current SAFEgress prototype handles simulation on a single floor plan. To simulate evacuation in multistory buildings, each level of the multistory building could be modeled as a separate virtual environment, and a new navigation object "staircase" could be defined to model a new kind of exit. When an agent exits from one level and enters into a staircase in the virtual environment, the agent is removed from the first level and "transferred" to the next lower level after a certain period of time that represents the time needed to travel down one level of the staircase. To model the transition time of an agent from one level to another, one could refer to existing empirical studies of occupants' travel speed on staircases [9].

8.3.2 Improving individual agent capabilities

Improving sound modeling

People gather information about emergencies through audio cues, such as booming sounds and public announcements. Currently, the simulated hearing capability of an agent is implemented using a simple distance test. More sophisticated functions considering the boundary effects of obstacles and audio cue loudness levels could be incorporated to model sound perception more accurately [46]. Moreover, the representation of audio cues could also be modified to provide additional characteristics of the sound source.

Modeling multiple cues and conflicting cues

In an emergency situation, people may receive multiple cues. The perceived cues can be consistent or conflict with one another. The current implementation simulates the impacts of various cues by combining these effects in a linear fashion. Different equations to model the combined effects of multiple cues could be explored further [61, 79]. Moreover, people who perceive cues that suggest the safety of the building may feel a lesser urge to evacuate. This kind of urge-reducing cue has not been considered in the current implementation. One possible way to incorporate the calming effects of cues is assigning a negative attribute value to the reaction time of the cue object. By assuming a negative reaction time, the urge-reducing cue would decrease an agent's urge to evacuate during the simulation.

Incorporating randomness in agent's behaviors

In the current implementation, agents are populated at random locations within the specified regions and are selected in a random order to exercise the agent behavioral cycle at each simulation step. Given the modularity of the SAFEgress framework, various stochastic processes could be introduced at different stages of the agent behavioral cycle to examine the possible outcomes with randomness. For example, an agent can be assigned to have a random level of emergency awareness, thus leading to different pre-evacuation delays even when perceiving the same cues during the interpretation stage. Then, at the decision-making stage, an agent can probabilistically determine the current behaviors based on previous choices. Moreover, at the execution stage, the agents can explore the exit route based on their partial knowledge of the building layout.

Considering effects of building familiarity on delay

The effect of building familiarity on evacuation delay is not explicitly modeled in SAFEgress because there are multiple and possibly conflicting mechanisms found in the literature. For example, normalcy bias suggests that familiar occupants are predisposed to filter slight and ambiguous environmental cues and tend to deem evacuation unnecessary [66]. However, empirical evidence shows that people who are familiar with the environment are more attentive to slight environmental change, hence initiate evacuation sooner [7, 61]. Currently, users can define high familiarity agents with different value assignments to the cue awareness factor to test various theories. For instance, the normalcy bias of an individual can be defined using an agent with a low level of cue awareness but high familiarity with the building. Furthermore, the interpretation stage of the agent behavioral cycle could be modified to account for the effects of familiarity on delay upon further study.

8.3.3 Enriching the modeling of group and crowd effects

Incorporating more social effects on individual's urge to evacuate

In the current SAFEgress prototype, the social effects increase an agent's urge to evacuate monotonically because the maximum urges among the group members and the crowds are considered in the urge updating function. As an extension of the model, other updating functions could be implemented to investigate different types of social influence. For example, Simmel's study of groups suggests that smaller groups, such as dyads and triads, have greater social influences on their members due to the intermediacy of their members' interactions [68]. Moreover, individuals with different levels of perceived social status of the can exert different level of influence toward other people [64].

Improving group interactions modeling

In SAFEgress, agents interact with their affiliated groups, and those interactions change exit routes and walking patterns. When deciding the escape route of a group, the leader makes decision of which route(s) to take and be adopted by the rest of the group. Other behavioral logic could be implemented to mimic other types of group decision-making processes, such as following majority preference or following the most experienced individuals [69]. Moreover, when walking in groups, agents tend to maintain proximity with groups. Other mechanisms, such as maintaining a body orientation that facilitates communication, could be explored to model the group-walking patterns [39].

Modeling "panic"

Although the myth of mass panic has been dispelled over time as empirical studies of past emergency accidents show little evidence of people becoming irrational and behaving ruthlessly [4, 5, 6]. Given the logic of behaviors, new behavioral models could be created to model even rare irrational behaviors, much like the demonstration of different behavioral models in Chapter 5.

Instead of ruthless and irrational behaviors, what is more commonly observed in an emergency situation is the spread of emotions, like fear among the crowd. SAFEgress allows the modeling of emotion contagion by equipping agents with simulated vision to detect a surrounding crowd. Potential development includes more sophisticated analysis on agents' trajectories to allow users to identify potential congestions and modifications to existing egress designs to ease the chance of overcrowding.

Modeling physical forces within crowds

Pushing among evacuees due to a lack of physical space is commonly observed in an extreme emergency situation. In most stampede incidents, pushing among evacuees is a decisive factor in injury and death. A means of identifying potential areas of danger as a result of overcrowding is simulating the physical forces on agents due to pushing. To simulate these pushing effects, the low-level locomotion algorithm of the agents would need to handle both collision detection and response and collision avoidance. In SAFEgress, because the low-level locomotion is separated from the high-level wayfinding capability of an agent, the locomotion algorithm could be modified to incorporate pushing in a high-density crowd [38, 90].

8.3.4 Improving framework usability and scalability

Developing user interface

Currently, simulation inputs are stored in text files with specific schemas that are interpreted by the Global Database to initialize the simulation. Each behavioral model is instantiated as a separate module, written in C++, and then added to the Agent Behavioral Models Database. With a good understanding of the framework, users can model different agent types by changing attribute values in the text input files. Nevertheless, providing a user interface to gather inputs would significantly improve the flexibility of the model. It is envisaged that, because model users would be able to define simulation input in a more interactive way and create new behavioral models without the need to program the source code, the tool would have a greater utility and a larger user base. Moreover, future development of SAFEgress could incorporate a centralized database containing all the shared behavioral models, allowing users to leverage the models built by others to study a diverse range of behaviors.

Categorizing different egress situations

SAFEgress simulations are set up based on user inputs that define the characteristics of buildings, occupants, and emergency events. To facilitate the simulation input process, templates could be provided to allow users to employ a set of initial values to simulate evacuations based on building types and occupants' characteristics, such as evacuation simulation in a shopping mall on a weekend. One noteworthy example of this approach is the EXODUS suite of evacuation simulation models that distinguish aircrafts evacuations (airEXODUS) from buildings evacuations (buildingEXODUS) [91].

Improving scalability

SAFEgress implemented several algorithms to facilitate simulations of large floor plans and crowds, such as pre-computation of the navigation map and the use of a grid method to locate neighbors. To improve the computational efficiency further, other techniques could be implemented. For example, agents' behaviors could be computed with multithreads instead of single-machine computation. Subdividing large floor plans into smaller areas for simulation would also provide another opportunity for multithreaded computation. Upon further improvement in scalability, SAFEgress would be able to not only simulate large and dense crowd movements for building evacuations, but also study general social phenomena observed in larger regions, such as the convergence of urban protests [92].

8.3.5 Integrating simulations with data

Validating egress simulation with real-life data

Data collection is an important aspect of egress simulations because it provides a means both to verify the assumptions proposed in social theories and to validate the usefulness of simulation tools employed. Although obtaining first-hand data in an emergency evacuation is often difficult, such information is becoming ever more accessible, owing to the increasing use of communication technologies and social media. For example, videos taken by participants in the 2010 Love Parade disaster are easily found on the Internet[5]. Even though these videos capture only local crowd patterns, they provide many valuable insights into human responses in real emergencies. Apart from video footage, data in other formats, such as chats on online social networks, post-disaster surveys and interviews, and evacuation drill records [3, 5, 9, 22], can also provide some perspectives of occupant behaviors in egress. Continual data collection is crucial for validating simulation models to produce reliable results.

Incorporating real-life data for predictive and adaptive crowd control

The advancement in sensing technology provides an opportunity to integrate crowd simulations with real-time data streams to facilitate crowd control. This kind of dynamic, data-driven simulation approach has been widely used in many applications, such as intelligent transportation systems [93]. Sensor data on occupants' movement could serve as a continuous input to the simulation, which would then produce real-time predictions of the crowd flow. After further improvement in computational efficiency, SAFEgress could be used as the predictive model to forecast crowd flow realistically considering individual and social behaviors and the egress situation context. This data-driven simulation could assist emergency responders to monitor crowd circulations and to implement effective crowd control measures to mitigate crowd accidents in time. Furthermore, with careful implementation, crowd simulation results could be integrated into the control algorithms of adaptive devices in buildings, such as automated lighting and signage systems, to provide evacuees with proper exit information during emergencies without the need for human intervention.

[5] Youtube channel with videos about the 2010 Love Parade stampede disaster: https://www.youtube.com/user/LoveparadeDuisburg (accessed on December 2, 2014)

Bibliography

[1] R. W. Bukowski and E. D. Kuligowski, "The basis for egress provisions in US building codes," in *Proceedings of InterFlam 2004*, Edinburgh, UK, vol. 1, pp. 375-386, 2004.

[2] *Means of egress,* International Building Code, 2012.

[3] G. Proulx, "Movement of people: The evacuation timing," in *SFPE Handbook of Fire Protection Engineering*, third ed., Quincy, MA: NFPA International, pp. 3:342 - 3:366, 2002.

[4] W. Challenger, W. C. Clegg and A. M. Robinson, "Understanding Crowd Behaviours: Guidance and Lessons Identified," The Cabinet Office Emergency Planning College, York, UK, 2009.

[5] B. E. Aguirre, M. R. Torres, K. B. Gill and H. Lawrence Hotchkiss, "Normative collective behavior in the station building fire," *Social Science Quarterly,* vol. 92, no. 1, pp. 100-118, 2011.

[6] J. Drury, C. Cocking and S. Reicher, "Everyone for themselves? A comparative study of crowd solidarity among emergency survivors," *British Journal of Social Psychology,* vol. 48, no. 3, pp. 487-506, 2009.

[7] E. D. Kuligowski, "Terror defeated: occupant sensemaking, decision-making and protective action in the 2001 World Trade Center disaster," Ph.D. dissertation, University of Colorado at Boulder, Boulder, CO, 2011.

[8] E. D. Kuligowski, "Modeling human behavior during building fires," NIST Technical Note 1619, National Institute of Standards and Technology, Gaithersburg, MD, 2008.

[9] J. D. Averill, D. S. Mileti, R. D. Peacock, E. D. Kuligowski, N. Groner, G. Proulx, P. A. Reneke and H. E. Nelson, "Federal building and fire safety investigation of the World Trade Center disaster: Occupant behavior, egress, and emergency communications," NIST NCSTAR 1-7, National Institute of Standards and Technology, Gaithersburg, MD, 2005.

[10] J. R. Hall, "How many people can be saved from home fires if given more time to escape?," *Fire Technology,* vol. 40, pp. 117-126, 2004.

[11] G. Santos and B. E. Aguirre, "A critical review of emergency evacuation simulation models," in *Proceedings of Workshop on Building Occupant Movement during Fire Emergencies*, Gaithersburg, MD, pp. 25-50, 2004.

[12] P. Thompson, J. Wu and E. Marchant, "Simulex 3.0: Modelling evacuation in multi-storey buildings," *Fire Safety Science,* vol. 5, pp. 725-736, 1997.

[13] M. Owen, E. Galea and P. Lawrence, "The EXODUS evacuation model applied to building evacuation scenarios," *Journal of Fire Protection Engineering,* vol. 8, no. 2, pp. 65-84, 1996.

[14] R. Fahy, "Exit89 – High-rise evacuation model –recent enhancements and example applications," in *Proceedings of International Conference for Fire Research and Engineering*, Orlando, FL, pp. 332-337, 1995.

[15] I. Donald and D. Canter, "Intentionality and fatality during the King ' s Cross underground fire," *European Journal of Social Psychology,* vol. 22, pp. 203-218, 1992.

[16] C. McPhail, "Blumer’s theory of collective behavior: the development of non-symbolic interaction explanation," *Sociological Quarterly,* vol. 30, no. 3, pp. 401-423, 1989.

[17] N. R. Johnson, W. E. Feinberg and D. M. Johnston., "Microstructure and panic: The impact of social bonds on individual action in collective flight from the Beverly Hills Supper Club fire," *Disasters, Collective Behavior and Social Organizations,* pp. 168-189, 1994.

[18] A. R. Mawson, "Understanding mass panic and other collective responses to threat and disaster," *Psychiatry,* vol. 68, pp. 95-113, 2005.

[19] C. McPhail, *The Myth of the Madding Crowd,* Aldine De Gruyter, New York, 1991.

[20] J. Fruin, *Pedestrian Planning and Design,* New York: Metropolitan Association of Urban Designers and Environmental Planners, Inc., 1971.

[21] J. Pauls, "Movement of people," in *SFPE Handbook of Fire Protection Engineering*, Quincy, MA, MD: NFPA International, pp. 3:263-3:285, 1995.

[22] R. F. Fahy and G. Proulx, "Toward creating a database on delay times to start evacuation and walking speeds for use in evacuation modeling," in *Proceedings of 2nd International Symposium in Human Behaviour in Fire*, Boston, MA, pp. 175-183 2001.

[23] D. Helbing and P. Mukerji, "Crowd disasters as systemic failures: analysis of the Love Parade disaster," *EPJ Data Science,* vol. 1, no. 7, 2012.

[24] *NFPA 101 Life Safety Code,* Quincy, MA: National Fire Protection Association, 2011.

[25] R. W. Bukowski and V. Babrauskas, "Developing rational, performance-based fire safety requirements in model building codes," *Fire and Materials,* vol. 18, no. 3, pp. 173-191, 1994.

[26] *ISO/TR 13387-8:1999 Fire safety engineering -- Part 8: Life safety -- Occupant behaviour, location and condition,* International Organization for Standardization, 1999.

[27] *SFPE Engineering Guide to Performance-Based Fire Protection Analysis and Design of Buildings,* Quincy, MA: National Fire Protection Association, 2000.

[28] D. A. Purser, "ASET and RSET: addressing some issues in relation to occupant behaviour and tenability," in Proceedings of *7th International Symposium On Fire Safety Science*, Worcester, MA, pp.91-102, 2002.

[29] D. A. Purser, "Toxicity assessment of combustion products," in *SFPE Handbook of Fire Protection Engineering*, Quincy, MA, MD: NFPA International, pp. 2:200-2:245, 2002.

[30] A. Mintz, "Non-adaptive group behavior," *Journal of Abnormal and Social Psychology,* vol. 40, pp. 150-159, 1951.

[31] H. Simon, *Models of Bounded Rationality,* Cambridge, MA: MIT Press, 1982.

[32] G. Gigerenzer and R. Selten., Bounded Rationality: The Adaptive Toolbox, Cambridge, MA: MIT Press, 2001.

[33] D. Tong and D. Canter, "The decision to evacuate: a study of the motivations which contribute to evacuation in the event of fire," *Fire Safety Journal,* vol. 9, pp. 257-265, 1985.

[34] G. Le Bon, *The Crowd,* New York: Viking, 1960.

[35] R. H. Turner and L. M. Killian, *Collective Behavior,* Englewood Cliffs, NJ: Prentice Hall, 1987.

[36] J. D. Sime, "Movement toward the familiar person and place affiliation in a fire entrapment setting," *Environment and Behavior,* vol. 17, no. 6, pp. 697-724, 1985.

[37] H. Tajfel and J. C. Turner, "The social identity theory of intergroup behavior," in *Psychology of Intergroup Relations*, W. S. and W. G. Austin, Eds., Nelson-Hall, pp. 7-24, 1986.

[38] D. Helbing, I. Farkas and T. Vicsek, "Simulating dynamical features of escape panic," *Nature,* vol. 407, p. 487–490, 2000.

[39] M. Moussaïd, N. Perozo, S. Garnier, D. Helbing and G. Theraulaz, "The walking behaviour of pedestrian social groups and its impact on crowd dynamics," *PLoS ONE,* vol. 5, no. 4, p. e10047, 2010.

[40] N. Pelechano, J. Allbeck and N. Badler, "Controlling individual agents in high-density crowd simulation," in *Proceedings of ACM SIGGRAPH Symposium on Computer Animation*, San Diego, CA, pp. 99-108, 2007.

[41] N.P. Waterson and E. Pellissier, “The STEPS pedestrian microsimulation tool - A technical summary”, Mott MacDonald Simulation Group, United Kingdom, 2010 (available at http://www.steps.mottmac.com, accessed June 2014).

[42] J. Tsai, N. Fridman, E. Bowring, M. Brown, S. Epstein, G. Kaminka, S. Marsella, A. Ogden, I. Rika, A. Sheel, M. E. Taylor, X. Wang, A. Zilka and T. M, "ESCAPES: Evacuation simulation with children, authorities, parents, emotions, and social comparison," in *Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems*, Taipei, Taiwan, vol. 2, pp. 457-464, 2011.

[43] S. Musse and D. Thalmann, "Hierarchical model for real time simulation of virtual human crowds," *IEEE Transactions on Visualization and Computer Graphics,* vol. 7, no. 2, pp. 152-164, 2001.

[44] X. Pan, "Computational Modeling of Human and Social Behavior for Emergency Egress Analysis," Ph.D. dissertation, Stanford University, Stanford, CA, 2006.

[45] S. Gwynne, E. R. Galea and P. J. Lawrence, "The introduction of social adaptation within evacuation modelling," *Fire and Materials,* vol. 30, no. 4, pp. 285-309, 2006.

[46] E. Goldstein, *Sensation and Perception,* Cengage Learning, 2009.

[47] T. Gärling, A. Böök and E. Lindberg, "Spatial orientation and wayfinding in the designed environment: A conceptual analysis and some suggestions for post-occupancy evaluation," *Journal of 566 Architectural and Planning Research,,* vol. 3, no. 1, pp. 55-64, 1986.

[48] A. Turner and A. Penn, "Encoding natural movement as an agent-based system: an investigation into human pedestrian behaviour in the built environment," *Environment and Planning B: Planning and Design,* vol. 29, no. 4, pp. 473-490, 2002.

[49] J. J. Gibson, *The Ecological Approach to Visual Perception,* Boston, MA: Houghton Mifflin, 1979.

[50] J.-C. Latombe, *Robot Motion Planning,* Boston, MA: Kluwer Academic Publishers, 1991.

[51] H. Choset, *Principles of Robot Motion,* Cambridge, MA: MIT Press, 2005.

[52] L. Kavraki, P. Svestka, J.-C. Latombe and M. Overmars, "Probabilistic roadmaps for path planning in high-dimensional configuration spaces," *IEEE Transactions on Robotics and Automation,* vol. 12, no. 4, pp. 566-580, 1996.

[53] H. H. Gonzalez-Banos and J.-C. Latombe, "Navigation strategies for exploring indoor environments," *The International Journal of Robotics Research,* vol. 21, no. 10-11, pp. 829-848, 2002.

[54] A. Kneidl, D. Hartmann and A. Borrmann, "A hybrid multi-scale approach for simulation of pedestrian dynamics," *Transportation Research Part C: Emerging Technologies,* vol. 37, p. 223–237, 2013.

[55] B. Aguirre, D. Wenger and G. Vigo, "A test of the emergent norm theory of collective behavior," *Sociological Forum,* vol. 13, no. 2, pp. 301-320, 1998.

[56] M. W. Macy and A. Flache, "Social dynamics from the bottom up: Agent-based models of social interaction," in *The Oxford Handbook of Analytical Sociology*, H. P and B. P, Eds., Oxford: Oxford University Press, pp. 245–268, 2009.

[57] R. Conte and M. Paolucci, "On Agent Based Modelling and Computational Social Science," *Front. Psychol.,* vol. 5, no. 668, p. Article 668, 2014.

[58] M. W. Macy and R. Willer, "From factors to actors: Computational sociology and agent-based modeling," *Annual Review of Sociology ,* vol. 28, pp. 143-166, 2002.

[59] G. Still, "Crowd Dynamics," Ph.D. dissertation, University of Warwick, Coventry, UK, 2000.

[60] G. Proulx, "High-rise Office Egress: the Human Factors," in *Proceedings of Symposium on High-Rise Building Egress*, New York, NY, pp.1-5, 2007.

[61] M. K. Lindell and R. W. Perry, "The protective action decision model: theoretical modifications and additional evidence," *Risk Analysis,* vol. 32, no. 4, pp. 616-632, 2012.

[62] G. Proulx, "A stress model for people facing a fire," *Journal of Environmental Psychology,* vol. 13, pp. 137-147, 1993.

[63] D. Kahneman and A. Tversky, "Variants of uncertainty," in *Judgement under Uncertainty; Heuristics and Biases*, Cambridge University Press, pp. 509-520, 1982.

[64] C. M. Zhao, S. M. Lo, S. P. Zhang and M. Liu, "A Post-fire Survey on the Pre-evacuation Human Behavior," *Fire Technology,* vol. 45, no. 1, pp. 71-95, 2008.

[65] B. E. Aguirre, "Emergency evacuations, panic, and social psychology," *Psychiatry: Interpersonal and Biological Processes,* vol. 68, no. 2, pp. 121-129, 2005.

[66] H. Omer and A. N, "The continuity principle: A unified approach to disaster and trauma," *merican Journal of Community Psychology,* vol. 22, no. 2, pp. 273-287, 1994.

[67] G. Proulx, "Understanding human behavior in stressful situations," in *Proceedings of Workshop to Identify Innovative Research Needs to Foster Improved Fire Safety in the United States*, Washington, D.C., pp. 1-5, 2002.

[68] G. Simmel, *The Sociology of Georg Simmel,* (Translated and edited by K. H. Wolff), New York: Free Press, 1950.

[69] L. R. Frey, D. Gouran and M. S. Poole, The Handbook of Group Communication Theory and Research, Sage, 1999.

[70] J. Drury and C. Cocking, "The mass psychology of disasters and emergency evacuations: a research report and implications for practice," ESRC Research Report, Ref. No: RES-000-23-0446, University of Sussex, Falmer, Brighton, 2007.

[71] J. Rydgren, "Beliefs," in *The Oxford Handbook of Analytical Sociology*, H. P and B. P, Eds., Oxford: Oxford University Press, pp. 72-93, 2009.

[72] X. Tu, "Artificial animals for computer animation: biomechanics, locomotion ,perception, and behavior," Ph.D. dissertation, University of Toronto, Toronto, ON, 1996.

[73] M. Costa, "Interpersonal distances in group walking," *Journal of Nonverbal Behavior,* vol. 34, no. 1, pp. 15-26, 2010.

[74] N. Kaya and F. E. Erkip, "Invasion of personal space under the condition of short-term crowding: A case study on an automatic teller machine," *Journal of Environmental Psychology,* vol. 19, pp. 183-189, 1999.

[75] W. Boles, "The effect of density, sex, and group size upon pedestrian walking velocity," *Man Environment System,* vol. 11, pp. 37-40, 1981.

[76] M. J. ONeill, "Effects of signage and floor plan configuration on wayfinding accuracy," *Environment and Behavior,* vol. 23, no. 5, p. 553–574, 1991.

[77] C. M. Clark, S. M. Rock and J.-C. & Latombe, "Motion planning for multiple mobile robots using dynamic networks," in *Proceedings of IEEE International Conference on Robotics and Automation*, vol. 3, pp. 4222 - 4227, Taipei, Taiwan, 2003.

[78] S. Gwynne and D. Boswell, "Pre-evacuation data collected from a mid-rise evacuation exercise," *Journal of Fire Protection Engineering*, vol. 19, pp. 5-29, 2009.

[79] E. R. Galea, L. Hulse, R. Day, A. Siddiqui and G. Sharp, "The UK WTC 9/11 evacuation study: an overview of findings derived from first-hand interview data and computer modelling," *Fire and Materials,* vol. 36, no. 5-6, pp. 501-521, 2011.

[80] P. L. Broadhurst, "Emotionality and the Yerkes-Dodson Law," *Journal of Experimental Psychology,* vol. 54, no. 5, pp. 345-352, 1957.

[81] P. Reneke, "Evacuation decision model," NISTIR 7914, National Institute of Standards and Technology, Gaithersburg, MD, 2013.

[82] J. Rydgren, "Beliefs," in *The Oxford Handbook of Analytical Sociology*, P. Hedström and P. Bearman, Eds., Oxford: Oxford University Press, pp. 72–93, 2009.

[83] E. R. Galea, "A general approach to validating evacuation models with an application to EXODUS," *Journal of Fire Sciences,* vol. 16, no. 6, pp. 414-436, 1998.

[84] *Interim Guidelines for Evacuation Analyses for New and Existing Passenger Ships,* International Maritime Organization, Marine Safety Committee, London, 2002.

[85] S. Gwynne and E. Rosenbaum, "Employing the Hydraulic Model in Assessing Emergency Movement," in *SFPE Handbook of Fire Protection Engineering*, Quincy, MA, NFPA International, pp. 373-396, 2008.

[86] S. Gwynne, E. Kuligowski, J. Kratchmanc and J. Milke, "Questioning the linear relationship between doorway width and achievable flow rate," *Fire Safety Journal,* vol. 44, no. 1, pp. 80-87, 2009.

[87] G. Proulx, "Occupant Behaviour and Evacuation," in *9th International Fire Protection Seminar*, Munich, Germany, pp. 219–232, 2001.

[88] W. Grosshandler, N. Bryner, D. Madrizykowski and K. Kuntz, "Report of the technical investigation of the Station Nightclub Fire," NIST NCSTAR 2, National Institute of Standards and Technology, Gaithersburg, MD, 2005.

[89] K. McGrattan and G. Forney, "Fire dynamics simulator (version 4) – User's guide," NIST SP 1019, National Institute of Standards and Technology, Gaithersburg, MD, 2004.

[90] S. J. Guy, J. Chhugani, S. Curtis, P. Dubey, M. Lin and D. Manocha, "Pledestrians: a least-effort approach to crowd simulation," in *Proceedings of the 2010 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, Madrid, Spain, pp. 119-128, 2010.

[91] E. Galea, M. Owen, P. Lawrence and L. Filippidis, "Computer based simulation of aircraft evacuation and its application to aircraft safety," in *Proceedings of International Aircraft Fire and Cabin Safety Research Conference*, Atlantic City, NJ, pp. 8-15, 1998.

[92] K. Starbird and P. Leysia, "(How) will the revolution be retweeted?: information diffusion and the 2011 Egyptian uprising," in *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*, Seattle, WA, pp. 7-16, 2012.

[93] J. Zhang, F. Y. Wang, K. Wang, W. H. Lin, X. Xu and C. Chen, "Data-driven intelligent transportation systems: A survey," *Intelligent Transportation Systems, IEEE Transactions on,* vol. 12, no. 4, pp. 1624-1639, 2011.