COMPUTATIONAL STUDY OF SOCIAL INTERACTIONS AND COLLECTIVE BEHAVIOR DURING HUMAN EMERGENCY EGRESS

By

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DEDICATION

To my parents
Xianzhi Fang and Manhui Fang

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During the past five years as a PhD student in the Department of Civil and Environmental Engineering at the University of Michigan, I received a lot of help and encourage from faculties, staffs, and my friends. I would like to take this opportunity to give my gratitude towards all of these people.

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Last and most importantly, my family, where give all my courage and faith. I would like to dedicate this doctoral dissertation to my parents, Xianzhi Fang and Manhui Fang.

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ABSTRACT

COMPUTATIONAL STUDY OF SOCIAL INTERACTIONS AND COLLECTIVE BEHAVIOR DURING HUMAN EMERGENCY EGRESS

Chair: Sherif El-Tawil

Egress of occupants from a facility is normally straightforward. Problems arise when an emergency is present and many occupants are attempting to egress as quickly as possible, at which point egress can become life threatening. There are many reported events in history where emergency egress resulted in extensive loss of life and injuries.

Egress research depends heavily on computational modeling because ethical and safety concerns preclude running experiments involving emergency crowd evacuations. However, to date, existing egress models rarely take into account meaningful social interactions and adherence to cultural norms, both of which are commonly present among egressing occupants and have significant influence on their egress response. The objective of this study is to develop a new methodology to address this gap using an Agent-Based computational platform.

A novel method, termed Scalar Field Method (SFM), is proposed to accomplish this goal. The new technique draws on an analogy to a charged particle in an electromagnetic field to simulate the decision making process of an agent as it navigates through a facility and considers social interactions in its quest to egress. Two categories of social interactions are accounted for: 1) pre-existing social relationships associated with social identities, and 2)

informal relations in collective behaviors such as lining up in counter-flow, queuing, and collective mobility. The latter is achieved by requiring an agent to establish informal and transient leader-follower relationships with others while adjusting its behavioral patterns as warranted by the situation.

Simulation results demonstrate the model's capabilities of handling social interactions, modeling reasonable egress behavior, and mimicking self-organized social gathering and collective behavior during egress. Comparisons with field studies show that the computational results correlate realistically with experimental data. A case study of the Station Nightclub fire that occurred in Rhode Island in 2003 and killed 100 occupants demonstrates that the proposed computational tools have strong potential for quantitatively exploring the influence of social level traits on egress situations.

CHAPTER 1

INTRODUCTION

1.1 Introduction and Motivation

Egress is the action of going out of a facility or leaving a place. Egress of occupants is generally straightforward under normal conditions. Problems arise when an emergency is present and many occupants are attempting to egress as quickly as possible, at which point egress can become life threatening. As shown in Table 1-1, there are many reported events in history where emergency egress resulted in extensive loss of life and injuries.

Although experiments on egress under non-emergency situations have been carried out by multiple research groups (Isobe *et al.* 2004a, b; Fang *et al.* 2010; Kretz *et al.* 2006a, 2006b), ethical and safety concerns preclude running experiments involving emergency crowd evacuations because of the risk of injuring participants. Therefore, research in this area typically focuses on analysis of actual previous events and/or computational modeling. Until now, good documentation of real events is generally scarce (Aguirre *et al.* (2011a), making computational simulation an important research tool in this field.

Dozens of egress models have been published over the past half century (Kuligowski 2008). The most realistic among these techniques is Agent-Based modeling, which is a computational simulation methodology used to build an artificial society. In such models, evacuees are represented by computer-driven entities (agents) that have their own characteristics, are adaptive and capable of interacting with each other and with their environment. The interactions of interdependent agents generate complex systems, potentially leading to emergent behavior at the system level (Aguirre *et al.* 2011a).

Table 1-1: List of egress-related disasters[1]

Year	Location	Event	Deaths (D) & Injuries (I)
2012	Port Said, Egypt	Disaster in football stadium	74 D
2011	Kerala, India	Stampede near Sabarimala temple	102 D, 100 I
2010	Phnom Penh, Cambodia	Stampede on bridge in festival	349 D
2010	Kenya	Stampede in stadium	7 D, dozens I
2010	Duisburg, Germany	The Love Parade disaster	21 D, 500 I
2010	Amsterdam, Netherland	Riot during ceremony on Dam Square	63 I
2010	Kunda, India,	Stampede after temple gate collapse	71 D, 200 I
2010	Uttar Pradesh, India	Stampede in temple	66 D, 40 I
2008	Rajasthan, India	Stampede in temple	147 D, 55 I
2008	Himachal Pradesh, India	Stampede in Naina Devi Temple	145 D, 100 I
2007	Sunchon, North Korea	Crowd crush in a stadium	6 D, 34 I
2006	Ibb, Yemen	Campaign rallies in stadium	51 D
2006	Manila, Philippines	Outside a stadium	71 D
2006	Mecca, Saudi Arabia	Stampede at entrance of a bridge	362 D
2005	Baghdad, Iraqi	Stampede on bridge because of rumor	1005 D
2005	Maharashtra, India	Stampede in a Hindu temple	300 D
2004	Beijing, China	Stampede during Lantern Festival	37D, 15I
2004	Mecca, Saudi Arabia	Stampede near a bridge	251 D
2003	Rhode Island, US	The Station nightclub fire	100 D
2003	Chicago, US	In the stairway after a pepper spray use	21 D
2001	Accra, Ghana	Fans riot in football stadium	126 D
2000	Denmark	Incidence in concert at Roskilde Festival	9 D
1999	Minsk, Belarus	Stampede at the Nemiga metro station	53 D
1998	Minas, Saudi Arabia	Minas bridge stampede	119 D, 180 I
1996	Guatemala City, Guatemala	Audience stampede in World Cup qualifying football match	90 D, 150 I
1994	Brazzaville, Congo (B)	Stampede during religious activity	150 D
1994	Mecca, Saudi Arabia	Stampede near a bridge	270 D
1993	Madison, US	A crowd crush after a football game at UW–Madison's Camp Randall Stadium	73 I
1993	Hong Kong, China	A crowd crush at Lan Kwai Fong	21 D, 48 I
1992	Munich, Germany	Crowd in pop star Michael Jackson's debut Dangerous concert	500 I

[1] Collated from online resources:
<http://wenku.baidu.com/view/26d889b81a37f111f1855bb0.html> "Bloody memory: review of severe stampede events"
and < http://en.wikipedia.org/wiki/Stampede> "Stampede" on Wikipedia

1990	Mecca, Saudi Arabia	Stampede in an underground walkways	1426 D
1989	Sheffield, England	The Hillsborough disaster	96 D, 300 I
1988	Kathmandu, Nepal	Stampede in stadium since weather	100 D, 300 I
1986, 1984	Harrisburg Deval, India	Stampedes	50 D, 200 D
1985	Brussels, Belgium	The Heysel Stadium disaster	39 D
1982	Moscow, Russia	Luzhniki disaster in eponymous stadium	66 D
1979	Cincinnati, US	The Who Concert Stampede	11 D

The vast majority of published models assume that evacuees are intent on leaving as quickly as possible without meaningful social interaction and adherence to cultural norms (Santos et al 2004). Many of the published egress models prior to the early 2000s were based upon the panic assumption, which has been discredited (Aguirre *et al.* 2011b). Some recent models still assume that competitive behavior dominates egress response (e.g. FDS+Evac, in Korhonen *et al.* 2010). However, recent field work has shown that evacuees perform complex maneuvers (Challenger *et al* 2009; Aguirre *et al.* 2011b) and behave deliberately rather than in a non-cooperatively competitive manner or mindless panic. Some of these studies show that social and social-psychological factors significantly influence pedestrians' movements (Santos *et al*. 2004; Moussaïd *et al*. 2010; Aguirre *et al.* 2011b). In particular, pedestrians can evacuate in an ordered and/or cooperative manner, and social collective behaviors are present and consequential during egress.

Adequate and rigorous validation of egress models is a common challenge. Simulation results are rarely calibrated by actual events, because disasters are stochastic and often poorly documented. Aguirre *et al* (Aguirre *et al* 2011a) summarize the shortcomings and key points of validation work of existing computational studies.

1.2 Objectives

The general objectives of this dissertation are to develop an Agent-Based computational platform for human egress simulation, investigate the effects of social interactions and culture norms on egress behavior, mimic realistic social gathering and collective behavior, and calibrate and validate the model with empirical results, experiments and real-world disasters. Specific objectives are as follows:

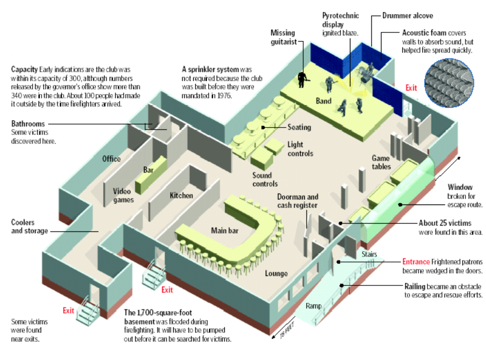
(1) Investigate physical characteristics, behavior traits and social relationships of human egress, and develop a method that can comprehensively address cultural norms and adequately incorporate social relationships that take place during egress.

(2) Using the new method, develop an Agent-Based computational platform that models rational behavior, simultaneously taking into account an evacuee's desire to egress and his/her social relationships. Test the model in proof-of-concept scenarios and calibrate it with empirical result of existing egress studies.

(3) Implement the developed Agent-Based platform to simulate social collective behavior in scenarios of queueing, collective mobility, and lining up in counter-flow. Calibrate and validate with field observations and experiments.

(4) Conduct case studies and validate the model through a real-world event, the Station Nightclub Fire (Figure 1-1), which occurred in 2003 and during which 100 people died.

(a) Ruins after the fire



(b) Plan view of the building before fire

Figure 1-1: The Station Nightclub Fire[2] (2003, Rhode Island)

[2] Pictures adapted from online resources:
<http://www.boston.com/news/local/articles/2008/09/21/the_cost_of_tragedy/> "The cost of tragedy"
<http://frogstorm.com/?p=3609> "The Station Nightclub Fire"

1.3 Structure of the Dissertation

This dissertation is comprised of seven Chapters. Chapter 1 introduces general information and objectives about this work. Chapter 2 reviews the existing studies related to human evacuation and egress simulation. Chapters 3 to 6 address objectives 1 to 4. The final chapter summarizes this dissertation and draws key conclusions. Following is a brief description of the 7 chapters:

Chapter 1: Introduction. General information about this study is provided and the objectives and structure of the dissertation are outlined.

Chapter 2: Literature Survey. This chapter discusses the state-of-the-art in human egress behavior studies and computational work, the latter of which specifically focuses on Agent-Based models.

Chapter 3: Scalar Field Method: Model Development. Based on rationality assumption, a new technique termed Scalar Field Method (SFM) is created to model human desire to take action. As a result, it can encompass rational agent behavior and is simultaneously able to account for a complex network of relationships at the social level.

Chapter 4: Scalar Field Method: Model Implementation and Preliminary Validation. Development of an Agent-Based platform named EgressSFM and preliminary validation are presented. The EgressSFM platform is comprised of building and environment model, autonomous agent model and other auxiliary modules (e.g. I/O control, display etc.). The agent model implements the SFM theory, and can explicitly simulate the "thinking" process of an occupant. Preliminary validation studies show the ability of the new software to mimic reasonable evacuation behavior, and its potential for exploring the significance of social relationships during egress.

Chapter 5: Modeling Social Collective Behavior. The EgressSFM platform is enhanced to include a leader-follower model. The model interprets local social interactions and collective behavior and then uses this information to mimic three particular scenarios: lining up in counter-flow, queuing, and collective mobility. To achieve this, an agent establishes informal and transient leader-follower relationships with others while adjusting its behavioral patterns as warranted by the situation. The proposed model is calibrated to existing field data and then validated using another set of field data, where it is shown that the new model is capable of reasonably simulating social collective behavior during egress.

Chapter 6: Case Study of the Station Nightclub Fire. The Station Nightclub event is simulated using EgressSFM, taking into account fire and smoke hazards. The simulation results are compared with actual data from the post-event investigation showing that the proposed model is reasonable. The capability of the proposed Agent-Based platform to quantitatively explore the influence of social level traits is demonstrated through a series of hypothetical exercises.

Chapter 7: Summary and Conclusions. The dissertation is summarized and the conclusions drawn from the research accomplished are presented in this chapter.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

This chapter discusses the state-of-the-art in theoretical and computational studies of human egress, with specific focus on Agent-Based simulation. Observations and discussion of human egress behavior based on field observations, experiments and real-world disasters are first described in Section 2.2. In Section 2.3, Agent-Based Modeling and other egress simulation techniques are reviewed. This is followed by a literature survey of existing Agent-Based egress models in Section 2.4.

2.2 Human Egress Behavior and Characteristics

Researchers have studied the egress response of humans, especially under emergencies, in multiple ways through the use of videos, field observations, surveys, experiments and simulation. The studies have generally focused on individual and group behaviors. The former mainly focuses on an evacuee's egress response as an unattached actor intent on rapid escape. The latter considers the evacuee's social attributes, e.g. formation of groups; interaction with family members, and self-organized collective behavior, e.g. line formation.

Study of an individual's egress behavior typically assumes that an escaping individual will move according to "least effort" (Still 2000), aiming to minimize time and costs, avoid congestion and maximize speed (Challenger *et al.* 2009). Typically, people will take the fastest route (Challenger *et al.* 2009), and prefer not to take detours (Helbing *et al.* 2001). In addition, evacuees try to keep a certain distance from other people and from walls and obstacles to avoid collisions (Thompson 2004; Challenger *et al.* 2009). Moreover, people prefer to move at their maximum walking speed rather than run to conserve energy (Challenger *et al.* 2009).

To capture an individual's egress behavior, early researchers proposed and used the "panic" assumption, e.g. Helbing et al. (2000). When panic dominates behavior, it is assumed that evacuees seek to egress without undergoing a rational thinking process, e.g. in a selfish, mad, instinctive manner. However, this point of view has been discredited (Aguirre et al. 2011b). As discussed in Aguirre et al. (2011a), there is strong evidence in the social science literature that evacuees act rationally and normatively during emergency evacuations and that panic response during crises is rare (also see Aguirre *et al.* 1998, 2005, 2011b; Kuligowski *et al.* 2010; Schadschneider *et al.* 2009). In addition, among members of evacuating gatherings, cooperative behavior is common and preexisting social affiliations have an important effect on the collective response of people (Santos *et al* 2004; Moussaid *et al* 2010).

One point of particular importance is the presence of preexisting social relationships (such as kinship, friendship, etc.) among evacuees (Yang *et al* 2005). It has been commonly observed that those evacuating tend to do so in groups (Challenger et al. 2009; Moussaid *et al* 2010; Chu *et al* 2012). Participants with meaningful social relations tend to stay together, potentially increasing the dangers they collectively face (Johnson *et al.* 1994). For example, in a thoughtful investigation of human behavior during the Station nightclub disaster that killed 100 and injured nearly 200 persons in 2003, Aguirre *et al* (Aguirre *et al* 2011a, b; Best 2013) summarized six type of social groups that influenced evacuees' social relationships: alone, co-worker, friend, dating partner, family member, and multiple level. They demonstrated that social relationships played important roles and many group members attempted to find other members in their social group instead of evacuating immediately. Besides the effect of preexisting social relationships, pedestrians can evacuate in an ordered and/or cooperative manner, and social collective behaviors are present and consequential during egress, rendering inappropriate the often-used practice of selecting the closest exit to describe egress behavior (Cialdini 1993; Pan 2006; Aguirre *et al*. 2011b; Chu *et al* 2012).

Counter-flow is a situation in which social collective behavior can occur. In counter-flow, groups of pedestrians walking in opposite directions meet head-on in a confined space. Field studies have shown that people form lines and follow an ad-hoc leader when pedestrian density is sufficiently high (Still 2000; Schadschneider *et al* 2009). Isobe et al (2004a) and Kretz et al (2006b) have conducted two independent experiments of counter-flow in narrow corridors. The former measured total passing time over the corridor, while the latter measured passing time through three locations. Both experiments showed a generally linear dependence of passing time on population size and automatic line forming during counter-flow was documented.

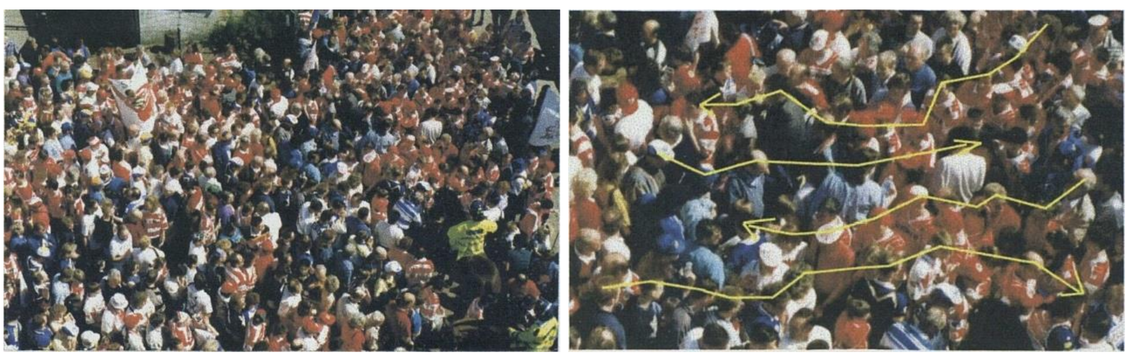


Figure 2-1: Counter flow movement (adapted from Fig. 9 & 10, p. 14-15, Still 2000)

Queuing and collective mobility are other examples of social collective behavior, for in them social and cultural emergence is common, as people have to learn to cooperate with strangers while being guided by new sets of social norms. When an emergency occurs, evacuees may not be fully aware of the extent of the hazard because they have not yet been alarmed by officials or by visible fire or smoke, for example. They thus start to egress in a relaxed manner and are under relatively low anxiety. They keep common cultural norms, for example by queuing up when congestion occurs before an exit or doorway. In contrast to competitive situations, queuing evacuees are considered to lead to more effective evacuation (Pan 2006, Challenger *et al* 2009). Collective mobility occurs when some evacuees are faced with uncertainties about what is going on and what they can do to protect themselves and others dear to them (Cialdini 1993; Pan 2006). For example, in a room with multiple egress points, evacuees who are uncertain about which way to move may choose to follow others who appear more deliberate in their actions.

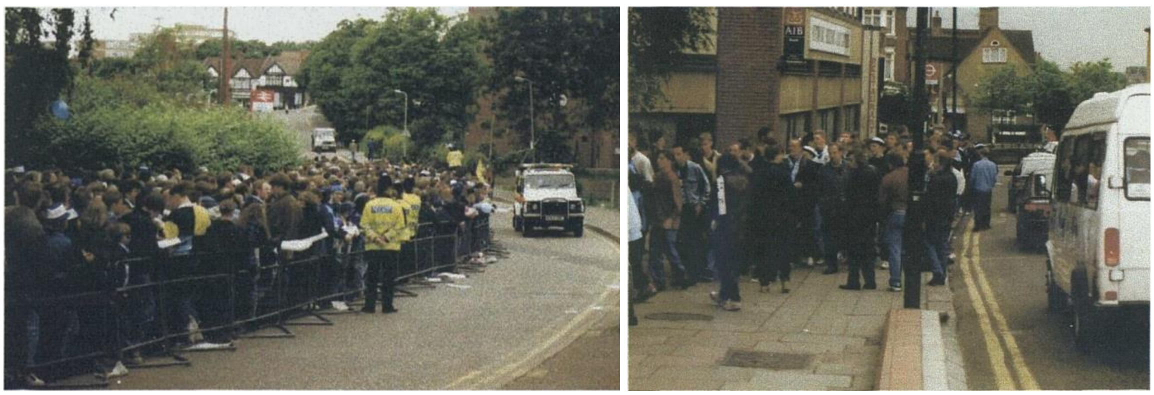


Figure 2-2: Queuing for egress (adapted from Fig. 25 & 26, p. 25-26, Still 2000)

Based on a synthesis of the research outlined in the past studies discussed above, this dissertation assumes that evacuees present rational and autonomous behavior generally influenced by three types of intent:

1. Egress behavior, which is driven by the intent to egress and influenced by obstacles and the surrounding environment. Evacuees are able to comprehensively consider multiple objectives, including the desire to exit a building, preserve private space, and not collide with walls and with other agents. An individual’s behavior tends to be competitive when this aspect of behavior is exclusively considered.

2. Incorporation of social relationships, where an occupant conducts protective behaviors elicited in an attempt to benefit kin, intimate partners, and work associates, among others. A typical observed behavior is that kin related evacuees

meet first before escaping as a group during extreme events, e.g. the so-called "backtracking" phenomenon (Bryan 1995).

3. Collective behavior, where an evacuee's behavior can be cooperative or uncommitted to the welfare of others in the collectivity. The impact of this aspect can be significant in some scenarios, such as queuing before a door/exit, collective mobility, and lining up in a narrow corridor.

The second and third behaviors are often considered as a single category of group behavior in the current literature (Moussaïd 2010; Chu *et al* 2012) primarily because social level relationships are not distinguished. However, in this work, they are viewed separately because of key differences among them. The former is often steady, permanent and with explicit specified objects associated with social roles and identities, whereas the latter is informal, temporary and without combined social identity. Another important distinction is that the former can act at a distance whereas the latter is normally invalid outside a limited zone, e.g. the visual field of an occupant.

2.3 Egress Simulation Techniques

Agent-Based Modeling (ABM) is a computational simulation methodology used to build an artificial society, and considered as one of the most realistic among existing egress simulation techniques (Aguirre *et al.* 2011a). In such model, evacuees are represented by computer-driven entities (agents) that have heterogeneous characteristics and are adaptive. Agents are autonomous units, capable of interacting with surrounding entities, the environment and other agents and able to make independent decisions. The interactions of interdependent agents generate complex systems, potentially leading to emergent behavior at the system level (Aguirre *et al*. 2011a). In particular, ABM allows modeling the complex social relationship network among agents to examine collective egress behavior during evacuation. A brief analysis of Agent-Based models is presented in section 2.4.

Most of the recently published agent-based egress models can be grouped into two categories based on their algorithms used for controlling the response of evacuees: pattern-based, e.g. MASSEgress (Pan 2006) and SAFEgress (Chu *et al* 2012), and force-based, e.g. Social Force Model (Helbing et al. 1995, 2007) and FDS + Evac (Korhonen *et al* 2007, Heliövaara *et al* 2012), also termed rule based models and social force models by Pelechano *et al.* (2007).

In typical pattern-based models, evacuees' behaviors are governed by pre-defined behavioral patterns, each comprised of a hierarchy of potential actions triggered by various conditional judgments. In general, a possible difficulty with many pattern-based models is that pre-defining social interactions between agents can be unwieldy and becomes increasingly complex to design or implement as the number of socially interacting agents increases.

Agents in force-based models are controlled by a mixture of real (physical) and virtual (social) forces. The motion of each evacuee is computed by solving the dynamic equations of motion of the system of particles representing a crowd (Helbing *et al* 1995, 2007). While early versions of such models did not address rotation of an evacuee, recent versions have overcome this difficulty by considering the torsional response of evacuees in the equations of motion (Langston *et al* 2006; Heliövaara *et al* 2012).

Force-based models have been criticized by a number of researchers. For example, Still (2000) noted that pedestrians will not necessarily conserve momentum as implied by solution of the dynamic equations of motion. In particular, in a number of situations they can stop and start at will and in spite of the imposed social forces. Furthermore, Schadschneider *et al.* (2009) asserted that interactions between pedestrians need not satisfy Newton's Third Law. A key limitation of force-based models is that they do not explicitly model the thinking process of an agent. As a result, the vectorial nature of adding social and physical forces, which is the basis of the method, becomes too restrictive for handling more complex social situations, e.g. groups of socially interacting agents, and the abrupt behavioral changes that occur in evacuations.

Most egress models strive to have evacuees moving freely in space in an effort to achieve the greatest realism possible. An alternative category of models, namely cellular automata (CA), is popular because of its simplicity. Typical CA models discretize space into a group of homogenous and discrete cells, which are normally rectangular, hexagonal or triangular. Each cell can be either empty or occupied by an evacuee or obstacle. An advantage of this type of model is that it can conveniently incorporate environmental hazards in the discretized space. For example, Tang *et al* (2008) incorporated a fire dynamics simulator (FDS) and geographic information system in CA to simulate evacuation in a fire scenario (Figure 2-3). By assuming occupants are "blind" because of smoke or darkness, Isobe *et al* (2004b) used CA models to compute the average escape time in a room without visibility. In general, however, CA models have difficulty in accurately representing human characteristics, including free movement (including rotation) and social traits. Because the grid cells are uniform, analysis of dense crowd could be problematic and depends on the model builder's skill (Pan 2006).

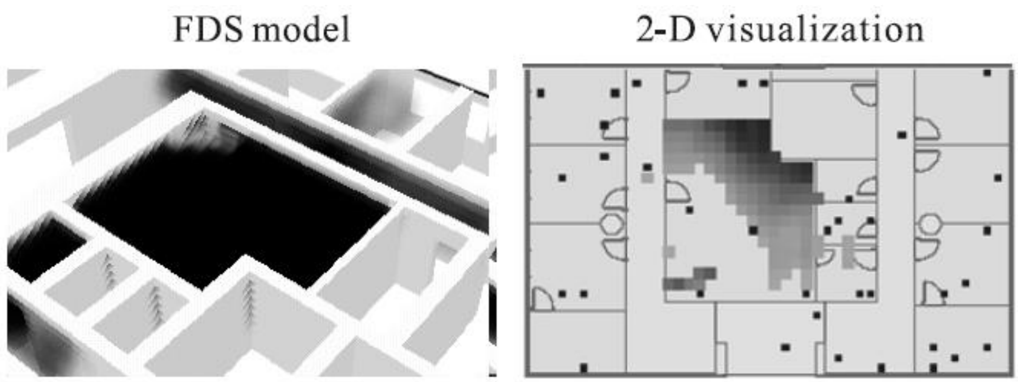


Figure 2-3: CA model developed by Tang *et al* (2008)

Another technique used for egress simulation is the flow-particle model. Such models, which are among the earliest egress models proposed, assume that evacuees move analogously to fluid-like particles from one room to another. Yet another early technique is the fluid dynamics approach, which uses fluid dynamics principles to provide a macroscopic description of human evacuation. In such models, it is assumed that escaping occupants are analogical to a gas with a Boltzmann-like distribution under specific conditions (Henderson 1974). The third early technique is the "Distance maps" model

(Thompson *et al* 1995). As shown in Figure 2-4, the model evaluates spaces based on travel distances to exits and draw contour lines over a floor plan (map) to compute the shortest escape route of occupants. These early models lack the realism of their modern counterparts, especially agent based models, and are considered obsolete.

2.4 Existing Agent-Based Egress Software

Simulex is considered to be the predecessor of most modern agent-based evacuation software (Santos *et al* 2004). Designed to evaluate the evacuation efficiency of buildings, the model was developed to simulate the escape movement of crowds through complex user-defined building geometries (Thompson *et al.* 1995). One strong suit is its ability to handle building geometry and human locomotion in free space combining calibrations with various resources such as video evidence (Thompson 2004). Simulex falls short of reality because it does not consider any social interaction or collective behavior.

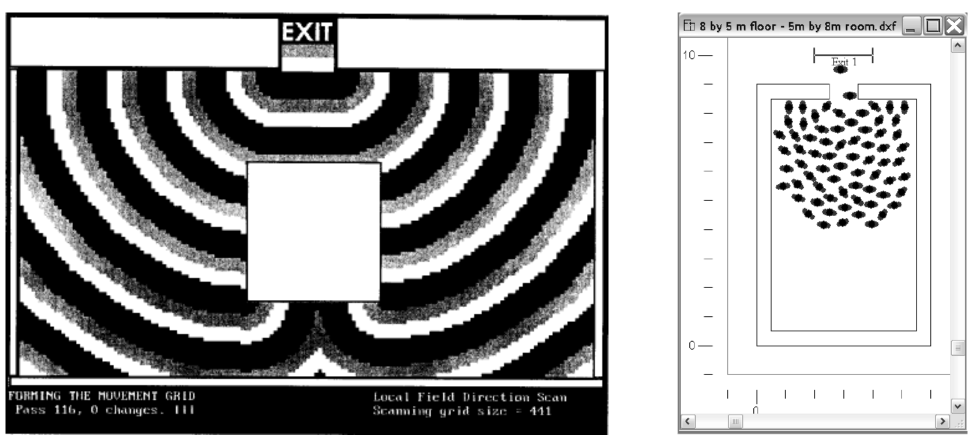


Figure 2-4: "Distance maps" and Simulex (adapted from Thompson *et al* 1995; 2004)

buildingEXODUS, created by the Fire Safety Engineering Group (Gwynne *et al.* 2001, 2006), is a commercially successful evacuation simulation tool. Based on Agent-Based modeling techniques, the software takes into account evacuees' various characteristics including positions, psychologies and physical restraints, and is comprised of six modules to simulate agent interaction: Occupant, Movement, Behavior, Geometry, Hazard, and

Toxicity. An advantage of this model is that it takes into account the influence of fire hazard by using a fluid dynamic model. However, the software has limitation in social and group effect treatment (Aguirre et al 2011a).

Pelechano et al (2007) developed HiDAC (High-Density Autonomous Crowds) to simulate large and dense crowds of autonomous agents for the computer graphics community. The model enables agents to select one of multiple patterns of response such as bi-directional flow, queuing, pushing, etc. Implementing the response pattern, each agent conducts two level of actions: High-level, such as navigation, learning, communication between agents, and decision-making; and low-level, perception and a set of reactive behaviors such as collision avoidance and detection. The tool can mimic reasonable responses, e.g. the formation of wide or narrow queues in non-panic situations, as shown in Figure 2-5. HiDAC implements the "panic" assumption which has been discredited, and fails to model a human's social level traits.

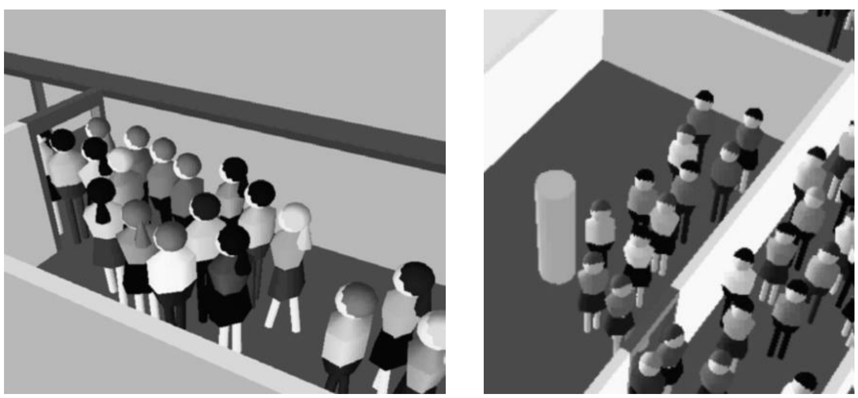


Figure 2-5: Queues in HiDAC system (adapted from Pelechano *et al* 2007)

MASSEgress is an Agent-Based model developed by Pan (2006) at Stanford University. Each agent is able to perceive the surrounding environment and choose one of several behavioral patterns including competitive, queuing, and herding (thereafter termed collective mobility) responses. These behavioral patterns are controlled by several perception-related parameters, such as importance, uncertainty, urgency and stress level. Each pattern is comprised of stochastic basic movements such as random walk, seek, target following and etc. The complexity of its behavioral engine allows agents to move independently and stochastically at the micro level, and enables collective behaviors such as queuing and collective mobility near doors/exits (Figure 2-6). A drawback is its inability to incorporate environmental hazards, which can lead to an agent's injury and death. Another limitation is that the model does not take into account social relationships and group effects among agents.

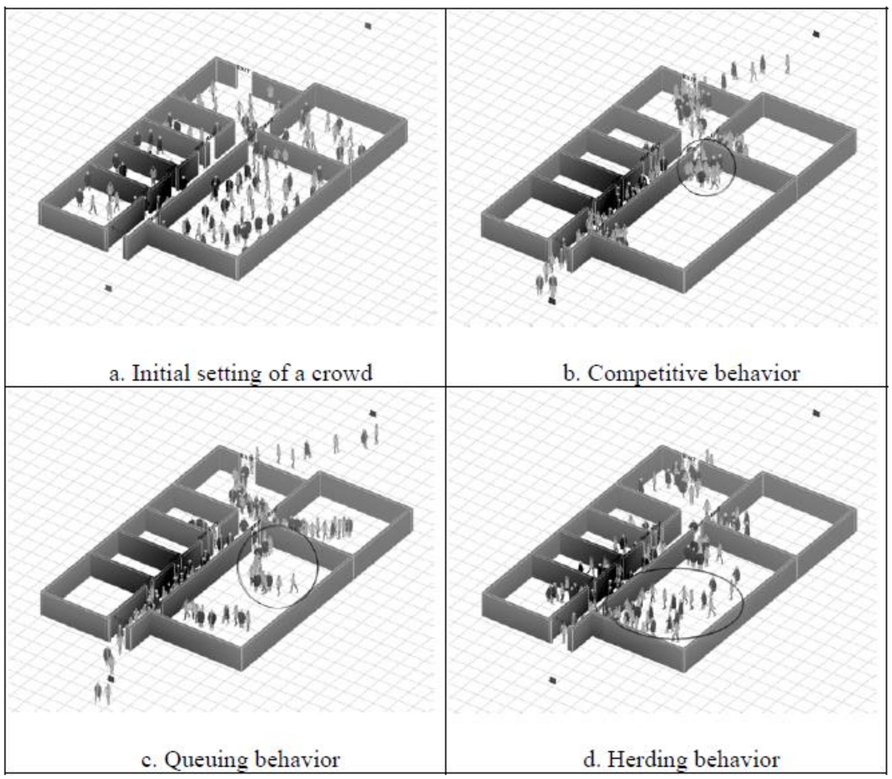


Figure 2-6: Behavioral patterns in MASSEgress (adapted from Pan 2006)

An upgraded version of MASSEgress, SAFEgress (Social Agent For Egress simulation), was developed by Chu et al (2012) at Stanford University. The new agent behavior models are comprised of individual behavioral models, group behavioral models, and crowd behavioral models. Like Figure 2-7 shows, SAFEgress implements three group behaviors including leader-following, group-member-following, and group-member-seeking responses. The prototype version of SAFEgress has produced preliminary results that exhibit certain grouping behaviors and interactions among the evacuees. Similar to MASSEgress, environmental hazards are not accounted for. In addition, the group behavior models need to be refined to account for the type of gathering and social relations such as kinship, friendship, etc.

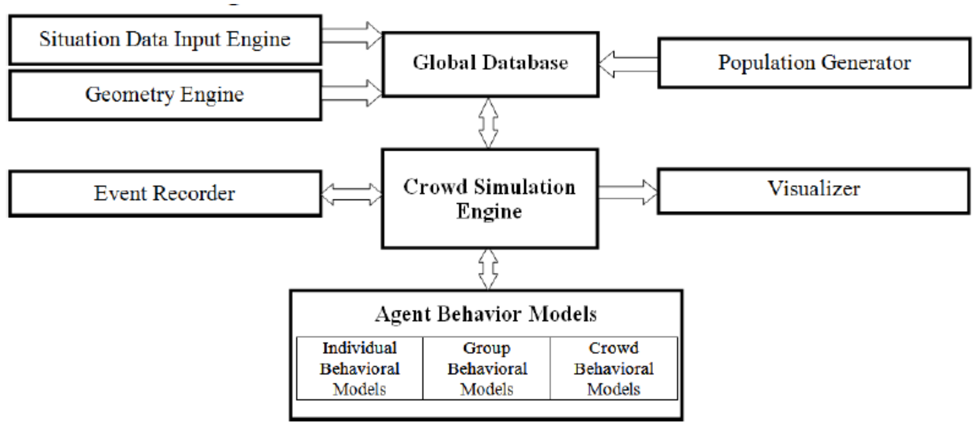


Figure 2-7: Model architecture of SAFEgress (adapted from Chu *et al* 2012)

The Social Force Model (Helbing *et al.* 1995, 2000, 2007) models human movement based on Newtonian mechanics. In it, each person in a crowd is represented by an agent. The agent is subjected to a series of virtual forces termed social forces and locomotion is computed by solving the dynamic equations of motion of the system of particles representing a crowd. The Social Force model has been shown to handle dense crowd situations well. As shown in Figure 2-8, older versions assumed an agent to be a circle and didn't take account rotation of the agent. Newer versions improved an agent's geometry, enabled agents to rotate and accounted for contact forces and moments between agents, e.g. the implementation in CrowdDMX (Langston *et al* 2006) and FDS + Evac (Korhonen *et al* 2007, Heliövaara et al 2012). Smith *et al* (2009) improved the CrowdDMX model's ability to represent counter-flow. FDS + Evac is one of the newest models developed based on the social force assumption. They examined the capabilities of the model in various tests by comparing to empirical results and experiments. In particular, Heliövaara *et al* (2012) modeled counterflow situations by assuming that right-hand road traffic rules govern a pedestrian's tendency to move in counter-flow situations.

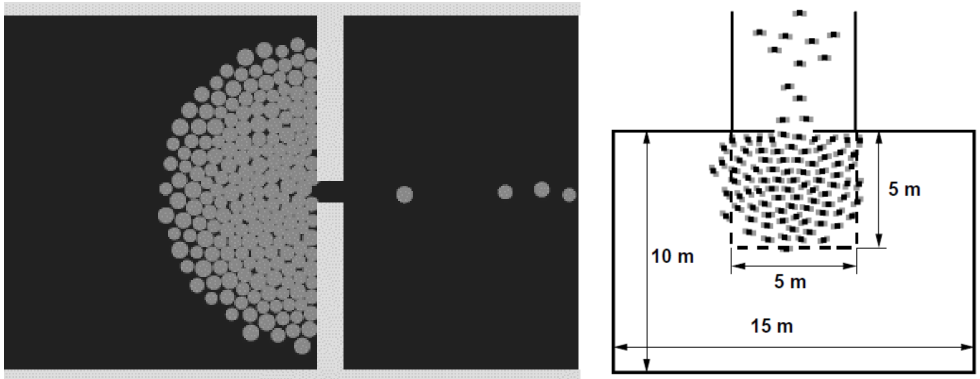


Figure 2-8: Social Force Model (Helbing *et al* 2000) and FDS + Evac (Korhonen *et al* 2007)

Researchers from University of Delaware and University of Michigan (Aguirre *et al* 2011a; Best 2013) conducted an investigation of human egress behavior during the Station nightclub disaster (2003) and developed an Agent-Based model to simulate the Station event. The model incorporated fire and smoke hazards and accounted for their effects on the egress process. Detailed demographic information and complex social group dynamics were incorporated. The model was validated by comparing its results to the observed field data, including the number of people injured and killed during the event. While powerful, the model's locomotion algorithm and social interaction capabilities are limited and significantly improved upon in this dissertation.

2.5 Summary

The state-of-the-art of theoretical and computational studies of human egress are reviewed in this chapter. A critical assumption of three types of intent that influence human egress behavior is presented based on a synthesis of past studies. The literature review reveals that existing Agent-Based models generally do not address meaningful social interaction and adherence to cultural norms, key issues that are addressed in this dissertation.

CHAPTER 3

SCALAR FIELD METHOD: MODEL DEVELOPMENT

3.1 Introduction

This chapter introduces the rational behavior assumption, discusses human egress characteristics, and then proposes a novel technique for modeling egress behavior. The new method, termed Scalar Field Method, draws on an analogy to a charged particle in an electromagnetic field. In the new model, virtual potential energies (VPEs), that can be made to represent both human will and social relationships, simulate the interactions that occur between an agent and its surrounding entities. Each agent has stochastic characteristics, is independent, and makes autonomous decisions regarding behavior by minimizing the VPE. Human physical characteristics and the rationality assumption are first presented in Section 3.2 and 3.3 respectively. Details of the Scalar Field Method is discussed in Section 3.4, followed by a description of how social relationships are incorporated in Section 3.5.

3.2 Human Physical Characteristics

Each agent is represented by a set of three circles (as shown in Figure 3-1), one for “torso” and two for “shoulders” at both sides. The radius of the “torso” is assumed to be an average of 0.15m, and each “shoulder” is 0.075m (0.45m is an average body width reported by Xu et al. (2010)). The centers of the two “shoulders” are located on the edge of the “torso,” and are on the same diameter, which crosses the center of the “torso”. The forward direction is defined by a bar starting from the "torso" center and perpendicular to the diameter connecting the "shoulder" centers. This three circle model was first defined by Fruin (1971), and widely used in many Agent-Based models, e.g. Thompson *et al* (1995), Pan (2006), and Langston (2006).

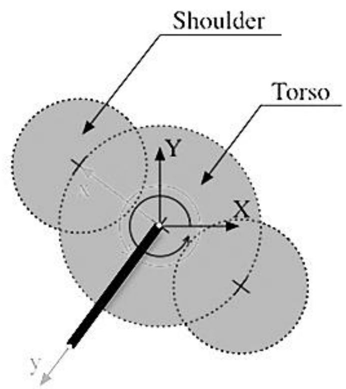


Figure 3-1: An agent's body geometry

An agent's mobility is constrained by its maximum rotational velocity and maximum translational velocities in four directions, i.e. forward, backward, and lateral (left and right). In one time-step, the agent's actual movement can't exceed those limits, but its movement can be accomplished toward any point within an area enclosed by those limits. Since the maximum velocity in the forward-facing direction is significantly higher than that associated with lateral and backward motion, the area reachable in one step is the egg-shaped shaded one in Figure 3-2. The border in each quadrant is assumed to be a quarter ellipse that connects smoothly with the ellipses of the other quadrants. In addition, the agent is allowed to rotate at a rate smaller than the maximum rotational velocity.

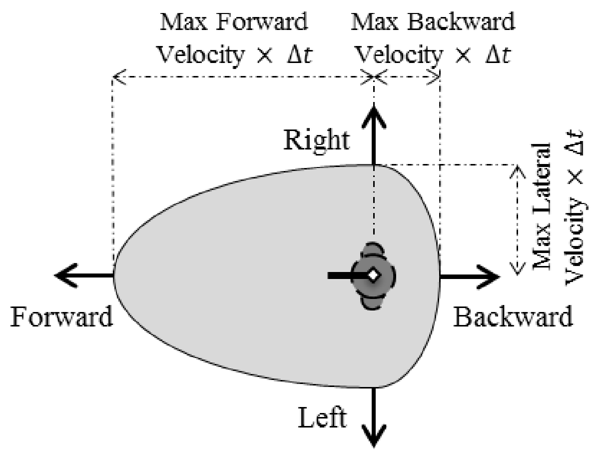


Figure 3-2: Agent's range of motion in one time step

Age is considered to be an important factor in an evacuee's mobility (Pan 2006). Adults are generally faster and more agile than children and seniors. Previous studies (Heliövaara *et al.* 2012; Thompson 2004) grouped the population into several categories with defined velocity ranges. In this study, only two categories are adopted: "adults", which contains both males and females 15 to 65 years old, and "children + seniors", which contains individuals with lower mobility than the first group. According to "CIA World Factbook" (Central Intelligence Agency 2013), the population distribution in the US is 20% children (≤14), 54% adults (15-64), and 26% seniors (≥65). Therefore, both categories are assumed to be equally represented in a group of agents as default in this work, although, for simplicity, all agents are assumed to have the same size.

To reflect the stochastic nature of moving individuals, the maximum speeds of each agent are randomly determined from ranges that dependent on its age category. Adult agents are assumed to have a maximum forward speed that is randomly selected from a range of 0.95 m/s to 1.55 m/s. Agents in the "children + seniors" category have a maximum forward speed in the range between 0.55 m/s to 1.25 m/s. The lateral speed limit is selected as 0.5 m/s and the backward limit 0.2 m/s for the "adults" and as 0.3 m/s and 0.1 m/s for "children + seniors". The maximum rotational capability is randomly determined between 3 rad/s to 4 rad/s for the "adults" and half of that value for "children + seniors". These speeds are based upon on information in previous studies (Tang 2008; Thompson 2004; El-Tawil *et al*. 2009). The initial orientation of each agent is allocated randomly.

To describe an agent's health condition, stamina is quantified as a scalar number termed energy level (terminology adapted from Aguirre et al 2011a and Best 2013). Environmental hazards are harmful and can lower the energy level. In particular, fire is assumed to kill the agent immediately, and the toxic effect of smoke is assumed to reduce an evacuees' stamina (Bryan 2002; Best 2013). The agent's mobility is dependent on its energy level (Pauls 1977; Klote 1992).

3.3 The Rationality Assumption

In contrast to the "panic" or unconscious decision-making assumption adopted by many older emergency evacuation models, this study assumes that an evacuee's physical behavior is driven by a rational "thinking process". Recent studies suggest that rational behavior is commonplace during an emergency evacuation (Aguirre *et al*. 1998, 2005, 2011b; Kuligowski *et al*. 2010; Schadschneider *et al*. 2009) and social and social-psychological factors can significantly influence an evacuee's behavior (Santos *et al.* 2004; Moussaïd *et al.* 2010). Agents are able to perceive and assess mental level factors, including desired goals and social and group relationships, and respond to those factors through locomotion. As discussed in Chapter 2, these desires may comprise the evacuee's need to exit, avoid collision with walls and other agents, move towards related agents, and keep private spacing.

Social and socio-psychological factors must be considered in assessing an evacuee's desire to take action. Social relationships, which describe the interaction between people at the social level, must also be considered. However, since social relationships between evacuees can be complex, until now only the most dominant relationships have been accounted for in existing modeling schemes, constituting a problem that is rapidly being superseded in the scientific literature. The rational behavior assumption made herein is applicable for both normal as well as crisis situations, for the literature shows that competitive behaviors that occur under crowding conditions are usually misunderstood as panic, for they show the absence of wishful intent to do harm. Although many events with a large numbers of deaths under extreme conditions have been reported, the majority of these events show that human responses are normative and pro-social (Aguirre et al. 2011a).

3.4 The Scalar Field Method

The Scalar Field Method (SFM) is proposed to control an agent's motion. The new method can comprehensively consider social level effects and handle a complex network of social relationships among agents. The essence of this method is to evaluate the accumulation of a series of scalar quantities, which can be made to represent human desires and social and group relationships, and then solve an extremum collective behavior problem reflecting a rational decision-making process.

SFM is based on the assumption that interactions exist between each object in the simulation, e.g. agent-to-agent, agent-to-wall, agent-to-exit, etc. These interactions can be quantified as scalar fields of virtual potential energy (VPE). The scalar fields can be easily and conveniently computed as a function of distance to other agents or objects in the environment, in a manner similar to what occurs for a charged particle in an electromagnetic field. In this analogy, agents are attracted to other related agents and exits similar to the attraction felts by particles with opposite charges. In addition, agents are repelled by barriers that impede their motion similar to particles with like charges. Because all the computations involve scalar quantities (hence the name of the method), the VPEs from various sources can be directly added together to form a comprehensive field around the agent that signifies the additive or subtractive effects of issues of importance to the agent. The analogy to electromagnetic fields implies that the desire to take action will be guided by the intent of minimizing the VPE. The premise of the model is that the lower the value of VPE, the greater will be the intent to take action, and vice versa. This makes it possible to model different social groups, which may be assumed to differ by the level of commitment of their members to each other, such as kinship groups versus groups of casual observers.

The proposed idea of VPE fields has some parallels to the Social Force Model proposed in (Helbing et al. 1995, 2007) but has several major advantages and benefits, including: 1) the scalar nature of the model makes handling it easier than the vector-based social force model; 2) social effects and physical forces are independent, unlike the social force model in which the two are mixed; and 3) it can accommodate rotational behavior by individual agents, which is ignored in many force-based models. The model also has some similarity to models that employ distance maps (Thompson 1995), but unlike such models is able to account for many more considerations in the decision making process.

3.4.1 Modeling Human Desire to Take Action

Several types of social behaviors can be included in the SFM, such as the desire to exit a building, preserve private space, not collide with walls and with other agents, and protective behaviors elicited in an attempt to benefit kin, intimate partners, and work associates, among others. Equations 3-1 through 3-8 are proposed for converting these sequences of behaviors into virtual potential energies as follows.

The first (desire to exit a building) can be generally represented by making the VPE associated with it directly proportional to the distance between the agent and an exit as represented by Equation 3-1. Other things equal, the shorter the distance to an accessible exit, the smaller the VPE, and hence, the greater the propensity to move in that direction. The need to avoid collision with other agents and preserve private spacing, and the desire to prevent collision with walls, can be generally represented by making the VPE for both situations reciprocal to the distance between an agent and an adjacent agent or obstacle (i.e. Eq. 3-2 and 3-3). Another way to express it is that the repulsion between an agent and other agents, the preservation of social space of each agent, as well as adjacent physical objects grows as the distance between them decreases. These issues are represented mathematically as follow:

$$E_{1s} = c_1 d_1 \tag{3-1}$$

$$E_{2s} = c_2 \frac{1}{d_2} \tag{3-2}$$

$$E_{3s} = c_3 \frac{1}{d_3} \tag{3-3}$$

where E_{1s}, E_{2s} and E_{3s} are the virtual potential energies of the three human desires or behaviors, agent to exit, agent to other agent, and agent to wall, respectively; c_1, c_2 and c_3 are constants; d_1, d_2 and d_3 are the distances between agent and exit, other agent and wall, respectively.

Equations 3-1 through 3-3 are conceptual equations and not general enough to permit practical implementation, so they are modified as shown in Equations 3-4 through 3-6. Graphical illustrations for these latter equations are presented in Figures 3-3 through 3-6.

$$E_1 = c_1(d_1 + D_{1a} - D_{1e}\cos(\Delta\theta_1)) \tag{3-4}$$

$$E_2 = \begin{cases} c_2\left(\frac{1}{(d_2 - R_A - R_{T,other})} - \frac{1}{D_{20}} + E_{2,counter}\right), & d_2 - 2R_A < D_{20} \\ 0, & d_2 - 2R_A \geq D_{20} \end{cases} \tag{3-5}$$

$$E_3 = \begin{cases} c_3\left(\frac{1}{(d_3 - R_T - R_S)} - \frac{1}{D_{30}}\right), & d_3 - R_T - R_S < D_{30} \\ 0, & d_3 - R_T - R_S \geq D_{30} \end{cases} \tag{3-6}$$

where E_1, E_2 and E_3 are the virtual potential energies of the three behaviors respectively; $\Delta\theta_1$ in Equation 3-4 is the absolute value of the angle difference between the forward facing orientation of an agent and the direction pointing to the target object (see Figure 3-3); D_{1a} is a positive constant added to ensure that Equation 3-4 remains positive. D_{1e} is a coefficient associated with the orientation of an agent. D_{20} and D_{30} indicate influence distances in Equations 3-5 and 3-6, respectively. Agents and other entities within the influence zone (as shown, for example, in Figure 3-5) can interact together in a VPE sense, otherwise they are unable to influence one another. R_A is the radius of an agent in the direction of interest. To simplify calculation of R_A, an agent is assumed to be enclosed by an ellipse with principal radii R_T and $R_T + R_S$, where R_T and R_S are the sizes of the torso and shoulder respectively. $R_{T,other}$ is the size of the torso of the other agent in Equation 3-5, numerically equal to R_T.

$E_{2,counter}$ is a term that accounts for an agents' dodging behavior in a counter-flow situation, where agents attempt to prevent face-to-face situations as they are approaching other oncoming agents. The details of this term are shown in Equation 3-5.a.

$$E_{2,counter} = \gamma_{2,c}\left(\frac{1}{d_2 - D_{2e}\left(\cos\left(\Delta\theta_{2,self}\right) + \cos\left(\Delta\theta_{2,other}\right)\right)} - \frac{1}{D_{20,c}}\right) \tag{3-5.a}$$

$$\gamma_{2,c} = \gamma_2\left(\cos\left(\Delta\theta_{2,self}\right) + \cos\left(\Delta\theta_{2,other}\right) + 3 * \cos\left(\Delta\theta_{2,self}\right)\cos\left(\Delta\theta_{2,other}\right)\right) \tag{3-5.b}$$

$E_{2,counter}$ is a piecewise function that equals non-zero only when the agent can see other oncoming agents. In mathematical terms, $E_{2,counter}$ has a finite value when $\Delta\theta_{2,self} < \frac{\pi}{2}$ and $d_2 - D_{2e}\left(\cos\left(\Delta\theta_{2,self}\right) + \cos\left(\Delta\theta_{2,other}\right)\right) < D_{20,c}$, otherwise it equals zero. $\gamma_{2,c}$ is a strength variable associated with $E_{2,counter}$, that becomes lower as agents are less aligned and higher otherwise. $\gamma_{2,c}$ is defined in Equation 3-5.b. $\Delta\theta_{2,self}$ is the absolute angle difference between the forward-facing orientation of an agent and the direction pointing to an adjacent 'other' agent, and $\Delta\theta_{2,other}$ is the corresponding angle difference, as seen by the other agent in Figure 3-6. D_{2e} is a coefficient associated with orientation angles. It increases the VPE when an agent faces another adjacent agent, encouraging the former agent to face away. $D_{20,c}$ is the influence distance of $E_{2,counter}$. γ_2 in Equation 3-5.b is the upper limit of the strength variable.

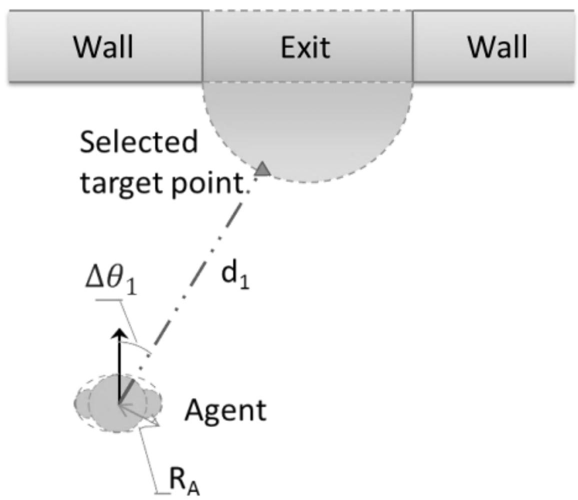


Figure 3-3: Interaction between an agent and exit

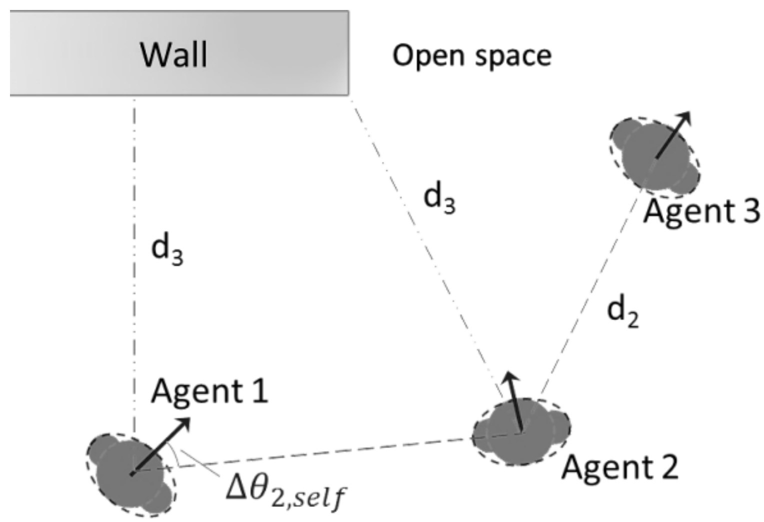


Figure 3-4: Interactions between an agent and wall, and between agents

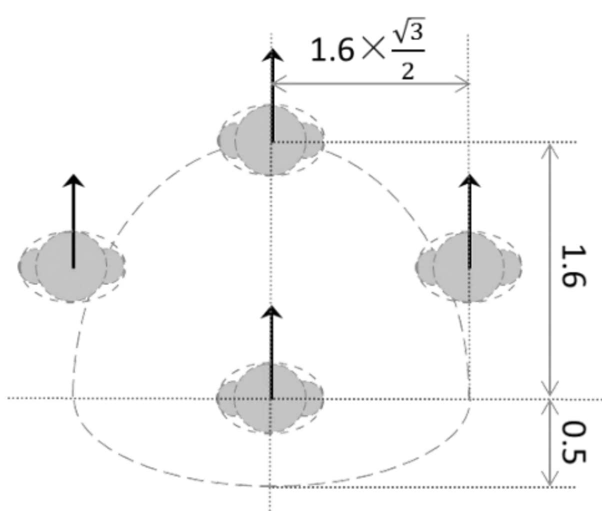


Figure 3-5: Influence distances for inter-agent interaction

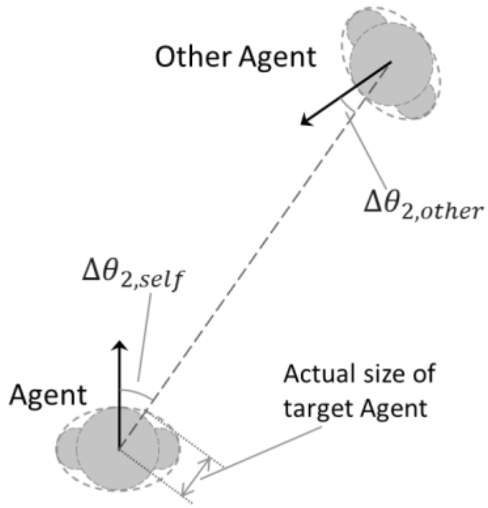


Figure 3-6: Angle differences for inter-agent interaction

3.4.2 Visualization of VPE Fields

To better visualize the spatial nature of the VPE field, consider Figure 3-7 and 3-8, which shows the VPE field for three agents located near a wall and an exit. As shown in Figure 3-7, the agent in the middle is the target agent, for which VPE computations are being made in this example. It is clear from the Figure 3-8 that the VPE field decreases away from the wall and towards the exit. Also, there are spikes at the locations of the other two agents. Knowing this information, the target agent can now unambiguously select a step to minimize the VPE. Doing so from the perspective of the target agent means that the agent will move towards the exit, avoiding the wall while being aware of the two other agents who may serve as obstacles to the agent's movement. It should be noted that Figure 3-8 shows the VPE field perceived by the target agent only. The other two perceive their own VPE fields and simultaneously minimize their VPEs to compute their motions. The models for locomotion and rotation are discussed in next chapter.

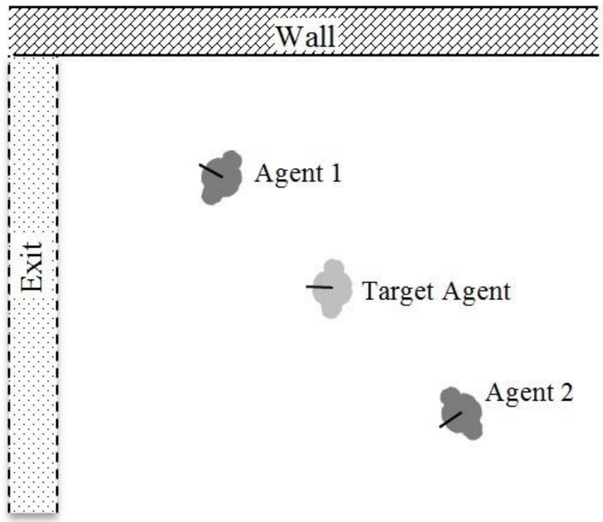


Figure 3-7: Example of VPE visualization: spatial arrangement of entities

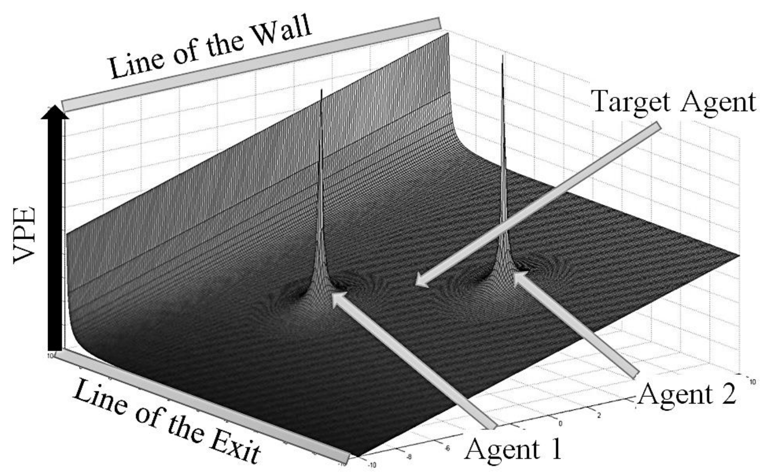


Figure 3-8: VPE field perceived by target agent

3.5 Egress Behavior Incorporating Social Relationships

Along the same lines described above, the general idea for modeling social relationships is that agents who are related (through kinship, dating partners and etc.) are attracted to one another more strongly than agents' weaker social relationships with friends. The attraction is assumed to be linear for family members and elliptic for friends and co-workers, as outlined in Equations 3-7 and 3-8, respectively, to reflect the relative strengths of these relationships. For blood relatives, the interaction is assumed to be effective over long distances, and its VPE is proportional to the distance beyond a conferral zone, within which the family can talk and achieve a collective decision. Equation 3-7.a shows a conceptual equation (similar to Equations 3-1 through 3-3), which is modified to be Equation 3-7.b for implementation. The interaction between friends is assumed valid for a limited distance beyond which it is considered ineffective. The value of the VPE for friends is negative, lowering the total energy when they move together.

As shown in Figure 3-9, the distance between kin-related agents is computed assuming a straight-line distance in the same room. When in different rooms, the distance is taken as the indirect distance needed to travel to one another, as shown in Figure 3-10. When kin-related agents are close enough to one another, i.e. in the conferral zone, within a radius of D_{4b}, shown in Equation 3-7.b, they are considered to have achieved contact and are able to decide on a collective course of action. In this case, they stop travelling towards one another and seek to exit as a group. The same ideas apply to the friend-relationship. Both sets of VPEs are expressed as:

$$E_{4s} = c_4 d_4 \tag{3-7.a}$$

$$E_4 = \begin{cases} c_4(d_4 - d_4'), & D_{4b} < d_4 \\ c_4 D_{4b}, & D_{4b} \geq d_4 \end{cases} \tag{3-7.b}$$

$$d_4' = \begin{cases} D_{4e}\frac{\Delta\theta_4}{\pi/2}, & \Delta\theta_4 < \pi/2 \\ 0, & \Delta\theta_4 \geq \pi/2 \end{cases} \tag{3-7.c}$$

$$E_5 = \begin{cases} c_5\sqrt{{D_{50}}^2 - {d_5}^2}, & D_{50} \geq d_5 \\ 0, & D_{50} < d_5 \end{cases} \tag{3-8}$$

where E_4 and E_5 are the virtual potential energies of the two social relationships considered: kin-relationship and friend-relationship, respectively; c_4 and c_5 are calibration constants for the two social relationships, respectively. The former constant is positive but the latter is negative to ensure that the VPE becomes lower as the agents get closer. d_4 and d_5 are distances between kin-related agents and between friend-agents, respectively; $\Delta\theta_4$ in Equation 3-7.c has a similar definition as $\Delta\theta_1$ in Equation 3-4; D_{4b} is the distance within which agents can communicate and decide on their collective action as discussed above; d_4' is a term employed to ensure that an agent achieves the correct orientation, towards its target; D_{4e} is a coefficient associated with the orientation angles. D_{50} is the influence distance of E_5.

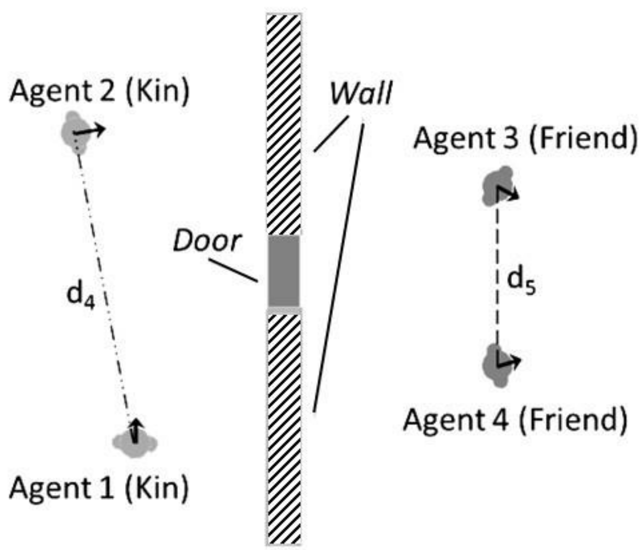


Figure 3-9: Modeling social relationships: when agents are in the same room

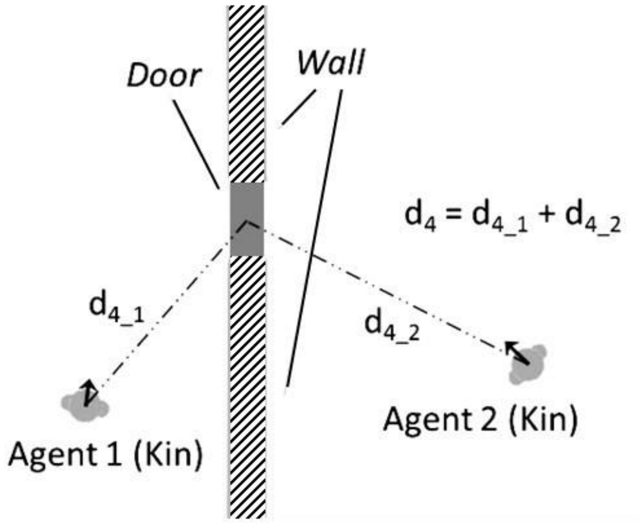


Figure 3-10: Modeling social relationship: when agents are in different rooms

To compute the distance between an agent and another object, a point on the agent and another on the object are needed. For agents, locations of the agents' center points are selected for computation. For surrounding entities, e.g. walls, the other point is selected as the point closest to the agent on the other object. Figure 3-4 shows how the distance is computed for an agent near a wall. To alleviate numerical and logical difficulties associated with an agent exiting through a doorway, the end point is selected as the closest point on an imaginary semi-circle located at the door, with a diameter equal to the door width (see Figure 3-3). After the agent enters the door area (within the imaginary semi-circle) and before it successfully exits through, the end point for calculating d_1 is specified 'far' (e.g. 10 m) behind the door to enable correct exit through the doorway region.

3.6 Summary

Based on the rationality assumption, the newly developed technique, Scalar Field Method, is presented herein to comprehensively model both human will and social level effects and to address a complex network of pre-existing social relationships among agents. The technique is based on an analogy to a charged particle in an electric field. Each agent (charged particle) considers the effects of the environment and other social influences (electric field) by algebraically adding the virtual potential energies of competing issues and selecting a decision that minimizes the total virtual energy. A discussion of physical characteristics during human egress is also presented.

CHAPTER 4

SCALAR FIELD METHOD: MODEL IMPLEMENTATION AND PRELIMINARY VALIDATION

4.1 Introduction

This chapter describes a newly developed Agent-Based egress platform implementing the Scalar Field Method, and shows several preliminary results. The platform, named EgressSFM, is comprised of a building and environment model, autonomous agent model, and other auxiliary modules such as display, output/reader, etc. The building and environment model outlines the geometric constraints and incorporates hazards like fire and smoke. The agent model contains nine modules with various functions, and can explicitly simulate the "thinking" and behavioral process of an occupant. The preliminary results show the ability of the new model to simulate reasonable egress behavior, and its potential for exploring the influence of social relationships during egress.

EgressSFM's architecture is first described in Section 4.2. Then the building and environment model, agent model, and the auxiliary modules are discussed in Section 4.3 through Section 4.5. In section 4.6, constants and randomness of the model are then summarized. Several preliminary results are presented in Section 4.7.

4.2 Model Architecture

The EgressSFM is comprised of the building and environment model, agent model, and auxiliary modules, which are organized as shown in Figure 4-1. The Building and Environment Model outlines building rooms with various functions, geometries, spaces, and environmental hazards. The Agent Model represents stochastic and autonomous escaping occupants. Other Auxiliary Modules enables functions of display, input/output control, and geometries. More details are discussed in Sections 4.3 through 4.5.

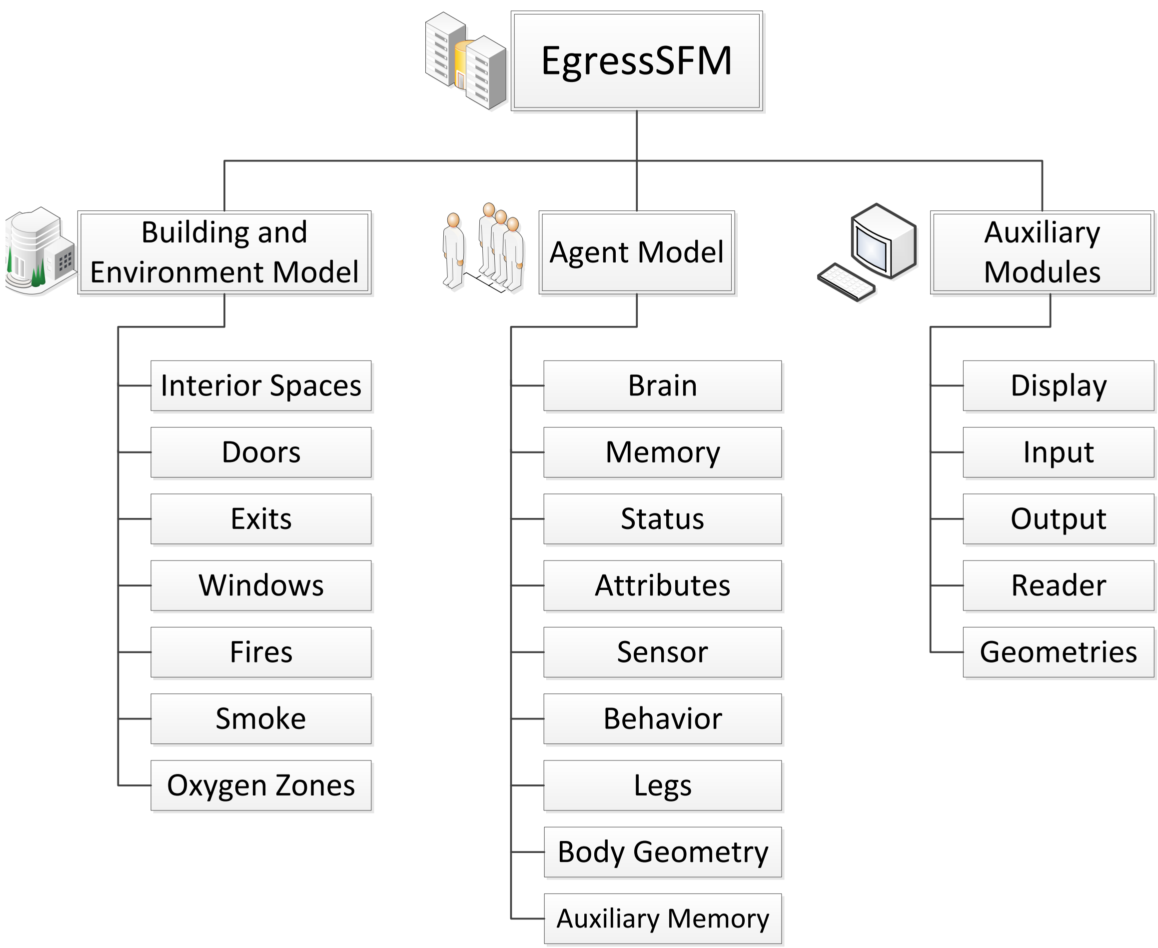


Figure 4-1: Model Architecture

4.3 Building and Environment Model

The building and environment model consists of the agents and the space they are in. The space is comprised of a collection of components which include four specific types: exits, doors, windows, and interior spaces (see example in Figure 4-2). Each component is characterized by information such as its location, geometry, and other connected components. One important feature of the building model is the presence of geometric constraints imposed by walls and other obstacles. Agents will avoid these obstacles according to Equation 3-6. Each building component is logically connected to neighboring components, e.g. in Figure 4-2 the connector between the kitchen and living room connects the interior spaces of these two components. When an agent stands inside one component, it has the ability to navigate to the adjacent area when computing its escape route, as shown in Figure 4-3. Therefore, an evacuation route can be formed as a chain of connected building components.

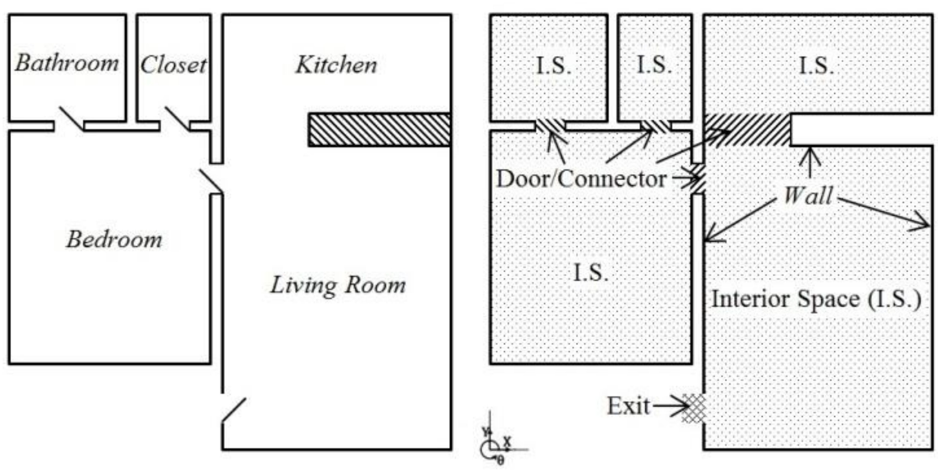


Figure 4-2: Building floor plan (left), components and walls (right)

Exits are special building components that serve as destinations for egress. Agents reaching exits are considered to have reached their destination and to have safely exited. Windows are another set of building components that are normally impassable. They can switch functions and enable egress after a specified time, reflecting the possibility of breaking them during an emergency. Around 100 people escaped through broken windows during the Station nightclub fire (Aguirre et al 2011a).

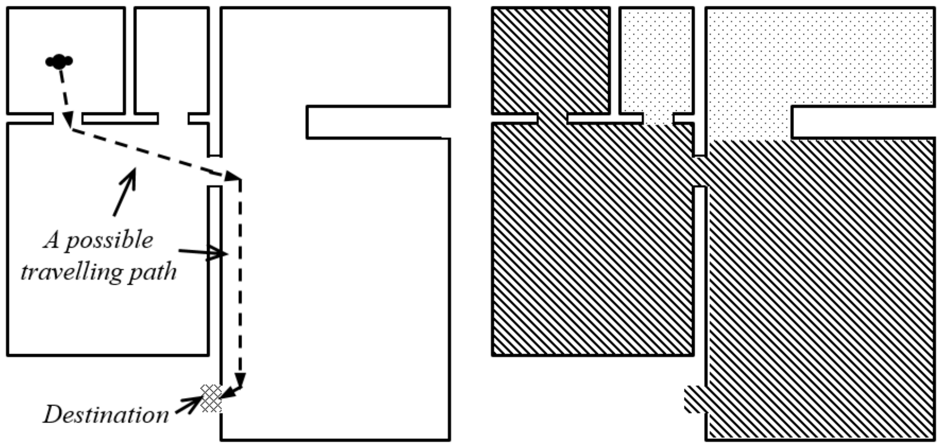


Figure 4-3: A possible egress route (left) through a chain of components (right)

The environment model takes into account fire and smoke hazards. Fire is assumed to start in a series of rectangle areas with stochastic sizes and start times. By switching on fire in adjacent areas, it is feasible to model the spread of fire (an example is shown as shaded areas in Figure 4-4.a through c and discussed in more detail in Chapter 6). An agent that is still present in an activated fire zone is considered to have been killed by the fire. As discussed in Chapter 6, the geometric information and start times of fire are currently hardwired in EgressSFM based on published fire analysis results for specific events. In the future, it can be incorporated in the overall platform through a fire dynamics module.

Smoke has a toxic effect on agents and reduces their energy level as discussed earlier. Unlike fire, which is localized, smoke is assumed to be widely spread over the entire building as soon as a fire starts. As done in Aguirre et al (Aguirre et al 2011a; Best 2013), the impairment due to smoke occurs gradually. It need to be mentioned that the toxic effect is assumed to be not present in some areas, termed oxygen zones (adapted from Best 2013). Such areas, e.g. dark area in Figure 4-4.d, are near windows and exits and have fresh air ventilation that prevents the toxic effect of smoke on agents. Agents in such areas suffer no additional reduction in energy level and continue at their current level, which would otherwise have been reduced due to smoke exposure.

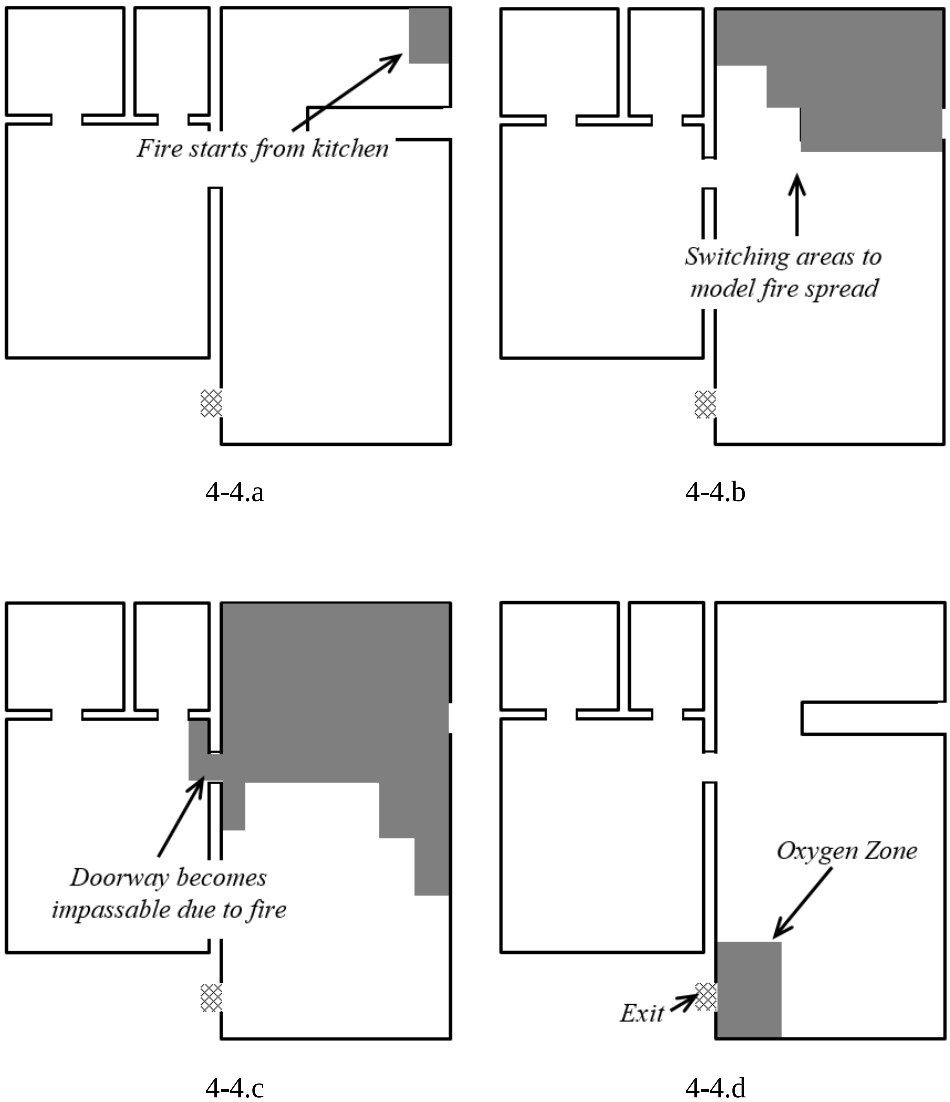


Figure 4-4: Simulation of fire (a-c) and oxygen zone (d)

4.4 Agent Model

Each agent model is comprised of nine modules: 1) brain, which calculates the VPE field and determines the most appropriate way to move within this field; 2) memory, which stores the agent's knowledge, including the building map, social relationships, movement history, etc.; 3) status, which represents the agent's state, such as healthy or injured; 4) attributes, which contains information about an agent's characteristics such as maximum velocity for forward, lateral, and backward motion, maximum rotating velocity, etc.; 5) sensor, which enables the agent to observe the environment and communicate; 6) behavior, which describes the agent's behavior pattern and decision-making process; 7) legs, which execute the locomotion decisions made by the brain; 8) body geometry, which sets up and draws the components of the agent's body for the purposes of animation, and 9) auxiliary memory that stores specific variables, including location and orientation information of the current and next time-steps, global numbering identity, etc.

Each agent is independent and autonomous, and its behavior can be summarized by 5 steps in every time-increment as shown in the procedure in Figure 4-5. The process is applied in random order to each agent to avoid providing preferential treatment to any particular agent.

1) Observe the environment and update "memory". Agents are allowed to communicate with each other when necessary, e.g. to exchange map information.

2) Compute the reachable area and associated "sampling points" based on the current location and orientation.

3) Search for an evacuation route through all building components, i.e. interior spaces, doors and exits.

4) Compute VPEs at the sampling points and reach an appropriate decision to move. To avoid overlapping, agents must take into account the projected action of adjacent agents and group members as discussed later on.

5) Wait until all agents reach their decisions, then execute all movements simultaneously.

The default condition is that each agent is assumed to be completely knowledgeable about the floor plan. The knowledge could also be specified as incomplete, e.g. an agent can be aware of only one exit when multiple exits are present. Using the available knowledge, each agent searches for all evacuation routes at every time-step, based on its current location and orientation. The search method is based on traversal algorithms, which explores all possible evacuation routes by implementing the connection information of the building and environment model. The preferred route, barring knowledge or social considerations, is the one that minimizes the estimated travel distance.

'Thinking' Process

```
Create the virtual environment;
Generate and initialize all agents;
WHILE not all agents have exited,
    FOR each active agent,
        Update perception of surroundings;
        Refresh T & R sampling points (see Fig. 4-6 & 4-7);
        Compute an evacuation route;
        Estimate others' moves through the 'one-step' procedure;
        Calculate the VPE for R points;
        IF The R point with lowest VPE is associated with the current
            orientation
                Caculate the VPE for T points.
                Select the one associated with lowest VPE for next
                    translation;
        ELSE
                Select the orientation associateed with R point of lowest
                    VPE for next rotation;
        ENDIF
    END FOR
    FOR each active agent,
        Execute move;
    END FOR
    Refresh visual output;
    Record paths;
    Increment simulation time and check whether all agents have evacuated;
END WHILE
```

Figure 4-5: Algorithm controlling an agent's response

An agent's locomotion is decomposed into translation and rotation. Before a movement is executed, an agent needs to first consider whether to rotate or not. To do so, the agent calculates the VPE field at 8 rotational sampling points (R points) as shown in Figure 4-6 (star markers), and rotates to face the direction with the lowest value. These R points are equidistant and located on a circle, centered with the center of the agent and radius 0.2m. Since rotational behavior is limited by the maximum angular velocity, the desired orientation may not be achieved in one time-step. The number of sampling points is selected based on sensitivity studies to be as low as possible to reduce computational demands yet, at the same time, reasonably cover the field around an agent.

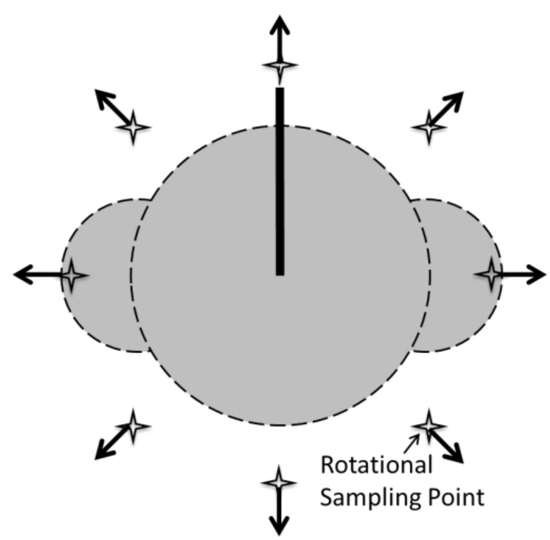


Figure 4-6: Rotational sampling points (R points)

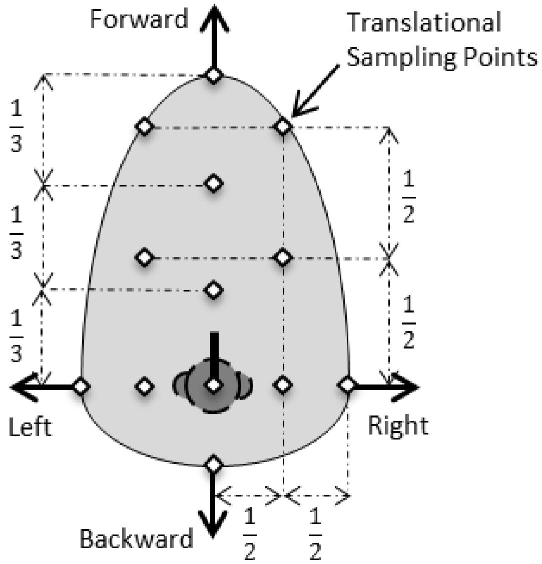


Figure 4-7: Translation sampling points (T points)

As outlined in Figure 4-5, an agent is ready to translate once an orientation decision is made, and can move within the finite egg-shaped area shown in Figure 4-7. VPE values are computed at 13 translational sampling points (T points, diamond-shaped points shown in Figure 4-7) and the agent then moves to the location with the lowest value. Lateral and backward movement can be accomplished in this step. The sampling points, both R points and T points, are updated and refreshed at each time-step based on the current location and orientation.

Before making a final locomotion decision, each agent must also consider the possible movements of others. A full analysis that accounts for every possible outcome for all interacting agents is computationally prohibitive. For example, the number of possible movement combinations for two neighboring agents is 13 x 13 = 169. The outcome of all these computations may also be incorrect if agents possess incomplete information or are not cooperating with each other. To overcome these difficulties, the agent model adopts a one-time approach to estimate the possible movements of other agents through the following algorithm.

Consider 3 agents A, B and C. 1) Agent A estimates B's and C's best solutions based on the Scalar Field Method. This is done by assuming insufficient information and non-cooperation. Specifically, agent A does not consider the possibility of rotational or social effects (since they do not know them) playing a role in the predicted actions of B or C. 2) When A is calculating its "actual" behavior, B and C's actual locations are replaced by their "estimated locations". 3) The same process is repeated for B and C. Because this one-time approach is computed based on the current locations of agents before movements are executed, the order of computing the estimations of other agents' behavior does not affect the result of the approach.

The implication of the steps described above is that an agent's decision, which describes the preferred location and orientation at the next time-step, will not be executed immediately after the calculation of the VPE field. Rather, it is executed after all other agents make their decisions as shown in the algorithm in Figure 4-5. If the agent's decision is to rotate, the agent will turn around in order to face the preferred orientation, but the changed angle will be less than or equal to the product of the maximum angular velocity and the time-step. If the decision is to translate, the agent will move to the preferred location while keeping the current orientation.

The proposed locomotion logic has several characteristics: 1) Agents are able to turn around when needed. 2) By rotating first, an agent opens up a larger potential movement space, i.e. the front of the rotated egg shaped space around it. 3) An agent can make minor adjustments laterally or forward/backward without changing its orientation, i.e. the agent is able to adjust its position when waiting at the edge of the gathering by moving laterally. 4) The decision-making process is separated from the physical execution of the motion. 5) Floor friction is assumed to be sufficient to permit the agent to suddenly turn around, start, stop or change its velocity. 6) Agents travel along reasonable paths of motion.

A perturbation process is used to prevent stalemate at a narrow door or passageway, where two agents can get stuck because they seek the same spot. This situation, which is a modeling anomaly, does not represent agents immobilized due to extreme crowding, a situation beyond the scope of this work. To resolve this issue, the process requires any active agent to check its movement history within the last 3 time-steps. If the agent appears stalled, determined from the fact that its position remains unchanged during this history, it moves a small distance in a random direction in an attempt to break the stalemate. Numerous exercises showed that this scheme is effective in resolving stalemate situations.

4.5 Auxiliary Modules

The display module enables real-time visualization of the evolution of parameters of the environment and agents, e.g. open or closed exit, initiation of fire, movement of agents, etc. As shown in Figure 4-8, when EgressSFM is running, the display module uses different colors to highlight various objects: interior spaces, doors, exits, and windows are white, yellow, green, and dark green respectively. Agents are also colored spectrally in several switchable ways to visualize their energy levels and social relationships, e.g. agents change colors from green to yellow to red gradually based on the remaining energy level compared to the initial level. Alternatively, agents in one group are given the same color to enable tracking of group effects.

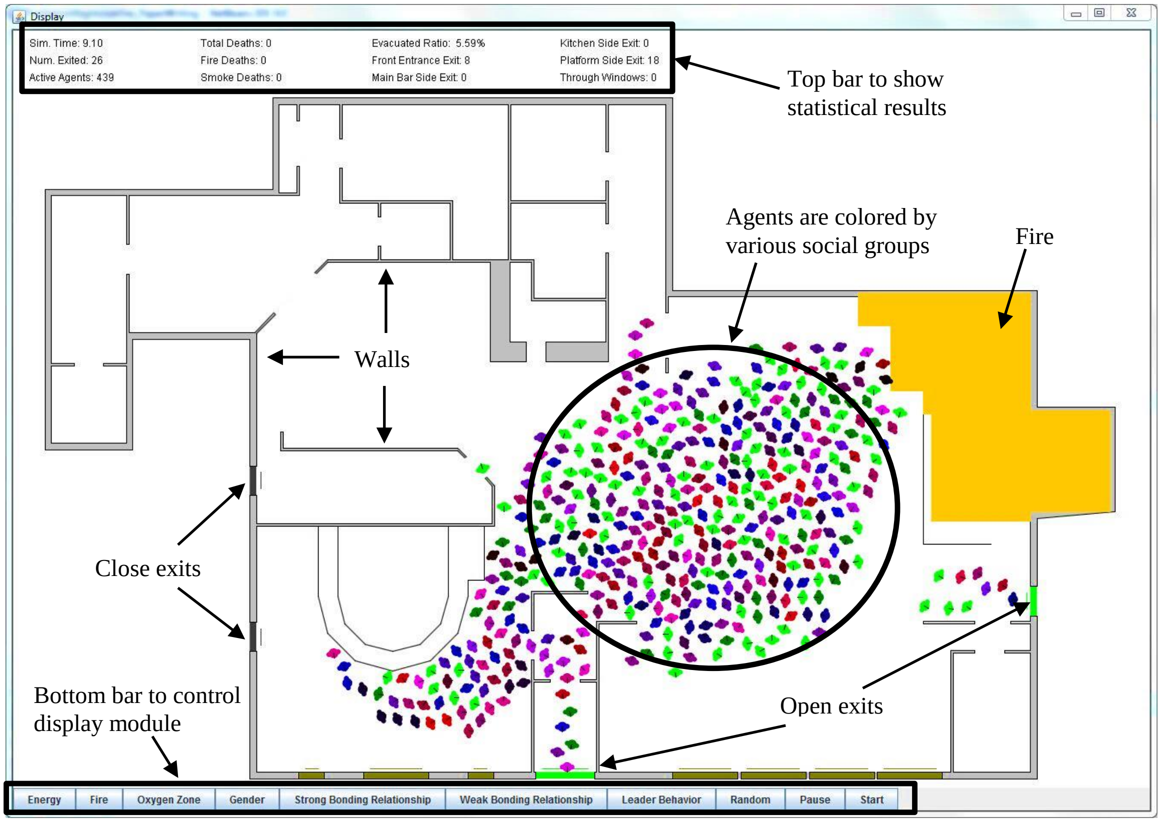


Figure 4-8: Display interface

EgressSFM's input and output control is achieved through input, output, and reader modules. The input module initializes the building, environment and agents. Besides providing real-time display capabilities, EgressSFM records all agents' profiles, including demographic information and behavioral histories in txt format through the output module. The reader module enables the model to read the txt format of past exercises and displays it. Therefore, as shown in Figure 4-9, EgressSFM has two ways of running: simulation mode, which runs new simulation based on given input, and playback mode, which reads and displays past simulations.

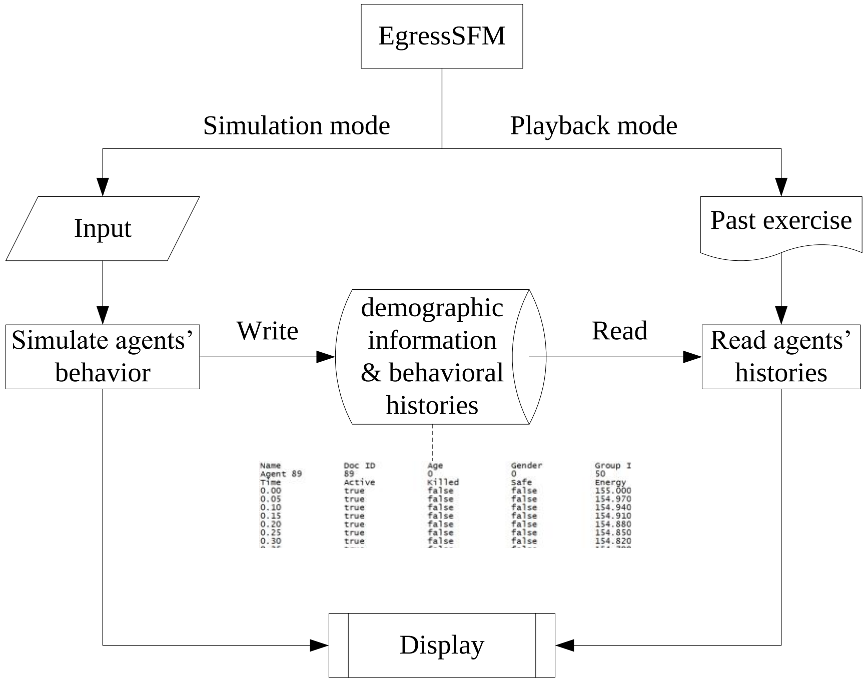


Figure 4-9: Simulation mode and playback mode of EgressSFM

There are several geometry-related modules, specifically point, location, orientation, and line modules. Each of them comprises related geometric information related to the entity they represent and contain several specified functions for geometry-related computations, e.g. computing the shortest distance from one point to a line segment.

4.6 Calibration Constants and Randomness

Selecting reasonable values for the 15 constants in Equations 3-1 through 3-8 is necessary for computing meaningful and robust VPE fields. The magnitudes of coefficients c_1 to c_5 fall into several categories as follows: 1) relatively weak interactions, e.g. c_2 in Equation 3-5 and c_5 and Equation 3-8, are assigned to be 5 and -5 respectively, and c_3 in Equation 3-6 is 1; 2) strong interaction, e.g. c_1 in Equation 3-4, is taken as 200; 3) primary interaction, e.g. c_4 in Equation 3-7, is 2000. Clearly, these are arbitrary values that were selected to ensure reasonable looking motion and interactions between the agents in a multitude of simulations as described later on. These values can be refined as future research clarifies and quantifies the issues addressed in this work.

As shown in Table 4-1, four parameters are associated with influence distances in Equation 3-5, 3-5a, 3-6 and 3-8: D_{20}, $D_{20,c}$, D_{30} and D_{50}. As shown in Figure 3-5, influence distance, D_{20} in Equation 3-5, is anisotropic, i.e. 1.6m for forward and 1.386m for lateral movements, based on Thompson's study (Thompson 2004). It is taken as 0.5m for backward movement. $D_{20,c}$ is assumed to be 2.5m, which is close to the dodging distance of 3.0m proposed by Heliövaara *et al*. (2012). D_{30} is assumed to be half of the lateral distance of D_{20}, i.e. 0.693m. D_{50} is an arbitrary large number chosen to be 10m.

The three constants associated with orientation angles, D_{1e}, D_{2e} and D_{4e} in Equations 3-4, 3-5a and 3-7c are taken as 0.5m, 0.25m and 1.0m respectively. γ_2, which is the upper limit of the strength parameter in Equation 3-5.b, is taken as 1.2. D_{1a}, the positive constant for reducing numerical difficulty in Equation 3-4, is an arbitrary large number, selected as 10m. The conferral distance, D_{4b} in Equation 3-7.b is taken as 1.0m.

Table 4-1: Constants of Equations 3-1 through 3-8

Constant	Description	Value
$\boldsymbol{c_1}$	Magnitude coefficient of Eq. 3-4, between agent and exit	200
$\boldsymbol{c_2}$	Magnitude coefficient of Eq. 3-5, private spacing between agents	5
$\boldsymbol{c_3}$	Magnitude coefficient of Eq. 3-6, wall spacing to an agent	1
$\boldsymbol{c_4}$	Magnitude coefficient of Eq. 3-7, between kin related agents	2000
$\boldsymbol{c_5}$	Magnitude coefficient of Eq. 3-8, between friends	-5
$\boldsymbol{D_{20}}$	Influence distance in Eq. 3-5, private spacing between agents	Anisotropic[3]
$\boldsymbol{D_{20,c}}$	Influence distance in Eq. 3-5a, dodging distance	2.5 m
$\boldsymbol{D_{30}}$	Influence distance in Eq. 3-6, wall spacing to an agent	0.693 m
$\boldsymbol{D_{50}}$	Influence distance in Eq. 3-8, between friends	10 m
$\boldsymbol{D_{1e}}$	Constant associated with orientation angle in Eq. 3-4	0.5 m
$\boldsymbol{D_{2e}}$	Constant associated with orientation angle in Eq. 3-5a	0.25 m
$\boldsymbol{D_{4e}}$	Constant associated with orientation angle in Eq. 3-7c	1.0 m
$\boldsymbol{\gamma_2}$	Upper limit of the strength parameter in Eq. 3-5.b	1.2
$\boldsymbol{D_{1a}}$	Positive constant for reducing numerical difficulty in Eq. 3-4	10 m
$\boldsymbol{D_{4b}}$	Conferral distance in Eq. 3-7.b	1.0 m

[3] See text for details

4.7 Preliminary Tests

Several proof-of-concept simulations are conducted with different environments and agent configurations to showcase the realism of the model and its potential to be used for exploring the influence of social relationships during egress.

4.7.1 Doorway Test

A doorway test is used to study the restrictive effect of door width on the specific flow rate (SFR). The SFR is the number of persons passing through each meter width of doorway per second. Randomly oriented agents are distributed in a square-shaped configuration (5m x 5m) centrally aligned with the target door as shown in the insert in Figure 4-10. They are then allowed to exit, passing through the door with the intention of reaching a 'destination' zone. The SFR is calculated at mid length of the passageway, and is computed for door widths ranging from 0.7m to 3m according to given equations as follows (Thompson *et al.* 1995):

$$Q = \begin{cases} \frac{80}{w(T_{90}-T_{10})} \ , \ w \geq 1.1m \\ \frac{65}{w(T_{70}-T_{5})} \ , \ w < 1.1m \end{cases} \tag{4-1}$$

where Q is the specific flow rate, w is the passageway width. T_5, T_{10}, T_{65}, and T_{70} represent the times that first 5, 10, 70 and 90 agents take to pass through the doorway respectively.

Because each simulation is stochastic, ten simulations are conducted for each door width. The results of the average SFR are plotted in Figure 4-10. The insert in Figure 4-10 shows that the well-known radial pattern forms, while the response curves show that the overall relationship between SFR and doorwidth is roughly bilinear. SFR is significantly restricted when the door width is less than 1.2m as earlier noted by Thompson (2004); similar bilinear relations were also observed in multiple references (Pan 2006; Heliövaara *et al*. 2012; Thompson 2004). Results from previous studies of MASSEgress and Simulex (extracted from Pan (2006)) are also included in Figure 4-10, and are close to the results from this study.

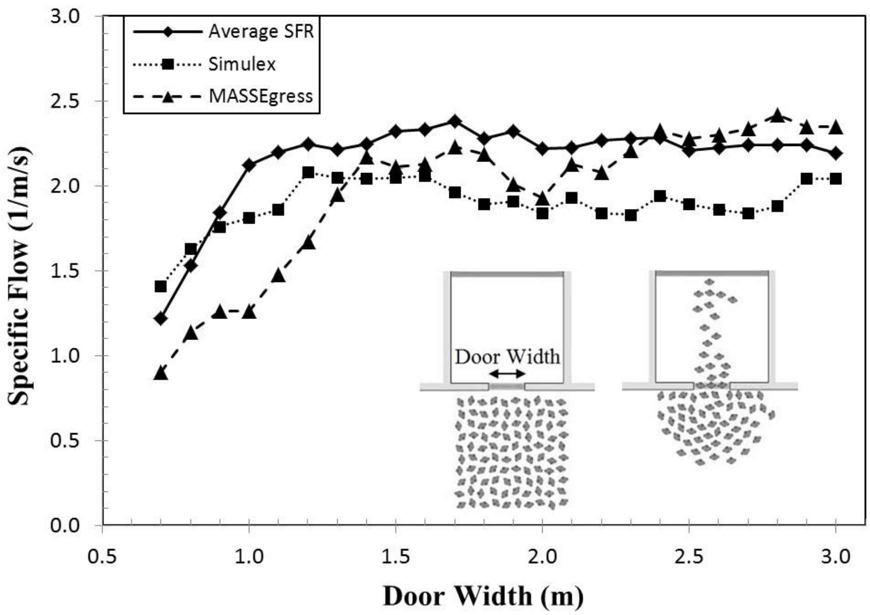


Figure 4-10: Doorway Test

4.7.2 Density Test

In order to study the dependence of SFR on agent density, a series of tests with various agent densities are conducted using an enclosed loop as shown in Figure 4-11. This exercise is similar to the corridor test by Heliövaara et al. (2012). SFRs are monitored when agents walk through four check lines shown in Figure 4-11. Test results in Figure 4-12 show that as the density increases from 0 to 3.2 persons/m^2, the specific flow rate first rises and then decreases after a critical density near 2.4. The shaded area in Figure 4-12 summarizes the range of results from two previous studies (Heliövaara *et al*. 2012; Daamen 2004). Clearly the proposed model is within the range of published results.

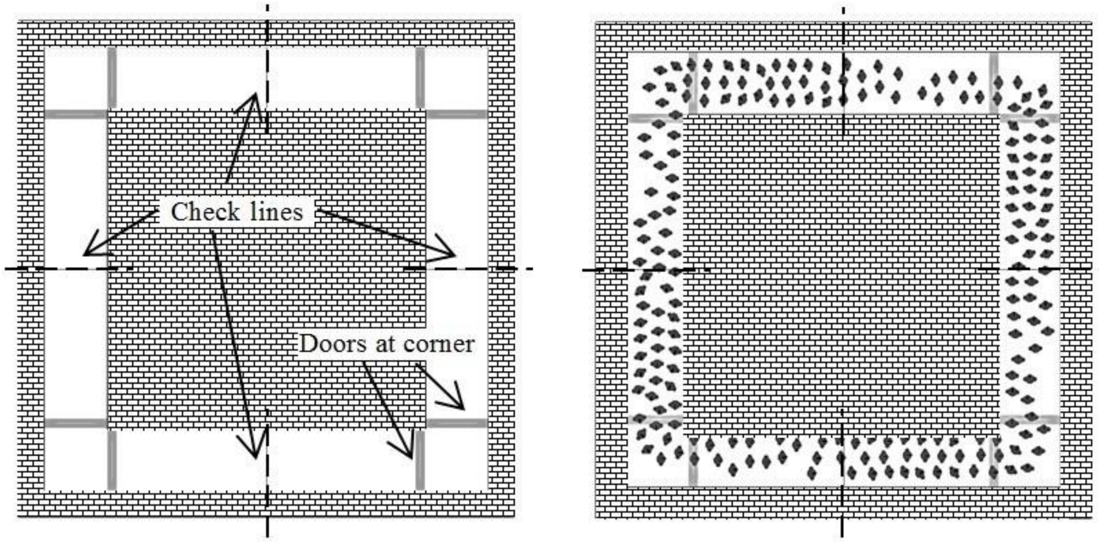


Figure 4-11: Snapshots of Density Test

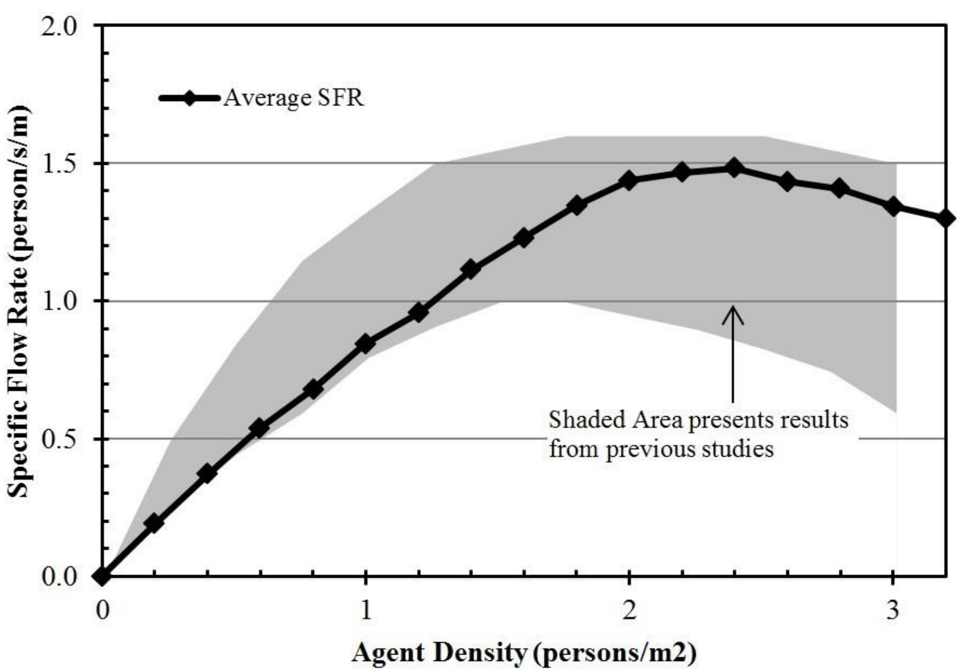
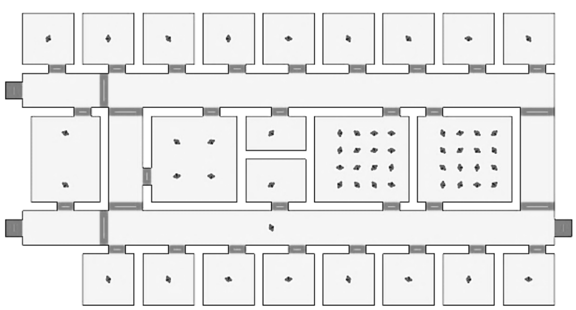


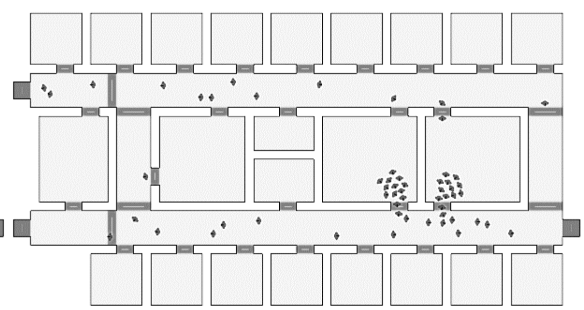
Figure 4-12: Specific flow rates under various agent densities

4.7.3 Egress from Multiple Rooms

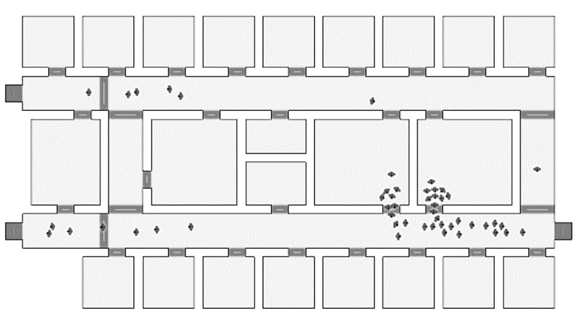
This exercise occurs in a building floor with multiple rooms. The floor is modeled after the CEE department's building (GG Brown Memorial Laboratory) at the University of Michigan as shown in Figure 4-13, where light grey spaces are spaces that can be occupied and dark grey areas are doors and exits. The initial conditions are shown as Figure 4-13.a, where 58 agents with random orientations are distributed in various rooms. Figure 4-13.b through 4-13.d presents snapshots at intermediate times in one simulation, and Figure 4-14 shows the recorded paths, which are autonomously selected by the agents to exit. A more careful observation of a single agent's behavior indicates that the model is working well. Each agent correctly waits or rotates when necessary, follows a smooth, logically selected path, and passes slower agents when necessary.



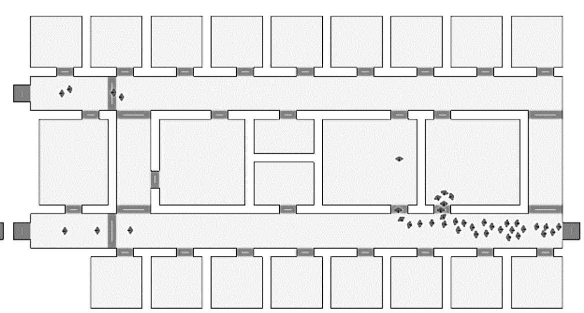
4-13.a



4-13.b



4-13.c



4-13.d

Figure 4-13: Egress from multiple rooms: snapshots at initial and intermediate times

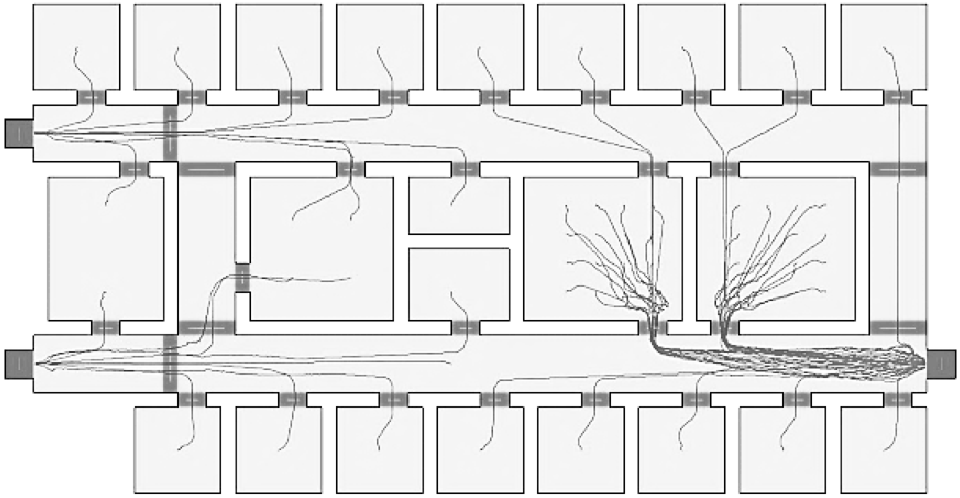
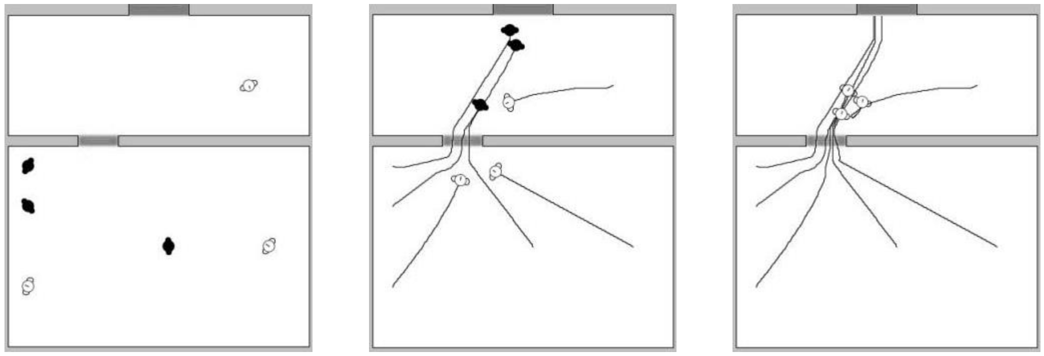


Figure 4-14: Egress from multiple rooms: escaping paths

4.7.4 Simple Social Relationship

When simple social relationships are introduced, the response of the agents significantly changes, compared to a situation where such relationships are not accounted for. In one test, shown in Figure 4-15, six agents with random orientations are initially located in two connected rooms (Figure 4-15.a). Three of them (light colored) are family-related. The other three (dark colored) are not related. During the process of evacuation, family members are attracted to one another first and meet at an intermediate point (within the specified conferral zone), before escaping as a group (Figure 4-15.b and 4-15.c). The other agents evacuate individually, and more quickly. Some observations from real-world events support such significant changes in agent response. For example, some couples, i.e. group members, were reported meeting first before escaping as a group during extreme events, as discussed in Aguirre *et al*. (2011b). Yang *et al*. (2005) also reveal the significance of kin behavior.

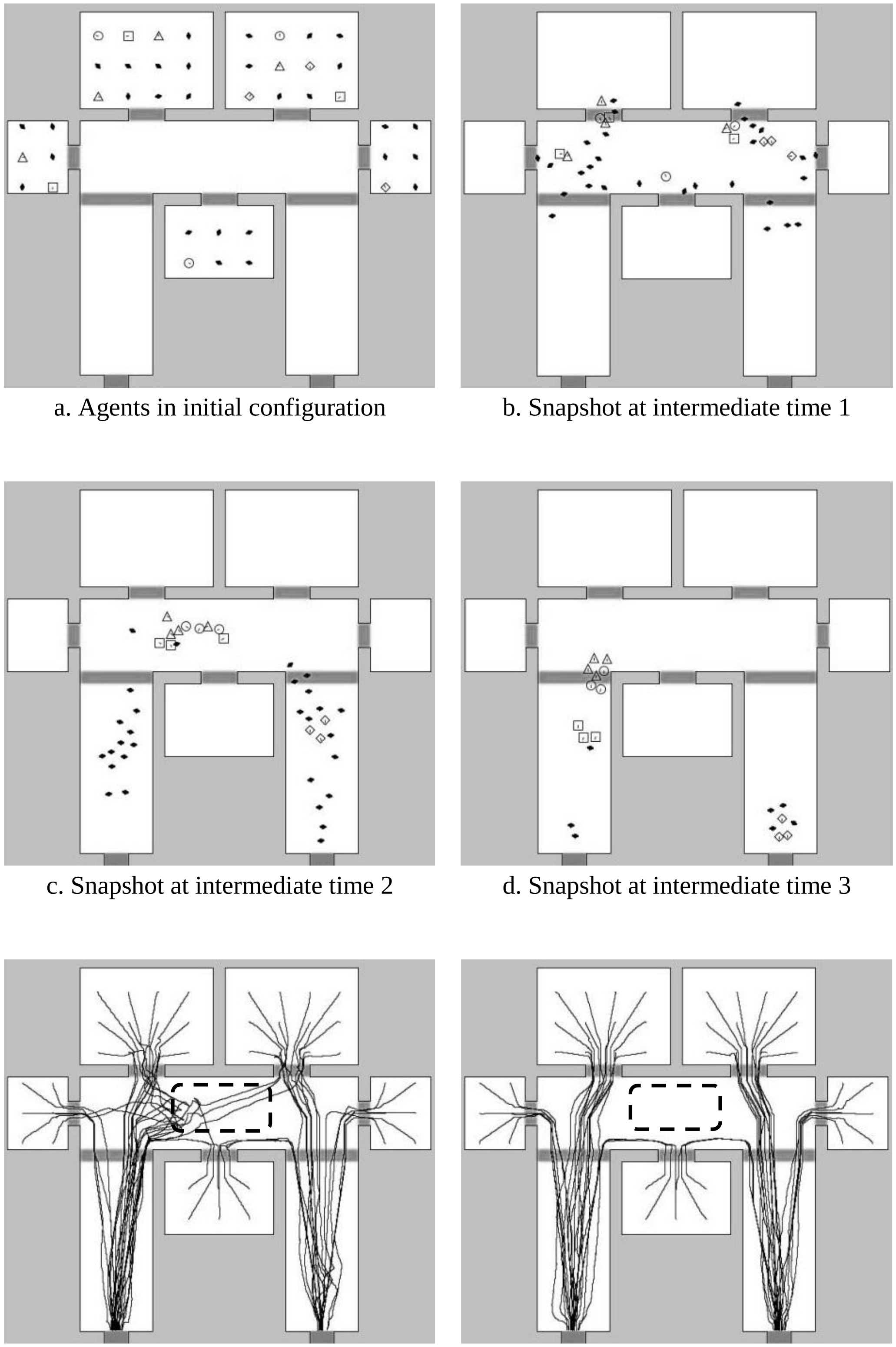


a. Initial configuration b. Family trying to reach conferral zone c. Family exiting as a group

Figure 4-15: Simple social relationship test

4.7.5 Dual Exits Egress Test

To further investigate the influence of the social relationship on an agent's behavior, especially in a more complex building environment, the dual exits egress test is proposed. A social relationships network involving four families is introduced. Snapshots in Figure 4-16 show one run of this test. Family members are represented as light colored with various shapes signifying different families. These families seek each other before egressing. Dark colored agents are not related. Each family forms a group with strong cohesive bonding, and moves together (Figure 4-16.b to 4-16.d). Two control tests between agents with and without such social relationships networks are compared and their paths are shown in Figures 4-16.e and 4-16.f. Their behaviors are significantly different due to the social effects, as evinced by the multitude of intersecting lines in the box with dotted lines in Figure 4-16e. The box shows where various agents impeded one another's motion in their attempt to reach a conferral zone and evacuate as a group. Based on test observations, these results duplicate findings by Aguirre et al. (2011b) that agents with strong social bonding (family related) also influence agents who behave individually. Crossing flow and walking in groups are also mentioned in the recent study by Chu *et al.* (2012).



a. Agents in initial configuration

b. Snapshot at intermediate time 1

c. Snapshot at intermediate time 2

d. Snapshot at intermediate time 3

e. Family relationships active

f. No family relationships

Figure 4-16: Dual exits egress test

4.8 Summary

By implementing the Scalar Field Method, the Agent-Based platform, EgressSFM, is developed and presented. The EgressSFM is comprised of the building and environment model, agent model, and other auxiliary modules. In particular, the agent model can explicitly simulate the "thinking" and behavioral response of an occupant during egress. The preliminary validations are conducted to show the EgressSFM's ability of mimicking reasonable egress behavior, and its potential for exploring the influence of social relationships during egress process.

CHAPTER 5

MODELING SOCIAL COLLECTIVE BEHAVIOR

5.1 Introduction

As discussed in Chapter 2, people can exhibit social collective behavior during egress, such as queueing, collective mobility, and lining up in counter-flow. Such behaviors are seldom correctly simulated in literature because most existing models lack the means for incorporating meaningful social interactions. In this chapter, a leader-follower model is proposed and implemented in conjunction with the Scalar Field Method (SFM) in the EgressSFM. The new model interprets local social interactions and collective behavior and then uses this information to mimic the three collective scenarios mentioned above. To achieve this, an agent establishes informal and transient leader-follower relationships with others while adjusting its behavioral patterns as warranted by the situation. The proposed model is calibrated to existing field data and then validated using another set of field data, where it is shown that the new model is capable of reasonably simulating social collective behavior during egress.

In the rest of this chapter, the theoretical background pertaining to social systems and collective behavior are presented first in Section 5.2. The follower behavior model is then introduced in Section 5.3, followed by a presentation of the model's development and its implementation in Section 5.4. Finally, a series of validation and capability-demonstration simulations are presented in Section 5.5 and 5.6.

5.2 Social System and Informal Rules

Collective behavior such as queueing, collective mobility, and lining up in counter-flow are self-organized social systems, since they develop stable patterned modes of interaction among participants (Parsons 1951). According to Parsons and Smelser (1957), social systems have several functional problems, the most distinctive of which is the integrative problem, which pertains to the emotional and social maintenance needed to tie members to the system. Mann (1969) studied Australian football queues and indicated that cohesion was achieved in the queue once informal rules were established, which allowed individual members to adjust to the normative behavioral pattern of the collectivity.

Inspired by Mann, aggregation and cohesion are considered in this work to be common collective behaviors in social systems occurring during egress. To maintain cohesion, egressing pedestrians must change their behavioral patterns such that queuing members merge with the queue, move and then exit in order; people in situations of collective mobility track leaders; and pedestrians line up in a counterflow to reduce congestion and ease movements. These behavioral changes occur because informal rules are established and take effect, as they do in real situations. The model proposed in this chapter develops four behavioral patterns that will be discussed in the following sections.

5.3 Follower Behavior, Informal Relations, and Social Collective Behavior

Although formal rules in different social systems have various formats and effects, one common result in any social system may be that an evacuee makes the decision to follow a leader. Follower behavior in this work is defined as that in which a pedestrian follows other pedestrians without establishing a formal and steady social relationship. This type of behavior is strongly supported by experimental observations. Isobe et al (2004a) and Kretz et al (2006b) did two series of experiments to study courter-flow in narrow corridor. They observed pedestrians choosing to follow closely behind other persons moving in the desired general direction. Follower behavior, as well as lane formation, is also discussed in many analysis and simulation studies, e.g. Helbing et al (2001), Burstedde et al (2001), Hoogendoorn et al (2005), and Schadschneider et al (2009). Queuing behavior, where pedestrians form a waiting line when a leading person stops, is also observed and discussed by many studies. Pan (2006) conducted simulations of competitive and queuing behavior in a doorway test and shows different passing times and flow rates for them.

Figure 5-1 People form lanes (adapted from Helbing et al 2001, Schadschneider et al 2009)

Follower behavior in this work is achieved by establishing a social interaction between each follower-leader couple. This transient social interaction is termed "informal relation" to differentiate it from the steady and formal social relationships that originate from social roles and identities in a group. The critical difference between the model proposed herein and previous research in this area is that social collective behavior, specifically queuing, collective mobility and lining up in counter-flow, is interpreted as variants of different follower behaviors driven by informal rules and relatively new social relations. For example, an agent in a high density counter-flow situation will recognize that confined space coupled with heavy oncoming traffic necessitates lane formation and subsequent follower behavior. In a non-emergency situation, agents queue up, and when there is uncertainty follow a moving leader.

5.4 Simulating Social Collective Behavior

In the present model the assumed follower behavior is implemented as an extension of the EgressSFM proposed in Chapter 4. The original Agent-Based platform assumes that an agent's movement is in response to only one normative behavioral pattern. In contrast, the leader-follower model proposed herein augments the decision making process with several distinct behavioral patterns triggered by four Boolean parameters (true-or-false): uncertainty or not, high or low stress level, besieged in a slow crowd or not, follower or leader status. The values of the four parameters are determined by the agent's "memory" and its perception of the surrounding circumstances. In this work, uncertainty means that floor plan in the agent's "memory" is incomplete to the point where it fails to compute a clear egress route. The stress level is considered to be either high or low based on whether hazards (such as fire and smoke) are visible or not, respectively. 'Besieged in slow crowd' is defined as a situation where an agent is surrounded by other agents and its cumulative speed rate (absolute value) over past five time-steps is lower than 0.05 m/s. Follower or leader status is the role an agent plays in a group.

The algorithmic steps of activating a specific behavioral pattern are shown in Figure 5-2. An agent first perceives its environment and surrounding agents, and then selects a behavioral pattern. Four behavioral patterns are specified in this work: competitive individual, besieged-in-crowd, queuing, and, collective mobility as defined next. Uncertainty is the first parameter to be considered: if there is uncertainty, the agent becomes part of a collective mobility entity; otherwise, the agent considers the other three patterns by estimating its stress level. If the stress level is high, the agent tends to be competitive unless it is besieged in a slow-moving dense crowd. In the latter condition, the agent follows the besieged-in-crowd behavioral pattern. When the stress level is low, the agent is more patient and queues when there is congestion or moves in a straightforward competitive manner in open spaces. These behavioral patterns are codified as follows:

- Competitive Behavior: the agent clearly knows the egress route, and moves directly toward the next target door/exit. During egress, no informal relationship is established with other agents and no group relationship slows the movement towards egress.

- Besieged-in-crowd: the agent, stuck in a slow-moving dense crowd, establishes an informal relationship with the agent directly in front, assuming that that agent is advancing towards the same target. In such a situation, the follower agent temporarily adopts the VPE computation of the leader agent to direct its movement.

- Queuing: the agent, deciding to join in and move with a queue, first searches for and follows the nearest queuing member in the queue. The agent then follows the agent ahead and nearest in the same queue after merging with the queue. The VPE computation between the agent and its egress door/exit is temporarily replaced by that between the agent and its leader.

- Collective mobility: the agent, having high uncertainty regarding its egress route, decides to follow a group of agents. After observing other agents' movements, the agent identifies the largest moving mass of agents. It then establishes an informal relationship with and follows the front and nearest agent in the moving mass. The VPE computation between the agent and its egress door/exit is temporarily replaced by that between these two agents.

Perceive environment;
Estimate the parameters of stress level, uncertainty, besieged in slow-moving crowd or not, leader or not;
If there is uncertainty,
    Conduct ***collective mobility*** behavior;
ELSE
    IF stress level is high,
        IF besieged in slow-moving corwd
            Conduct ***besieged-in-crowd*** behavior;
        ELSE
            Conduct ***competitive*** behavior;
    ELSE
        IF a queue is formed at a door or exit
            Conduct ***queuing*** behavior;
        ELSE
            Conduct ***competitive*** behavior;

Figure 5-2: The major algorithm steps of choosing a behavioral pattern

As described in Chapter 3, an agent makes decisions regarding behavior by minimizing the VPE. Due to its nature, the competitive individual pattern employs the basic SFM relationships described by Equations 3-4 through 3-6. However, the other three behavioral patterns incorporate additional considerations. In particular, the follower agent temporally replaces Equation 3-4 (which models agent-exit interaction) with Equation 5-1, which models the interaction of the informal relation between follower-leader couple. Equation 5-1 is identical to Equation 3-4, except that d is replaced by d_1', the distance between the follower and the leader and E_1' is the virtual potential energy of the informal relation. As a result of minimizing the VPE, the follower agent tends to shorten the distance to the leader agent, and therefore follow the leader.

$$E_1' = c_1\left(d_1' + D_{1a} - D_{1e}\cos(\triangle\theta_1)\right) \tag{5-1}$$

An agent who is a leader to a follower agent may itself be a follower of yet another leader. The agent at the front of a group is termed the absolute leader (AL). When an AL agent meets on-coming non-AL agents, the advancing AL conducts VPE computations with the on-coming non-AL agents who are not in the same group. To give the AL agent priority commensurate with the fact that it is leading a group, the VPE in Equation 3-5 is modified as shown in Equations 5-2 and 5-3. The factor λ_{AL} is selected to be 4.0 based on a series of sensitivity studies as discussed later on.

$$E_{2\,non-AL\,to\,AL} = \lambda_{AL} E_2 \tag{5-2}$$

$$E_{2\,AL\,to\,non-AL} = \frac{1}{\lambda_{AL}} E_2 \tag{5-3}$$

where $E_{2\,non-AL\,to\,AL}$ is the virtual potential energy perceived by a non-AL agent, reflecting the interaction between itself and an on-coming AL agent; $E_{2\,AL\,to\,non-AL}$ is the VPE perceived by an AL agent reflecting the presence of the non-AL agent. E_2 is the basic inter-agent interaction computed by Equation 3-5 and modified by Equations 5-2 and 5-3 when warranted. λ_{AL} is the absolute leader priority factor. When there are AL to AL or non-AL to non-AL interactions, and between group members, Equation 3-5 governs.

Once the VPE computations are done, the decision-making process and locomotion execution are generally consistent with the original model. An agent first observes the environment and refreshes its perception of the current situation. It then computes the surrounding accessible space that it can achieve in one time-step, and associated "sampling points" associated with rotation and translation for VPE computations. As described in Chapter 4, "sampling points" are a limited number of points that cover the area reachable by the agent during one time-step. The agent next searches for an egress route and use the computed VPEs at the sampling points to reach an appropriate locomotion decision. The informal rules and behavioral patterns described above take effect at this step since the informal relations are now established. As described earlier, the agent then waits until all other agents reach their decisions, and they execute their movements simultaneously.

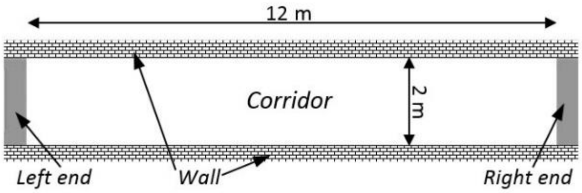
5.5 Calibration and Validation of Counter-Flow Test with Experiments

Counter-Flow tests are conducted to show that the model has the ability to reasonably handle a counter-flow scenario, and to calibrate and validate its results against experimental field data. Two independent research groups, Isobe *et al* (2004a) and Kretz *et al* (2006b), conducted counter-flow experiments involving university students. Selected experiments from the former study are used to calibrate the proposed model. Then, experiments from Kretz *et al.* (2006b) are used to validate the calibrated model.

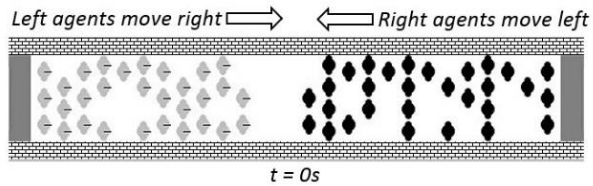
5.5.1 Calibration with Isobe's Counter-flow Test

Isobe *et al* (2004a) conducted counter-flow experiments in a 12 m by 2 m corridor with open boundaries at both ends as shown in Figure 5-3.a. Two groups of pedestrians with an equal number of people (ranging from 5 to 35 individuals) walked in opposite directions from one end of the corridor to the other (Figure 5-3.b), and their movements were monitored and measured. In Figure 5-3, the opposing groups of agents have different colors (light and dark) and AL agents are specially designated (have no infill) and linked via a line to follower agents. Figures 5-3.b, 5-3.c and 5-3.d show snapshots of one simulation of the test where agents form self-organized counter flow movement involving long chains of people passing each other. The chains and counter flow movement are supported by field observations (see Figure 2-1, adapted from p.p. 14-15 in Still 2000).

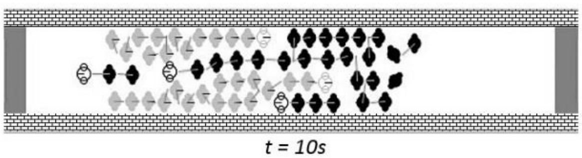
A single person's passing time is defined as the time spent travelling from the initial location to the final destination, and the average passing time is the average of the passing times of all people. Based on Isobe's data, an unimpeded pedestrian walks with a speed between 1.1 m/s and 1.3 m/s. In the following simulations, agents walk at speeds randomly selected from this range. To account for the stochastic nature of the simulations, ten runs are conducted for each situation and average results are presented. Extensive sensitivity studies showed that ten simulations are sufficient to adequately reflect the range of variability in the simulations.



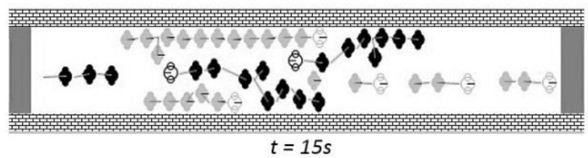
2.a



2.b



2.c



2.d

Figure 5-3: Counter-flow simulation of Isobe's test

The test is simulated by the proposed leader-follower model and the results are shown in Figure 5-4. The solid markers in Figure 5-4 show the computed average passing time for priority indices, λ_{AL} (Equations 5-2 and 5-3) ranging from 3 to 5. The hollow markers in Figure 5-4 show the experimental data. Trends of the test results are generally consistent with the experiments that the average time rises when more pedestrians are in the corridor. It is important to note that the trends change when the number of agents reaches 50. At this point, the response of the group transitions from competitive, due to the relatively abundant space in the corridor, to besieged-in-crowd, as the group slowed down to deal with the increased congestion. Accordingly, the influence of λ_{AL} is negligible at low population density, but becomes more significant as the number of individuals increases. Based on comparisons between simulation and experimental data, λ_{AL} is selected to be 4.

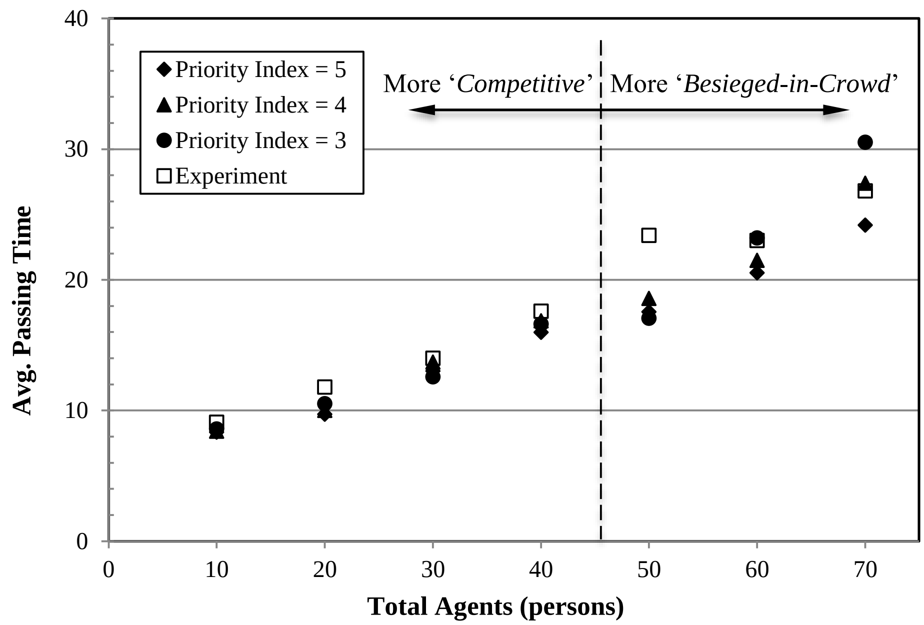


Figure 5-4: The average passing time of Isobe's counterflow test

5.5.2 Validation with Kretz's Counter-flow Test

Kretz *et al* conducted another series of counter-flow experiments in which up to 67 participants were divided into two groups (not necessarily equal in size) and allowed to interact in a head-on manner in a corridor. As shown in Figure 5-5, the researchers set up 3 cameras spaced at 5m along the corridor to monitor the experiment. In contrast to Isobe's experiment that measured the total time required for all agents to move to the exit destination, Kretz *et al* measured the passing time needed by one group to pass a particular camera station.

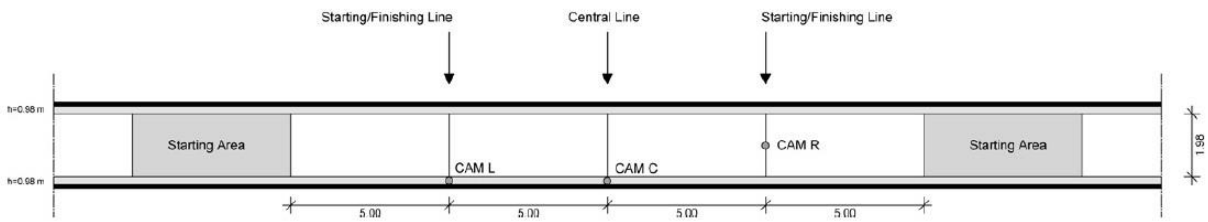


Figure 5-5: Kretz's counter-flow test (extracted from Kretz *et al* 2006b)

The proposed leader-follower model (using λ_{AL}=4) is used to simulate a particular situation tested by Kretz *et al*., in which a 50% counter-flow situation is used and in which participants were divided into two equal groups. Groups of 5, 16 and 32 agents (each side) respectively were modeled. The maximum walking speed of the agents in the following exercises is selected with a range of 1.2 m/s to 1.7 m/s as measured in the experiment. The initial distribution of agents was assumed to be random at the starting time although this is not reported by Kretz *et al*. The experiment and simulation results are shown in Figure 5-6 and 5-7, in which the hollow markers are the averages of 10 runs and the bars show the range of experimental results (Figure 5-6). Figure 5-7 shows that the passing times grow almost linearly with group size, which is consistent with Kretz's observation. Moreover, the simulation results fall well within the range of experimental data.

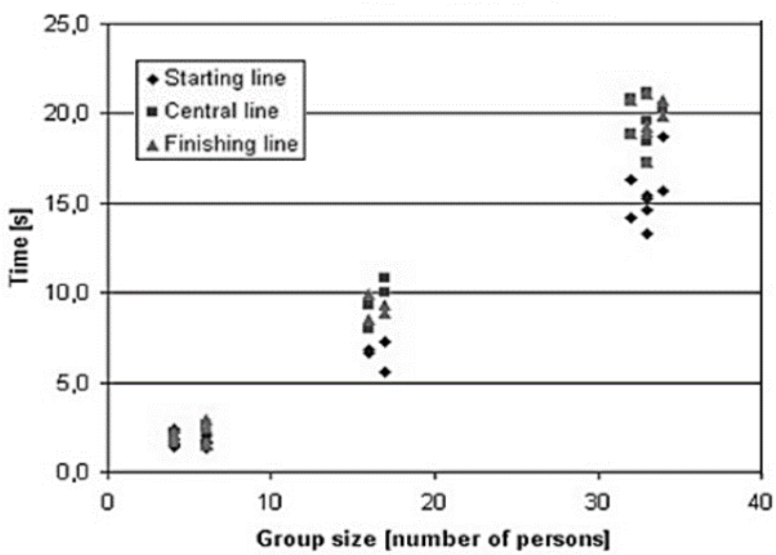


Figure 5-6: Experiment result (Kretz et al 2006)

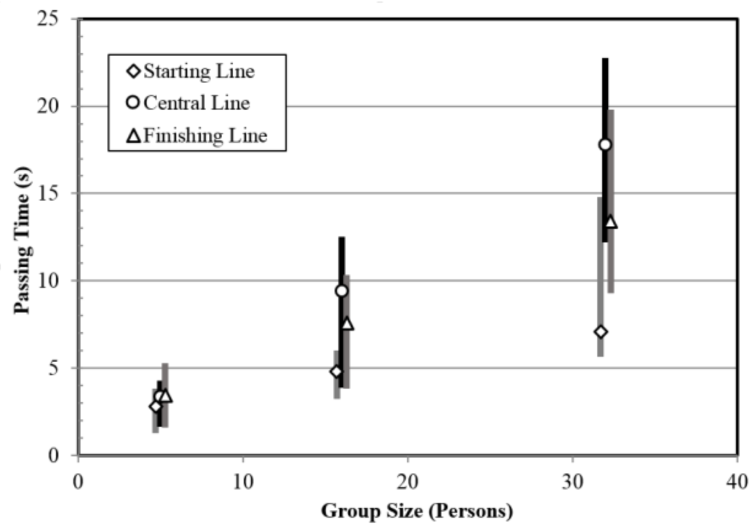


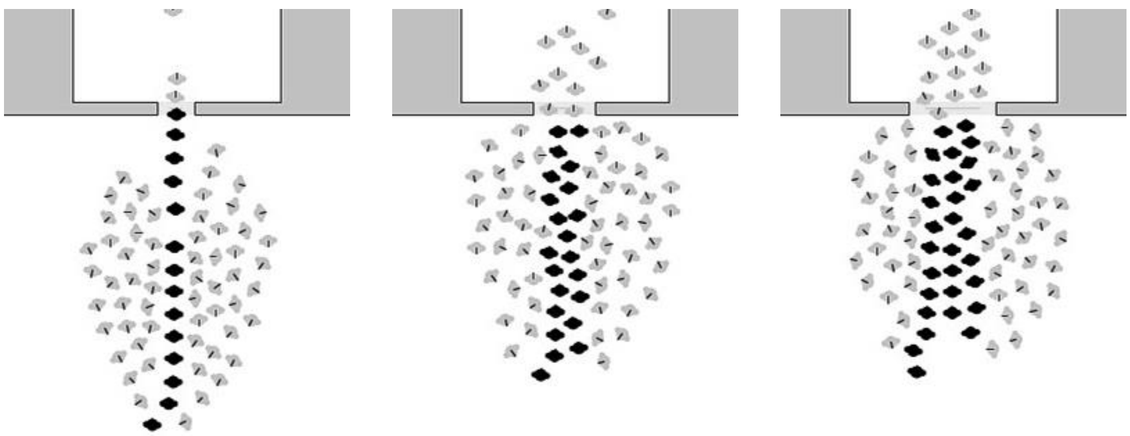
Figure 5-7: Simulation result of Kretz's counterflow test

5.6 Simulation of Queuing and Collective Mobility

Two series of simulations are conducted to showcase the proposed model's ability to mimic social collective behavior of queuing and collective mobility. Unlike Section 5.5, the population of agents are assumed to be the same as discussed in Chapter 3, i.e. both categories of "adults" and "children + seniors" are assumed to be equally represented among agents. Accordingly, for "adults" the maximum velocities in forward, lateral, and backward are 0.95 - 1.55 m/s, 0.5 m/ s and 0.2 m/s respectively; and for "seniors and children", these numbers are 0.55 - 1.25 m/s, 0.3 m/s and 0.1 m/s.

5.6.1 Doorway Test with both Competitive and Queuing

Doorway tests are conducted under two distinct behavioral patterns, i.e. competitive and queuing, and the results are presented in Figures 5-8 through 5-10. Similar to the doorway test shown in Section 4.7.1, 100 randomly oriented agents are distributed in a square-shaped configuration (5m x 5m) centrally aligned with the target door. They are then allowed to exit, passing through the door with the intention of reaching a 'destination' zone. The specific flow rate (SFR), i.e. the number of persons passing through each meter width of doorway per second, is computed for door widths ranging from 0.7m to 3m and is calculated at mid length of the passageway.



Single-Line Queuing Double-Line Queuing Triple-Line Queuing

Figure 5-8: Doorway test with competitive and queuing (dark agents are queuing)

The relationship between SFR and door width for competitive agents has been studied by multiple researchers (Thompson et al 1995; Pan 2006; Heliövaara et al 2012; also see Section 4.7.1) and is often considered to be a monotonically increasing curve with a roughly bilinear trend. Figure 5-9 shows the computed "Competitive" response, which follows the expected bilinear trend. Section 4.7.1 discussed comparisons between this computed response and other well established data. When queuing is present, however, the SFR response changes. The proposed model predicts a flat SFR response, denoted "Queuing" in Figure 5-9, while Pan (2006) predicts a descending curve, designated "MASSEgress" in Figure 5-9. The discrepancy is related to the assumption made by Pan (2006) that only a single-line queue can form, whereas in the current work, the number of queues increases as the door width grows, a fact supported by field observations (e.g. Still 2000). As shown in Figure 5-8, single, double, triple (or more) lines can form as the door width increases. The dark colored agents in Figure 5-8 are queuing members, whereas light-colored agents are not, but instead are on their way to merge with the queue(s). Figure 5-10 shows that multiple queues lead to faster exit times than a single queue as the door width grows.

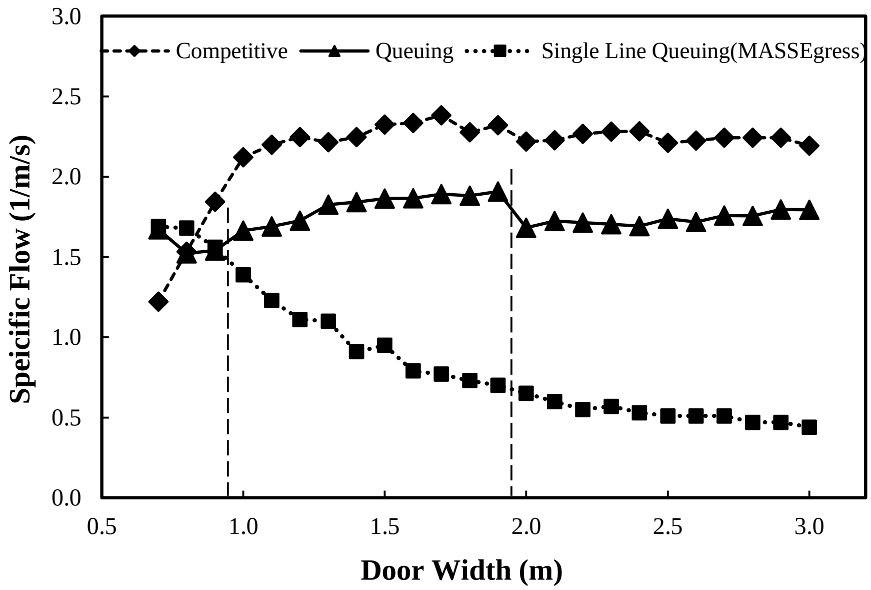


Figure 5-9: Specific flow in doorway test with competitive and queuing behaviors

As noted by others (Pan 2006, Challenger et al 2009) and predicted by the proposed model (Figures 5-9 and 5-10), queueing leads to a higher SFR and, therefore, lower egress time than competitive behavior when the door is narrow (less than about 0.9 m). Narrow doorways promote clogging of competitive agents. In contrast, queuing agents are well-organized and cooperative so they pass through faster. However, when the door is wide, the opposite happens, i.e. the SFR of competitive agents is higher and exit time is lower than those of queuing agents. Since queuing members move in order, the group's moving velocity is constrained by the slowest members, and hence the average speed of the group tends to be smaller than that of a similar group of competitive agents. Moreover, the wider door alleviates the tendency for competitive agents to clog up the exit.

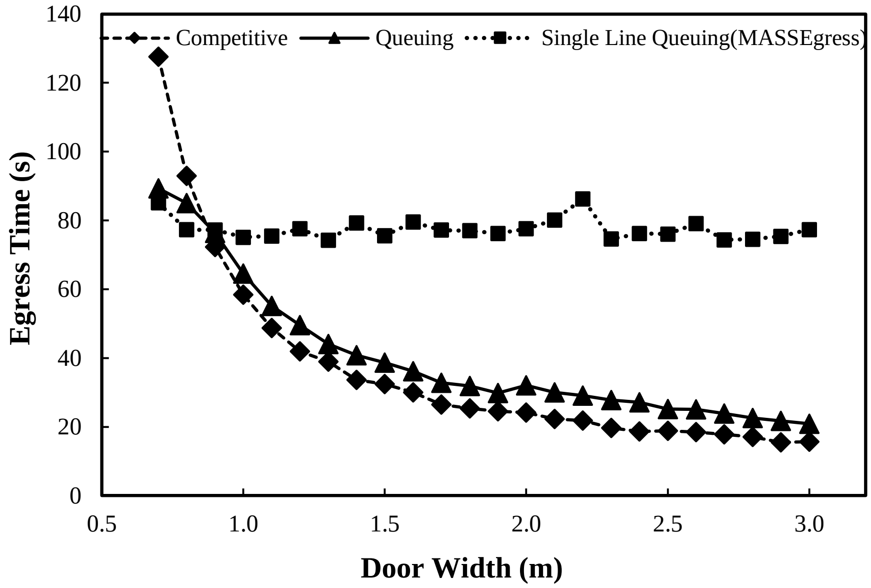


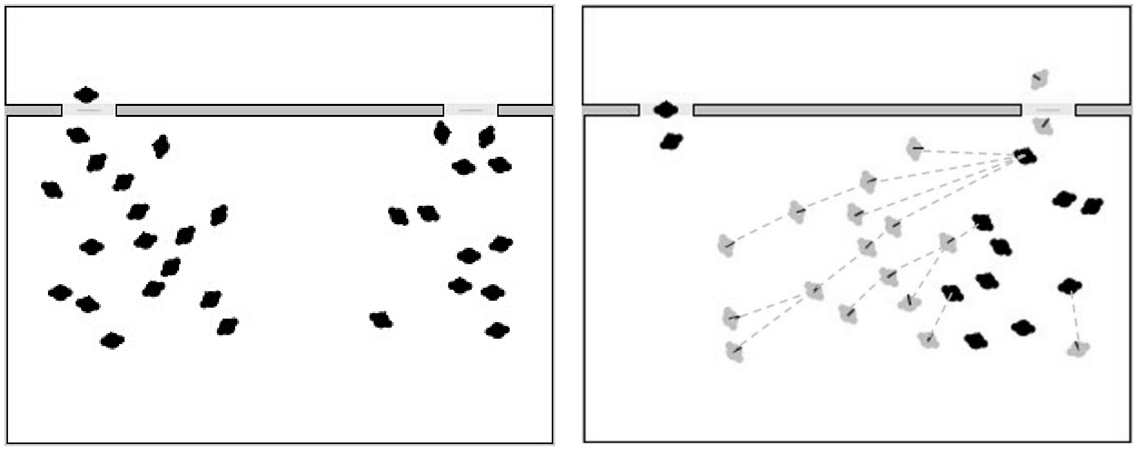
Figure 5-10: Egress time in doorway test with competitive and queuing behaviors

The SFR curve of queuing members in Figure 5-9 shows three stages of development over the ranges of 0.7-0.9 m, 1.0-1.9 m, and 2.0-3.0 m divided by two vertical dashed lines in Figure 5-9. Each stage is related to the number of queues formed, i.e. single, double or triple lines, respectively. Transition from single to double then triple lines is gradual. For example, in the range of 1.0.-1.9 m, two queuing members move initially in single file but occasionally switch to two lines when the door width is around 1.0 m. When the door width is in the second stage, there are predominantly two queues. As the door width grows, the behavior gradually switches to three lines and so on. The proposed leader-follower model compares well with MASSEgress in the range of 0.7-0.9m. However, since MASSEgress is only able to simulate single-line queuing, its results are not applicable for the other ranges.

The simulations presented are driven by the presence of informal relationships that allow agents outside the queue to either join in the middle part of the queue or travel to the rear of the queue to join it. The merging location is determined by the agent's location with respect to the line. If the agent is close to queuing members and finds space in the queue, it merges immediately. Otherwise, it waits for an opportunity to open up; alternatively, the agents who do not find an opportunity to merge tend to move to the rear of the line. Agents inside the queue follow the member in front and wait in line when the AL stops or maneuvers slowly. When the doorway is narrow, more agents tend to move to the end of the queue and the queue ends up being very long. As shown in Figure 5-8, the queue shape is not necessarily a straight line. Instead, the queue propagates from follower to follower and its shape can be irregular.

5.6.2 Egress from 2 Exits with Competitive and Collective Mobility Behaviors

The situation in Figure 5-11 is intended to demonstrate the differences between competitive and collective mobility behaviors. It shows a lobby with 30 agents placed at random locations and with random orientations. The lobby has two exits leading to an adjacent corridor. Dark-colored agents are familiar with the floor plan, but light-colored ones are not. In a room with multiple exits, agents who are not familiar with the floor plan outside the room have difficulty computing a clear egress route. These agents are uncertain about what to do and decide to egress by patterns of collective mobility characterized by following the movement of other actors, as shown in Figure 5-11. When egress commences, in contrast to agents who are not experiencing uncertainty, agents who know the floor plan well select the closest exit and respond in a "competitive" manner (Figure 5-11.a). Agents with uncertainty observe the situation and then, failing to select an egress route, decide to follow an existing group. The dashed lines in Figure 5-11.b represent the informal follower-leader relationships established in this process.



a. Competitive b. Collective Mobility

Figure 5-11: Egress from 2 exits with competitive and collective mobility behaviors

5.7 Summary

This chapter extends the SFM models and the corresponding EgressSFM platform to model certain key aspects of social collective behavior during human egress. The leader-follower model is based on the premise that informal and transient relationships can be established between an agent and others, temporarily modifying its egress response and essentially making the agent a follower. Three categories of follower behavior are addressed: queuing, collective mobility, and lining up in counter-flow. A calibration exercise followed by a validation study involving the use of published experimental data with human subjects show that social collective behavior during lining up in counter-flow situations can be reasonably modeled. Two series of simulations are presented to mimic social collective behavior of queuing and collective mobility.

CHAPTER 6

CASE STUDY OF THE STATION NIGHTCLUB FIRE

6.1 Introduction

This chapter describes the deployment of EgressSFM to conduct a case study of the Station Nightclub fire, which occurred in Rhode Island in 2003. The Station building fire occurred on the night of February 20, 2003, and resulted in 100 fatalities. Of the many disasters that have occurred in the past, the Station Nightclub fire is unique because: 1) it is well documented, and 2) about 400 of the 465 occupants were members of various social groups such as spouses, dating partners, friends, and coworkers. As discussed earlier on and in Aguirre *et al.* (2011b), people in such social groups and relationships respond differently than unattached individuals during disasters. The developed EgressSFM platform is used study the event, focusing in particular on the calibration of various modeling parameters and comparisons between model results and the actual numbers of occupants evacuated and killed. After calibration, parametric studies are conducted to quantitatively investigate the influences of the presence of social relationships and familiarity of the building floor plan on the death and injury tolls.

The background of the Station Nightclub fire is first presented in the remainder of this chapter. Assumptions of the computational case study are then discussed, followed by a presentation of the model's calibration and implementation. Finally, a series of parametric simulation exercises are presented, showcasing the technique's strong potential to quantitatively investigate the impact of social behaviors on egress.

6.2 Background of the Station Nightclub Fire

The Station building fire occurred on the night of February 20, 2003 in a crowded nightclub, which is a single-story building with a wood frame. As shown in Figure 6-1, the building is comprised of multiple rooms such as the main hall (including a dance floor and raised platform), sunroom, main bar, kitchen, dart room, etc., and has four exit accesses designed for egress purpose: the front entrance exit, main bar side exit, kitchen side exit, and platform side exit. There are two groups of windows adjacent to the main bar and the sunroom.

According to post-event investigation conducted by Grosshandler *et al.* (2005), the fire started at 11:08 pm after an ignition of polyurethane foam insulation near the raised platform. It spread quickly to the whole building in a few minutes and ultimately destroyed the building. Thirty seconds after the ignition, the band stopped playing and the crowd began to evacuate. The latest observed survivor escaped from the building at 4 minutes and 8 seconds after the ignition. Around 5 minutes after the ignition, flames extended out of the building. For the purposes of this study, the simulation's timeline count starts the moment the crowd began to evacuate (i.e. 30 seconds after ignition).

When the disaster occurred, more than four hundred occupants were inside the building. Due to the fire, the platform side exit was destroyed and became impassable about 20 seconds after ignition. Only 24 occupants escaped through the platform exit. The majority of the crowd tried to evacuate through the front entrance exit or the main bar side exit, and approximately 200 of them escaped safely. However, hundreds of evacuees clogged the spaces of the main hall, the main bar, and the corridor of the front entrance. To explore alternative accesses for evacuation, around 100 seconds after egress started, some occupants broke windows in the main bar room and sunroom, and 105 occupants fled out the building using these broken windows. Unfortunately, there were 100 occupants who died in this event because of fire and smoke injuries.

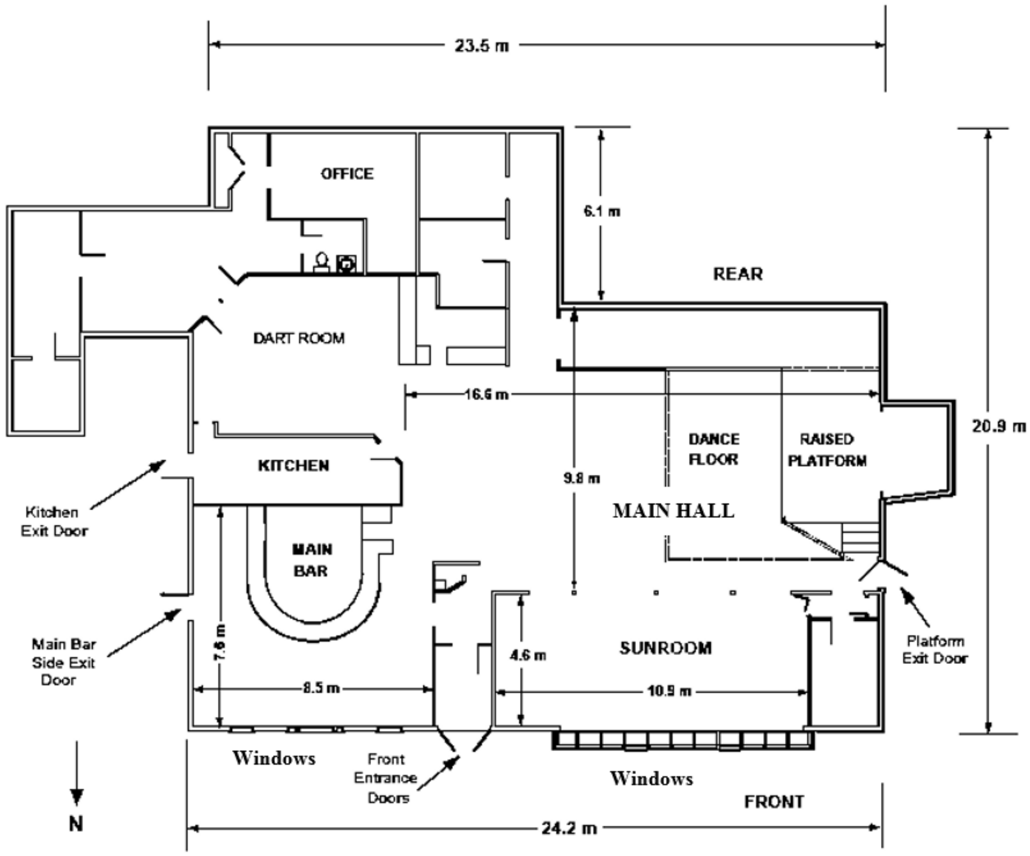


Figure 6-1: The Station building floor plan (adopted from Grosshandler *et al.* 2005)

The availability of detailed demographic and interview data of the 465 occupants makes a numerical study feasible (Aguirre *et al.* 2011a, b; Torres 2010). Such data is comprised of occupants' personal information, their familiarity with the building, their locations when the fire began, observations about social relationships, their behavioral responses, and the outcome of their escape effort. As discussed earlier, the evacuees are related at the social level through 179 groups including spouses, dating partners, friends, and coworkers. By deploying the Scalar Field Method, these relationships and groups can be comprehensively modeled, and quantitatively analyzed as shown later on.

6.3 Assumptions and Model Implementation

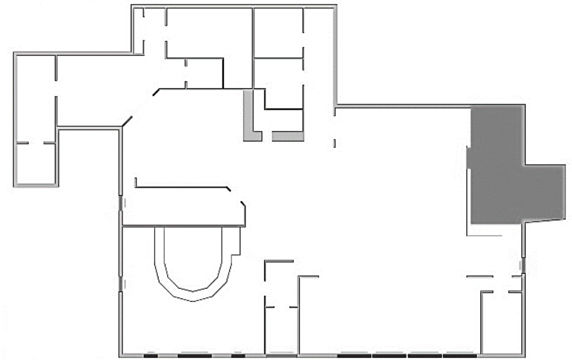
Environmental hazards and estimation of an agent's energy level are discussed in the following sections. They are combined and used to quantitatively describe impairments an agent's stamina due to the hazards. This is followed by a presentation of their implementation in EgressSFM and interpretation of the surveyed data mentioned in Section 6.2.

6.3.1 Environmental Hazards

As discussed earlier, environment hazards are harmful to an occupant's health. In particular, fire can lead to burning and fatality, and the toxic effect of smoke reduces an agent's energy level (EL). EL is a non-negative quantity, and the agent's mobility is assumed to be dependent on its energy level. The lower the energy level is, the more damage the agent receives. Once the energy level is zero, the agent is assumed to have died.

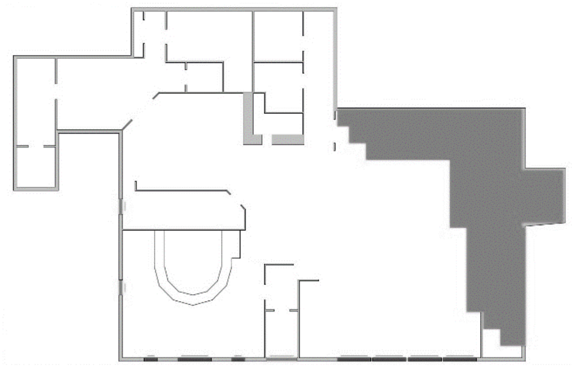
The building and environment model of EgressSFM takes into account fire and smoke hazards. As described in Chapter 4, fire is presented as a series of rectanglular areas with stochastic sizes and start times. The progression of fire is hardwired into the platform based on an analysis of the event documented by the National Institute of Standards and Technology (Grosshandler et al. 2005). The documented spread of fire is shown as shaded areas shown in Figure 6-2.a through 6-2.e. An agent that is still present within an activated fire zone is considered to have been killed by the fire.

Smoke has a toxic effect on agents and gradually reduces their energy level over the entire building as soon as the fire starts. As shown in Aguirre et al (Aguirre et al 2011a; Best 2013), the impairment due to smoke takes effect gradually. As discussed earlier, the toxic effect is assumed to be not present in the oxygen zones shown as dark areas in Figure 6-2.f. Due to the fresh air ventilation near such areas, agents in these zones suffer no additional impairment and start to recover their energy level.

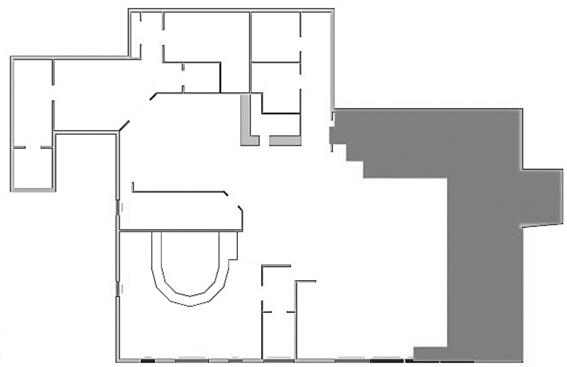


6-2.a Fire at t = 5s

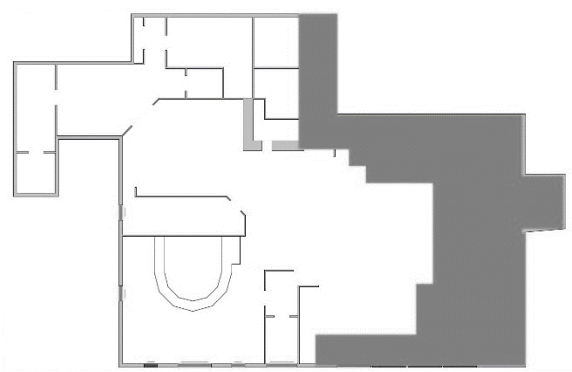
6-2.b Fire at t = 20s



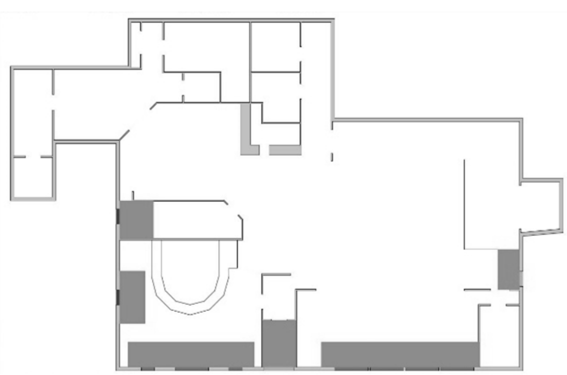
6-2.c Fire at t = 50s



6-2.d Fire at t = 100s



6-2.e Fire at t = 200s



6-2.f Oxygen zones

Figure 6-2: Simulate fire (a-e) and oxygen zones (f) in the Station event

6.3.2 Agent's Energy Level

Before the fire occurs in the simulation, each agent is assumed to have an initial energy level. The initial energy levels of the occupants are based on occupant demographics with a stochastic element added to account for variability. The initial EL values are taken from previous researchers Aguirre *et al.* 2011b, Torres 2010, and Best 2013. After the simulation begins, each agent in the building suffers smoke damage over time, manifested by a reduction in energy level, until it is either evacuates or is killed. Its energy level is computed as follows (based on Best 2013):

- When an agent is present in an active fire region, its energy level drops instantaneously to zero. This signifies that it is deceased.

- Smoke leads to a gradual reduction in an agents' energy levels in all building spaces except as noted next. The EL changes at the rate of -0.6, -0.8, and -1.2 EL/second during the time periods of 0 – 50 second, 50 – 100 second, and after 100 second, respectively.

- Based on an analysis of oxygen volume fractions conducted by Grosshandler *et al.* (2005), as shown in Figure 6-3, agents in the main bar room are assumed to suffer damage at a decreased rate (80% of values specified above) because: 1) this room is far away from the fire, and the fire and smoke are impeded by the walls of the front entrance corridor and kitchen; and 2) this room accesses one side exit and multiple windows that can provide more fresh air than other rooms.

- When an agent is present in an oxygen zone, the damage rates of EL are divided by a factor of -1.2 (Gill et al. 2010) to recognize the beneficial effects of oxygen. As a result, the EL gradually increases in oxygen zones.

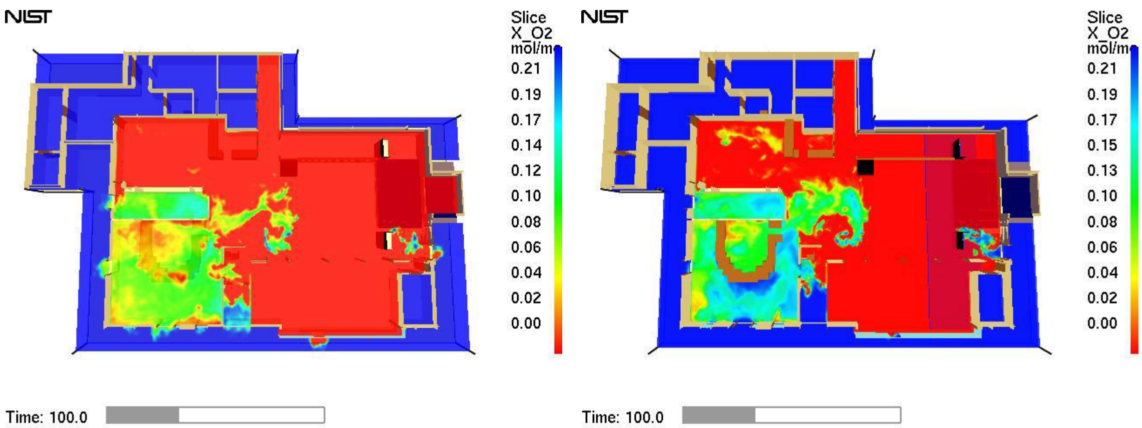


Figure 6-3: Oxygen volume faction at 1.5m (left) and 0.6m (right) above the floor at 100s (adapted from Grosshandler *et al*. 2005)

An injured agent is assumed to suffer mobility loss that is linearly dependent on the ratio of its current energy level to its initial energy level. If the energy level is equal to or higher than 80% of the initial energy level, the agent's maximum velocities are not influenced. Otherwise, the agent's maximum velocities in various directions are lowered in a linear correlation with the remaining energy level as shown in Equation 6-1.

$$\frac{max.v}{original\ max.v} = \begin{cases} 0.2 + \frac{energy\ level}{initial\ energy\ level}, & \frac{energy\ level}{initial\ energy\ level} < 0.8 \\ 1.0 & , \frac{energy\ level}{initial\ energy\ level} \geq 0.8 \end{cases} \tag{6-1}$$

6.3.3 Egress Model Implementation

As modeled in EgressSFM, the Station building model is comprised of a collection of exits, doors, windows, and interior spaces. Agents that reach exits are considered to have safely exited. Each exit has an open time and close time that determine whether this exit is available (passable) or not, respectively. Application of such open/close times is necessary to account for dynamic conditions during the fire, e.g. the side exits closed when the fire started in the Station event. Windows are a special set of exits that are normally impassable.

They can switch functions to enable egress after a specified open time is reached, reflecting the possibility of breaking them during an emergency. The building model automatically updates functions and availability of exits and windows according to the specified open times and close times shown in Table 6-1. Such times are based on the simulation timeline starting when the crowd begins to evacuate, and are adapted from Grosshandler et al. (2005).

Table 6-1: Time of openings and closings of exits and windows

Locations	Open Time / s	Close Time / s
Front Entrance	0	None
Platform Side Exit	0	30
Main Bar Side Exit	15	None
Kitchen Side Exit	30	None
All Windows	100	None

The agent's normative behavior is controlled by the Scalar Field Method as discussed earlier in the dissertation. Unlike the multiple choices of behavior patterns in Chapter 5, agents herein are considered to have a high stress level because they can see smoke and fire and therefore behave in a competitive manner. A similar assumption was implemented in Pan (2006). The agent model is implemented to address the demographic and interview data of the Station Fire as follows:

1. Personal demographic information of age, gender, initial energy level, and prior visit experience are considered. The term 'prior visit experience' pertains to whether the agent has visited the building before the night of the fire, i.e. it accounts for familiarity with the floor plan.

2. Initial location and orientation. Initial location of each occupant is determined based on coding of survivor interviews (Aguirre et al. 2011b; Torres 2010). Each agent's initial orientation is randomly selected for each simulation.

3. Social affiliation. Each agent is related to one of the 179 social groups and characterized by a specified type of relationship: alone, co-workers, friends, dating partners, family members, and multiple level. The first term refers to an individual without pre-existing relationship to others. The last term means a group has multiple types of relationships among its group members.

4. Group leader. A social group can have a leader that influences other members' decisions in this group. In the case of the Station scenario, group leaders were identified and coded based on survivor interview data (Aguirre *et al.* 2011; Torres 2010) and discussion by Best (2013).

Age determines an agent's mobility before being injured. As previously discussed, adults (15-64 yrs.) are generally faster and more agile than children (⩽14 yrs.) and seniors (⩾65 yrs.). To reflect the stochastic nature, the maximum speeds of each agent are randomly determined from ranges that depend on its age category. For adults, the maximum velocities in forward, lateral, and backward motion are 0.95 - 1.55 m/s, 0.5 m/s, and 0.2 m/s respectively; and for the rest, these numbers are 0.55 - 1.25 m/s, 0.3 m/s and 0.1 m/s.

Prior visit experience influences an agent's awareness of side exits, and can make the agent miss a closer exit because of lack of awareness. The surveyed data (Aguirre *et al* 2011a, b) shows almost half of the evacuees have no prior visit experience, and Grosshandler *et al.* (2005) mentions 2/3 of the occupants believed the main entrance to be the only exit. In this study, prior visit experience is assumed to determine an agent's knowledge of the floor plan when the evacuation starts: an agent without prior visit experience is aware of the front entrance exit and main bar side exit only, and may be unaware of other side exits; an agent who visited the building previously is assumed to knows all the exits. However, an agent can learn from its perception of the surrounding environment. When an agent who has no prior visit experience arrives in the building component adjacent to a side exit, i.e. the agent sees the exit, this agent updates its knowledge and may consider the exit as an alternative destination.

Each agent establishes the same type of social relationships to other group members in the same group. Spouses and dating partners are interpreted as kin-related in the SFM, and co-workers and friends are categorized as friend relationships. Multiple level is assumed to be friend-related for simplicity. If no group leader is specified in a social group, or this group is in response to weak interactions such as friends, group members are affiliated at social level from one to another uniformly. Otherwise, if a group leader is specified in a strongly bonded relationship like spouses, the group leader is responsible to lead the group, and the other group members are assumed to follow the leader. To do so, the leader establishes kin-related interaction with each of the other group members, but non-leader members only set up a single interaction with the leader. In addition, the non-leader members duplicate the leader's decision of escape route an approach the same exit.

An agent has multiple choices of destination for egress, since there are four exits and two sides of windows. Selecting the right exit, particularly the platform exit, was discussed by previous researchers such as Grosshandler *et al.* (2005) and Pan (2006), and is necessary to obtain a reasonable number of agents passing through each exit. Both studies assumed the occupants to always select the closest exit and applied other algorithms to control their decisions. The former used two software packages, buildingEXODUS and Simulex. In the simulation with buildingEXODUS, the platform exit was assumed to be impassable after 30s, and the front entrance was blocked at 90s. In the Simulex simulation, Grosshandler *et al.* (2005) first calculated number of occupants who would use the platform exit, which totaled 39, and then made the platform exit only visible to these 39 occupants. The latter study conducted by Pan (2006) assumed that only 20 occupants were aware of the existence of platform exit and 2/3 of the occupants believed that the main entrance was the only exit.

In this study, the agent generally selects one exit to which the travel distance from the agent's current location is the shortest. However, the final decision is dependent on availability of exits, prior visit experience, and leadership, as discussed above. To address the platform exit and the fact that only a limited number of people escaped through it, a penalty is added to each agent's perception of this particular exit's distance to make it less desirable as an exit. This empirical approach is motivated by two facts: 1) the exit door swung inwards rather than outwards and hardware on the door was broken (Grosshandler *et al.* 2005), and 2) the exit was close to the fire and covered by heavy smoke shortly after the fire ignited (Figure 6-4). A 9-meter penalty is selected to be imposed through the parametric study shown in Figure 6-5, in which the number of agents using the platform exit is simulated with various penalty distances. As can be seen, the correct number of agents using the exit corresponds to the use of a 9 m penalty.

Figure 6-4: The platform exit was covered by fire and smoke (Grosshandler *et al*. 2005)

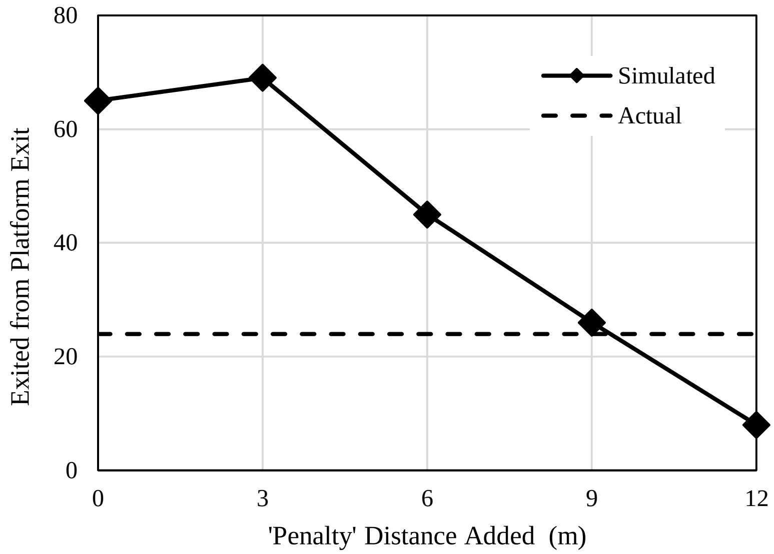


Figure 6-5: Parametric study of the 'penalty' distance to the platform exit

6.4 Validation and Hypothetical Investigations of Social Traits

The egress scenario in the Station Building Fire is modeled, and the simulation results, which include number of occupants using each exits and people dying, are compared with the actual numbers as shown in Table 6-2. Because of the stochastic nature of the simulations, twenty simulations are conducted and average values are reported. Clearly, the simulation results match the actual statistical data well.

Table 6-2: Simulated and the actual data of escaped and deceased

	Main exit	Bar exit	Kitchen exit	Platform exit	Windows	Deceased
Actual	128	78	17	24	105	100
Simulated	135	81	12	26	106	105
Standard Deviation	14	9	6	1	6	12

To give an impression of how the simulation progresses, snapshots at the initial starting point and a series of intermediate times during one run of simulation are taken and presented in Figure 6-6. An important observation is that during the egress process, pre-existing social relationships are taking effect and influencing agents' decisions and behaviors. It can be seen that group behavior driven by strong interactions influences neighboring agents and is observed to lead to clogging and delays in egress. For example, in Figure 6-7.a agents in social groups (color coded in Figure 6.7a) are responding to kin-related interactions thereby delaying others (green). Generally, the main exit, bar exit, and windows played primary roles for egress; on the other hand, other side exits were ignored by most agents. The toxic effect of smoke impaired agents' health and lowered injured agents' mobility, which impeded their egress.

6-3.a t = 0s

6-3.b t = 5s

6-3.c t = 10s

6-3.d t = 20s

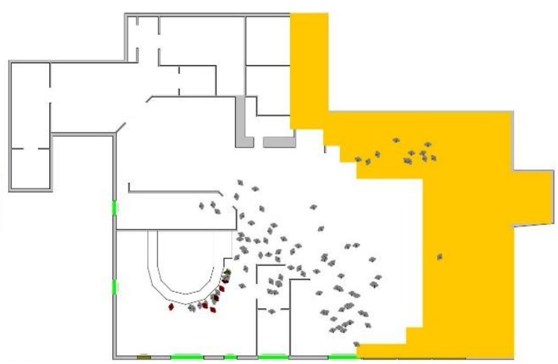
6-3.e t = 30s

6-3.f t = 50s

6-3.g t = 70s

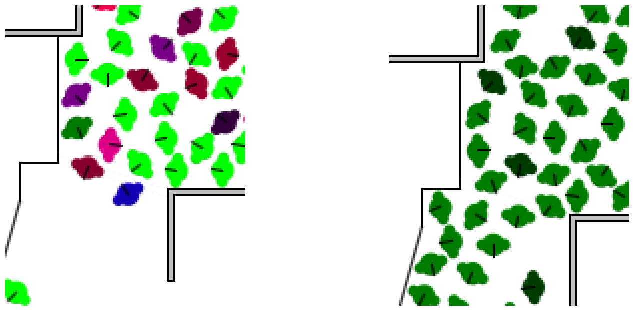
6-3.h t = 100s

6-3.i t = 130s



6-3.j t = 160s

Figure 6-6: Egress from the Station building: snapshots at initial and intermediate times



6-4.a 6-4.b

Figure 6-7: Agents pass narrow area when social relationships are present (a) or not (b)

Two areas, as highlighted in Figure 6-8, are found to be critical for overall egress efficiency of the occupants in the building: the connection between the main bar and main hall, and the connection between the front entrance and main hall. Along with the corridor of the front entrance exit, these areas are filled with agents and become problematic because of the presence of strong social interactions, e.g. spouses and dating partners. Agents driven by such interactions tend to approach their groups, and such gatherings lead to traffic clogs in the connection areas. As a result, the overall egress is delayed by these bottlenecks.

Figure 6-8: Crowded areas in the egress simulation

To investigate the influence of social traits in a quantitative manner, two series of simulations are conducted and then shown. The former one is based on a hypothesis termed "break down"— that each agent has a certain probability to ignore its social affiliations. The latter one is a control test to present the influence of prior visit experience. All simulations shown hereon are conducted twenty times to account for the stochastic nature of the problem.

6.4.1. "Break Down" of Social Relationships

As shown in Table 6-3, the numbers of agents using various exits and those that are deceased are compared in a sensitivity study of "break down" probabilities of 0%, 20%, 40%, 60%, 80%, and 100%. In particular, the case of 0% assumes that every agent responds to its pre-existing relationships, and the case of 100% assumes that all agents ignore their social affiliations and egress alone as individuals.

Table 6-3: Sensitivity study of "break down" probability

Probability	Main exit	Bar exit	Kitchen exit	Platform exit	Windows	Deceased
0%	135	81	12	26	106	105
20%	145	88	13	26	100	93
40%	147	95	15	27	98	83
60%	156	110	14	27	91	66
80%	170	116	14	28	84	53
100%	178	123	11	29	79	45
Actual	128	78	17	24	105	100

Four plots are drawn in Figure 6-9 to showcase the tendencies of using front entrance exit, main bar exit, kitchen exit, and deceased agents versus the "break down" probability, respectively. They are generally linearly dependent on the probability. More agents successfully evacuate through the front entrance exit and main bar exit as the break down probability increases. An example of the case of 0% is given in Figure 6-7.b to show the difference of clogging near narrow area to the case of 100% in Figure 6-7.a. On the contrary, the number of agents using windows to evacuate decreases because the number of remaining agents in the building decreases when the windows become passable at 100 seconds. As a result, the number of deceased agents decreases and is almost half of the 0% condition when every agent drops its social relationships. Clearly, the presence of social relationships increases potential risk and delays the overall egress. This result is consistent with many previous studies, e.g. Johnson *et al* (1994), Cornwell (2003), and Aguirre *et al* (2011b).

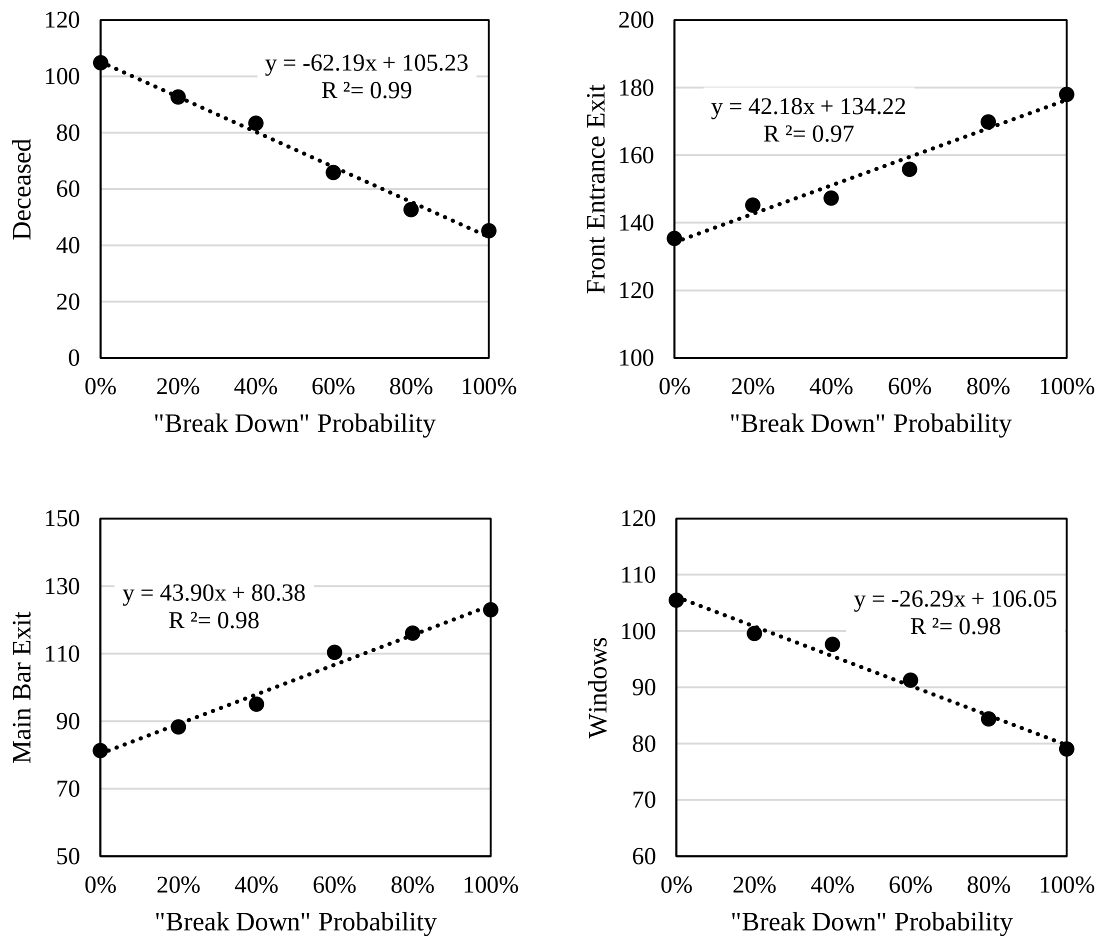
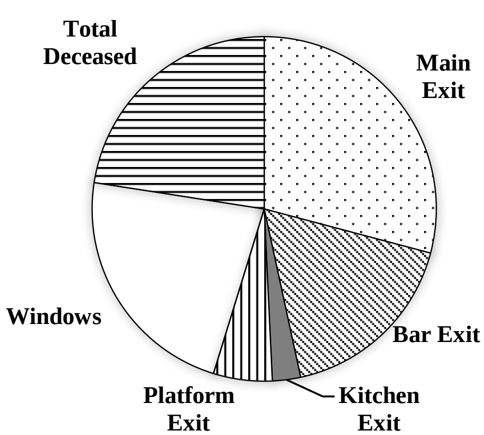


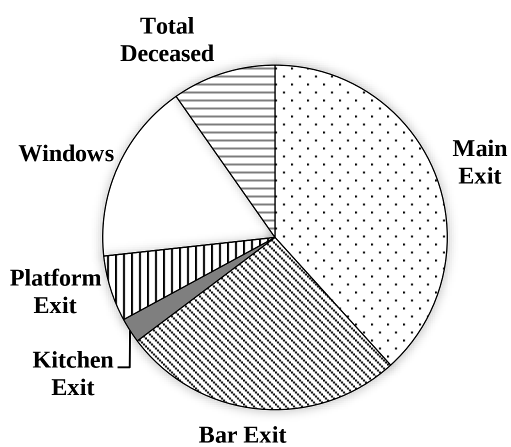
Figure 6-9: Sensitivity study of the “break down” hypothesis

6.4.2. Prior Visit Experience

As discussed earlier, an agent who has no prior visit experience is considered to be aware of only a limited subset of exits, i.e. the kitchen exit and platform exit. To explore the influence of such limitations, a set of control tests, which are comprised of 0% and 100% "break down" cases are conducted under a hypothesis that all agents have prior visit experience and awareness of the full floor plan. The simulation results are drawn in four pie charts as shown in Figure 6-10, in which the numbers of agents using various exits and deceased agents are divided by the total agent number and presented as different components. In Figures 6-10.a and 6-10.b are results extracted from the exercises conducted previously where agents' prior visit experience were pre-described according to the survey data (Aguirre *et al* 2011a, b), followed by the results where all agents are aware of the full floor plan shown in Figures 6-10.c and 6-10.d. Comparing Figure 6-10.a to 6-10.c and 6-10.b to 6-10.d, the effect of no prior visit experience can be viewed for both 0% and 100% "break down" conditions. As expected, significantly more agents evacuate through the platform exit and kitchen exit, so the deceased agents are fewer. On the other hand, the number of agents who use the front entrance exit and the main bar exit are not affected because they are recognized in both series of tests.

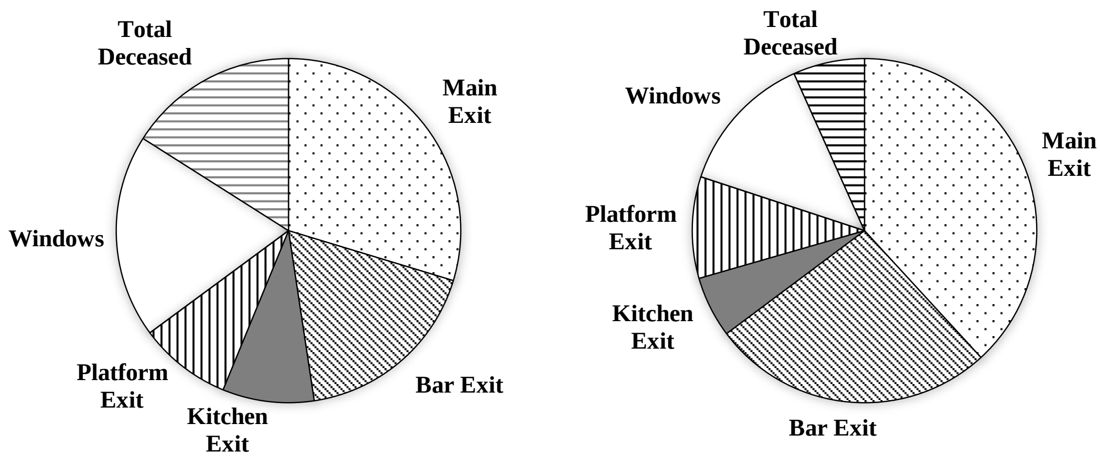


6-10.a



6-10.b

Agents with pre-described prior visit experience incorporating "break down" of 0% (a) and 100% (b).



6-10.c 6-10.d

All agents have prior visit experience with “break down” of 0% (c) and 100% (d).

Figure 6-10: Influence of the Prior Visit Experience

6.5 Summary

This chapter reports on the use of the EgressSFM platform to model a historical egress scenario, the Station Building Fire. The platform is modified to incorporate environmental hazards of fire and smoke, and enabled to compute each agent’s stamina as an energy level, which impacts mobility. The case study considers the demographic and survey data of the occupants in the building when the fire happened. When calibrated, the simulation can capture the realism of the actual data, and shows EgressSFM’s ability to reasonably handle the complex social relationships and group behaviors present during egress. The parametric simulation exercises show that the presence of pre-existing social affiliations can delay the overall egress, and, logically, that lack of knowledge of the building floor plan can be an issue in limiting exit choices and the number of safe evacuations.

CHAPTER 7

SUMMARY AND CONCLUSIONS

7.1 Summary

This dissertation developed: 1) the Scalar Field Method, 2) implemented it in the EgressSFM platform to model human social interactions and collective behavior during emergency egress, and 3) presented a series of validation studies and implementation exercises to showcase the fidelity and capabilities of the new technique. The study started with a survey of the literature on human egress research on individuals and groups. Key characteristics of the egress process were then described. Previous technologies and numerical studies on egress behavior were also reviewed, followed by an analysis of existing Agent-Based models for simulating egress behavior. Gaps in the literature were identified and used to formulate the research goals of this study.

A key problem of modeling an evacuee's "thinking" process was to comprehensively take into account social interactions, and it has been solved in this work by the newly proposed SFM. By drawing analogy to a charged particle in an electric field, the SFM evaluates the accumulation of a series of scalar quantities, which are made to represent human will and social relationships, to simulate the interactions that occur between an agent and its surrounding entities. The result of the "thinking" process of an agent is a 'decision' that minimizes the total virtual potential energy.

The developed EgressSFM platform is comprised of the building and environment model, agent model, and other auxiliary modules. In particular, the building and environment model outlines the geometric constraints and incorporates hazards of fire and smoke, and the agent model explicitly simulates the "thinking" process and behavioral response of an occupant. The preliminary validation studies show the ability of the EgressSFM to mimic reasonable egress behavior, and demonstrate its potential for exploring the influence of social relationships during egress.

The social collective behaviors of queuing, collective mobility, and lining up in counter-flow were analyzed and modeled through a newly proposed follower-leader model, in which an agent can establish informal and transient leader-follower relations with others while adjusting its behavioral patterns as warranted. The model is capable of reasonably simulating self-organized collective behavior during egress, and is calibrated and validated using experiment data.

In the last phase of this work, a well-documented event, the Station Nightclub Fire, was simulated by using the EgressSFM platform. Based on the demographic and surveyed information, a validation exercise was conducted, and its results were found to be reasonably close to the observed data. The EgressSFM platform was then exercised through a series of parametric simulations to quantitatively investigate the influence of social traits on egress behavior.

7.2 Conclusions

Within the scope of the studies conducted in this dissertation, conclusions can be drawn as follows:

1) The Scalar Field Method is capable of handling a complex network of social relationships and comprehensively accounting for both human will and social level effects during egress. Based on SFM, the Agent-Based platform, EgressSFM, has

been shown to realistically model egress behavior through a series of validation and capability tests. In particular, the case study of the Station Nightclub Fire demonstrates that the EgressSFM is valuable for exploring human behavior and social interactions during egress.

2) Social interactions are critical to group gathering and collective behavior during egress. Both pre-existing social relationships and informal relations are important and can change an evacuee's "thinking" processes or behavioral patterns.

3) Group gathering are related to social relationships. The type of the relationship correlates with people's social identities, and determines the intensity by which people influence one another.

4) Social collective behavior of queuing, collective mobility, and lining up in counter-flow can be interpreted as variants of different follower behaviors, driven by a series of informal rules and temporary social relations. Particularly, such local and informal social interactions are critical to form self-organized collective behavior during egress.

5) Effects of social level factors for human emergency egress can be quantitatively studied by implementing the EgressSFM platform. In particular, this work quantifies how and confirms that the presence of pre-existing social affiliations can delay overall egress of occupants, and lack of knowledge of a building floor plan can adversely influence the egress progress.

7.3 Recommendations for Future Research

The following topics are recommended for future research to further explore the effects of social interactions and collective behaviors during emergency egress:

1) *Improving Building and Environmental Model*: The building and environment model of the EgressSFM can be further developed and refined. For example, a fire dynamic simulator can be created to incorporate with the EgressSFM, so that the new model will be eligible for more events. Another possibility is to incorporate structural deformations of the building in disasters, e.g. earthquakes.

2) *Studying Coupling Effects of Hybrid Social Interactions of Pre-Existing Social Relationship, and Informal and Temporary Relations*: The influence of these two types of social interactions are studied independently in this dissertation. However, it is possible that both of them exist and take effect simultaneously. Therefore, studying the coupling effects of such types of relations can be interesting and valuable for learning about a more complex society.

3) *Investigation of the Influence of Social Traits through Hypothetical Exercise*: More hypothetical exercises can be conducted to study the influence of social traits similar to the "break down" and prior visit experience of the Station event presented in Chapter 6. Such exercises can be implemented to help researchers better understand the roles played by social level factors during egress.

4) *Assessment of Floorplan Design or Optimal Design of Egress*: SFM and the EgressSFM platform have shown their abilities for modeling realistic egress behavior, so they can be employed to assess floorplans and discover improper design that may lead to potential danger, and to further improve egress response in large scale facilities.

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