THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

HAROLD AND INGE MARCUS DEPARTMENT OF INDUSTRIAL AND MANUFACTURING ENGINEERING

MULTI-AGENT NETWORK MODELING FOR RAPID RESPONSE AGAINST PUBLIC EMERGENCIES IN COMMUNITIES

XIAORU SHI
FALL 2023

A thesis
submitted in partial fulfillment
of the requirements
for baccalaureate degrees
in Computer Science and Economics
with honors in Industrial Engineering

Reviewed and approved* by the following:

Hui Yang
Professor
Harold and Inge Marcus Department of Industrial and Manufacturing Engineering
Thesis Supervisor

Catherine Harmonosky
Associate Professor and Associate Department Head
Harold and Inge Marcus Department of Industrial and Manufacturing Engineering
Honors Thesis Adviser

*Signatures are on file in the Schreyer Honors College.

Abstract

Heavily populated communities such as cities, universities, and townships are at heightened threat when facing public emergencies, susceptible to significant financial losses and casualties due to their intricate landscapes and high population mobility. The critical need for robust and effective emergency response policies is acknowledged by community administrations. However, there exists a lack of comprehensive analysis of community-wide response processes. Furthermore, little progress has been achieved in establishing a community pedestrian network model to scrutinize response procedures for multiple concurrent and diverse emergencies. Thus, there is an urgent need to develop a simulation model that reflects community layout, and pedestrian flow and accurately represents pedestrian behavior in response to diverse emergencies. This paper unveils a multi-agent community network model to simulate and assess pedestrian response processes in emergency scenarios. First, we develop a community network model that represents different complex real-world communities with flow networks, utilizing publicly accessible map data. Second, we propose human and hazard agents to model pedestrians with diverse pedestrian behaviors and emergencies with distinct characteristics. Lastly, simulation experiments are conducted to assess the correlation between the panic level and the efficacy of response procedures. The designed multi-agent community network model is corroborated through experiments involving simulated emergency responses staged at a large-scale campus under uncertainties from pedestrian flow and hazard occurrences. Experimental results validate the ability of the proposed approach to represent pedestrian flows on complex campuses and provide sufficient environments for response process evaluations. The outcome analysis of simulation experiments provides valid evidence that matches

the nuances of pedestrian behavior proposed in the model in response to diverse emergencies in complex communities. This advancement offers significant potential to aid community administrators and researchers in developing and testing resilient emergency response strategies in case of public emergencies.

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Acknowledgements

The four and half years I spent at Penn State, particularly at the Complex Systems Monitoring, Modeling, and Controls Lab, represent a period of remarkable personal and professional growth. Such accomplishment would not have been possible without the dedicated support of those I deeply appreciate, including Prof. Hui Yang, Hankang Lee, Cheng-Bang Chen, my family, and my partner Ada. First, I would like to express my profound gratitude to Prof. Yang for his generosity in extending the incredible opportunity to gain hands-on professional research experience starting from my first year in college. This early involvement allowed me to accumulate comprehensive experience in numerous parts of the research process, ranging from conducting literature surveys to performing revisions on my manuscript. I am eternally grateful for his confidence in my research capabilities, evidenced by his entrusting me to become the principal investigator for my own project. His insightful guidance and constant encouragement have served as the beacon guiding my journey of research. From him, I learned how to truly present the novelty of my work through compelling storytelling. His wisdom extends beyond academia; he taught me that life is replete with challenges, and neither evasion nor self-doubt is a solution. Therefore, I am committed to confronting difficulties head-on and proactively seeking solutions.

Next, I wish to extend my appreciation to Hankang for his generous mentorship throughout the development of my paper and model. I am genuinely thankful for his patience and guidance. Completing this research would have been unattainable without his step-by-step instructions, engaging discussions, and constructive feedback. He taught me the essence of being a professional and responsible researcher and the nuances of conducting research in a collaborative environment.

Moreover, I acquired numerous invaluable research techniques from him, which will assist me significantly in my forthcoming endeavors as a Ph.D. student. Reflecting on the initial drafts I produced, I recognize the substantial improvements I have made in academic writing, thanks to Hankang's committed mentorship. Despite periods when my research progress was not entirely satisfactory, Hankang remained supportive and consistently provided me with patient guidance. In my view, Hankang is an exceptionally qualified teacher who will become an exemplary professor.

Cheng-Bang served as my initial mentor when I embarked on my research journey. As a novice with no prior research experience, I discovered my passion for research under his guidance. His encouragement was instrumental in helping me identify a novel research gap, leading me to develop my own project. Through his mentorship, I relished the rare privilege of immersing myself fully in research, which is seldom afforded to undergraduate students.

I also wish to express my gratitude to my family, including my partner, Ada, for their unwavering support and nurturing over these years. Their presence has been my pillar through times of adversity. Their love continually replenishes my strength and fortitude, enabling me to face and overcome challenges throughout my research experience. From my family, I have learned the importance of staying humble, regardless of my successes or struggles. With a humble spirit, I have been able to learn and enhance myself day by day.

At last, I would like to acknowledge the National Science Foundation (NSF) award (NSF-CMMI-2026875) and NSF's Research Experiences for Undergraduate program (REU) are acknowledged for their financial support of this research. The author acknowledges that the findings and conclusions in this work are independent and do not necessarily reflect the view of the funding agency.

Chapter 1

Introduction

In the past years, the occurrence of public emergencies and disasters witnessed in society with devastating impacts has been increasing. Such emergencies can cause devastating financial losses, injuries, and fatalities, especially in densely populated communities characterized by intricate layouts of buildings and high mobility. For example, college campuses with intricate pathway networks connecting numerous buildings are particularly vulnerable to such incidents. To enhance transportation convenience, college administrations install numerous paths from each campus building. However, such implementation of pathways contributes to the challenge of selecting the optimal route for evacuating a building to a safe space on campus and can result in congestion at key pathway intersections. When facing emergency situations, the complex structures of college campuses pose significant challenges for disaster relief units to conduct optimal path-sorting to respond to the scene of hazardous impact efficiently. Multiple instances of public emergencies were reported approaching the end of 2022, including shootings, threats of explosives, and chemical leakages at large institutions [1], [2], [3]. In each case, decision makers activated emergency response protocols and enforced evacuations of numerous buildings, which significantly impacted the mental and physical wellness of community members and severely disrupted campus operations [4]. To minimize the disturbance from emergencies, community authorities recognize the necessity of implementing effective response protocols against diverse emergency situations.

Communities with substantial geographical scales, such as cities and townships, pose significant challenges to administrators when implementing response policies due to the physical layout of communities and the unpredictable nature of emergencies. These challenges are further intensified by diverse factors, such as traffic dynamics, community infrastructure, and emergency-induced disorder. Due to such challenges, evaluations of response policies are difficult to achieve through real-world drills. Simulation models are effective in assessing response policies in diverse communities while considering such challenges. Such models enable the evaluation and refinement of response strategies in a controlled environment. Moreover, simulation models provide valuable details on how to optimize complex response procedures. Thus, simulation models have the potential to ensure the safety of society in times of emergency situations.

Furthermore, simulation models for emergency responses provide a flexible and cost-efficient solution to examining and assessing response procedures in complex communities. Unlike physical response drills, simulated experiments are effective in modeling response dynamics under a particular set of hypothesized scenarios while reducing risk and conserving real-world resources. However, little work has been done on developing community models that are capable of simulating responses in communities with distinct structures and demographics. Conventional response models were designed solely for specific communities, limiting their ability to evaluate emergency response processes in other community environments. Thus, there is an urgent need to develop community models for response assessment that can flexibly represent the structure of various communities by utilizing map data.

Simulation models of emergency response evaluation involve considerable structural complexity, such as non-linear pedestrian flow dynamics and the spread of emergencies. Within a community, pedestrians can be categorized into identity groups based on demographic factors and can also behave differently with respect to personality and travel objectives. The nature of pedestrians results in diverse characteristic attributes among the pedestrian population, increasing the challenge for a comprehensive configuration of the model. Each pedestrian makes routing decisions based on their surrounding environment and interaction with other pedestrians. This further contributes to the complexity of the model. Therefore, a community-wide emergency response model necessitates an effective approach that reflects the complex individual and interactive behavior of pedestrians.

In addition, while conventional approaches to rapid response involve a single emergency, in fact, emergencies can co-exist in real-world scenarios, and one incident can result in subsequent emergencies. For example, a severe fire may break out after an explosion. Improperly facilitated emergency response in densely populated communities can lead to a stampede due to mass panic, causing additional casualties and injuries. Hence, it is indispensable to develop response protocols with an effective approach that considers multiple occurrences of various emergencies.

This paper introduces a multi-agent community network model to simulate dynamic pedestrian behavior in response to various emergencies. First, we develop a community network model with open-source map data to imitate structures and pedestrian flow of different real-world communities. The community network model is designed to capture complex features of communities, including the network of pathways connecting buildings and intersections. Second, we propose human and hazard agents via the approach of multi-agent modeling. Human agents reflect the non-linear and diverse behavior of pedestrians in response to emergencies. Hazard agents represent the sources and impacts of different types of emergencies. Finally, we conduct simulation experiments in the form of a case study to evaluate the correlation between panic levels and response effectiveness in campus environments of public universities. The panic level is designed as the combination of the group panic rate and the background panic rate. The group panic rate represents the likelihood of panic among different pedestrian groups, and the background panic rate reflects the degree to which an inability to fully observe surroundings adversely influences evacuation decisions. Experimental results demonstrate the efficacy of the proposed multi-agent community network model in a case study of complex campuses. Simultaneously, the observed correlations between the background panic level and the pedestrian evacuation outcome and effectiveness rates validate the proposed model in diverse evacuation environments. This work has two novel contributions to aid the evaluation of community-wide evacuation procedures to enhance the planning and testing of community evacuation strategies for authorities and researchers:

1. the **community network model** that reflects the structural features of communities in the form of a flow network. This feature provides an efficient solution for representing communities with diverse layouts of buildings and pedestrian flow leveraging geographical data. Moreover, this model yields vital insights into the environment in which pedestrians travel and evacuate.

2. the **human agent and hazard agents** that are designed with the proposed multi-agent modeling approach. This design allows the modeling of dynamic and decentralized evacuation decision-making processes in response to nearby emergencies and the community environment. Furthermore, this approach provides an opportunity for assessing evacuation effec-

tiveness across various scenarios within large communities.

The remainder of this thesis is organized as follows: Chapter 2 introduces the research background of rapid response studies; Chapter 3 details the proposed methodology of the multi-agent network model; Chapter 4 provides experimental design; Chapter 5 validates the proposed methodology and evaluates the effectiveness of response processes; and Chapter 6 concludes this research.

Chapter 2

Research Background

As public emergencies in communities become increasingly frequent, community authorities and researchers recognize the necessity for effective and systematic emergency response protocols. However, the complex structural features and dynamic pedestrian flow of communities pose significant challenges to practicing community-wide emergency response drills with realistic resource capacity. Although previous studies have investigated emergency responses and evacuations in various settings, including manually simulated college campuses [5], public squares [6], internal structures of college campus buildings [7], and high school complexes [8], these environments differ from the intricate pathway networks and dynamic pedestrian flow found in heavily populated, complex communities. Thus, configurations of simulation-based emergency response planning in communities require additional consideration of these unique community features to minimize the impact of incidents.

The nature of complex communities leads to significant challenges in implementing effective and realistic emergency response strategies due to their complex structures and dynamic environments. Such environments are subject to distributed impacts, such as pedestrian traffic, physical details of infrastructures, and subsequent emergencies that occur in the community during the evacuation. While the theoretical foundation of decentralized behavior modeling is available for simulation studies [9], little work has been made on the dynamic and network-based emergency response beyond case studies. Furthermore, conventional case studies on emergency response simulation depended on high-cost and manually crafted models that limit the scale of simulated environments and their applicability to representing systematic emergency responses in other communities.

Each community possesses a distinctive structure, consisting of intricate pathway networks that interconnect buildings of varied purposes [10], [11]. The number of buildings and paths varies significantly across different community environments. Such characteristics of complex communities further challenge the construction of simulation models. For instance, sophisticated surveys that account for varying path lengths are necessitated to reflect the relative position of buildings in a community accurately. Furthermore, detailed investigations of building and pathway features are essential for estimating pedestrian flow capacity at different locations. The result data from these surveys and investigations of different communities significantly differs, requiring flexible and effective mechanisms to model parameters across communities of different sizes and demographics.

To overcome this challenge, geographical data can be conveniently extracted from open sources such as OpenStreetMap [12] to form network models of communities [13]. Networks capture connection patterns of intricate systems by accurately representing the system as a topology. Network models not only reflect interactions between people [14] or sensors [15], but also capture connections in large-scale areas, such as a college campus [16], a county [17] or a state [18]. Therefore, in this work, we represent the structural features of a community as a network of pathways connecting buildings and intersections.

Although network modeling provides an opportunity to simplify the complex environments of communities, additional challenges remain in characterizing decentralized decision-making. The approach of multi-agent modeling effectively represents various individual and interactive behaviors of pedestrians. Agents actively interact with each other based on their differentiated characteristics and autonomous actions [19]. Researchers have conducted agent-based emergency response and evacuation simulation models [20], [21], [8]. These studies have focused on simulations of emergency response and evacuation with a homogeneous set of pedestrian behaviors. In a community, there exist various groups of pedestrians with diverse pedestrian behaviors by characteristics according to factors in the community demographics. Even pedestrians in the same group behave differently based on their identities or travel intentions [22], [23]. The heterogeneous nature of distinct groups of pedestrians further results in different values of pedestrian behavioral parameters, including the likelihood of panic and traveling speed. Specifically, the likelihood of panic is negatively correlated with life experience and positively proportional to age. The movement speed of pedestrians is negatively related to age [24]. Therefore, in this study, we design human agents via multi-agent modeling to describe the diverse individual and group behavioral patterns of pedestrians in the community.

Furthermore, emergencies are highly unpredictable and can rapidly spread within the community. Without proper protocols, the availability of resources and disaster relief efforts in the area of impact can be vastly limited at the time of an emergency outbreak [25]. However, an efficient emergency response can save many lives and prevent subsequent financial losses. An emergency can be defined by the combination of its cause and the area impacted by the hazard [26]. When facing a community-wide disastrous situation, multiple types of emergencies can arise simultaneously or sequentially, posing significant threats to pedestrians. Such threats magnify particularly for large complex communities, where emergencies can occur at different locations within the community, resulting in decentralized hazardous impact. Therefore, there exists an urgent need to develop a community emergency response model that accounts for the cumulative influence of a set of heterogeneous emergencies. Conventional emergency response models have demonstrated that emergencies can trigger other hazards of similar or different types [5], [7]. However, there has been little focus on modeling the concurrence of various emergencies. To address this gap, we design hazard agents with multi-agent modeling to represent heterogeneous emergencies that impact the community.

Chapter 3

Methodology

Table 3.1: Nomenclatures of methodology

Notation	Definition
v_i	Node
s_{v_i}	Coordinate of the location of v_i
c_{v_i}	Capacity of v_i
$f_{v_i}(t)$	Pedestrian flow on v_i at t
A_{v_i}	Attribute set of v_i
e_{ij}	Edge between v_i and v_j
$l_{e_{ij}}$	Total length of e_{ij}
$c_{e_{ij}}$	Capacity of e_{ij}
$f_{e_{ij}}(t)$	Pedestrian flow on e_{ij} at t
h_i	Hazard agent
$t_0^{h_i}$	Time when h_i is emerged in the network
ζ_{h_i}	Lifespan of h_i
$s_{h_i}(t)$	Center of area impacted by h_i at t
$a_{h_i}(t)$	Radius of area impacted by h_i at t
A_{h_i}	Attribute set of h_i
$\mathcal{V}_{h_i}$	Movement speed of $s_{h_i}(t)$
$\mathcal{V}_{h_i}^s$	Expansion speed of $a_{h_i}(t)$
θ_{h_i}	Type identity of h_i
p_i	Human agent
d_{p_i}	Destination node of p_i
$s_{p_i}(t)$	Location of p_i at t
ϕ_{p_i}	The route that p_i is following
$cp_{p_i}(t)$	Position of p_i in terms of the network
$v_{p_i}(t)$	Indicator that the node p_i is positioned at t
$e_{p_i}(t)$	Indicator that the edge p_i is positioned at t
$S_{p_i}(t)$	State of p_i at t
A_{p_i}	Attribute set of p_i
$\mathcal{V}_{p_i}(t)$	Traveling velocity of p_i at t
θ_{p_i}	Group identity of p_i
ϵ_{p_i}	Panic rate of p_i
$S_{p_i}^{\text{End}}$	Binary list indicating the end state of p_i upon exiting the network

In this chapter, we present a multi-agent community network model to simulate and evaluate emergency response processes in complex communities. The proposed model captures the reactive and interactive behavior of pedestrians in response to the physical features of the community and the dynamic impacts and spread of public emergencies. As illustrated in Fig. 3.1, the proposed model consists of three components:

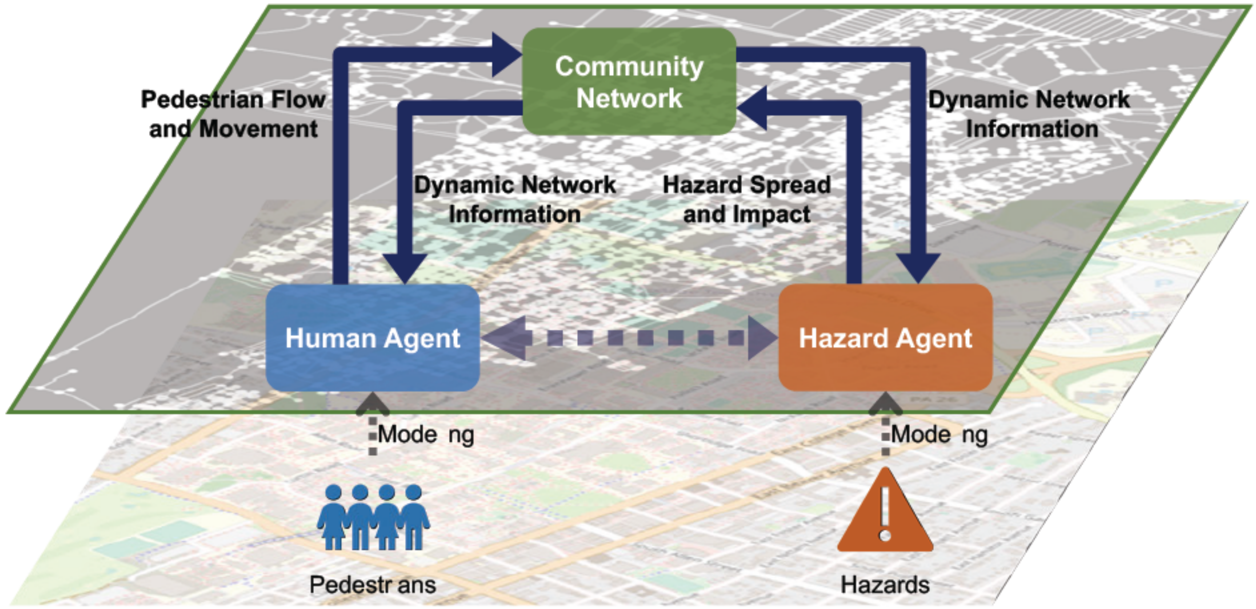

Figure 3.1: The structural overview of the multi-agent community network model.

1. the **community map network model** to flexibly reflect the structural properties of different communities in the form of a network of pathways connecting buildings and intersections;

2. the **hazard agent** that models emergencies by capturing their dynamic spread and impact;

3. the **human agent** that represents pedestrians by reflecting their behavior and reactions to emergencies.

Technical notations in this chapter are outlined in Table 3.1 with definitions.

3.1 Community Network Model

Large and complex communities necessitate the representation of their maps as networks comprising interconnected pathways linking buildings and intersections. However, conventional studies on rapid emergency responses heavily rely on time-consuming and manually crafted simulation models to reflect the intricate environments of each community. As the complexity of the community environment increases, the associated cost rises. Each community environment possesses a distinct network pattern characterized by varying quantities of buildings, pathways, and intersections. Consequently, separate network crafting is indispensable when conducting simulation studies across diverse communities. Therefore, the model construction is considerably constrained by the limited size of the community environment being represented, as well as the applicability of the model in describing other communities with differentiated physical infrastructures. Hence, there is an urgent need to develop community network models with a cost-effective mechanism that can accurately and flexibly represent various large and complex community environments. In this section, we introduce a map-based community network model that captures the dynamics of pedestrian flow across diverse community environments. To achieve this, flow networks are constructed from extracted data from real-world community maps.

The community map is transformed into a multi-graph flow network defined as $G = (V, E)$, where V and E are the sets of nodes and edges, respectively. The node set is finite as every community has a well-defined, and closed geographical boundary. Therefore, the node set V in the community network is defined as follows:

$$V = \{v_i | i \in [1, n_v]\} \tag{3.1}$$

where n_v denotes the number of nodes in the network. In this study, all buildings, road intersections, and open grounds within the community network are explicitly defined as nodes. These nodes are further categorized as building or non-building nodes. Building nodes encompass a variety of typical community buildings, such as commercial buildings, residential buildings, administrative offices, and public purpose centers. Non-building nodes represent intersections as well as open grounds within the community, including parks, lawns, and parking lots.

Each node v_i in the network is defined as follows:

$$v_i = (s_{v_i}, c_{v_i}, f_{v_i}(t), A_{v_i}) \tag{3.2}$$

where s_{v_i} denotes the coordinate of location of v_i, and A_{v_i} represents the set of attributes reflecting the characteristics of v_i, such as its type, area, and whether it is a building or non-building node. In this model, pedestrian flow $f_{v_i}(t)$ is the dynamic count of pedestrians located at node v_i at time t. Pedestrian capacity c_{v_i} of each node is defined as the maximum value of $f_{v_i}(t)$ that can be sustained without exceeding the infrastructure constraints of v_i. Capacity c_{v_i} is estimated based on information from open-source amenity data of the community.

In the community network, an edge represents a pathway between two nodes. Thus, the edge set E is defined as follows:

$$E = \left\{ e_{ij} = (v_i, v_j) | v_i, v_j \in V^2, \text{and} \neq j \right\} \tag{3.3}$$

where each edge e_{ij} is denoted as follows:

$$e_{ij} = \left(l_{e_{ij}}, f_{e_{ij}}(t), c_{e_{ij}} \right) \tag{3.4}$$

where $l_{e_{ij}}$ represents the total distance pedestrians need to travel along e_{ij} to reach v_j from v_i. Pedestrian flow $f_{e_{ij}}(t)$ reflects the number of pedestrians moving along e_{ij} at time t. Edge capacity $c_{e_{ij}}$ is defined as the maximum value of $f_{e_{ij}}(t)$ that can be sustained without exceeding the designed path constraints. In this study, the edge length $l_{e_{ij}}$ is estimated as:

$$l_{e_{ij}} = \lfloor l^b_{e_{ij}} \cdot w_{e_{ij}} \rfloor \tag{3.5}$$

where $l^b_{e_{ij}}$ represents the Euclidean distance between v_i and v_j, and $w_{e_{ij}}$ is the degree of curvature of e_{ij}. Furthermore, $c_{e_{ij}}$ is formally defined as:

$$c_{e_{ij}} = l_{e_{ij}} \cdot D_{max} \tag{3.6}$$

where D_{max} is the maximum pedestrian volume sustainable per each unit length of $l_{e_{ij}}$.

Safe spaces are defined as nodes representing open grounds and public purpose centers during the emergency response. The set of safe spaces is denoted as:

$$V_{sp} = \left\{ v_{sp_i} | i \in [1, n_{v_{sp}}] \right\} \tag{3.7}$$

where $V_{sp} \subset V$, and $n_{v_{sp}}$ is the number of safe spaces in the network. The safe spaces are designed to withstand hazardous impacts due to their resilient physical structures and the supervision provided by community authorities or public administrations. Moreover, such spaces serve as control centers for necessary support and disaster relief efforts. Capacity $c_{v_{sp_i}}$ for each safe space denotes its maximum shelter capacity, which is determined by the available amounts of resources and services at v_{sp_i}. When a pedestrian is affected by an emergency, they will actively respond to the effect by evacuating toward the nearest safe space to avoid subsequent hazardous impact. Once an evacuee arrives at any v_{sp_i}, they are considered evacuated.

3.2 Hazard Agents

In complex communities, multiple types of emergencies can occur simultaneously or sequentially. As a result, the hazardous impact becomes decentralized when multiple emergencies are distributed throughout the community environment. The severity of emergencies can vary depending on their type, and even emergencies of the same type can exhibit different characteristics, such as differences in the radius of the area impacted by an emergency. Therefore, there is an urgent need to develop a modeling approach that captures the cumulative hazardous influence on the community by aggregating the decentralized impact of individual emergencies. Multi-agent modeling is an effective approach for representing the variance among emergencies and simulating the negative influence from a heterogeneous set of emergencies. In this section, we propose the design of hazard agents to represent the emergencies that actively impacting the community. These hazard agents serve as dynamic entities that embody the characteristics and behavior of different emergencies, allowing us to capture their collective impact on the community and its pedestrians.

The set of hazard agents impacting the network is denoted as follows:

$$H = \{h_i | 1 \leq i \leq \mathcal{H}_{\text{max}}\} \tag{3.8}$$

where $\mathcal{H}_{\text{max}}$ is an input parameter to the simulation representing the maximum number of emergencies that impact the community throughout the simulated emergency response. Emergencies are characterized by the composite of their causes and their corresponding circular impact areas. For example, during the occurrence of a chemical leakage emergency, the source can be identified as a leaking chemical container. The severity of the emergency is determined by the combined characteristics exhibited by both the source and the hazardous impact area. To effectively model the stochastic nature of hazardous impacts, each hazard agent h_i is defined as a tuple of parameters as follows:

$$h_i = (\zeta_{h_i}, s_{h_i}(t), a_{h_i}(t), A_{h_i}) \tag{3.9}$$

where ζ_{h_i} represents the duration from the emergence of h_i until its end, either by complete management through response effort or natural cessation. $s_{h_i}(t)$ denotes the coordinate of hazard agent h_i at time t, indicating the center of the impact area. $a_{h_i}(t)$ corresponds to the radius of the circular impact area. During the simulation setup, the values of ζ_{h_i} and the initial $a_{h_i}(t)$ are defined for each hazard type.

To capture the inherent distinctions among various types of emergencies and emergencies of the same type, each hazard agent h_i has a set of characteristic attributes denoted as A_{h_i}. These attributes describe the distinct properties of the hazard agent, facilitating a comprehensive understanding of its nature and impact. A_{h_i} is defined as:

$$A_{h_i} = \left\{\mathcal{V}_{h_i}, \mathcal{V}^s_{h_i}, \theta_{h_i}\right\} \tag{3.10}$$

where $\mathcal{V}_{h_i}$ reflects the traveling speed of the hazard agent h_i, and $\mathcal{V}^s_{hi}$ is the spread speed of h_i within its impact area. Furthermore, θ_{h_i} represents the hazard type of h_i. Alternatively, $\mathcal{V}_{hi}$ and

$\mathcal{V}_{hi}^s$ correspond to the rates of change for s_{h_i} and $a_{h_i}(t)$, respectively. Thus, the dynamic scale of $a_{h_i}(t)$ at simulation time t is denoted as:

$$a_{h_i}(t) = \mathcal{V}_{hi}^s \cdot (t - t_0^{h_i}) + a_{h_i}(t_0^{h_i}) \tag{3.11}$$

where $t_0^{h_i}$ indicates the simulation time when h_i emerged into the network. The values of $\mathcal{V}_{hi}^s$, $\mathcal{V}_{hi}$, and θ_{h_i} are determined during the setup phase for each simulation trial, based on the specific hazard type being considered.

3.3 Human Agents

Within each community, pedestrians can be categorized into various groups based on demographic factors. Pedestrians exhibit diverse characteristics according to their identities and personal backgrounds. Each pedestrian makes travel decisions and interacts with other pedestrians and the surrounding environment based on their current observation, increasing complexity and non-linearity in the modeling of pedestrian flow. Therefore, it is imperative to develop a modeling approach that represents the heterogeneous characteristics and varied behavior of different groups of pedestrians in a community network. Thus, we introduce human agents to reflect the autonomous behavior of each pedestrian. We further propose two iterative algorithms to simulate the dynamic and interactive behavior of pedestrians.

The pedestrian population in the community network is represented as a set of human agents P denoted as follows:

$$P = \{p_i | 1 \leq i \leq \mathcal{P}_{\text{max}}\} \tag{3.12}$$

where $\mathcal{P}_{\text{max}}$ denotes the maximum volume of pedestrian flow in the community. Similar to $\mathcal{H}_{\text{max}}$, $\mathcal{P}_{\text{max}}$ is an input parameter upon simulation setup. To capture the autonomous behavior of pedestrians, each human agent p_i is defined as follows:

$$p_i = (d_{p_i}, s_{p_i}(t), \phi_{p_i}, cp_{p_i}(t), S_{p_i}(t), A_{p_i}) \tag{3.13}$$

where d_{p_i} denotes the destination of p_i, and $s_{p_i}(t)$ represents the location of p_i at simulation time t. The traveling route ϕ_{p_i} followed by p_i from $s_{p_i}(t)$ to d_{p_i} is denoted as follows:

$$\phi_{p_i} = (V_{p_i}, E_{p_i}), V_{p_i} \subset V, E_{p_i} \subset E \tag{3.14}$$

where n nodes in V_{p_i} and $n-1$ edges in E_{p_i} are interconnected alternately to form the route. Specifically, $e_j = (v_j, v_{j+1})$ for $0 \leq j \leq n-1$. The route is dynamically updated based on the observation of p_i on the network and hazards.

The node or edge where pedestrian p_i is located at time t is denoted by $cp_{p_i}(t)$, which is defined as follows:

$$cp_{p_i}(t) = (v_{p_i}(t), e_{p_i}(t)) \tag{3.15}$$

where $v_{p_i}(t)$ and $e_{p_i}(t)$ are the time-dependent variables that indicate the node and edge where p_i is positioned at t, respectively. Unlike the specific coordinate $s_{p_i}(t)$, $cp_{p_i}(t)$ represents the location of p_i relative to the community network G. At each simulation time t, p_i is exclusively positioned at either a node or an edge. For example, if p_i is located in $v_{p_i}(t) \in V$ at t, then $cp_{p_i}(t) = (v_{p_i}(t), \emptyset)$.

The state of p_i is captured by $S_{p_i}(t)$, which is a binary state list denoting the following states: "Normal," "Impacted," "Queuing," and "Exiting." $S_{p_i}(t)$ governs the decision-making process of p_i during the emergency response. For example, when the hazardous impact from a nearby emergency influences p_i, $S_{p_i}(t)$ is labeled as "Impacted," and p_i initiates active evacuation. At each t, if traffic congestion or inaccessibility to nodes and edges induced by hazardous conditions prevent p_i from following their current route, the human agent enters the "Queuing" state. There are two scenarios for queuing:

1. if all outgoing edges from node $v_{p_i}(t)$ are congested, p_i queues at $v_{p_i}(t)$;

2. if the edge $e_{p_i}(t) = (v_m, v_w)$ or the end node v_w is congested, p_i queues at $e_{p_i}(t)$.

Once p_i arrives at their destination safely, p_i leaves the network and enters the "Exiting" state. Additionally, the initial state of p_i is "Normal", and the state remains as "Normal" if p_i has never been labeled as "Impacted," "Queuing," or "Exiting."

To capture the diverse characteristics among distinct groups of pedestrians, each human agent p_i is designed with a set of attributes denoted as A_{p_i}. These attributes include factors such as traveling speed, demographic information, and the propensity to panic during emergencies. A_{p_i} is defined as follows:

$$A_{p_i} = \left\{ \mathcal{V}_{p_i}(t), \theta_{p_i}, S_{p_i}^{\text{End}}, \epsilon_{p_i} \right\} \tag{3.16}$$

where $\mathcal{V}_{p_i}(t)$ represents the traveling speed of p_i at time t, and θ_{p_i} denotes the group to which p_i belongs. $S_{p_i}^{\text{End}}$ indicates the end state of p_i when they exit the network. $S_{p_i}^{\text{End}}$ is a binary state list denoting the following end state: "Arrival," "Survival," and "Casualty."

The panic rate ϵ_{p_i} represents the likelihood of panic when the human agent p_i is considered "Impacted." Once panic, the human agent deviates from its optimal evacuation route. The panic level varies across different pedestrian groups and depends on the completeness of the observation necessitated for rapid emergency response. Therefore, the panic rate ϵ_{p_i} is a combination of two types of panic rates: the group panic rate and the background panic rate. The group panic rate $\epsilon_{p_i}^{\text{grp}}$ captures the varying likelihood of panic among different groups of pedestrians. On the other hand, the background panic rate $\epsilon_{p_i}^{\text{bg}}$ accounts for the negative influence on decision-making due to incomplete background information obtained concerning the community. Such information includes the knowledge of community network structures and actions of the community authority. The design of $\epsilon_{p_i}^{\text{bg}}$ is based on the understanding that panic is positively related to the degree of uncertainty, which increases with the incompleteness of the observation set. When pedestrians are more informed, they can make more effective evacuation decisions.

During the response to emergencies, pedestrians rely on the most recent observation available from their surroundings to make informed decisions. This observation encompasses information about the community networks and hazards. To reflect the process of capturing this information and making evacuation decisions, we propose two interaction algorithms: (1) Human-Network Interaction Algorithm and (2) Human-Hazard Interaction Algorithm.

Algorithm 1: Human-Network Interaction Algorithm $HuInterN(t)$.

forall $p_i \in P$ **do**
  if $s_{p_i}(t) \neq d_{p_i}$ **then**
    if $v_{p_i}(t) \in V$ **then**
      if $f_{v_{p_i}}(t) \geq c_{v_{p_i}}$ **then**
        if $f_{e_j} \geq c_{e_j}, \forall e_j \in E(v_{p_i}(t))$ **then**
          p_i is considered "Queuing"
        else There are non-congested surrounding edges
          if p_i is in panic **then**
            p_i randomly selects $e_j \in E(v_{p_i}(t))$
          else p_i is not in panic
            p_i re-routes
          end
          Update $s_{p_i}(t+1)$ based on $\mathcal{V}_{p_i}(t)$
          Update $cp_{p_i}(t+1)$ based on $cp_{p_i}(t)$, ϕ_{p_i}, $s_{p_i}(t)$
        end
      else no congestion
        Update $s_{p_i}(t+1)$ based on $\mathcal{V}_{p_i}(t)$
        Update $cp_{p_i}(t+1)$ based on $cp_{p_i}(t)$, ϕ_{p_i}, $s_{p_i}(t)$
      end
    else $e_{p_i}(t) \in E$
      if $f_{e_{p_i}}(t) \geq c_{e_{p_i}}$ **then**
        p_i is considered "Queuing" and $\mathcal{V}_{p_i}(t) \leftarrow 0$
      else no congestion
        Update $s_{p_i}(t+1)$ based on $\mathcal{V}_{p_i}(t)$
        Update $cp_{p_i}(t+1)$ based on $cp_{p_i}(t)$, ϕ_{p_i}, $s_{p_i}(t)$
      end
    end
  else p_i reaches d_{p_i}
    if $S_{p_i}(t) =$ "Normal" **then**
      $S_{p_i}^{\text{End}} \leftarrow$ "Arrival"
    else $S_{p_i}(t) =$ "Impacted"
      $S_{p_i}^{\text{End}} \leftarrow$ "Survival"
    end
    $S_{p_i}(t+1) \leftarrow$ "Exiting"
  end
end

Interactions between human agents and the community network are modeled for each p_i at every simulation time t, following Algorithm 1. The algorithm captures how human agents travel and evacuate while having limited information concerning the network. This interaction plays a crucial factor in forming pedestrian flow, which directly influences the overall outcome of the rapid emergency response process. At each time t, the properties of each human agent $p_i \in P$ are simultaneously updated, considering the current status of the community network and the observation from the immediately preceding time. This interaction mechanism allows the behavior of each human agent to be influenced by the evolving network conditions and observed information, leading to a more realistic representation of pedestrian dynamics during the rapid response process.

Congestion arises when pedestrian flow approaches the capacity at any node or edge in the network, resulting in a proportional reduction in pedestrian traveling speed. If p_i is "Queuing" at node $v_{p_i}(t)$, p_i searches for an alternative path within the set of outgoing edges $E(v_{p_i}(t))$ from $v_{p_i}(t)$. Also, it is assumed that only non-panic human agents can make effective rerouting decisions. When human agents panic and are on congested nodes, they make detour decisions based on rationality determined by ϵ_{p_i}. While p_i is not panicking, p_i plans and follows a new route to d_{p_i} after detouring at $v_{p_i}(t)$. When p_i is "Queuing" at edge $e_{p_i}(t)$, their traveling speed $\mathcal{V}_{p_i}(t)$ becomes zero. Upon arriving at the destination d_{p_i}, the end state $S_{p_i}^{\text{End}}$ of p_i is determined based on the current state $S_{p_i}(t)$.

Algorithm 2: Human-Hazard Interaction Algorithm $HuInterH(t, \epsilon_{p_i}^{\text{bg}}, \epsilon_{p_i}^{\text{grp}})$.

```
forall p_i ∈ P do
    if s_{p_i}(t) ∈ a_{h_j}(t), ∀h_j ∈ H then
        p_i is considered "Impacted"
        Compute whether p_i becomes casualty
        if p_i becomes casualty then
            S_{p_i}^End ← "Casualty"
            S_{p_i}(t + 1) ← "Exiting"
        else p_i is evacuating
            Compute ε_{p_i} based on ε_{p_i}^bg and ε_{p_i}^grp
            Determine if p_i is in panic based on ε_{p_i}
        end
    end
end
```

Interactions between human and hazard agents are reflected in the decision-making process of individual p_i at each simulation time t, following Algorithm 2. This algorithm depicts how p_i actively observes the hazard agents in their immediate vicinity while having limited information regarding the set of hazards H that is impacting the community. Furthermore, this algorithm captures the detrimental effects of hazard agents on the survivability and decision-making of p_i during the evacuation process. The adverse impact of hazard agents on human agents is manifested in two aspects. First, human agents will initiate evacuation when they directly encounter the hazard by locating in the impact area of a nearby hazard. Additionally, evacuation is initiated when human agents become aware of the impacts of any hazard agent within a predetermined radius. Second, irrational evacuation behavior is represented as continuous deviations from the prescribed route ϕ_{p_i} if the panic state of p_i persists.

Chapter 4

Experimental Design

The proposed multi-agent community network model is assessed in two steps, including (1) verification of the community network model and (2) validation of the multi-agent modeling approach on human and hazard agents. The first step is accomplished through simulation experiments implementing pedestrian flow on large university campuses. The second phase is achieved through a case study on a complex public campus that examines the effectiveness of the simulated rapid emergency response across varying panic levels.

4.1 Experiment on the Community Network Model

Three college campuses are selected as representative communities to verify the modeling ability of the community network model utilizing map data. These campuses encompass the University Park campus of the Pennsylvania State University (PSU-UP), the Charlottesville campus of the University of Virginia (UVA-C), and the Blacksburg campus of Virginia Tech (VT-B). University campuses represent intricate and large communities with diverse layouts of buildings, complex pathways, and substantial pedestrian flow. The community network model is constructed based on geographical data extracted from OpenStreetMap [12], [13].

The simulation outcomes provide an in-depth portrayal of the network modeling results that represent the structural features of these campuses. This includes network model attributes like nodes and edges illustrating the connection patterns of the community. Furthermore, the result includes the visualized spatial distribution of pedestrian flow that is captured and displayed on the community map. Depiction of dynamic pedestrian flow in community networks provides significant insights into the environment that pedestrians consult while making movements and evacuation decisions against presenting emergencies. To validate the capabilities of the standardized community network model, five simulation experiments were conducted for each campus scenario. Environmental and policy-related factors were fixed as $\mathcal{P}_{\max} = 2{,}000$, $\mathcal{H}_{\max} = 5$, and $\epsilon_p^{\mathrm{bg}} = 10\%$.

4.2 Case study on the multi-agent modeling approach

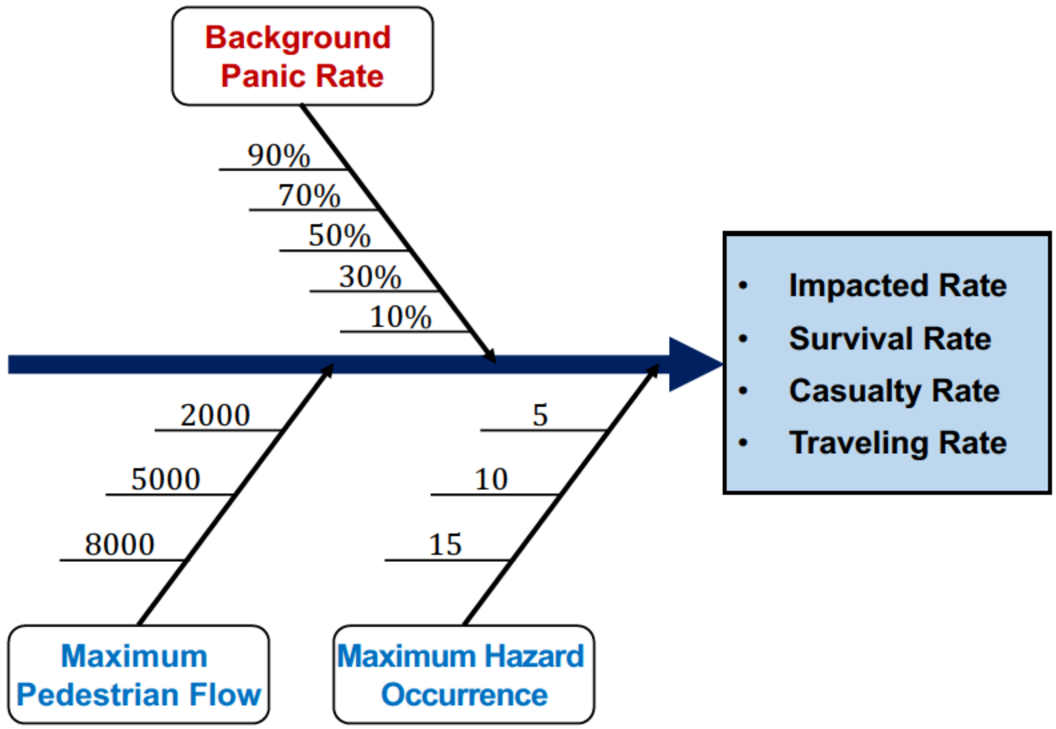

Figure 4.1: Experimental design of the case study

The proposed multi-agent is validated through a case study evaluating rapid response procedures according to varying panic levels under conditions of uncertainty regarding the pedestrian population and hazard occurrence. As shown in Fig. 4.1, this study identifies three control factors to capture the impact of diverse response policies on the outcome of evacuations and the uncertainties inherent in pedestrian flow and hazard occurrences. The impact arising from distinct rapid response policies is encapsulated by the concept of the background panic rate (ϵ_p^{bg}). This factor quantifies the negative influence on response decisions based on the degree to which ambient observations are imperfect due to different emergency response policies. Because all pedestrians are assumed to have equal access to the knowledge and information of emergency response processes, pedestrians are postulated to share a uniform background panic rate throughout the simulation process. In each experimental configuration, the scope of the background panic rate spans from 10% to 90%.

The influence stemming from pedestrian flow and hazard occurrences is regulated through the manipulation of two control factors: the maximum pedestrian flow within the community ($\mathcal{P}_{\max}$) and the maximum number of hazard occurrences ($\mathcal{H}_{\max}$). Within the simulation framework, both human and hazard agents are generated stochastically to represent pedestrians and emergencies. In the scenario configuration, $\mathcal{P}_{\max}$ varies between 2,000 and 8,000, and $\mathcal{H}_{\max}$ is set between 5 and 15. These control factors ensure the generation of diverse emergency scenarios in the community, thereby furnishing a comprehensive spectrum for evaluating the robust efficacy of rapid response protocols.

Table 4.1: Human Agents Group Parameters

Identity	Age Range	Speed (m)	Panic Rate (%)	portion (%)
Group 1	[18,25]	96	60	60
Group 2	[25,50]	84	50	20
Group 3	[40,60]	72	20	20

Table 4.2: Hazard Agent Type Parameters

Type	Lifespan (minute)	Area as Radius (m)	Expansion Speed (m/s)	Movement Speed (m/s)
Type 1	[130,170]	[150,200]	[25,35]	[30,42]
Type 2	[30,50]	[20,80]	[0,10]	[90,102]
Type 3	[120,170]	[200,400]	[100,120]	[102,204]

The diversity inherent in pedestrian behavior is captured through the definition of human agent groups. In this case study, three pedestrian groups are defined, as outlined in Table 4.1. These group parameters are designed to reflect correlations between age and likelihood to panic and traveling speed [24], [27]. Similarly, we define three hazard agent types in this case study, represented by distinct parameters, as presented in Table 4.2. These parameters indicate attributes of emergency characteristics, including lifespan, impact area, movement and spreading speeds of the hazard.

Evaluation of rapid response performance is analyzed in two stages: 1) impact assessment of environmental factors and 2) policy factor effectiveness analysis. Four performance metrics are defined to capture the response effectiveness in different aspects, as shown in Fig. 4.1. The impacted rate (R_{I}) is designed to evaluate the influence of environmental factors on the degree of pedestrians impacted by hazards. The ratio is defined as:

$$R_{\mathrm{I}} = \frac{n_{\mathrm{I}}}{\mathcal{P}_{\max}} \tag{4.1}$$

where n_{I} represents the number of pedestrians affected by any hazards. Assessment of policy factor effectiveness is encapsulated by three performance metrics: success rate (R_{S}), casualty rate (R_{C}), and traveling rate (R_{T}). Each metric is a ratio to the number of pedestrians impacted by hazards. They can be defined as:

$$R_{\mathrm{S}} = \frac{n_{\mathrm{S}}}{n_{\mathrm{I}}} \tag{4.2}$$

$$R_{\mathrm{C}} = \frac{n_{\mathrm{C}}}{n_{\mathrm{I}}} \tag{4.3}$$

$$R_{\mathrm{T}} = \frac{n_{\mathrm{I}} - n_{\mathrm{S}} - n_{\mathrm{C}}}{n_{\mathrm{I}}} \tag{4.4}$$

where n_{S} and n_{C} denote the number of survivors and casualties, respectively. These measures provide valuable insights into the effectiveness of rapid response policies across a range of emergency scenarios in the community. The simulation results of five iterations in each scenario were collected in the case study for assessing response effectiveness. The scenarios are based on different levels of control factors that are outlined in Fig. 4.1.

Chapter 5

Experimental Results

Table 5.1: Network Stats

Network	Node Volume	Edge Volume
PSU-UP	7,623	19,799
UVA-C	2,541	7,095
VT-B	2,517	6,929

In this section, the proposed multi-agent community model is assessed using data from simulation trials. First, a presentation is given on each campus featuring the map and skeleton network with an analysis of the spatial network flow. Subsequently, the simulated response data from each emergency scenario in the case study are compared against their respective configuration of control factors to validate the capability of the model in elucidating emergency response processes.

5.1 Verification of Community Network Model

As presented in Table 5.1, each college campus is represented by a network with distinct numbers of nodes and edges. Among the campuses, PSU-UP exhibits the most intricate network, comprising 7,623 nodes and 19,799 edges. Nevertheless, every campus network encompasses over 2,500 and 6,500 edges. This result underscores the notable variability in the number of buildings, intersections, and pathways across communities, even when these communities share similarities in the functionality of buildings, demographic profiles, and pedestrian orientation.

The illustration of the campus community map and the corresponding skeleton network representation of PSU-UP, UVA-C, and VT-B are shown in Fig. 5.1. Within each skeleton graph, white dots signify nodes, with their interconnections being edges. While each campus manifests a unique network topology, a non-linear arrangement of buildings, intersections, and pathways exists. The intricacy of communities, such as college campuses, emphasizes the importance of employing network modeling and simulation in assessing community-wide rapid response processes against diverse emergencies. The conventional method requires significant computational effort to survey each campus for the relative positions of buildings and intersections and the varying path lengths

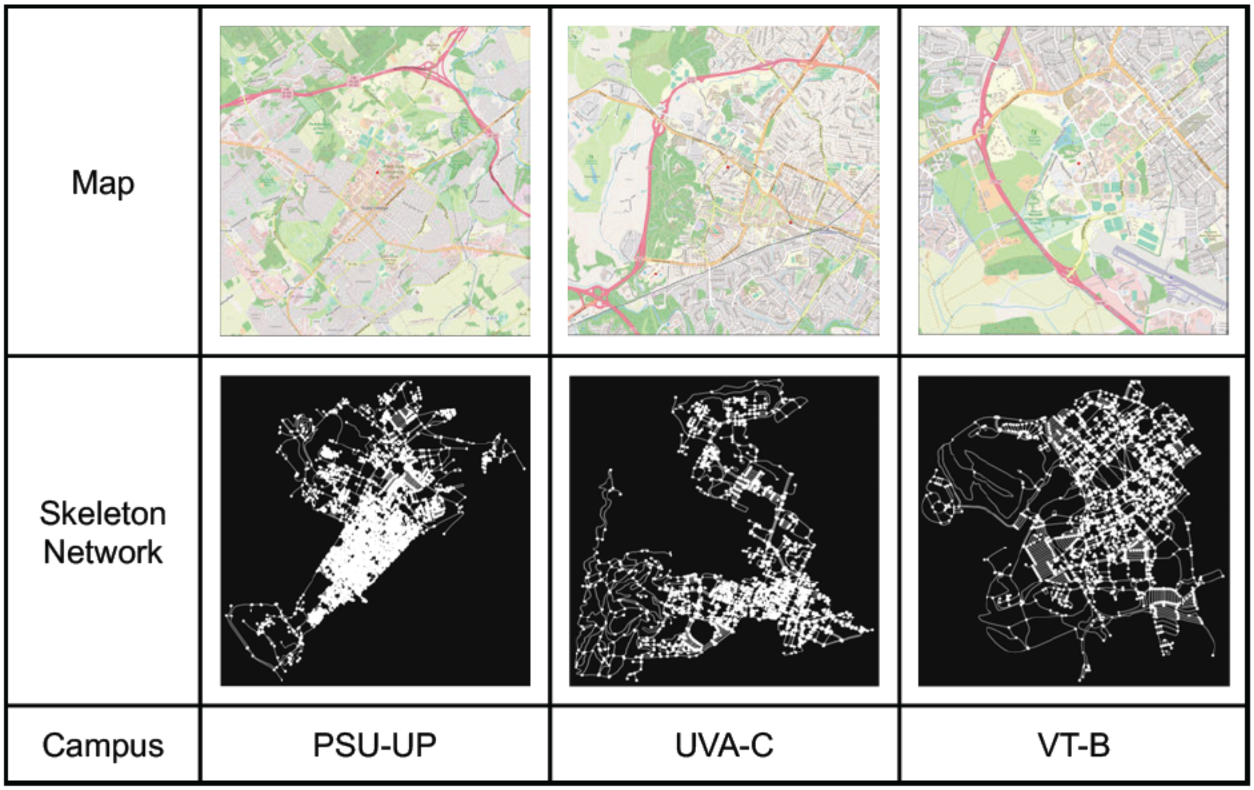

Figure 5.1: Illustrations of maps and skeleton networks of PSU-UP, UVA-C, and VT-B.

connecting them. In contrast, the proposed community network model demonstrates flexibility and accuracy in representing the structural features of each campus as a corresponding fully connected network when provided with only the geographical indicator of the community.

While holding $\mathcal{P}_{\max}$ at 2,000, $\mathcal{H}_{\max}$ at 5, and ϵ_p^{bg} at 10%, the spatial distribution of pedestrian flow on each campus at t of 0, 30, 60, 90, and 120 are shown in Fig. 5.2. Red dots symbolize pedestrians. Notably, the spatial distribution of the pedestrian flow of each campus aligns closely with the structural features depicted by the skeleton network of each campus. This congruence validates the proficiency of the community network model in predicting dynamic pedestrian flow patterns. Furthermore, this model can effectively represent the spatial distribution of pedestrian flow in communities based on captured features with flow networks. As the simulation progresses over time, noticeable reductions in pedestrian flow are observed at each campus, suggesting successful and rapid response and route navigation by pedestrians while consulting the community flow network.

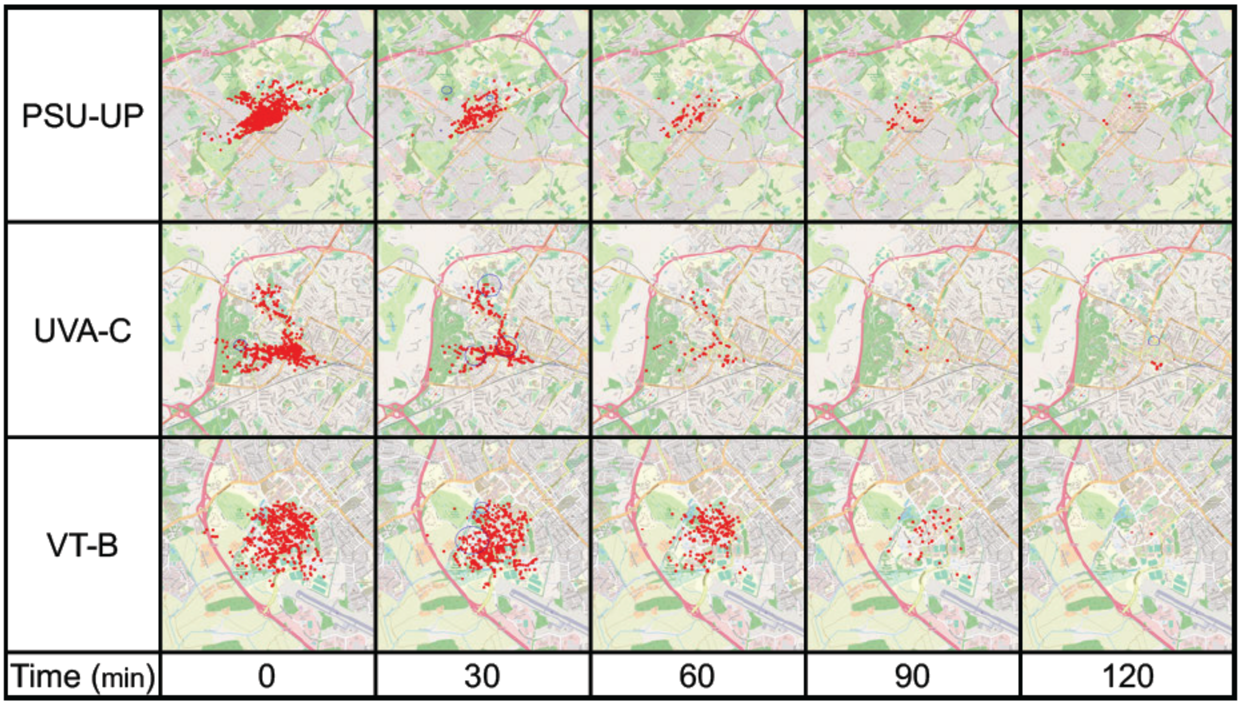

Figure 5.2: Pedestrian flow and evacuation progress over time from 0 to 120 during evacuation on each campus where $\mathcal{P}_{\max} = 2000$, $\mathcal{H}_{\max} = 5$, and $\epsilon_p^{\text{bg}} = 10\%$.

The flow networks provide the necessary representation of the real-world community environment pedestrians travel and evacuate. Additionally, the spatial distribution of pedestrian flow yields valuable details on where the pedestrian flow can be congested during an emergency response, providing vital details for response process evaluation. Thus, the community administrations can leverage the simulated flow network and pedestrian flow distribution to plan and implement response policies accordingly to avoid traffic congestion and reduce subsequent costs, including injuries, financial damage, and casualties.

5.2 Case Study: Assessment of Rapid Response Outcome across Panic Levels

The case study is designed to assess the efficacy of the multi-agent modeling approach in scrutinizing emergency response processes. It exemplifies how the multi-agent community network model can be employed by researchers and community authorities to design and appraise rapid response policies or study potential factors that affect response outcomes. The study consists of two primary steps:

1. **Impact Assessment of Environmental Factors**: This phase evaluates the effects of diverse emergency scenarios on the cumulative number of pedestrians affected by hazards within the community. The number of affected pedestrians provides insight into the severity of the impact the community is facing. Specifically, the influence of $\mathcal{P}_{\text{max}}$ and $\mathcal{H}_{\text{max}}$ on R_{I} is examined.

2. **Policy Factor Effectiveness Analysis**: The stage scrutinizes how policy affects response outcomes in different emergency scenarios. More precisely, A nuanced correlation analysis is conducted to elucidate the pronounced influence of ϵ_p^{bg} on R_{S}, R_{C}, and R_{T}. Then, the summarized R_{S}, R_{C}, and R_{T} are compared across different $\mathcal{P}_{\text{max}}$ and $\mathcal{H}_{\text{max}}$ levels.

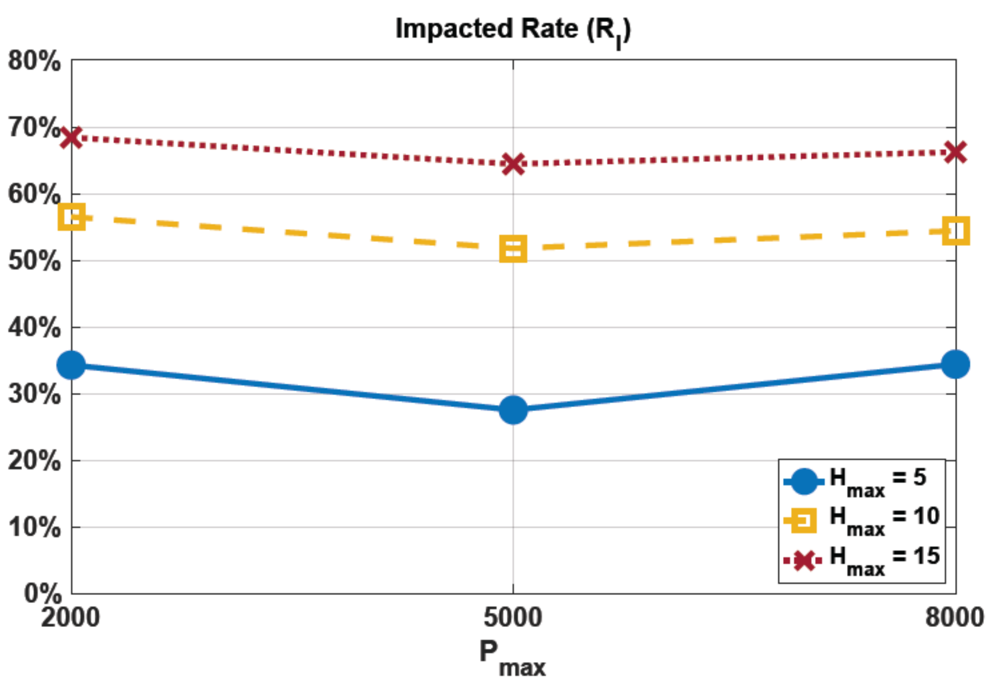

Figure 5.3: Impacted rate of pedestrians according to maximum pedestrian flow and maximum number of hazard occurrences.

The average R_{I} observed at different levels of $\mathcal{P}_{\text{max}}$ and $\mathcal{H}_{\text{max}}$ are depicted in Fig. 5.3. A significant observation is the rise in R_{I} with the increase in $\mathcal{H}_{\text{max}}$. An increase in $\mathcal{H}_{\text{max}}$ signifies

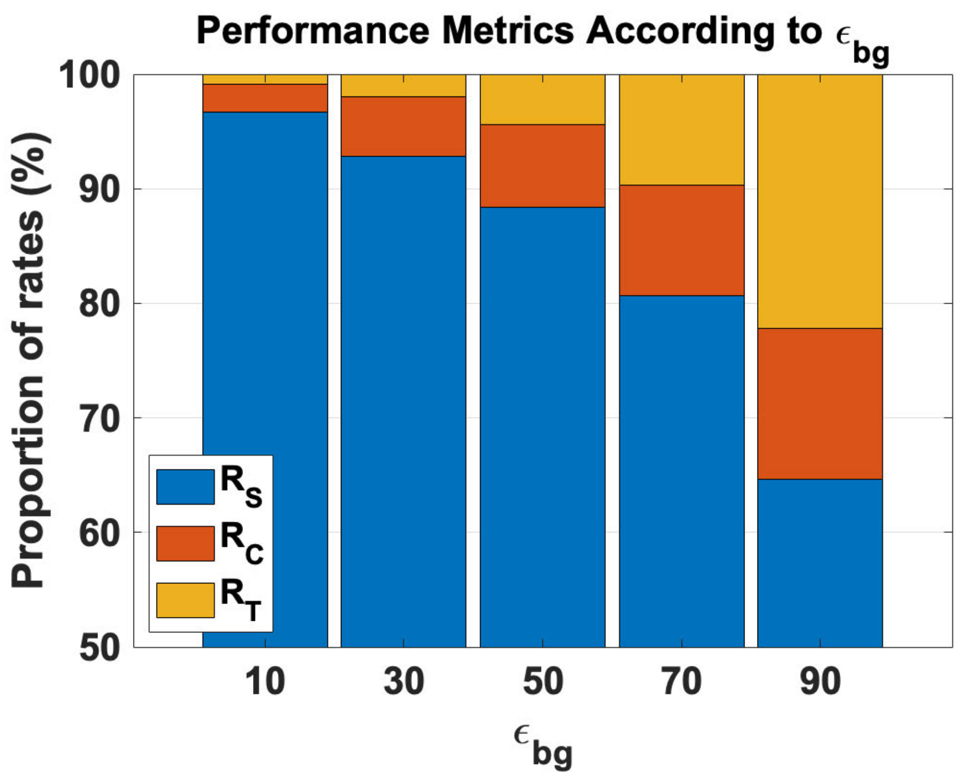

Figure 5.4: Proportional performance metrics (R_S, R_C, and R_T) with respect to background panic rate.

that more cases of emergencies are impacting the community, resulting in an expansion of the total hazardous impact area within the community network. Given that pedestrians disperse across the community network at a fixed $\mathcal{P}_{\text{max}}$ level, a surge in the aggregated impact area implies that an increasing number of nodes and edges in the community are affected, leading to a spike in the number of impacted pedestrians. For illustration, with $\mathcal{H}_{\text{max}}$ set at 5 and $\mathcal{P}_{\text{max}}$ at 8,000, an average of 34.4% of pedestrians encounter at least one emergency. However, at $\mathcal{H}_{\text{max}}$ of 10 and 15, the percentage of pedestrians affected rises to 54.4% and 66.2%, respectively. A parallel trend is observed at other $\mathcal{P}_{\text{max}}$ levels, such as when $\mathcal{P}_{\text{max}}$ is at 2,000. For instance, at $\mathcal{H}_{\text{max}}$ of 5, the average R_{I} stands at 34.3%. However, this value increases to 56.5% and 68.4% at $\mathcal{H}_{\text{max}}$ of 10 and 15, respectively. Consequently, R_{I} exhibits a positive correlation with $\mathcal{H}_{\text{max}}$. Such observation highlights the need for a nuanced understanding of the intensity of interaction between pedestrians and emergencies.

The degree of background panic rate influences the emergency response effectiveness, as illustrated in Fig. 5.4. This data visualizes the mean R_S, R_C, and R_T aggregated from results across each $\mathcal{P}_\mathrm{max}$ and $\mathcal{H}_\mathrm{max}$ levels. First, a distinct negative relationship between ϵ_p^bg and R_S is observed. When ϵ_p^bg is low, almost all impacted pedestrians follow the optimal route at each simulation time until they reach to a safe space. To elucidate, at ϵ_p^bg of 10%, 96.6% of impacted pedestrians successfully evacuate to a safe space within 120 simulation time. However, a rise in ϵ_p^bg intensifies the panic level among impacted pedestrians, subsequently diminishing their evacuation decision-making rationality. An elevated panic state among pedestrians leads to a surge in the number of panicking pedestrians. These pedestrians continuously deviate from their optimal, thereby reducing their likelihood of successful and timely evacuation. This analysis is supported by observation in R_S at higher ϵ_p^bg levels. For instance, when ϵ_p^bg to 50% and 90%, only 88.3% and 64.6% of impacted pedestrians safely evacuated from the community network, respectively.

An increasing probability of casualty of impacted pedestrians is observed simultaneously with the diminishing likelihood of successful evacuation. It is evident from Fig. 5.4 that an elevation in ϵ_p^bg correlates to an uptrend in observed average R_C. A low value of ϵ_p^bg entails that most of the necessary information valuable to successful emergency response and evacuation in the community is known by pedestrians. Impacted pedestrians are unlikely to panic when they are confident that their sufficient knowledge of evacuation boosts their likelihood of survival. Evacuating pedestrians actively utilize the obtained information to avoid becoming casualties. Therefore, a low ϵ_p^bg level results in a small number of panicking pedestrians, leading to a low casualty rate. For instance, when ϵ_p^bg is 10%, 2.5% of affected pedestrians become casualties due to persisting and severe hazardous impact. Panicking pedestrians are less likely to escape from hazardous impact areas in a timely manner while following random paths in their surroundings, compared to rational evacuees. At each simulation time, each affected pedestrian has a defined probability of becoming a casualty due to the intensified influence of the impacting emergency. The prolonged exposure of a panicking pedestrian to hazardous effects due to a persisting panic state proportionally elevates the likelihood of casualty. Therefore, a high ϵ_p^bg correlates to a high R_C value.

Moreover, the loss of rationality in decision-making during emergency response is reflected by an elevation in observed mean R_{T}, when ϵ_p^{bg} rises. Similar to R_{C}, the value of R_{T} is insignificant at a low ϵ_p^{bg} level. It is assumed that the panic state of panicking pedestrians cannot be reverted. Thus, even if panicking pedestrians escaped from the hazardous impact area, they achieved minimal progress in traveling toward their desired safe spaces. While away from active hazardous impact, these pedestrians are unlikely to reach any defined end state, such as casualty or successful evacuation. The response time required for panicking pedestrians to achieve successful evacuation significantly increases. Therefore, these pedestrians are unlikely to evacuate upon the end of the simulated response at t equal to 120, contributing to R_{T}. When the effect of background panic rate is minimal, the number of panicking pedestrians is relatively low compared to the count of impacted pedestrians. For example, at ϵ_p^{bg} of 10%, the observed mean value of R_{T} is 0.85%. Consequently, evidence from the case study data shows that rises in R_{T} are observed due to a surge in the number of panicking pedestrians when ϵ_p^{bg} increases. For instance, when ϵ_p^{bg} stands at 70% and 90%, the corresponding R_{T} has the values of 9.73% and 22.1%.

Furthermore, as ϵ_p^{bg} rises, R_{T} increases at faster rate than R_{C}. For instance, between the ϵ_p^{bg} levels of 10% and 30%, the difference in observed R_{C} is 2.71% while the change in the observed R_{T} is 1.13%. However, between the ϵ_p^{bg} levels of 70% and 90%, the difference in observed R_{C} is 3.66% while the change in the observed R_{T} is 12.4%. At higher ϵ_p^{bg} levels, panicking pedestrians causes concentrate at key community intersections and paths that are near or within the areas impacted by hazards. Furthermore, nodes and edges in these areas that are heavily utilized by evacuating pedestrians are vulnerable to congestion. Such congestion results in longer response time for community authorities and disaster relief support to arrive at the scene of hazardous impact. The congestion reduces the efficacy of evacuation for affected pedestrians. Moreover, when nearby safe spaces are filled, pedestrians who are still evacuating must reroute to a safe space of further distance, increasing the time required to evacuate. An elevated time requirement reduces the likelihood of successful evacuation in a predefined time duration.

Nevertheless, it is pertinent to note that the proportion between R_{S}, R_{C}, and R_{T} remain stable at each $\mathcal{P}_{\max}$ across ϵ_p^{bg} levels, as shown in 5.5. At any fixed level of hazard occurrence, the

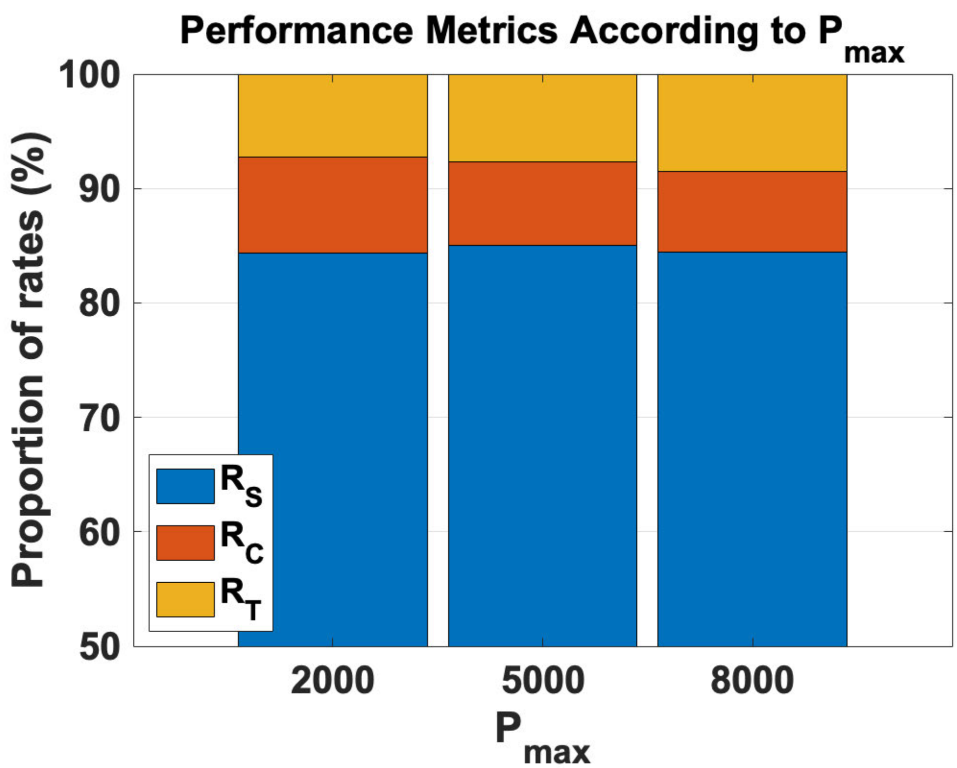

Figure 5.5: Proportional performance metrics (R_S, R_C, and R_T) in terms of maximum pedestrian flow.

probability of a pedestrian being impacted remains unchanged when the hazard type properties are held constant. When ϵ_p^{bg} is fixed, the probability of a pedestrian experiencing panic remains invariant. The outcome of the case study supports this claim. Specifically, the observed mean value of observed R_{S}, R_{C}, and R_{T} show minimal change across $\mathcal{P}_{\text{max}}$. For instance, when $\mathcal{P}_{\text{max}}$ stands at 2,000, the observed R_{S}, R_{C}, and R_{T} are 84.38%, 8.34%, and 7.27%. Similarly, at $\mathcal{P}_{\text{max}}$ of 8,000, the R_{S}, R_{C}, and R_{T} are 84.42%, 7.02%, and 8.55%. Such finding demonstrates that although the max number of pedestrians in the community has an impact on the count of impacted and panicking pedestrians in different evacuation scenarios, $\mathcal{P}_{\text{max}}$ show minimal influence on the overall emergency response and evacuation effectiveness.

Furthermore, while R_{S}, R_{C}, and R_{T} stay relatively stable at each $\mathcal{H}_{\text{max}}$ across ϵ_p^{bg}, and $\mathcal{P}_{\text{max}}$ levels, it is worth noticing that R_{S} decreases and R_{T} increases, when more hazards are impacting the community. The number of impacted pedestrians elevates when $\mathcal{H}_{\text{max}}$ increases, as illustrated in 5.6. At a fixed ϵ_p^{bg}, a rise in the number of impacted pedestrians proportionally increases the

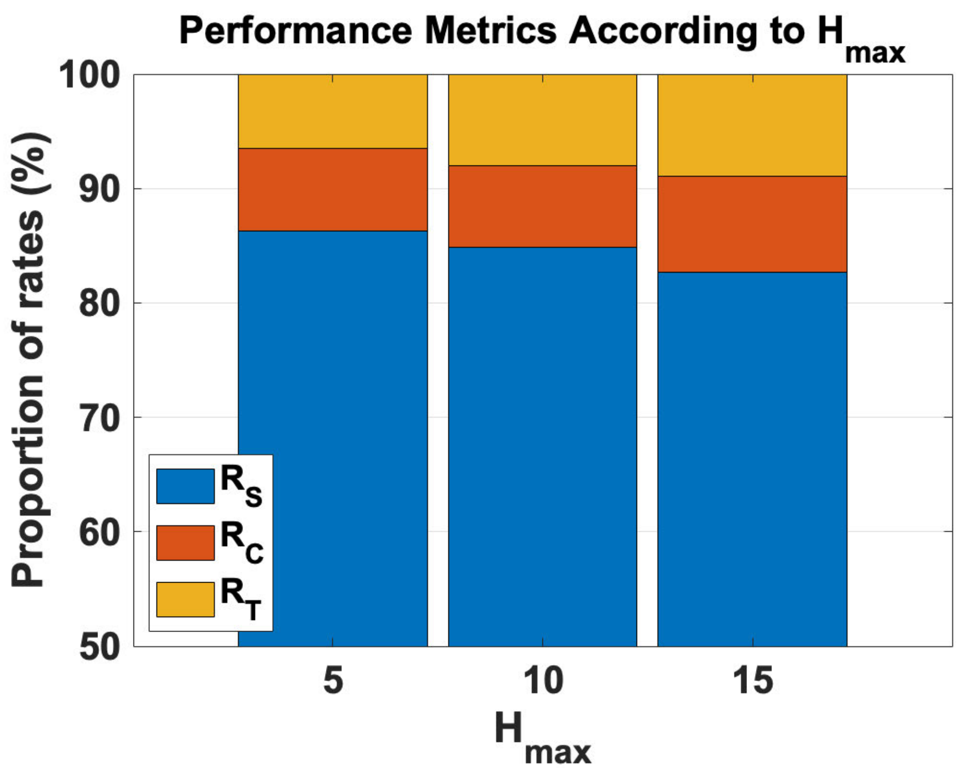

Figure 5.6: Proportional performance metrics (R_S, R_C, and R_T) in terms of maximum number of hazard occurrences.

count of panicking pedestrians. Simultaneously, an elevation in $\mathcal{H}_{\text{max}}$ increases the cumulative area in the community impacted by hazards. Given that panicking pedestrians form congestion in traffic within and near impacted community areas, an increase in $\mathcal{H}_{\text{max}}$ leads to more severe and widespread congestion across the community. Such development contributes to the elevation in R_{T} and reduction in R_{S} when the total volume of hazards affecting the community surges. This trend can be observed by comparing the average R_{S} and R_{T} between each consecutive $\mathcal{H}_{\text{max}}$ levels. To elucidate, when $\mathcal{H}_{\text{max}}$ stands at 5, the observed R_{S} is 86.3%, but R_{S} decrease to 84.9% and 82.7% at $\mathcal{H}_{\text{max}}$ of 10 and 15, respectively. In contrast, at $\mathcal{H}_{\text{max}}$ of 5, the value of R_{T} is at 6.53%. However, the corresponding R_{T} data for $\mathcal{H}_{\text{max}}$ of 10 and 15 are 8.03% and 8.91%, respectively. The continuous increases in R_{T} and decrease in R_{S} with the rises in $\mathcal{H}_{\text{max}}$ demonstrate the influence of cumulative hazardous impact to evacuation effectiveness through changes in traffic dynamics. Thus, the overall experimental result demonstrates the efficacy of the proposed evacuation model in evaluating the emergency response process against various emergencies for complex communities.

Chapter 6

Conclusion

6.1 Factor Survey and Future Focus

A detailed survey is crucial for collecting accurate data on the outlined control factors, human agent parameters, and hazard agent types. Accurate configurations on these parameters ensure the alignment between the dynamics of simulated and real-world evacuations. Simulation levels for pedestrian flow should accurately reflect traffic in the community during emergencies, adhering to residential demographics from census data. In the context of this case study, it is assumed that the average population flow at PSU-UP throughout a weekday, where lectures are held based on a regular schedule, ranges from 2,000 to 8,000. Census data is vital to understanding pedestrian group characteristics. Simulation values for hazard types should draw from historical emergency data and account for potential hazard sources in similar communities, considering demographics, building layouts, and geographical scales. Furthermore, the configuration of the hazard types should consider potential hazard sources in the community.

Further work is required to fully address the nature of decentralized evacuation in large-scale community environments. First, in this work, the background panic rate is held constant throughout the case study. However, the real-world evacuation background information that each pedestrian can observe at different times is dynamic due to the evolving emergency situations and other moving pedestrians in its surrounding environment. The fluctuating observed information set results would result in a floating background panic rate throughout the simulated emergency response. Optimizing emergency response through effective evacuation plans is essential to save lives and assets while preserving disaster relief resources. Thus, it is crucial to enhance the multi-agent community network model in this work to assess the effect of evacuation plans. In this experiment, each simulated emergency response began at the maximum human agent population level. However, the pedestrian volume in the community can fluctuate. Therefore, a continuous population growth function that estimates the dynamic pedestrian flow throughout the community should be developed.

6.2 Conclusion of Work

In recent years, our society has witnessed increasing public emergencies in densely populated communities, leading to severe casualties and financial losses. While community authorities recognize the necessity of implementing effective rapid response plans against various emergency scenarios, factors such as dynamic traffic, complex infrastructures, and emergency-induced disorders complicate the testing and configuring such response plans through real-world response drills.

To resolve this challenge, this work presents a multi-agent community network model that leverages computational simulations to mirror and assess rapid response actions across various communities. Two modeling approaches are featured in this work as novel contributions to enable the effective and flexible representation of emergency responses while considering uncertainties in total hazardous impact, maximum volume of pedestrians, and community structures. First, the community network model is designed to capture complex features of communities, such as the network of pathways connecting buildings and intersections. The captured features of communities are transformed into flow-based networks to represent the real-world environments in which pedestrians evacuate. Then, human and hazard agents are designed via multi-agent modeling techniques to represent pedestrians and emergencies. The hazard agents reflect the sources and dynamic development of different types of emergencies, enabling community authorities and researchers to capture the collective hazardous impact on the community and its pedestrians. Furthermore, the human agents represent the autonomous decision-making process and behavior of individual pedestrians belonging to various identity groups. The design of human agents helps administrators learn the difference in emergency response performance due to different community population demographics.

To validate the performance of the model, simulation experiments are conducted in two stages. First, the effectiveness of the community network model is assessed on three public university campuses using open-source map data. The model demonstrated flexibility and accuracy in representing community features. Additionally, the spatial distributions of pedestrian flow observed throughout the simulations accurately reflected effective responses to emergencies and the route navigation of pedestrians. Second, we evaluated the performance of the proposed multi-agent modeling approach through a case study. The observed correlations validated the capability of the multi-agent modeling method in representing the dynamic and decentralized interactions among pedestrians, emergencies, and the structural features of the community. Moreover, the case study results proved the modeling approach's ability to simulate emergency response processes under various emergency scenarios. Overall, the multi-agent community network model holds great potential for assisting community administrators and researchers in enhancing community-wide evacuation plans through simulated emergency responses.

Bibliography

[1] C. Robertson, J. Fortin, S. Saul, and R. Tumin, “Gunman charged with killing three fellow students at the university of virginia,” Nov 2022. [Online]. Available: https://www.nytimes.com/2022/11/14/us/gunman-charged-uva-shooting.html

[2] M. Oxenden, “Package explodes at northeastern u. in boston, injuring an employee,” Sep 2022. [Online]. Available: https://www.nytimes.com/2022/09/13/us/northeastern-university-boston-package-detonation.html

[3] A. Weisend, “Breaking: Students evacuated from multiple halls due to chemical spill,” Nov 2022. [Online]. Available: https://www.dailyemerald.com/news/breaking-students-evacuated-from-multiple-halls-due-to-chemical-spill/article_d4e1c8ca-7042-11ed-a7b5-0789ac8e9d65.html

[4] M. A. Tkachuck, S. E. Schulenberg, and E. C. Lair, “Natural disaster preparedness in college students: Implications for institutions of higher learning,” *Journal of American college health*, vol. 66, no. 4, pp. 269–279, 2018.

[5] K. J. Long, F. J. Zajaczkowski, S. E. Haupt, and L. J. Peltier, “Modeling a hypothetical chlorine release on a college campus.” *J. Comput.*, vol. 4, no. 9, pp. 881–890, 2009.

[6] S. Liu, J. Liu, and W. Wei, “Simulation of crowd evacuation behaviour in outdoor public places: A model based on shanghai stampede,” *International Journal of Simulation Modelling*, vol. 18, no. 1, pp. 86–99, 2019.

[7] M. Xu and D. Peng, “Pyrosim-based numerical simulation of fire safety and evacuation behaviour of college buildings,” *International Journal of Safety and Security Engineering*, vol. 10, no. 2, pp. 293–299, 2020.

[8] P. Lu, D. Chen, Y. Li, X. Wang, and S. Yu, “Agent-based model of mass campus shooting: Comparing hiding and moving of civilians,” *IEEE Transactions on Computational Social Systems*, 2022.

[9] R. Zhou, Y. Cui, Y. Wang, and J. Jiang, “A modified social force model with different categories of pedestrians for subway station evacuation,” *Tunnelling and Underground Space Technology*, vol. 110, p. 103837, 2021.

[10] L. L. Cove and J. Edwin Clark, “Modeling pedestrian volumes on college campuses,” *Transportation Research Record*, vol. 1405, p. 43, 1993.

[11] Z. Fang, Q. Li, Q. Li, L. D. Han, and D. Wang, “A proposed pedestrian waiting-time model for improving space–time use efficiency in stadium evacuation scenarios,” *Building and Environment*, vol. 46, no. 9, pp. 1774–1784, 2011.

[12] M. Haklay and P. Weber, “Openstreetmap: User-generated street maps,” *IEEE Pervasive computing*, vol. 7, no. 4, pp. 12–18, 2008.

[13] G. Boeing, “Osmnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks,” *Computers, Environment and Urban Systems*, vol. 65, pp. 126–139, 2017.

[14] S. Zhang, M. J. Ventura, and H. Yang, “Network modeling and analysis of covid-19 testing strategies,” in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2021, pp. 2003–2006.

[15] H. Yang, C. Kan, A. Krall, and D. Finke, “Network modeling and internet of things for smart and connected health systems—a case study for smart heart health monitoring and

management," *IISE Transactions on Healthcare Systems Engineering*, vol. 10, no. 3, pp. 159–171, 2020.

[16] S. Zhang and H. Yang, "Spatial modeling and analysis of human traffic and infectious virus spread in community networks," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2021, pp. 2286–2289.

[17] S. Zhang, S. Yang, and H. Yang, "Statistical analysis of spatial network characteristics in relation to covid-19 transmission risks in us counties," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2021, pp. 2278–2281.

[18] R. Liu and H. Yang, "Spatial tessellation of infectious disease spread for epidemic decision support," *IEEE Robotics and Automation Letters*, vol. 7, no. 1, pp. 626–633, 2021.

[19] A. Dorri, S. S. Kanhere, and R. Jurdak, "Multi-agent systems: A survey," *Ieee Access*, vol. 6, pp. 28 573–28 593, 2018.

[20] J. Shi, A. Ren, and C. Chen, "Agent-based evacuation model of large public buildings under fire conditions," *Automation in Construction*, vol. 18, no. 3, pp. 338–347, 2009.

[21] A. Asgary and P. L. C. Yang, "Simulating campus evacuation: case of york university," in *SCSC '16: Proceedings of the Summer Computer Simulation Conference*, 2016, pp. 1–6.

[22] X. Li, Q. Li, and C. Claramunt, "A time-extended network model for staged evacuation planning," *Safety science*, vol. 108, pp. 225–236, 2018.

[23] T. Lilasathapornkit and M. Saberi, "Dynamic pedestrian traffic assignment with link transmission model for bidirectional sidewalk networks," *Transportation research part C: emerging technologies*, vol. 145, p. 103930, 2022.

[24] Y. Wang, M. Kyriakidis, and V. N. Dang, "Incorporating human factors in emergency

evacuation–an overview of behavioral factors and models," *International Journal of Disaster Risk Reduction*, vol. 60, p. 102254, 2021.

[25] M. Yu, C. Yang, and Y. Li, "Big data in natural disaster management: a review," *Geosciences*, vol. 8, no. 5, p. 165, 2018.

[26] N. Kaur and H. Kaur, "A multi-agent based evacuation planning for disaster management: a narrative review," *Archives of Computational Methods in Engineering*, vol. 29, no. 6, pp. 4085–4113, 2022.

[27] M. Schimpl, C. Moore, C. Lederer, A. Neuhaus, J. Sambrook, J. Danesh, W. Ouwehand, and M. Daumer, "Association between walking speed and age in healthy, free-living individuals using mobile accelerometry—a cross-sectional study," *PloS one*, vol. 6, no. 8, p. e23299, 2011.

Xiaoru Shi

241 Leonhard Building, The Pennsylvania State University, University Park, PA, 16802
Work Email: xxs141@psu.edu • Personal Email: tonyshixiaoru@gmail.com
Mobile: +1-484-987-0802

RESEARCH INTERESTS

- Multi-agent system
- Simulation modeling
- Artificial intelligence
- Industrial organization modeling

EDUCATION

The Pennsylvania State University *University Park, PA* Aug 2019 - Dec 2023
B.S. *in Computer Science* [redacted]
B.S. *in Economics*
Honors *in Industrial Engineering*

- Advisor: Dr. Hui Yang
- Thesis Title: Multi-Agent Network Modeling for Rapid Response Against Public Emergencies in Communities

PUBLICATION

- **Shi, X.**, Lee,H., Yang, H.*, "Multi-agent Network Modeling for Evacuation Planning in Public Emergency", *IEEE Transactions on Automation Science and Engineering*, Work-in-progress

(*: Corresponding Author)

PRESENTATION

- **Shi, X.***, Yang, H., "Simulation Application for Emergency Evacuation Management on Open Street Networks", *Penn State Undergraduate Exhibition*, Apr. 2021, University Park, PA, USA (Poster Presentation)
- **Shi, X.***, Chen, CB., "Emergency Evacuation Management utilizing Moving Object Simulation", *Penn State Undergraduate Exhibition*, Apr 2020, University Park, PA, USA (Poster Presentation)

(*: Presenter)

ACEDMIC EXPERIENCE

The Pennsylvania State University *University Park, PA*

- **Undergraduate Research Assistant** at Complex Systems Monitoring, Modeling, and Control Laboratory (Supervisor: Dr. Hui Yang), *Community-wide Evacuation Simulation Modeling* (Sponsor: NSF-REU) Sept. 2019 - Present
- **Undergraduate Research Intern** at The RAISE Lab (Supervisor: Dr. Amulya Yadav), *Multi-agent Interaction System in Wildlife Reserve* Sept. 2021 - Dec. 2021
- **Honors Student Researcher** at honors project in ECON 444 (Supervisor: Dr. Paul Grieco) *Predatory Pricing in Airline Industry* Jan. 2023 - May 2023

Northwestern University *Evanston, IL*

- **Undergraduate Research Intern** at Communications and Networking Laboratory (Supervisor: Dr. Ermin Wei), *Multi-agent Reinforcement Algorithms*

June 2022 - Aug. 2022

WORKING EXPERIENCE

Listrak Inc. *University Park, PA*

- **Co-Op Team Lead**, *Smart Customer SMS Response Prototype* Sept. 2022 - Dec. 2022

AWARDS

- **Research Experience for Undergraduate Scholarship** from National Science Foundation

2020, 2021

- **Phi Beta Kappa** Feb 2022 - Present
- **Tau Beta Pi** Feb 2022 - Present

- **Eta Kappa Nu** Feb 2022 - Present

TECHINICAL SKILLS

Computer Languages

- Python, MATLAB, Java, C

Statistical Programs

- Stata, R

LEADERSHIP

University Park Student Fee Board

- **Steering Committee Member** facilitated the operation and mandated the policy of the board Apr. 2022 - Apr. 2023
- **At-large Representative** served to construct recommendation of budget allocation of $24 million per year Apr. 2020 - Apr. 2023