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Dynamic Multilevel Modeling in the design of Decision Support Systems for rescue simulation : combining Agent-based and Mathematical approaches

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NGUYEN Thi Ngoc Anh

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**Dynamic Multilevel Modeling in the design of
Decision Support Systems for rescue simulation :
combining Agent-based and Mathematical
approaches**

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Abstract

One of the world's worst natural disasters are Tsunamis, in particularly when they hit a crowded coastal city. Coastal cities need to be prepared for such disasters in order to mitigate losses. Preparedness for such an event would mean building Early warning information systems, Emergency shelter systems, Evacuation scenarios, Rescue systems, etc. However, Tsunami evacuation drills or Tsunami experiments are very difficult to carry out. This explains why modeling and simulating are extensively used to address such issues, in other to best prepare cities/countries against Tsunami outbreaks. One major problem would be to find the best evacuation procedure in evacuating a coastal city so as to minimize the number of casualties. In this thesis, we address the problems which involved scaling up simulations for evacuating Pedestrians on a road network of a city.

A lot of evacuation models have been researched with different scale from Micro models to Macro models. There are seven common models to study the crowd evacuation, such as Cellular automata, Lattice gas, Social force, Agent-Based, Game theory and Experiments with animals. To support simulations for Macro and Micro models, there are a lot of softwares such as NETSIM and NETVACI for Macro simulations and MITSIM, TRANSIMS for Micro simulations. However, these softwares are often developed for small-scale environments such as couple of buildings, subway stations, ships, rooms in an area etc. They are not suitable for large-scale environment such as networks, city, etc. Now, GAMA platform, Geographic Information Systems & Agent-based Modeling Architecture, can simulate both Micro and Macro simulations. GAMA platform aims at providing field experts, modelers, and computer scientists with a complete modeling and simulation development environment for building spatially explicit ABM simulations. We use it to study different Micro and Macro evacuation simulation for the road network of a city.

Firstly, Equation-Based Models (EBMs) are abstracted real problems with equations. EBMs has the advantage of solving the big problems in acceptable time. Therefore, we choose EBMs for optimizing sign placement system. We proposed modeling human behavior as semi-Markov chains for Equation-Based Model. Based on this model, we proposed an original formulation of the sign placement prob-

lem, which we called Minimization of Average Evacuation Time (MAET). Next, we showed that this problem could be represented as a Mixed Integer Linear Programming (MILP), using powerful open-source MILP solvers. In addition, we use Lighthill, Whitham and Richards model (LRW) of Pedestrian flow on a road network. Pedestrians are homogeneous with a space time continuum. More precisely, the conservation law formulation proposed by LWR represented the fluid dynamics by partial difference equations. However, they are difficult to consider the problem in detail with different realistic factors. To consider the problem in detail, Agent-Based Models are the approach (ABMs).

Agent-Based Models (ABMs) take into account the heterogeneity of Pedestrians' behaviors and the unspecified road network conditions. In addition, modelers using ABMs consider the initial population distribution based on the factors such as time and the tourist season in the coastal cities. However, the computational cost was huge when applied for larger number of evacuees and large dynamic environment. The result of simulation using ABM requires huge experiments, so the speed of simulation is a problem that we want to investigate. We consider an Hybrid-Based Model (HBM) combining the advantages of both ABM and EBM.

Thirdly, the problem of speeding up very large environment in ABMs such as the ones used in Crowd simulation is key to support realistic Decision Support Systems. The key idea is to exploit the advantages from both Macro and Micro modeling. A case study to prepare Nha Trang(city) Tsunami-Ready based on Hybrid modeling shows a more efficient execution than Micro modeling, as well as an improved simulation quality when compared with Macro modeling. In the evacuation simulation, dynamic environment includes various parts having different levels of importance. On the road network, the junctions are important because many complex behaviors lead to the different decisions of Agents. ABM is used for junctions and EBM is used for the stretch road between two junctions. In addition, Solving MAET problems by EBM is an unrealistic conditions. Otherwise, solving MAET by ABM requires running a lot of simulations. We integrate these two models to obtain better optimization results. Firstly, we used the MAET result applied to ABM. Then, we loop the integrated simulations to find out the best sign placement. We apply these studies to verify the validation of scenarios in Nha Trang city in Vietnam. The methodology applied to the city of Nha Trang can be used for preparing other coastal cities.

Last but not least, the results achieved in the thesis are: (i) Formulating the problem of evacuation; (ii) Formulating the optimal alert signs system; (iii) Describing the initial population distribution of the city depending on time of the day and season(tourist); (iv) Simulating Tsunami evacuation on road network of Nha Trang city using ABM; (v) Building the Hybrid-Based Model to speed up

simulation; (vi) Integrating ABM and MAET to make the results better for the optimal alert signs system.

Future work would involve (i) Exploring various behaviors of Pedestrians; (ii) Finding the way to validate the evacuation simulations; (iii) Finding the threshold factor for effective Hybrid-Based simulations. (iv) Using more models for different important parts of a road network; (v) Building a model takes into account the capacities of the Shelters.

Key words: Simulation, Crowd movement, Tsunami evacuation, Equation-Based Model, Agent-Based Model, Hybrid-Based Model, Mixed Integer Linear Programming.

Glossary

ABM Agent-based model . 9, 12, 26, 40, 52

AET Average Evacuation Time. 51, 74

CPLEX Optimizer was named for the simplex method as implemented in the C programming language. 73, 75

EBM Equation-based model. 7, 12, 40

fox A fox is defined as a pedestrian who has been trained on evacuation procedures or has knowledge of how get to the safe place efficiently. 53, 81, 96

GIS Geographic Information System. 6, 34, 61, 77, 96

HBM Hybrid-based model. 9, 40, 61

IBM Individual-based model . 9, 26

IGP Institute of Physical Geography Vietnam. 4, 103, 134

LWR It is a Equation-based model proposed by Lighthill and Whitham (1955) and Richards (1956). 23, 41

MAET Minimization of Average Evacuation Time. 51, 72, 75, 92, 96, 137

MAS Multi-Agent System. 28

MILP Mixed Integer Linear Programming. 72, 75, 95, 163

ML-ABM Multi-Level Agent-Based modeling. 36

NP-hard Non-deterministic Polynomial-time hard. 72

PAET Population Average Evacuation Time. 51, 73, 74

PDE Partial Differential Equations. 23

SDSS Spatial Decision Support System. 34

sheep The pedestrian evacuating randomly at junctions or following one fox agent is called sheep agent. 53, 82, 96

tube is a middle stretch of the road is described by an edge of a directed graph. 61

Chapter 1

Introduction

1.1 Foreword

This chapter introduces the research motivation which is about preparing for tsunami outbreaks. The research question involves tsunami evacuation on road networks as the objectives and contributions of this thesis. These issues presents the foundation of this thesis. The structure of this thesis is revealed in the following pages.

1.2 Motivation

One of the world's worst natural disaster are tsunami mainly caused by the immense force of the tidal waves hitting the shoreline of a country or places. tsunamis occurring at densely populated coastal cities are very dangerous because they often results in enormous losses. In fact, millions of people have been killed by tsunamis in the last hundred years. Damage caused by tsunamis on a population results in financial losses, injuries, death tolls, psychological problems for people and many countless problems in the places of occurrence. The effect of tsunami strikes in disaster prone areas and countries can't be overemphasized. For example, the case of tsunami outbreak in the Indian Ocean on the 26th of 2004, struck many coastal areas in Asian countries leaving more than 230,000 people reportedly dead and millions of people destitute and displaced. Another example, a tsunami devastated large parts of the coastline in Japan on 11 March 2011. Japanese National Police Agency report confirmed 15,885 deaths; 6,148 injured, and 2,623 people missing across twenty prefectures, as well as 127,290 buildings totally collapsed, with a further 272,788 buildings 'half collapsed', and another 747,989 buildings partially damaged [Agency 2014]. Therefore, many countries in the circum-Pacific belt where 90%

of the global undersea earthquakes take place prepare for tsunami-Ready to mitigate losses such as Japan, Chile, United States of America, Taiwan, Philippines, Vietnam etc.

To prevent loss of life and damage of tsunamis, the National Oceanic and Atmospheric Administration (NOAA) of the United States of America operate two tsunami warning centers that are The Pacific tsunami Warning Center and The National tsunami Warning Center [Oceanic 2014]. Many researches for tsunami mitigation have been done in the countries Japan, Chile, United States of America, Taiwan, Philippines, Indonesia, Malaysia etc [Nandasena 2012, Parwanto 2013, Wu 2009, Little 2007]. For example, Nathan Wood et al solved tsunami vertical-evacuation planning in the U.S. Pacific Northwest as a geospatial, multi-criteria decision problem [Wood 2014]. Another example, COMCOT (Cornell Multi-grid Coupled tsunami Model) is a tsunami modeling package, capable of simulating the entire lifespan of a tsunami, from its generation, propagation and run up/rundown in coastal regions that applied in many countries such as Malaysia, Brunei, Singapore, Taiwan, Philippines, etc [Liu 2009, Fritz 2011, Megawati 2009, Wu 2009, Koh 2009, Chai 2014]. Meanwhile, Vietnam position is in the tsunami dangerous area that has four major deep faults of the South China Sea and its adjacent regions. They are the earthquakes resources of tsunami to Vietnam and the other South East countries (a) North margin fault of the Central Basin of South China Sea. (b) Western margin fault of the Central Basin of South China Sea. (c) Manila Trench. (d) Nansha trough fault [Liu 2007]. Under such circumstances, Vietnam should prepare what to mitigate tsunami losses.

The presence of a long coastline with over 3,260 kilometers may cause Vietnam to be affected by tsunamis resulting from the earthquake sourced from the East Vietnam sea [Nguyen Hong Phuong 2011]. Moreover, along the coastline of Vietnam, there are many urban areas with crowded population and has not been prepared against tsunamis. On the other hand, researchers from the Institute of Physical Geography Vietnam (IGP) have been informed that the Manila trench located in the earthquake belt is one of the most dangerous earthquake sources facing the Vietnamese coast (see Fig. 1.1). These researches estimated that if there is an earthquake from the Manila trench to Vietnam, it takes about 120 minutes for a tsunami to hit the Vietnamese central coast. However, if an earthquake occurs in the East Vietnamese Sea, it takes about 30 minutes for a tsunami to strike Vietnam coast. In this short time, if inhabitants of a city do not have the early warning or preparedness for such trauma, the damage will be enormous. Although tsunami is a rare event, Vietnam has to pay serious and more attentions to evaluation, early warnings for tsunamis in the coastal areas and islands [Phuong 2012].

In order to avoid enormous destruction, early preparation as well as readiness

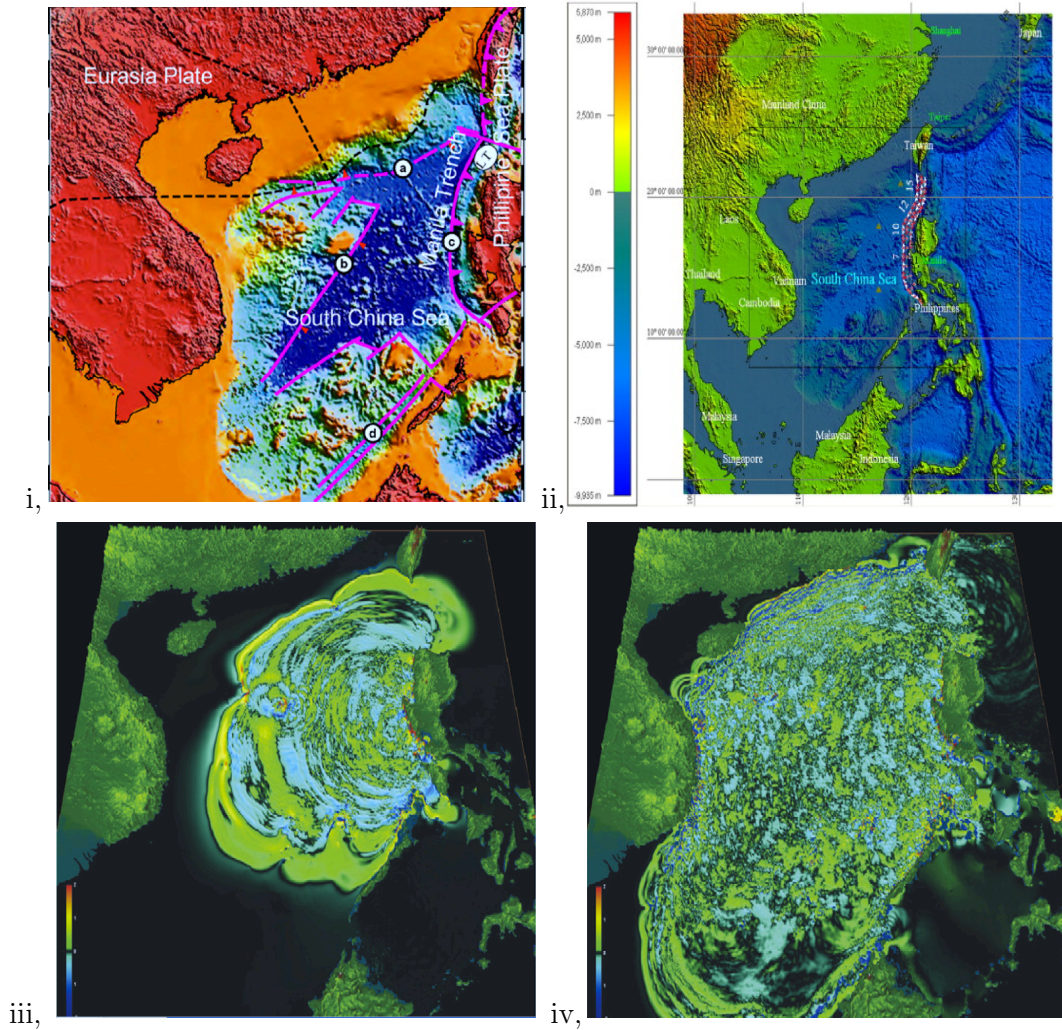


Figure 1.1: i, Major deep faults of the South China Sea and its adjacent regions that are the earthquakes resources of tsunami to Vietnam and the other South East countries (a) North margin fault of the Central Basin of South China Sea. (b) Western margin fault of the Central Basin of South China Sea. (c) Manila Trench. (d) Nansha trough fault [Liu 2007]; ii, Manila Trench imposes the most dangerous earthquake resource of tsunami to Vietnam's coast and islands [Nguyen Hong Phuong 2011]; iii, iv, Simulation of the linear tsunami wave propagation 215 minutes, 484 minutes with hypothetical seismic event occurs southwest to the Philippines ($14.5^{\circ}N$, $119.2^{\circ}E$), with a magnitude of 7.5. tsunamis may occur to many countries such as Philippines, Taiwan, Vietnam, Indonesia, Malaysia, China etc [Liu 2007].

to combat tsunamis and related issues. Scientists want to build Early warning information systems against tsunami outbreaks, Evacuation scenarios, Shelter systems, Rescue systems and so on [Scheer 2012, Koh 2009, Megawati 2009, Phuong 2012]. However, tsunami evacuation drills or tsunami experiments are very difficult to conduct. Therefore, in order to be ready to cope with tsunamis, it is necessary to model and simulate for coastal cities.

The advantage of simulations is that it generates and captures ideas, parameters, data at greater speed and at lower cost. Furthermore, real world experiments of natural disasters like Flooding, Volcanic eruptions and tsunamis are impossible. In addition, simulations are possible to set up, adapt, expand, and experiments can be rapidly executed at a low cost as described in (Fig. 1.2). Another advantage is the possibility of increasing the volume of experiments as virtual world has no limits and therefore allows for a thorough exploration of possibilities. A modeler can enhance predictive power and also improve the predictive values of experimentation by computer experiments, which collects, aggregates, and tracks many individual predictions of success. Consequently, the advantage of simulations is its capacity to scale up and deploy successful experiments more rapidly, comprehensively and disseminate information about successes through online knowledge platforms or virtual training.

Normally, if a tsunami takes place in urban areas, it's often characterized with high vulnerability. The modeling and simulations of evacuations for the road network of a city should be considered. Since urban areas include complicated road networks, evacuation of the population in these road network is difficult [said EL HMAM 2008, G.Lovas. 1994, McCreaa 2010, MAGNE 2000]. In addition, each urban area has its own peculiarities because of the differences in topology, infrastructures and road networks, etc. Road networks of many cities are now available and represented in *Geographic Information Systems* (GIS) supporting realistic simulations. In developing countries, the devices to support evacuation need to be simple and cheap. The tsunami warning signs are good devices for emergency evacuation. In developing countries, the means to support evacuation include simple road signs since everyone cannot afford a smartphone with 3G capabilities that would support the reception of personalized evacuation routes as available in Japan for example [Sugimoto 2003, Koshimura 2006, Teshirogi 2009]. Furthermore, even in Japan, there are tsunami route signs that support the evacuation and increase the awareness of tsunamis. The problem of placing signs in cities to minimize casualties and evacuation time is thus critical. The simulations of tsunami in this case introduces an approach that helps with analyzing the result of saving people and mitigating damage.

A tsunami evacuation on road network problem is a complex system which is

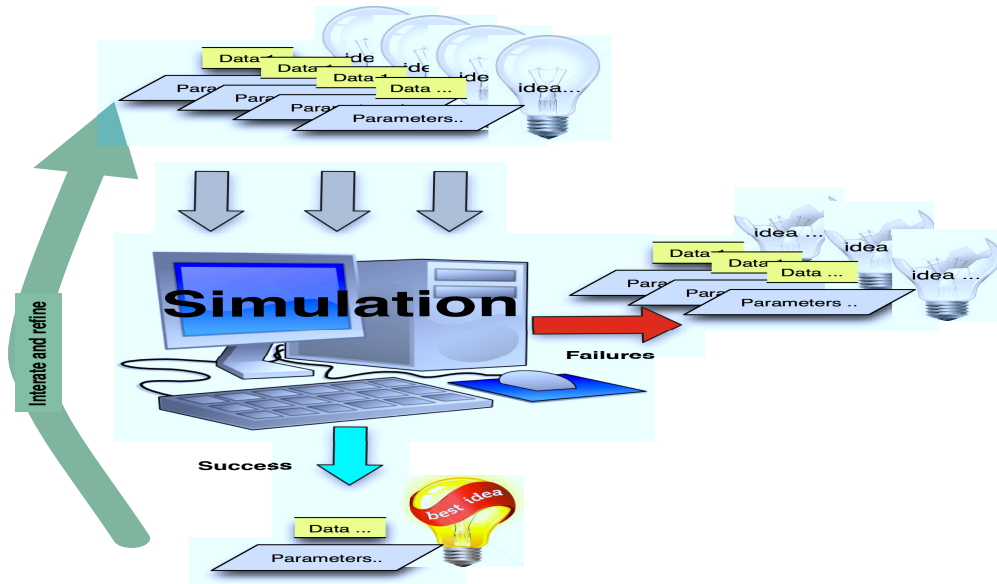


Figure 1.2: tsunami evacuation drills or tsunami experiments are very difficult to conduct. Therefore, in order to be ready to cope with tsunamis, it is necessary to model and simulate for coastal cities. The advantage of simulations is that it generates and captures ideas, parameters, data at greater speed and at lower cost.

not like physical problems such as a flood due to a dam (See Fig. 1.3). The methodologies applied in Vietnam can be dramatic for the other coastal areas. Designing a *Decision Support System* (DSS) is important to mitigate human losses and damaged properties.

1.3 The research problems

Equation-Based Model (EBM) is a model that captures system characteristics by identifying system variables and describing the system with sets of equations relating these variables. Usually, for a complex system a simple closed analysis form is not possible. Thus it has to be modeled by identifying a group of key states and formulating the dynamical procedures of state changes into partial/ordinary differential equations. The procedure involved in the simulations of the system is to help solve these equation. Equation-based Modeling has a long history. It has been heavily used in many research areas, particularly in social sciences fields such as Epidemiology, Innovation diffusion and Business cycles and many other areas. Although facing competence from Agent-based modeling, it is still widely used because of its strengths [Tang 2007].

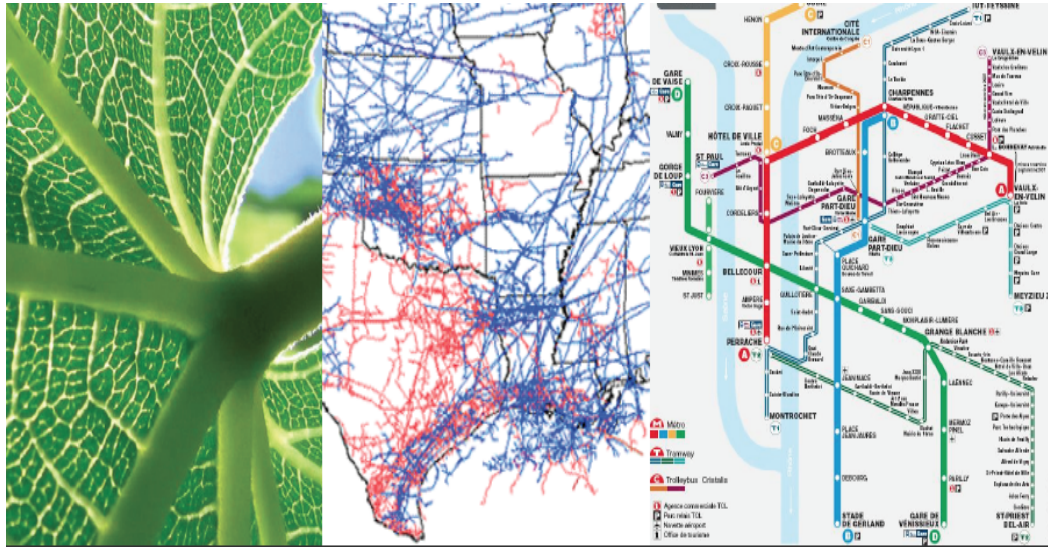


Figure 1.3: Complex system environments: a) nutrient transportation network of a leaf, b) road network of a city, c) public transportation network of a city.

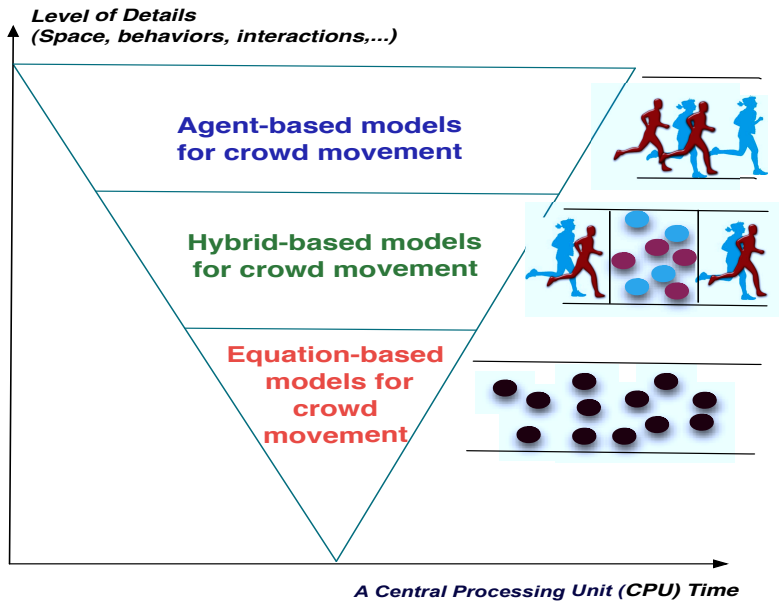


Figure 1.4: Hierarchy models represented in this chapter follows the level of detail (space, behaviors, interactions, etc). Hybrid-based model takes advantage of the strengths and thereby, limits weaknesses of from Agent-based model and Equation-based model. The range simulations of CPU time for Hybrid-based model are acceptable. This figure will be referred in the section 2.1.

Agent-Based Model (ABM), a relatively new computational modeling paradigm, is the modeling of phenomena as dynamical systems of interacting agents. Another name for ABM is *Individual-based Model* (IBM). One powerful technique for analyzing the complex systems is ABM. In fact, the Agent-based approach is of particular interest to social/management scientists because human groups such as organizations and societies may also be considered as agents interacting with each other. Emergence has meaningful orderly patterns from nonlinear interactions between autonomous disaggregated parts (i.e. agents) and landscape [Guo 2008]. Moreover, ABM enables us to simulate the individual actions of diverse agents and measure the resulting system behaviors and outcomes overtime. The essential idea of ABMs is that many phenomena, even very complex ones, can best be understood as systems of autonomous agents that are simple and follow relatively simple rules of interaction [Guo 2008]. The products of ABMs are Agent-based systems and Agent-based simulations. An Agent-based system (i.e. a Multi-Agent System) is designed to solve collectively a specific problem, while an Agent-based simulation do not try to solve problem, but are interested in real phenomena.

There are a lot of different approaches to study tsunami evacuation models. Among them; EBM has some advantages such as fast computation and simple representation. However, it require a lot of strict constraints. These reasons led mathematical approaches far from the truth of life problems. Meanwhile, ABM has many advantages since it can describe a problem in a natural way and retaining the truth of it's real life existence but ABM needs the relatively long time for computation. Therefore, the aim of this thesis is to propose a *Hybrid Based Model* (HBM) which can integrate the advantages of both models thereby, limiting their weaknesses through an Hybrid model. (see Fig. 1.4) [Anh 2011, Anh 2012, Abouaissa 2014].

More concretely, this thesis considers the evacuation simulations in a road network of a city. We assume that a city has N pedestrians, P shelters and a complicated road network including R roads and I intersections. We deal with the issues:

- a) What is the distribution of the population depending on time?
- b) How many people can survive in the time less than T ?
- c) The average time Pedestrians spent during evacuation?
- d) How to speed up the simulation?
- e) What is an Optimal alert sign system?

Research Objective and contribution

This work has theoretical and practical issues represented as Problem in the research section. Theoretical approaches are using mathematical and informatics

models to describe the problem. Thus, we investigate the switching into hybrid model (ABM and EBM) and integrating tsunami Evacuation Simulations on Road networks for Optimizing Sign Placement. We also apply these studies to verify the validation of scenarios in Nha Trang problem given by [Phuong 2012]. In addition, since this contribution is in computer science and applied mathematics, It considers:

- 1) Building an algorithms for evacuation,
- 2) Finding the Pedestrians dynamic,
- 3) Applying the simulation in the cities when tsunamis strikes.

1.4 Structure of the manuscript

This thesis consists of six chapters. The Introduction, The state of the art, A hierarchy of models for crowd evacuation on road networks, Solving and simulating evacuation models, Experimentation and analysis, Discussion and Conclusion. The schema (Fig. 1.5) describes the relationship between sections and chapters of the manuscript.

In the Introduction chapter, An overview and the structure of the manuscript is provided (Fig. 1.5) which should help readers easily read the thesis.

Chapter I addresses the state of the art, representing the knowledge that contents many useful concepts regarded in Chapter two and Chapter three. Concretely, we presented the complex systems, Multi-Agents Systems, Spatial Decision Support Systems. Furthermore, this chapter describes the literature review about the crowd movement including evacuation simulations.

In Chapter II, we are concerned with a hierarchy of models of crowd evacuation on road networks. From simple to complicated models that many researchers have used, we use them by combining and integrating them for effective evacuation simulations. This chapter briefs the Equation-based models and Agent-based models used and how to integrate and combine them together.

Chapter III, Solving and Simulating Evacuation models, presents in detail what was introduced in the previous chapter. Firstly, supporting decisions for different objects in the evacuation, we consider the problem associated with sign system. Then, we discuss the Agent-based model on the road network of a city. In the quest of achieving an effective simulation and representation of the research question, we consider this problem by combining Agent-based models and Mathematical models.

In Chapter IV, Experimentation and Analysis, presents how we did the simulation and analysis problem based on the results of the simulation model.

In Chapter V, the Discussion and Conclusion chapter which is the last chapter contains the investigated problems and approaches used are closed. A new set of problems are exposed for future study and research.

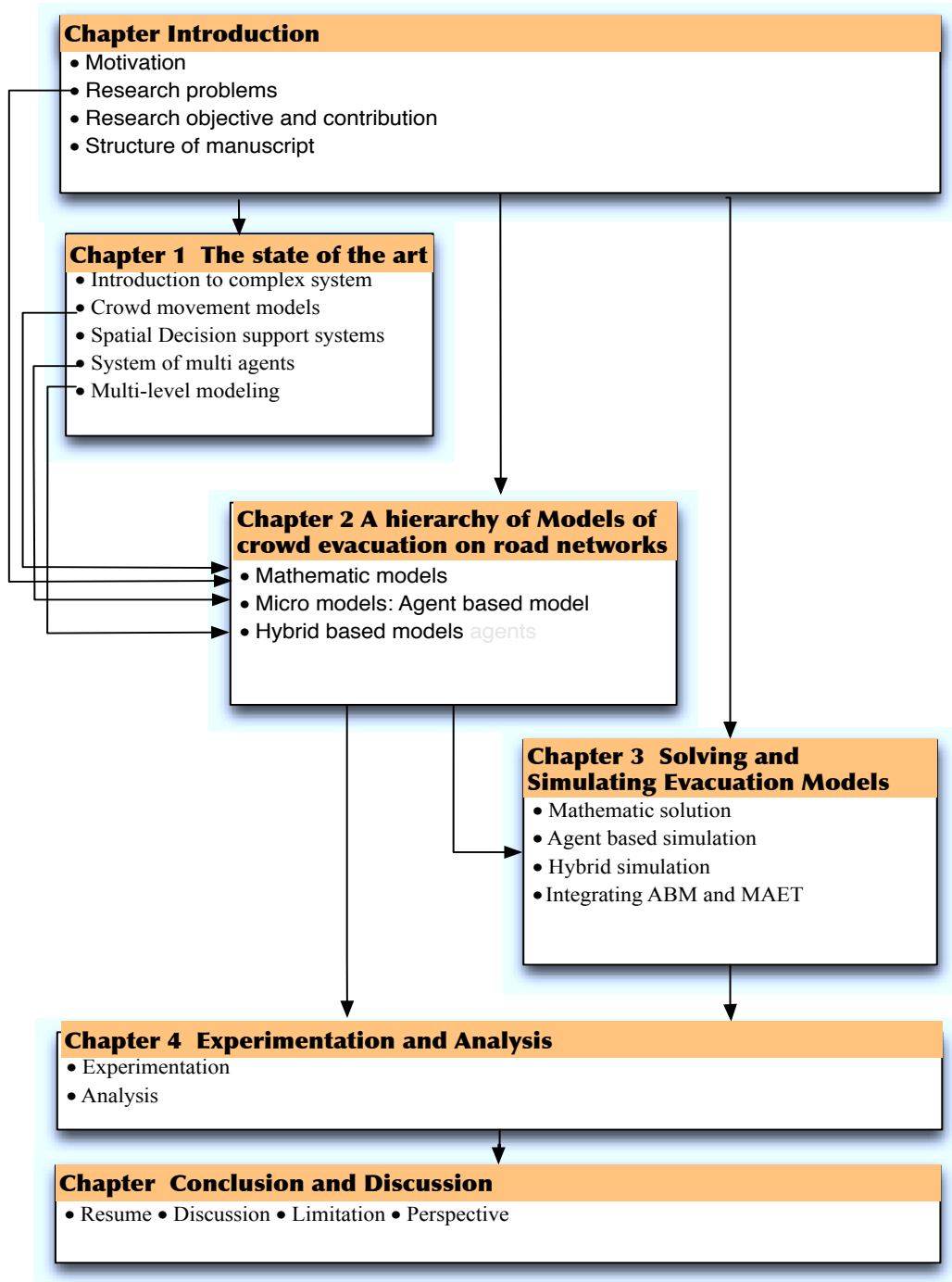


Figure 1.5: This schema describes the relationship between chapters and sections of the manuscript.

This chapter mentioned the work done, domains cover and major contributions of this thesis. Specifically, the motivation for the necessity for a research on tsunami evacuation in the road network of a city.

Finally, this research contribution focused on finding optimal sign placement, integrated two models EBM and ABM. Each of the chapters in this report has a close relationship with the other. The next chapter, we will regard the context and the background concepts used in the thesis.

Chapter 2

Decision support for rescue: The State of the art

Contents

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2.1 Foreword

In this chapter, the state of the art is communicated and highlighted, thereby, reflecting the important relevant knowledge in this thesis. On one hand, we represent many relevant concepts that were concerns in previous chapters. These includes the understanding of complex systems, crowd movement models, Multi-agent System, Multi-level Agent-Based modeling and Spatial decision support system for rescue that helps readers will understanding this report as thorough as possible. On the other hand, we describe the literature review on the crowd movement models and simulations that have been interested in recent years by many researchers [Navarro 2011, Kachroo 2008, Sugimoto 2003].

In the review about Crowd movement models, many models are researched such as some models published by [said EL HMAM 2008, G.Lovas. 1994, McCreaa 2010, MAGNE 2000]. We investigated carefully two models i.e Equation-Based models and Agent-Based models [Kachroo 2008, Taillandier 2010] as well as using them with the different views in large dynamic environments. Concretely, we applied these models for the tsunami evacuation models on the road network of a city. The crowd movement problem in a city is as complex system. What are complex systems and why study them?

2.2 Introduction to complex system

In the year 2000, a famous Physicist Stephen Hawking said: *"I think the next century will be the century of complexity"*. Indeed, complex systems are found in many fields ranging through social systems, global climate, economies, ant colonies, immune systems, crowd movement to disaster management system and so on. Particularly interesting ones are social systems areas formed out of people, the brain formed out of neurons, molecules formed out of atoms, the weather formed out of air flows, biological systems [Moncion 2010, Hutzler 2006].

Although there are a lot of definitions, there is no particular definition of a complex system for all fields. Some of the definitions that has been found widely popular are: Herbert A. Simon [Simon 1962] defined in 1962 *"A system analyzed into many agents having relatively many relations among them, so that the behavior of each agent depends on the behavior of others"*. In 2006, Ali A. BarYam et al [Dan 2006] defined *"Complex systems are systems with multiple interacting components whose behavior cannot be simply inferred from the behavior of the components"*. In 2011, M. E. J. Newman in [Newman 2011] defined *"A complex system is a system composed of many interacting agents, such that the collective behavior of those agents together is more than the sum of their individual behaviors"*. In

2012, S. Grauwin et al [Jensen 2012] defined "A system is a complex system if it is made of many interacting elements and if the dynamics of these interactions govern the behavior of the system, giving it a unity appearance from the point of view of an external observer". Etc. Therefore, I suggest a definition of a complex system inspired from the previous ones:

Definition 2.1 *A complex system is a dynamic system with multiple interacting agents whose emergent behavior cannot be simply inferred from the behavior of the agents.*

Obviously, complex systems relate to all fields of science, as well as engineering, management, and medicine, etc. In such systems, the components and the interactions between them often lead to large-scale behaviors which are not easily predicted from a knowledge only of the behavior of the individual agents. Such collective effects are called emergent behaviors. Examples of emergent Behaviors include short and long-term climate changes, price fluctuations in markets, foraging and building by ants, Immune systems with the ability to distinguish self from others and to protect the former and eradicate the latter [Mitchell 2002].

To recognize a complex system, we know that a complex system doesn't necessarily mean systems that are complex in appearance literally. This introduces the question what makes up a complex system [Simon 1962, Dan 2006]:

- Description:
 - What are the agents or components?
 - What is the emergent behavior?
 - How can we describe both levels accurately?
- Understanding: What is the link between the agent's behavior and global emergent behavior?
- How we make the process of formation of complex systems through pattern formation and evolution.

In this thesis, we consider evacuation systems as complex systems because these systems are composed of many agents such as people, vehicles, shelters, warning sign systems, communication systems, disaster managers, etc (Fig. 2.1). Especially, people agents possess different behaviors during a disaster. Therefore, these systems need to research with various behaviors for different agents. Moreover, emergent behaviors of these systems is targeted at our research on tsunami evacuation systems.

We introduce the evacuation system to find out the decision support that helps the different types of users such as evacuees, disaster managers, etc. In this thesis, we investigate the pedestrians evacuation on road network models that are called traditionally crowd movement models. In the next section, we consider the different crowd movement models that have been researched in the last few years.

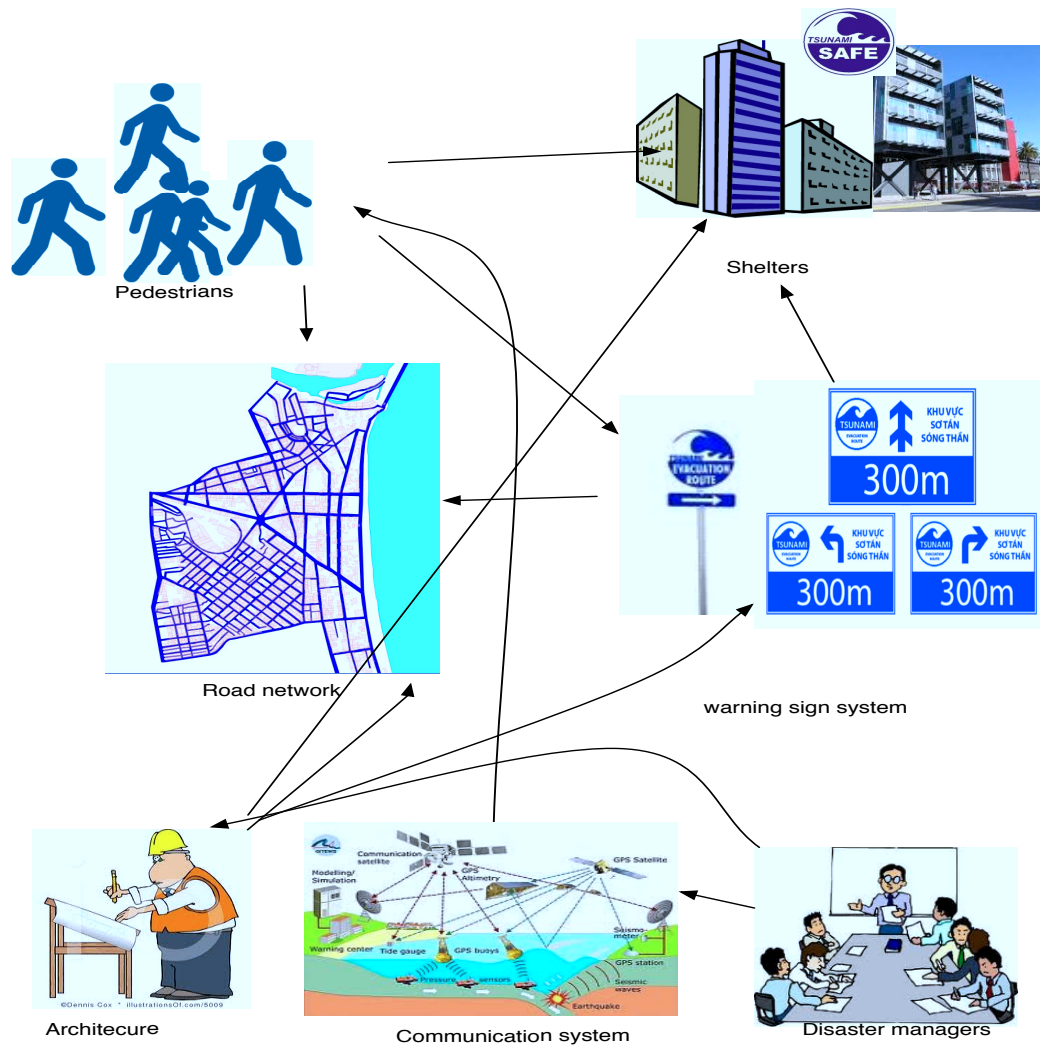


Figure 2.1: Evacuation systems view as a complex system with multiple interacting agents because these systems compose of many agents such as people, vehicles, shelters, warning sign systems, communication systems, disaster managers, etc.

2.3 Crowd movement models

In recent years, a lot of crowd movement models have been used in researches. Three main methodologies are used: Macroscopic models, Microscopic models and Hybrid models that combine the effective of the two former methodologies. Macroscopic models are concerned with homogenous behavior, such as traffic density, average speed and homogenous environment such as fluid dynamics. Meanwhile, Microscopic models are based on individual behavior such as cellular automata, lattice gas, social force, agent-based, game theory and experiments with animals. Here is a survey about the crowd movement models [Fang 2008, Zheng 2009, Kachroo 2008, Schreckenberg 2001, Klingsch 2010] that is shown in (Table. 2.1).

2.3.1 Cellular automata models

were first discovered in the 1940s by Stanislaw Ulam and John von Neumann [Zheng 2009, Reggia 1998]. They are discrete dynamic systems consisting of a regular grid of cells. A cellular automata model evolves at each discrete time step, with the value of the variable at one cell determined by the values of variables at the neighboring cells (see Fig. 2.2a). The variables at each cell are simultaneously updated based on the values of the variables in their neighborhood at the earlier time step and according to a set of local rules. At present, cellular automata models have been successfully applied to various complex systems, including traffic models and ecological fields over the last decade or so [Mathey 2008, Perez 2012, Craig 2010]. Basically, to help describe pedestrian dynamics during evacuations, researchers have applied cellular automata models. The model divides the space in a uniform grid that can read detail in [Reggia 1998]. Cellular automata models are combined with other approaches to investigate the evacuation process.

2.3.2 Lattice gas models

are often considered as a special case of cellular automata where additional constraints apply, such as conservation or spatial exclusion of pedestrians. The cells on the lattice can take a certain number of different states [Zheng 2009, Tajima 2001b, Tajima 2001a, Tajima 2002]. These models became popular in the 1980s. The various states are pedestrians with certain velocities. Evolution of the simulation is done in discrete time steps. After each time step, the state at a given cell can be determined by the state of the cell itself and neighboring cells, before the time step. These models are used to study the crowd of particle features by means of probability and statistics (see Fig. 2.2 b). inspire

Models	Scale	Agents/groups	Space and Time	Publications
Cellular automata	Microscopic	Homogeneous	Discrete	[Reggia 1998, Zheng 2011, Pelechano 2008]
Lattice gas	Microscopic	Homogeneous	Discrete	[Zheng 2009, Tajima 2001b, Tajima 2001a, Tajima 2002]
Social force	Microscopic	Homogeneous	Continuous	[Helbing 1993, Helbing 2002, Song 2013a, Duives 2013, Parisi 2009, Wei-Guo 2006]
Fluid dynamics	Macroscopic	Homogeneous	Continuous	[Al-nasur 2006, Fang 2003, Smith 2009, Singh 2009, Friesz 2013, Wong 2002, Lu 2008, Jin 2012, Luh 2012, Song 2013b, Parisi 2009, Duives 2013, Ha 2012]
Agent-based	Microscopic	Heterogeneous	Discrete	[Zhang 2009, Shendarkar 2008, Qiu 2010, Navarro 2011, Song 2013b]
Game theory	Microscopic	Homogeneous	Discrete	[Lo 2006, Lachapelle 2011, Zheng Xiaoping 2009]
Experiments with animals	Microscopic	Homogeneous	Discrete	[Klingsch 2010, Helbing 2003, Calvez 2007]

Table 2.1: The seven common models often are used in researching crowd movement. These models are applied to study separately and in combinations. This table shows the different of these models in scale, characteristics of agent or group, the time and space.

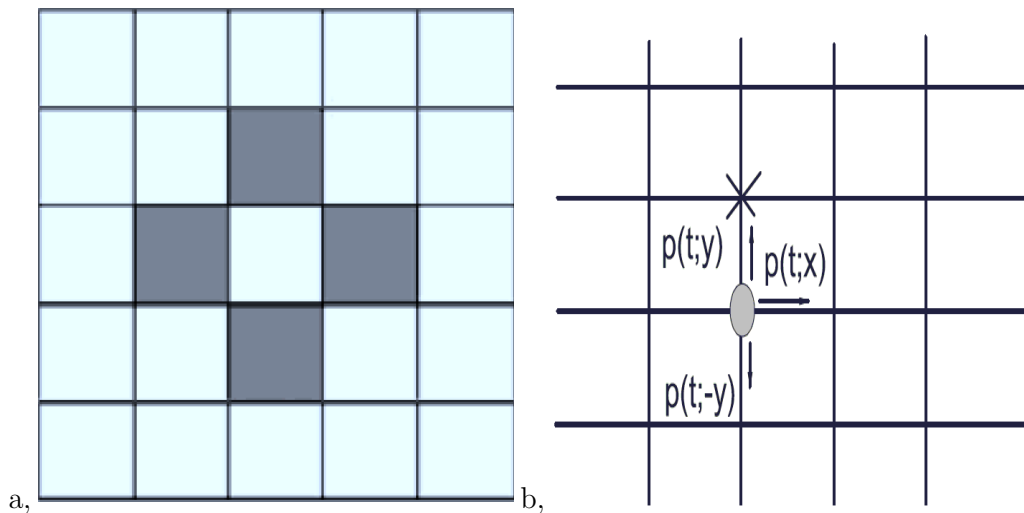


Figure 2.2: a, Cellular automata models are discrete dynamic systems consisting of a regular grid of cells, the figure displays that each cell the Von Neumann neighborhood. b, Lattice gas models are a special case of cellular automata where the cells on the lattice can take a certain number of different states. The state at a given cell can be determined by the state of the cell itself and neighboring cells.

The state at each cell is purely boolean. At a given cell, there's either a pedestrian moving in each direction or there is not. At each time step, two processes are carried out, propagation and collision. In the propagation step, each particle will move to a neighboring cell determined by the velocity that particle had. Barring any collisions, a particle with an upwards velocity will after the time step maintain that velocity, but be moved to the neighboring cell above the original cell. The so-called exclusion principle prevents two or more particles from traveling on the same link in the same direction.

In the collision step, collision rules are used to determine what happens if multiple particles reach the same cell. These collision rules are required to maintain mass conservation, and the total momentum conservation. The block cellular automaton model can be used to achieve these conservation laws. Note that the exclusion principle does not prevent two particles from traveling on the same link in opposite directions, when this happens, the two particles pass each other without colliding.

These models are also used to study the characteristics of particle flow in different building structures. Lattice gas models of particle flow have been applied to simulate crowd flow going outside a hall [Tajima 2001a]. Lattice gas models of biased random walkers have been proposed to simulate particle channel flow at a

bottleneck [Tajima 2001b, Tajima 2002].

2.3.3 Social force models

The Fluid Crowd modeling method of Henderson (1974) has been pointing to the *social force model* [D. Helbing 1995, Helbing 2002, Helbing 1993, Wei-Guo 2006]. The latter model is a microscopic continuous model with Deterministic Force-Based interactions. The concept is based on the assumption that changes in the movement of pedestrians are guided by social force fields. The notion of this model can be summarized as the superpositioning of attractive and repulsive effects determining the behavior of individuals. The exact effects might differ between pedestrian instances and models. All social force models are used to study the movements of pedestrians at a microscopic level. Since the effects or forces do not have to be physical in appearance, also other effects such as evacuation exits, sound effects, light effects, stress levels and gradients can be modeled by means of a social force model. The model assumes that pedestrians mostly face standard conditions. Therefore, they apply optimized behavioral strategies that they have learned over time such as Cooperation and Object avoidance. The actual movements of pedestrians are thus partly based on macroscopic behavior of the crowd and less on the personal characteristics of the pedestrian (Fig. 2.3).

The motion of a pedestrian is determined by the following main effects: (1) The fact that she/he wants to reach a certain destination; (2) The fact that she/he keeps a certain distance from other pedestrians; (3) The fact that she/he also keeps a certain distance from borders of obstacles such as walls; (4) The fact that she/he is sometimes attracted by other persons (e.g., friends) or objects (e.g., window displays). The total effect of pedestrian α is determined by

$$\begin{aligned}
 \underbrace{\vec{F}_\alpha(t)}_{\text{Total Effect}} &:= \underbrace{\vec{F}_\alpha^0(\vec{v}_\alpha, \vec{v}_\alpha^0 \vec{e}_\alpha)}_{\text{Effect of pedestrian's desire}} + \underbrace{\sum_\beta F_{\alpha\beta}^\vec{r}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}_\beta)}_{\text{Repulsive of pedestrian } \beta} \\
 &+ \underbrace{\sum_B F_{\alpha B}^\vec{r}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}_B)}_{\text{Repulsive of Border B}} + \underbrace{\sum_i F_{\alpha i}^\vec{r}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}_i, t)}_{\text{Attractive Effective}}
 \end{aligned}$$

The social force model is now defined by

$$\frac{d\vec{v}_\alpha}{dt} := \vec{F}_\alpha(t) + \text{fluctuations}$$

where

– \vec{v}_α is the actual velocity of pedestrian α ,

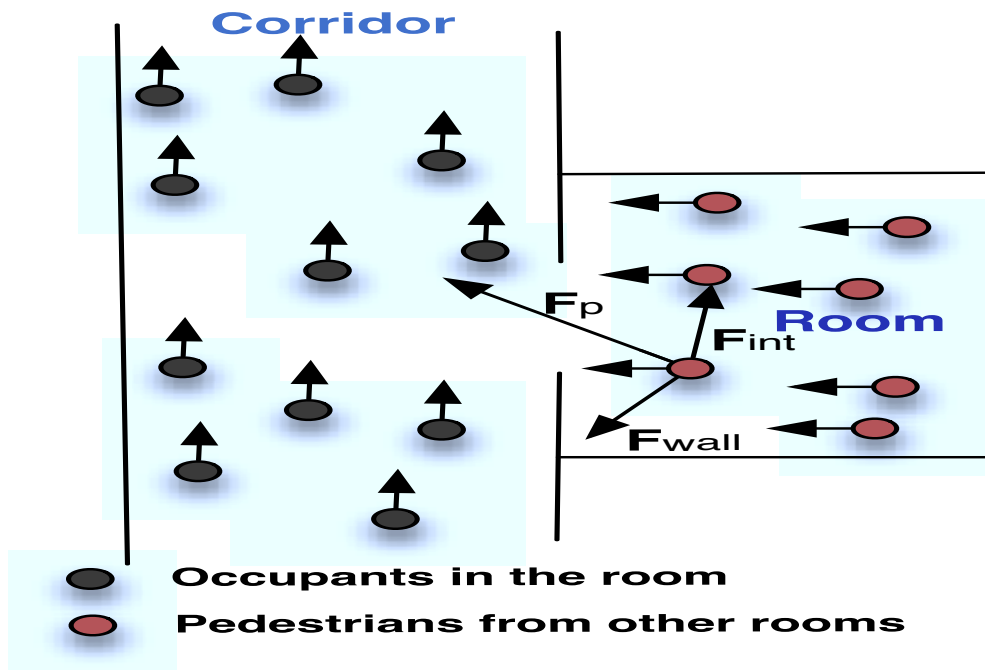


Figure 2.3: The motion of pedestrian is determined by: F_p Personal desire force, F_{int} interaction other pedestrians force, F_{wall} obstacles borders such as walls force.



Figure 2.4: In 2000, Helbing et al [Helbing 2002] developed another social force model to simulate panic situations. The model describes human crowd behavior with a mixture of socio-psychological and physical forces. This figure was used by Mehran, R et al in [Mehran 2009].

- \vec{v}_α^0 the certain desired speed of pedestrian α ,
- \vec{e}_α the desired motion direction of pedestrian α ,
- $\vec{r}_\alpha, \vec{r}_\beta$ the actual position of pedestrian α, β at time t ,
- \vec{r}_B is the location of border (e.g., wall) B that is nearest to pedestrian α

In 2000, Helbing et al [Helbing 2002] developed another social force model to simulate panic situations. The model describes human crowd behavior with a mixture of socio-psychological and physical forces. The social force model is determined by the Acceleration equation for the pedestrian i :

$$\underbrace{m_i \frac{dv_i}{dt}}_{\text{Acceleration}} = \underbrace{m_i \frac{v_i^0(t)e_i^0(t) - v_i(t)}{\tau_i}}_{\text{Driving Force}} + \underbrace{\sum_{j(\neq i)} f_{ij} + \sum_W f_{iW}}_{\text{Interaction forces}},$$

where

- m_i is the mass of pedestrian i ,
- \vec{v}_α^0 the instantaneous velocity of pedestrian i ,
- \vec{v}_α^0 the certain desired speed of pedestrian,
- \vec{e}_α the certain direction of pedestrian,
- τ_i a certain characteristic time interval,
- f_{ij} pedestrian i tries to keep a distance from other pedestrians j using interaction forces,

- f_{iW} is pedestrian i trying to keep a distance from the walls W using interaction forces.

Social force models has attracted great attention from so many researchers and have been further developed to study Crowd evacuation systems [Parisi 2009, Duives 2013, Ha 2012].

For example, the social force models of Helbing, et al. [D. Helbing 1995, Helbing 2002, Helbing 1993] are famous continuous models for describing pedestrian dynamics that qualitatively reproduces many self-organizing phenomena like lane formation, clogging or “faster is slower”. First, these models are ideally suited for describing the physical movements for many pedestrians. They can simulate the most typical phenomena observed in pedestrian dynamics. Secondly, social force models achieve very realistic simulation results. Third, they are successful in reproducing some observed behaviors of pedestrian flow. However, the disadvantages of these models are assumptions oversimplified, consideration mainly of three terms corresponding to the acceleration, impossibly take in to account perceptions of individuals and local decisions, and the environments being simple geometries.

2.3.4 Fluid-dynamic model

is a macroscopic level modeling that is concerned with group behavior and deals with a crowd as a whole. Crowded pedestrian have been described with fluid like properties. Fluid-Dynamic models describe how density and speed change over time with the use of *Partial Differential Equations* (PDE). Therefore, detailed interactions are overlooked, and the model’s characteristics are shifted toward continuum density flow and average speed [Al-nasur 2006, Kachroo 2008].

P.P.E. Kachroo et al represent fluid-dynamic models their book in Chapter 2 [Kachroo 2008]. He illustrates the close relationship between the three variables: density, velocity and traffic flow.

S. Al-nasur and P. Kachroo presente a model for a two-dimensional pedestrian movement flow [Al-nasur 2006]. The model is derived by extending a one-dimensional vehicle traffic flow model that uses two coupled partial differential equations (PDEs) to govern vehicular motion. This model modifies the vehicular traffic model so that bidirectional flow is possible, and also the pedestrian movement can be controlled to model different behaviors. The model satisfies the conservation principle and is classified as a hyperbolic PDE system.

One of the important milestones in the development of continuum pedestrian flow modeling dates back to the 50s, when *Lighthill and Whitham (1955) and Richards (1956)* (LWR) independently proposed a simple continuum model to describe the characteristics of traffic flow. The LWR model is one of the simplest

continuum pedestrian flow models in literature. In this model, a traffic stream model is supplemented by the continuity equation of vehicles, and the resulting PDE presumably could be solved to obtain the density as a function of space and time. For a specific form of pedestrian flow model, the solution can be obtained analytically. Although aiming at providing a coarse representation of pedestrians behavior, the LWR model is capable of reproducing qualitatively a remarkable amount of real pedestrians phenomena such as shock formation [Wong 2002]. The extension of LWR model to networks has been studied extensively in the literature [Wong 2002, Lu 2008, Jabari 2012, Jin 2012, Luh 2012]. The *LWR* models will be represented detail in the Chapter 3.

Wong et al extended the Lighthill, Whitham and Richards (LWR) model with heterogeneous drivers is formulated [Wong 2002]. The model takes into account the distribution of heterogeneous drivers characterized by their choice of speeds in a traffic stream, which models the dynamic behavior of heterogeneous users whereby faster vehicles could overtake slower ones under uncongested condition as well as congested condition (though less easily), and slower vehicles would slow down the faster ones.

Yadong Lu et al [Lu 2008] explicitly construct the entropy solutions for the LWR traffic flow model with a flow-density relationship which is piece-wise quadratic, continuous, concave, but not differentiable at the junction points where two quadratic polynomials meet, and with piecewise linear initial condition and piecewise constant boundary conditions. The explicitly constructed solutions provide a fast and accurate solution tool which may be used for predicting traffic or as a diagnosing tool to test the performance of numerical schemes.

Saif Eddin Jabari et Henry X. Liu offer a new stochastic model of traffic flow [Jabari 2012] in research LWR. The source of randomness in the proposed model is the uncertainty inherent in driver gap choice, which is represented by random state dependent vehicle time headways. A wide range of time headway distributions is allowed. From the random time headways, counting processes are defined, which represent cumulative flows across cell boundaries in a discrete space and continuous time conservation framework. Saif Eddin Jabari et Henry X. Liu show that their construction implicitly ensures non-negativity of traffic densities and that the fluid limit of the stochastic model is consistent with cell transmission model based deterministic dynamics.

Wen-Long Jin [Jin 2012, Luh 2012] presents a theory of multi-commodity network traffic flow based on the LWR model. In particular, we attempt to analyze kinematic waves of the Riemann problem for a general junction with multiple upstream and downstream links. In this theory, kinematic waves on a link can be determined by its initial condition and prevailing stationary state. In addition to a

stationary state, a flimsy interior state can develop next to the junction on a link. In order to pick out unique, physical solutions, he introduces two types of entropy conditions in supply-demand space such that (i) speeds of kinematic waves should be negative on upstream links and positive on downstream links, and (ii) fair merging and First-In-First-Out diverging rules are used to prescribe fluxes from interior states. For a simple model of urban or freeway intersections with four upstream and four downstream links, we demonstrate that theoretical solutions are consistent with numerical ones from a multi-commodity Cell Transmission Model. In a sense, the proposed theory can be considered as the continuous version of the multi-commodity Cell Transmission Model with fair merging and First-In-First-Out diverging rules.

Many researchers have expanded the original PDEs to the new models with the other models or conditions such as: Boltzmann equation, stochastic partial differential equations, path delay model, queues and delay model, Nash-like equilibrium conditions, First-in-first-out conditions, Route information condition, etc [Friesz 2013, Singh 2009, Dogbe 2012].

Friesz et al present a continuous-time network loading procedure based on the Lighthill-Whitham-Richards model [Friesz 2013]. A system of differential algebraic equations is proposed for describing traffic flow propagation, travel delay and route choices. Friesz et al employ a novel numerical apparatus to reformulate the scalar conservation law as a flow-based partial differential equation (PDE). This approach allows for an efficient computational scheme for large-scale networks. Friesz et al proposed the dynamic user equilibrium model. The dynamic user equilibrium model is solved as a differential variational inequality using a fixed-point algorithm.

Dogbe derives a macroscopic version of his Boltzmann-type equation for pedestrian dynamics [Dogbe 2012]. He shows how the distribution function can be used to recover gross macroscopic information on the overall state of the system by weighted moments, and derive a system of equations similar to Euler's. An important goal in the study of interacting particles systems is to understand how, given a large scale, deterministic evolution equations emerge from microscopic dynamics.

Fluid-dynamic models advantage by represented non-linear partial differential equations and satisfied unsteady situations. However, fluid-dynamic models are not represented model in detail. They are difficult by highly non-linear and set up based on several hypotheses. They are not flexible and Limited value except at dangerously high-crowd densities.

2.3.5 Agent-Based models

An agent is a discrete entity with its own goals and behaviors and autonomous with a capability to adapt and modify its behaviors. Agents are diverse and hetero-

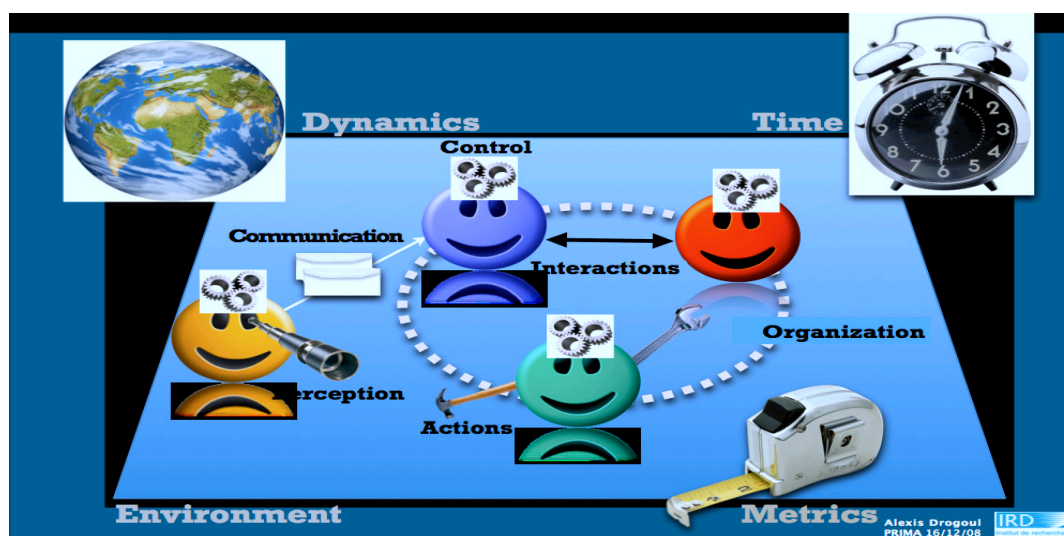


Figure 2.5: An agent is an autonomous entity in a spatial environment. It has skills to achieve its goals and tendencies together with many characteristics such as autonomy, communication, interactions, actions, perception, reactivity, sociality, initiative, cooperation, and intelligence. This figure was shown in the Alexis Drogoul’s representation in the PRIMA conference 2008 [Drogoul 2008].

geneous. Agent-based complex systems are dynamic networks of many interacting agents; examples include ecosystems, financial markets, and cities [Grimm 2005, Grimm 2006].

An *Agent-based model* (ABM), a relatively new computational model paradigm, is the model of phenomena as dynamical systems of interacting agents. Modeler use ABM to simulate the actions and interactions of autonomous agents (both individual or collective entities such as organizations or groups) with a view to assessing their effects on the system as a whole. It combines elements of Game theory, Complex systems, Emergence, Computational Sociology, Multi-Agent Systems, and evolutionary programming. Particularly within ecology, ABMs are also called *Individual-Based models* (IBM) [Hutzler 2005, Treuil 2008, Drogoul 2008].

In ABM, an agent is an autonomous entity. It has skills to achieve its goals with many characteristics such as autonomy, communication, interactions, actions, perception, reactivity, sociality, initiative, cooperation, and intelligence. An agent can perceive its environment and communicate with others to accomplish complex actions such as aggregating or departing and can represent more types of agent behavior than Cellular automata [Drogoul 2008].

It is difficult to represent ABMs, Grimm et al propose a standard protocol for describing ABMs (including IBM, multi-agent simulation, or multi-agent sys-

Overview	Purpose
	State variables and scales
	Process overview and scheduling
Design concepts	Design concepts
Details	Initialization
	Input
	Submodels

Figure 2.6: This protocol consists of three blocks (Overview, Design concepts, and Details), which are subdivided into seven elements: Purpose, State variables and scales, Process overview and scheduling, Design concepts, Initialization, Input, and Sub-models [Grimm 2006].

tems) [Grimm 2006]. A standard protocol for the description of ABMs would make reading and understanding them easier because readers would be guided by their expectations. He explain how understanding is facilitated when writers take readers' expectations into account: readers are better able to absorb information if it is provided in a familiar, meaningful structure (Fig. 2.6). Grimm et al explain Overview, Design concepts, and Details which aspects of a model should be described in each element, and they present an example to illustrate the protocol in use.

In the last few years, the ABM technique has been used to study crowd evacuation in various situations [Lämmel 2011, Wan 2013]. ABM are generally more computationally expensive than cellular automata, lattice gas, social force or fluid-dynamic models. However, their ability to allow each pedestrian to have and display unique behaviors makes it easier to model heterogeneous humans and more realistic. For instance, Helbing presents an ABM based on the social force model to simulate impacts of different floors, walls, and obstacles on agents, and interactions among agents in emergency situations [Helbing 2003].

In the evacuation simulation, evacuees are agents. Some of attributes of agents are static, including identify definition, age, mass, start position, maximum speed, and minimum speed. Whereas other attributes are dynamic, including location, speed, and acceleration. With statistical data, the value of agent static attribute can be set before the simulation. While the quick variation of agent dynamic

attribute makes it a necessity to collect the agent dynamic attribute by mobile phone or others mobile device real time. That increases the difficulty of agent dynamic attribute data acquisition and processing. In evacuation simulation, we can set original parameter value and constraints based on agent behavior model and behavior rule before simulation, and then compute and revise the agent dynamic attribute data real time [Song 2013b, Zhang 2009].

There is another similar ABM definition is Multi-agent System. Multi-Agent System and Agent-based model are considerable overlap, a Multi-Agent System is not always the same as an Agent-Based model (ABM). A *Multi-Agent System* (MAS) is a computerized system composed of multiple interacting intelligent agents within an environment. Multi-Agent Systems can be used to solve problems that are difficult or impossible for an individual agent or a monolithic system to solve. Intelligence may include some methodic, functional, procedural or algorithmic search, find and processing approach [Niazi 2011]. The goal of an ABM is to search for explanatory insight into the collective behavior of agents (which don't necessarily need to be "intelligent") obeying simple rules, typically in natural systems, rather than in solving specific practical or engineering problems. The terminology of ABM tends to be used more often in the sciences, and MAS in engineering and technology. Topics where Multi-Agent Systems researches may deliver an appropriate approach including online trading, disaster response, and modeling social structures[Niazi 2011].

The advantage of ABMs is that models can capture emergent phenomena, provide a natural description of a system, be flexible and describe successfully detail pedestrian behaviors. However, the task to model human agents' behavior is difficult [Hutzler 2005, Treuil 2008]. Cognitive models are highly sophisticated, so they require large computation. Because of ABMs' advantage, we use ABM for the tsunami evacuation simulation. Pedestrians are agents with different behaviors and attributions for many scenarios. The detail description ABM for tsunami evacuation simulation will be presented in the chapter 3.

2.3.6 Game Theoretic models

More formally, Game theory models are the study of mathematical models of conflict and cooperation between intelligent rational decision-makers. In some particular models, game theory models attempt to look at the relationships between participants and predict their optimal decisions. With a game theory model, a mathematical description of a social situation in which two or more individuals, or players, interact are provided. The players may be competitive or cooperative. With more than two players there may be collusion among subsets of the players. Games may involve several sequential steps or one step for each player. Competitive

situations may be repeated or be faced only once. Information concerning the rules of engagement and the payoffs may be known to all players or imperfectly known to some [Lachapelle 2011, Lo 2006].

Lachapelle et al propose a new approach to model crowd motions [Lachapelle 2011] called mean field games. A particular appealing feature is that the approximating macroscopic mean field model is derived from a mean-field game as the number of players tends to infinity. Furthermore Lachapelle et al treat players as \bar{O} smart individuals which try to optimize their path with respect to a particular goal. The main feature of mean field games is the forward-backward structure, the usual forward part describes the crowd evolution while the backward gives the process of how the expectations are built.

If the interactive decision process of the evacuees is rational, game theory can be adopted to describe the interactive behavior [Zheng Xiaoping 2009]. S.M. Lo et al presents a game theory-based method that can be incorporated within an evacuation model and effectively models the exit selection process in an evacuation process [Lo 2006]. In a game, several agents (the evacuees) strive to maximize their (expected) utility index by choosing particular course of actions (selecting particular route), and each agent's final utility payoffs will depend on the profile of the course of actions chosen by all agents. The interactive situation, specified by the set of participants, the possible courses of action of each agent, and the set of all possible utility payoffs, is called a Game. When evacuees and the congestion state of a route achieve a Nash Equilibrium, the strategy is optimal [Lo 2006].

S.M. Lo et al propose a game theory approach to model the behavior of selecting exits. The approach has been used in traffic assignment problems. There are two steps incorporated in the model. In the first step, they treat all the evacuees as a whole entity and assign them to the exits. A game is envisaged between the crowd of evacuees seeking an exit to minimize the expected travel time and a virtual entity imposing the blockage influence on the evacuees to maximize the expected travel time. This is assumed to be a two-player, non-cooperative, zero sum game. In this game, the evacuees will guess which exit will be congested and the virtual entity will guess which exit will be chosen. According to the spirit of game theory, the mixed strategy Nash equilibrium for this game gives a reasonable probability-based result of exit selection. Actually, the result of this step indicates the attraction of all the exits to the crowd. In the second step, S.M. Lo et al need to determine the decision of each evacuee. The factor of distance to the exits is considered. This information is used to adjust the probability values obtained in step one. (Fig. 2.7) briefly illustrates this approach.

The pos of Game theory model is ideally suited to analysis of human reasoning and strategic thinking in an evacuation. However, the outcome of a game is char-

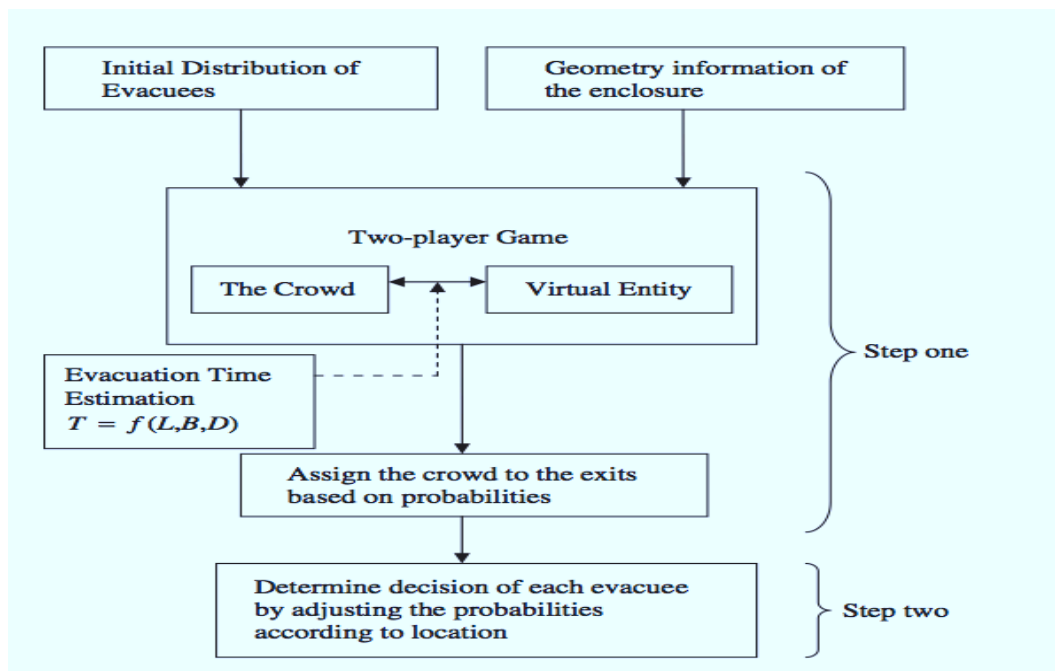


Figure 2.7: S.M. Lo et al propose a game theory approach to model the behavior of selecting exits. There are two steps incorporated in the model. In the first step, they treat all the evacuees as a whole entity and assign them to the exits. In the second step, S.M. Lo et al need to determine the decision of each evacuee [Lo 2006].

acterized by a payoff matrix. In addition, it is difficult to identify the large number of “players”.

2.3.7 Approaches based on experiments with Animals

The use of animals is a new approach for studying crowd evacuation. Experiments in genuine escape panic are difficult, especially with humans because of possible ethical and even legal concerns. The dynamics of escape panic are not completely understood because studies have been largely confined to numerical simulations [Zheng Xiaoping 2009].

Some researcher studied the ant models [Calvez 2007, Dorigo 1999]. Modelers use ants as pedestrians, they demonstrated the validity of such prediction through experiments in which low panic and high-panic scenarios were examined [alo 2003]. The theoretical predictions reported by Helbing et al. [Helbing 2003] for humans, and suggest that some features of the collective behavior of humans and ants are quite similar when escaping under panic.

Approaches based on experiments with animals are successful in the realistic crowd evacuation. These approaches can be understood very easily such as escaping behaviors of mice and ants. However, human beings are greatly different from mice and ants in experiments.

2.4 Hybrid-based model

In oder to reduces the computational complexity of the task at stake, the abstractions and the hybrid-based model that consider the different levels of details are investigated.

2.4.1 Abstractions

Abstraction is commonly used to account for the use of various levels of details that is the ability to change from one level to another while preserving useful properties. Moreover, abstraction is defined as a mapping between formalisms that reduces the computational complexity of the task at stake. An abstraction is a change of representation, in a same formalism, that hides details and preserves desirable properties. [Saitta 2013, ZUCKER 2003]. One of informal presentation of abstraction is the domain aggregation that is a transformation that corresponds to abstraction where objects are composed to build new ones. Zucker JD had chosen transformations of images to illustrate the domain aggregation. For example, on top of a table, there are a monitor, a PC tower, a keyboard and a mouse as individual

Models	Pos	Cons	Publications
Cellular automata/Lattice gas	(1)Be suited for large-scale in simulations. (2)Represent many collective behaviors. (3)Describe some phenomena during crowd evacuations.	(1)Cannot properly take high-pressure characteristics into account. (2)Ignored some prominent effects such as falling, injury etc.	[Reggia 1998, Zheng 2011, Pelechano 2008][Zheng 2009, Tajima 2001b, Tajima 2001a, Tajima 2002]
Social force	(1)Simulate the most typical phenomena observed in pedestrian dynamics. (2)Achieve very realistic simulation results. (3)Reproduce some observed behaviors of pedestrian flow.	(1)Assumptions oversimplified. (2)Consist mainly of three terms corresponding to the acceleration (3)Cannot consider perceptions of individuals and local decisions.	[Helbing 1993, Helbing 2002, Song 2013a, Duives 2013, Parisi 2009, Wei-Guo 2006]
Fluid dynamics	(1)Represented non-linear partial differential equations. (2)Satisfy unsteady situations.	(1) Not detail (2) Highly non-linear and set up based on several hypotheses. (3)Not flexible. (4) Limited value except at dangerously high-crowd densities.	[Al-nasur 2006, Smith 2009, Singh 2009, Lu 2008, Jin 2012, Luh 2012, Parisi 2009, Duives 2013, Ha 2012]
Agent-based	(1)Capture emergent phenomena, (2)Provide a natural description of a system (3)Be flexible (4)Describe successfully pedestrian behaviors.	(1)The task to model human agents' behavior is difficult. (2)Cognitive models are highly sophisticated. (3)Require large computation.	[Zhang 2009, Shendarkar 2008, Qiu 2010, Navarro 2011, Song 2013b]
Game theory	(1)Be ideally suited to analysis of human reasoning and strategic thinking in an evacuation.	(1)The outcome of a game is characterized by a payoff matrix. (2)It is difficult to identify the large number of "players".	[Lo 2006, Lachapelle 2011, Zheng Xiaoping 2009]
Experiments with animals	(1)Realistic crowd evacuation can be understood very easily such as escaping behaviors of mice and ants.	(1)Human beings are greatly different from mice and ants in experiments	[Klingsch 2010, Helbing 2003, Calvez 2007]

Table 2.2: Summary the pos cons of the seven models common used in crowd movement.

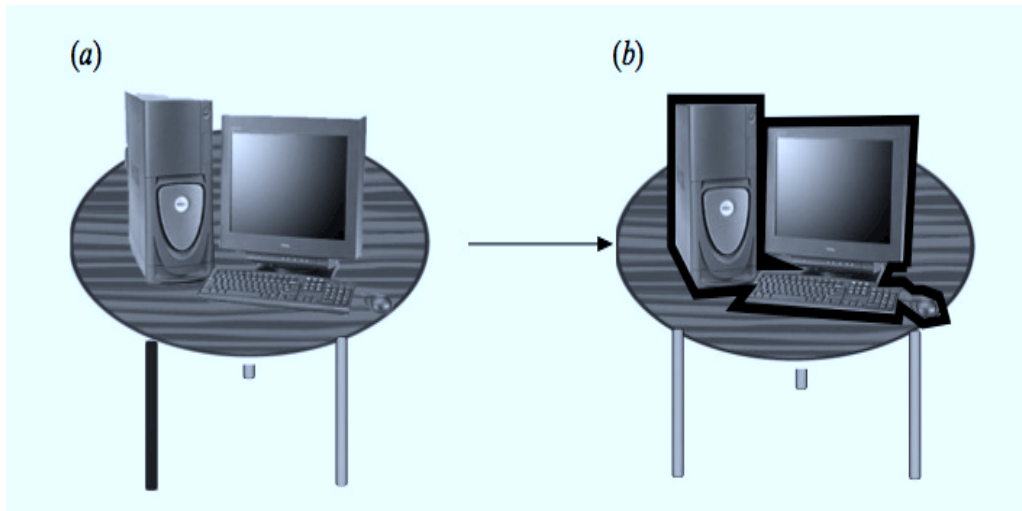


Figure 2.8: a, On top of a table, there are a monitor, a PC tower, a keyboard and a mouse as individual objects. b, a more abstract image, a computer is viewed as a whole is obtained by aggregating them [ZUCKER 2003].

objects (Fig. 2.8a). A more abstract image, a computer is viewed as a whole, is obtained by aggregating them (Fig. 2.8b). The different levels of details that using domain aggregating idea is used in the hybrid-based model. .

2.4.2 Hybrid-based model

What the current state of discussion about integrated simulation models is, and the research questions are as follows: (i) When is it appropriate to use hybrid simulation models? (ii) Why is it appropriate to use hybrid simulation models? and (iii) How can hybrid simulation models be developed? [Lattila 2010]

Leclercq Ludovic represented the Hybrid Models that combine ABM and EBM for a road network [Leclercq 2007, Leclercq 2012]. LWR model can be numerically solved in two different manners: the classical Eulerian scheme and a Lagrangian scheme following the N curves. This method leads to the same Discrete time expression as the car following models based on Newell's optimal velocity approach. Both discretization schemes converge to the same solutions. This highlights that the way traffic is represented does not influence the results. This case, a microscopic and a macroscopic models leads to the same solutions. The model properties are governed by the behavior rule rather than by the traffic representation.

Many researcher combined the basic models in one Hybrid model. The real advantage of Hybrid models is not only their ability to provide a trade-off between

accuracies and computational complexities, but also its overall performance and robustness in modeling traffic flow in large road networks.

The main issue in Hybrid Modeling lies in the interfaces between the models to be coupled. Beside the compatibility problems between the models to be coupled (e.g. parameters' compatibility), one has to address issues relating to consistencies of the coupling conditions. In order to get rid of these operational issues, usually encountered when developing a Hybrid-based model, this work propose a new Hybrid approach based exclusively on Macroscopic models, by taking full advantage of continuum Mathematical Models and Knowledge-Based Models: this new Hybrid approach takes into account the Stochastic traffic patterns at junctions via Knowledge-Based Modeling, whereas continuum models are used to describe traffic dynamics along stretches of roads. More interestingly, such a Hybrid approach enables exploiting both space and time correlation of traffic flow in road networks [McCrea 2010]. This model was applied for the English main road network (Fig. 2.9). In [Lammel 2010], Klingsch, Wolfram W. F et al represented the Hybrid-based model for the road network, they considered the Pangdang case combined queue approach and ABM. Another Hybrid-based model for road network in [Abouaissa 2014], they divided each junction to 5 patches called 5 clusters. For each cluster, different models were used. We also combined LWR and ABM for the Hybrid-based model.

The advantage of HBM is taking strong points of each model that helps modeler pass the obstacle in modeling a system. The disadvantage of HBM is difficult of transferring from a model to the others.

2.5 Spatial Decision Support Systems

The evacuation problems address Decision Support System for habitants, disaster managements, etc. To realize Decision Support System, Geographic Information System that contains spatial data are used in this thesis. The Spatial Decision Support System definition need to give. Indeed, *Spatial Decision Support System* (SDSS) are applied in many fields in dedicate with the fast *Geographic Information System* (GIS) data development and high computing performance [Coutinho-Rodrigues 2011, Santos 2011]. In order to analyze decision problems, the need to integrate spatial data with algorithmic techniques has been given rise to a research stream in the context of decision support systems. These systems are concerned with how to integrate spatially referenced information in a decision making environment in order to positively affect the performance of decision makers, showing how spatially integrated DSS can be used to bridge the gap between policy makers and complex computerized models [Coutinho-Rodrigues 2011].

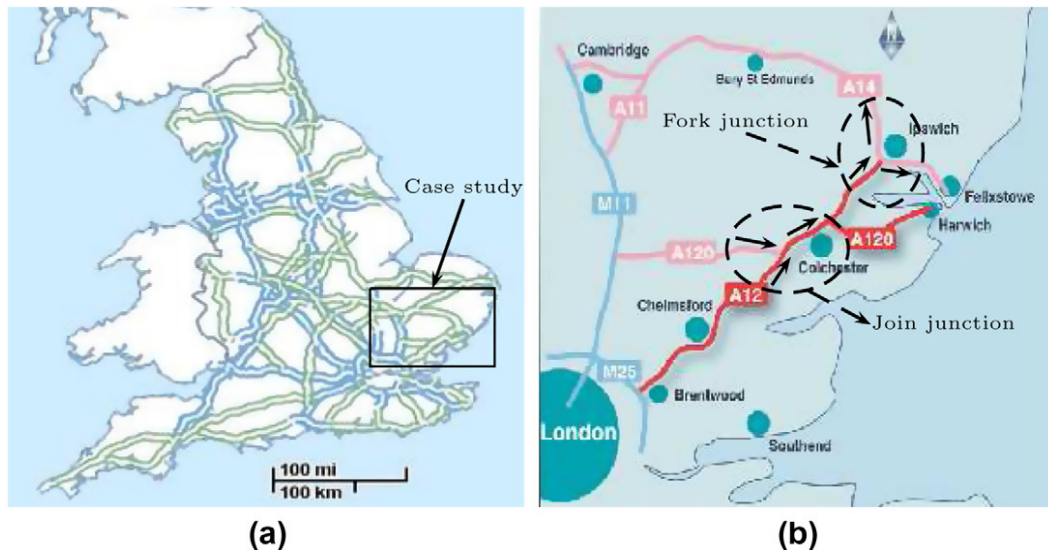


Figure 2.9: Hybrid approach based exclusively on Macroscopic models, by taking full advantage of continuum Mathematical Models and Knowledge-Based Models. This model was applied for the English main road network: a, English main road network b, Case study in [McCrea 2010].

Geographic Information System module supports storage and visualization of maps. It provides functions for spatial analysis. This module is supported on ArcView [Azevedo 2014], which was selected due to several reasons. It can perform the geographical data storage and visualization requirements of decision makers and can be programmed to perform the spatial analysis. Also, it includes built-in spatial analysis functions. GIS now has become a multi source spatial information database to extract, analyze, and visualize the valuable information. With the extensibility of GIS database, it is convenient to import custom defined entities and facilitate the efficiency of real time or time series data operation [Tang 2008].

A SDSS is a *Decision Support System* (DSS) using GIS. In case of evacuation on road network problems, it may entail the display of feature such as the road networks, shelters, sign placements, population density of a city. In a particular application requiring geographic information, SDSS can greatly enhance the support system.

Traditional pedestrians evacuation Decision Support System uses paper maps that aids moving from one junction to another. Mathematical models often use Traditional pedestrian evacuation Decision Support System that obviously tend to produce evacuation paths which link neighboring junctions. Thus, the result is not realistic. However, GIS data are available and variety of GIS softwares exist. A SDSS is needed to combine appropriately the evacuation algorithms with GIS

spatial data handling technique [Keenan 1998].

Because SDSS can greatly enhance the support system, using SDSS for evacuation simulation not only helps realization the problems but also visualization of evacuation maps. Therefore, we chose SDSS to research tsunami evacuation for a road network of a city.

2.6 Multi-Level Agent-Based model

In many systems, the researchers want to consider the changes of the global system, it is difficult to use ABMs for such activities. Thus, combination of different levels in a simulation is proposed. Obviously, it is very difficult to get the results of the different levels in the same simulation. Many levels are taken to overcome the disadvantages of ABM on the same system. Definition of *Multi-Level Agent-Based modeling* (ML-ABM) are proposed in recent years [Morvan 2012c, Morvan 2012a, Morvan 2012b]. Morvan gave the definition of as follows [Morvan 2012b]: "Integrating heterogeneous ABMs, representing complementary points of view, compared called levels (of an organization, observation, analysis, granularity,...) of the same system". **Integration** is understood that the entities such as environments, agents, etc ... are shared or interact by ABMs. **Heterogeneity** in this definition is understood that the ABMs integrated in a ML-ABM can be based on different models (equation-based model, force-based model, etc.), use different spatial and temporal scales. Multi-Level Agent-Based modeling often used in solving problems such as:

- coupling different models,
- transferring models in the same simulation to reduce disadvantage of each model,
- modeling of different level interactions, e.g., an explicit top-down feedback control.

A multi-level agent-based model is thus an agent-based model in which the agents are organized by the modeler into different levels. Several reasons may justify the development of a multi-level agent-based model. One reason may come from models that need to take into account entities at different spatial or organizational scales. Once identified, these "observables" may be explicitly defined by the modeler and play a significant role in the outcome of the simulation. In such a case, the modeler needs the possibility to take into account and represent with agents, at the same time, the emergent structures and the agents that 'compose' them. This problem of multi-level representation and articulation between agents at different levels is considered as one of the hardest issues to be tackled in the domain of complex systems modeling [Drogoul 2008, Treuil 2008, Hutzler 2005, An 2012].

The goal of the modelers was to show that modeling a tsunami evacuation could help deciders to test and evaluate in advance evacuation strategies in different scenarios. Obviously, the most important concern in that case is to be able to simulate realistic displacements of crowds of pedestrians on the city road network [An 2012].

2.7 Chapter conclusion

Complex systems relate to all fields of science, as well as engineering, management, and traffic, etc. In such systems, the components and the interactions between them often lead to large-scale behaviors which are not easily predicted from a knowledge only of the behavior of the individual agents. We introduce the evacuation system to find out the decision support that helps the different types of users such as evacuees, disaster managers, etc. We investigate the pedestrians evacuation on road network models that are called traditionally crowd movement models. A lot of crowd movement models have been used in researches. Three main methodologies are used: Macroscopic models, Microscopic models and Hybrid models that combine the effective of the two former methodologies. Macroscopic models are concerned with homogenous behavior, such as traffic density, average speed and homogenous environment such as fluid dynamics. Meanwhile, Microscopic models are based on individual behavior such as cellular automata, lattice gas, social force, agent-based, game theory and experiments with animals. The pos cons of the seven models common used in crowd movement are shown. From these pos cons, we choose two models Agent-based and Fluid dynamic for our problems.

A multi-level agent-based model is thus an agent-based model in which the agents are organized by the modeler into different levels. Several reasons may justify the development of a multi-level agent-based model. One reason may come from models that need to take into account entities at different spatial or organizational scales. The goal of the modelers was to show that modeling a tsunami evacuation could help deciders to test and evaluate in advance evacuation strategies in different scenarios.

Chapter 3

A Hierarchy of Models for Crowd Evacuation on Road Networks

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3.1 Foreword

There are different models available to study crowd evacuation such as the seven classical crowd movement models with advantage and disadvantage for each model discussed in the State of the art chapte. We show the hierarchy of models for crowd evacuation in this chapter. This hierarchy models for crowd evacuation on road network from simple to complicated models researchers have studied. The idea of combining models have been used in past researches as well. The idea of combining models is applied in this research in order to promote, enhance the model's strengths and invariably limit the weaknesses from any of the individual models.

Concretely, the hierarchy models represented in this chapter follows the level of detail such as space, behaviors, interactions, etc. Firstly, Mathematical models called *Equation-Based Models* (EBMs) are considered with the bottom level of detail. Secondly, we represent the top level of detail with *Agent-Based Models* (ABMs) because of strength to detail systems and environments. Example, ABMs can represent environments using GIS form with layers such as roads, buildings, terrains, etc and different behaviors of agents. Thirdly, *Hybrid-Based Models* (HBMs) are represented at the Intermediate level of computation complexities, comparing it with the previous models (Fig. 1.4).

Our aim is to solve tsunami evacuation problems on a road network of a city through simulation. Formulation the evacuation problems are represented in this chapter by using two models that are EBM and ABM. First, the EBMs can handle large environment such as counties, cities or a countries. However, they are difficult by highly non-linear and set up based on several hypotheses that require a lot of conditions and so far from reality. In addition, they are not flexible and limited value except at dangerously high-crowd densities. Agents in EBMs often assume homogeneous behaviors and simple. Secondly, the ABMs solve the evacuation problem in the small environments such as building size, the rooms, the station, etc. The behaviors of the agents are described in more details than the first model. These models puts a lot of different behaviors into consideration such as behavioral psychology, behaviors depending on gender, age, etc. We also used two models with a new observation and find ways to combine them together to solving a large number of agents.

3.2 Mathematic models

In the crowd movement, there are two basic of models macroscopic and microscopic. Macroscopic models concerned with average behavior such as average speed, density of agents (pedestrians, cars, vehicles,etc) and module area. Meanwhile,

microscopic models are considered individual behavior of each agent. However, microscopic models are computationally expensive. Therefore, macroscopic models are good approaches to describe the crowd agent flow. One of the main macroscopic model to concern crowd agent flow is LWR model. LWR was proposed by *Lighthill, Whitham and Richards* (LWR) in 1956 [Kachroo 2008, Xie 2013]. It is non-linear, first-order hyperbolic partial differential equation based on conservation law of agent density. The below subsection, LWR for pedestrian flow for a road and for a road network are represented. In LWR model, pedestrians are homogeneous with average speed. More precisely, the conservation law formulation represented the pedestrian flow by partial difference equations [Leclercq 2007, Leclercq 2012] This non-linear framework is simply based on the conservation law of pedestrian density.

3.2.1 Equation-Based Models for a road

The LWR model with pedestrian flow is often considered in a road or a road network. To simplify, we firstly investigate the LWR model for a road. LWR shows the relation between density, velocity and flow pedestrians. The models for pedestrian flow, whether they are one equation or system of equations, are based on the physical principle of conservation. Indeed, in physical domain, quantities remain the same during some process, these quantities are said to be conserved [Kachroo 2008, Klingsch 2010]. This principle using for a mathematical representation will make it possible to predict the densities and velocities patterns at future time.

Suppose there is a road with pedestrians moving with constant velocity v_0 , and constant density p_0 such that the distance between the pedestrians is also constant as shown in the (Fig. 3.1a). Now let an observer measure the number of pedestrians per unit time τ that pass a observer (i.e. pedestrian flow q). In τ time, each pedestrian has moved $v_0\tau$ distance, and hence the number of pedestrians that pass the observer in τ time is the number of pedestrians in $v_0\tau$ distance. Since the density p_0 is the number of pedestrians per unit area and there is $v_0\tau$ distance, then the pedestrian flow is given by $q = p_0v_0$. This is the same equation as in the time varying case, i.e.,

$$q(p, v) = p(t, x) \times v(t, x). \quad (3.1)$$

To show this, the number of pedestrians that pass point $x = x_0$ in a very small time Δt are considered. In this period of time the pedestrians have not moved far and hence $v(t, x)$, and $p(t, x)$ can be approximated by their constant values at $x = x_0$ and $t = t_0$. Then, the number of pedestrians passing the observer occupy a short distance, and they are approximately equal to $p(t, x) \times v(t, x)\Delta t$, where the pedestrian flow is given by the equation (3.1).

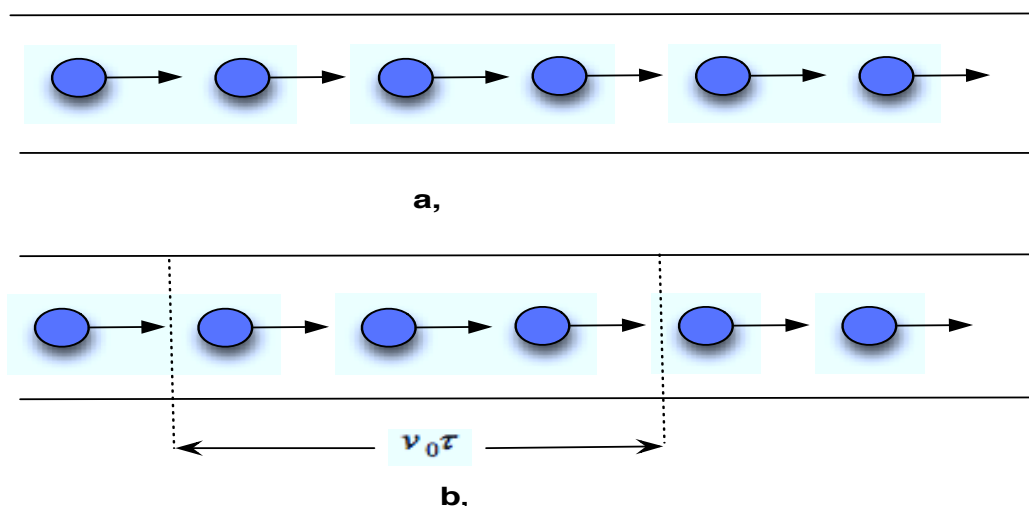


Figure 3.1: a, shows pedestrians moving with constant velocity v_0 , and constant density p_0 such that the distance between the pedestrians is also constant. b, displays the number of pedestrians that pass the observer in τ time is the number of pedestrians in $v_0\tau$ distance [Kachroo 2008].

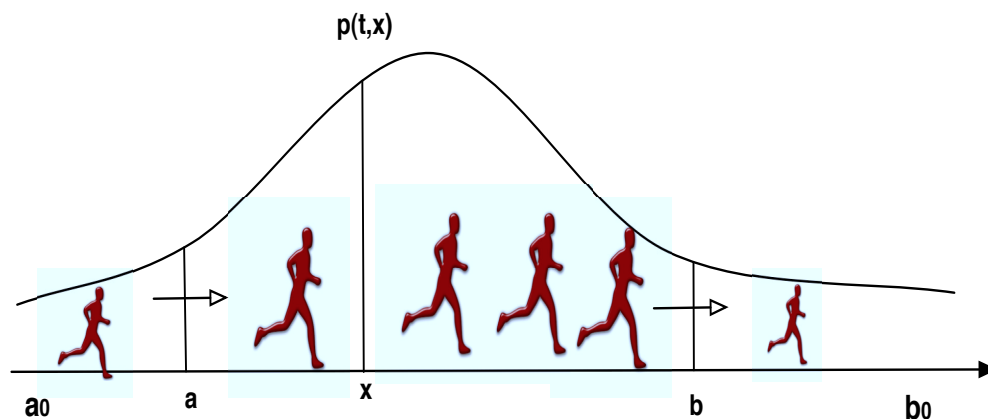


Figure 3.2: The Conservation law of density of pedestrians flow change at time t in the interval $[a, b]$. The pedestrians flow change at time t in the interval $[a, b]$ equals to the number of pedestrians incoming at a minus the number of pedestrians outgoing at b , $p(t, x)$ is the density of pedestrians at position x and the time t .

The number of pedestrians within $[a, b]$ at a given time t is the integral of the pedestrian density $p(t, x)$ given by

$$N = \int_a^b p(t, x) dx. \quad (3.2)$$

In the equation (3.2), it is implied that the number of pedestrians within $[a, b]$ is at maximum when pedestrian density is equal to congestion density p_{max} that is associated with the maximum number of pedestrians that could possibly fit in a unit area. The number of pedestrians can still change (increase or decrease) in time due to pedestrians crossing both ends of the interval a, b . The change of the number of pedestrians is due to the change at the boundaries only. We denote a road section by $I_0 = [a_0, b_0]$. The pedestrians change at time t in the interval $[a, b]$ equals to the number of pedestrians incoming at a minus the number of pedestrians outgoing at b . Therefore, the rate of change of the number of pedestrians is given by

$$\frac{dN}{dt} = q_a(p, v) - q_b(p, v) \quad (3.3)$$

Concretely, the conservation law of pedestrian density change at time t in the interval $[a, b]$ described by (Fig. 3.2). Since the number of pedestrians per unit time is the flow $q(p, v)$. Combining (3.2), and (3.3), yields the integral conservation law

$$\frac{d}{dt} \int_a^b p(t, x) dx = q_a(p, v) - q_b(p, v) = v(t, a).p(t, a) - v(t, b).p(t, b). \quad (3.4)$$

This equation represents the fact that change in number of pedestrians is due to the flows at the boundaries. Now let the end points be independent variables (not fixed with time), then the full derivative is replaced by partial derivative to get

$$\begin{aligned} \frac{\partial}{\partial t} \int_a^b p(t, x) dx &= q_a(p, v) - q_b(p, v) \\ &= - \int_a^b \frac{\partial}{\partial x} q(p, v) dx. \end{aligned} \quad (3.5)$$

From the last two equations, we have

$$\int_a^b \left[\frac{\partial}{\partial t} p(t, x) + \frac{\partial}{\partial x} q(p, v) \right] dx = 0 \quad (3.6)$$

Assuming $p(t, x)$, and $v(t, x)$ are both smooth, the conservation law is found to be

$$\frac{\partial}{\partial t} p(t, x) + \frac{\partial}{\partial x} q(p(t, x), v(t, x)) = 0 \quad (3.7)$$

where

- $(t, x) \in \mathbf{R} \times \mathbf{R}_+$ are time variable and spatial variable,
- $p = p(t, x) \in [0, p_{max}]$ is the density of pedestrians,
- $q(p, v) = p(t, x) \cdot v(t, x)$ is the pedestrian flow,
- $v = v(t, x)$ is the average velocity pedestrians.

LWR model considered the relationship between velocity and density $v(t, x)$ and $p(t, x)$

$$v(p) = v_{max} \left(1 - \frac{p}{p_{max}} \right). \quad (3.8)$$

As we all observe in real situation, pedestrians start to accelerate from high density (low speed) to low density (higher speed). We have LWR equation:

$$\frac{\partial p}{\partial t} + \frac{\partial}{\partial x} q(p) = 0. \quad (3.9)$$

or we can write the conservation law as following:

$$p_t + q(p)_x = 0 \quad (3.10)$$

We will using the solution of the initial value problem and also called the Cauchy problem given by

$$\begin{cases} p_t + q(p)_x = 0, \\ p(0, x) = p_0(x). \end{cases} \quad (3.11)$$

Although initial density is discontinuous, since our solution cannot be multi-valued, the solution shown cannot be smooth. A theory of discontinuous solutions, or shock wave solution is used. This model is appropriate to reveal shock formation as it is natural for conservation laws whose solutions may develop discontinuities in finite time. Due to the discontinuity of the density $q(p)$, one seeks for a weak entropy solution to (3.9), i.e. a solution $p = p(t, x)$ such that for every smooth positive test function $\varphi = \varphi(t, x) : I \times \mathbf{R}_+ \rightarrow \mathbf{R}_+$ compactly supported in $I \times (0, +\infty)$ the following relation holds

$$\int_0^\infty \int_a^b (\eta(p) \frac{\partial \varphi}{\partial t} + \psi(p) \frac{\partial \varphi}{\partial x}) dx dt \geq 0, \quad (3.12)$$

for any convex function $\eta \in C^1(\mathbf{R}, \mathbf{R})$ and any function $\psi \in C^1(\mathbf{R}, \mathbf{R})$ such that $\psi' = q'\eta'$.

If there is an initial value, the equation (3.9) is called Riemann. The initial values is chosen as following

$$p(x, 0) = \begin{cases} p_l & \text{if } x \leq 0, \\ p_r & \text{if } x > 0, \end{cases}$$

where p_l, p_r are two parameters being constant values. Because the function $q(p)$ is concave, the weak solution of the Riemann problem that published in [McCreaa 2010, Kachroo 2008, Leclercq 2007]. There are many different solution for (3.9), we show one weak solution that is popular in LWR model [McCreaa 2010, Kachroo 2008, Leclercq 2007]:

(i) if $p_l < p_r$ the solution including a shock wave is given by

$$p(t, x) = \begin{cases} p_l & \text{if } x \leq v_{max} \left(1 - \frac{p_r + p_l}{p_{max}}\right) t, \\ p_r & \text{if } x > v_{max} \left(1 - \frac{p_r + p_l}{p_{max}}\right) t. \end{cases} \quad (3.13)$$

(ii) if $p_l < p_r$ the solution of the equation is

$$p(t, x) = \begin{cases} p_l & \text{if } x \leq v_{max} \left(1 - \frac{2p_l}{p_{max}}\right) t, \\ \frac{p_{max} v_{max}}{2v_{max} + p_{max}} & \text{if } v_{max} \left(1 - \frac{2p_l}{p_{max}}\right) t \leq x \leq v_{max} \left(1 - \frac{2p_r}{p_{max}}\right) t, \\ p_r & \text{if } x > v_{max} \left(1 - \frac{2p_r}{p_{max}}\right) t. \end{cases} \quad (3.14)$$

(iii) if $p_l = p_r$ the solution is constant and given by:

$$p(t, x) = p_l. \quad (3.15)$$

This weak solution of the LWR model is successful in predicting the pedestrian flow in the future time. Therefore, LWR model is good approach for modelers compute the pedestrian flow. However, this model was displayed for only one road. We want to extend LWR for the road network in the subsection below.

3.2.2 Equation-Based Models for road network

To research LWR model on the road network, the road network using in the macroscopic model is needed to defined. Indeed, the road network in Equation-based model is represented as a finite directed graph $G = \{E, V\}$. Edges and vertices of the directed graph are roads and junctions of the road network respectively. E is the set of roads and V is the set of junctions. At the junction $V_n \in V$, let δ_n^- (resp. δ_n^+) the set of indices of all the incoming roads to V_n (resp. outgoing roads from V_n). Every edge $(u, v) \in E$ has a non-negative, real-valued capacity $c(u, v)$. If $(u, v) \notin E$, we assume that $c(u, v) = 0$. Each road i is modeled by an interval $I_i = [a_i, b_i]$, possibly with either $a_i = -\infty, b_i = +\infty$. In the case of the LWR model [McCreaa 2010], the conserved quantity is the variable $p_i = p_i(t, x) : I_i \times \mathbb{R}_+ \rightarrow \mathbb{R}_+$ so that on each edge i of the network, the traffic is governed by the following scalar conservation law:

$$\frac{\partial}{\partial x} f(p_i) + \frac{\partial}{\partial t} p_i = 0; \forall i \in \mathcal{I}. \quad (3.16)$$

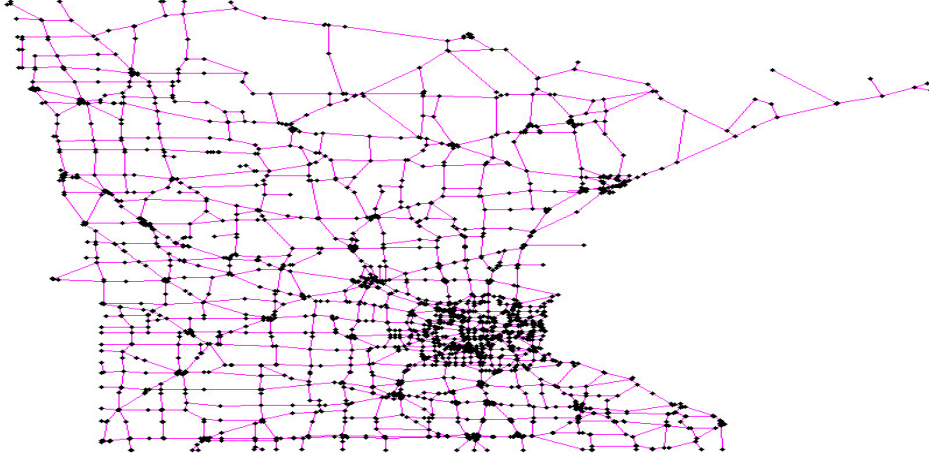


Figure 3.3: Road network are modeled as directed graph $G = \{E, V\}$, where edges and vertices correspond to roads and junctions, respectively and E and V denote the sets of edges and vertices.

- The solution p_i is required to be a weak entropy solution to (3.16) on road $i \in \mathcal{I}$ such that for every smooth positive test function $\varphi_i = \varphi_i(t, x) : I_i \times \mathbb{R}_+ \rightarrow \mathbb{R}_+$ compactly supported in $(a_i, b_i) \times (0, +\infty)$ the following relation holds

$$\sum_{i \in \mathcal{I}} \int_0^\infty \int_a^b (\eta(p) \frac{\partial \varphi}{\partial t} + \psi(p) \frac{\partial \varphi}{\partial x}) dx dt \geq 0, \quad (3.17)$$

for any convex function $\eta \in C^1(\mathbb{R}, \mathbb{R})$ and any function $\psi \in C^1(\mathbb{R}, \mathbb{R})$ such that $\psi' = q'\eta'$.

- Furthermore, the test function φ_i is assumed to be smooth across the junction, ie $\varphi_i(b_i, \cdot) = \varphi_j(a_j, \cdot), \forall i \in \delta_n^-$ and $\forall j \in \delta_n^+$.
- $p_i = p(\cdot, t)$ satisfies a Kirchhoff-like condition in conservation law theories:

$$\sum_{i \in \delta_n^-} q(p(b_i^-, t)) = \sum_{j \in \delta_n^+} q(p(a_j^+, t)), \text{ for almost every } t \geq 0.$$

At junction, there are many difference models to describe the transition of pedestrian flow. These approaches include statistical models such as generalized linear models, non-parametric statistical methods, etc. Most of these statistical methods are mainly based on some assumptions, such as stationarity of the time series, known statistical distributions of traffic parameters, etc. The major flaw of

statistical models is their tendency to concentrate on the means and miss the extremes; whereas, in practice, traffic conditions exhibit a highly fluctuated behavior with extreme peaks. Recent advances in uncertain reasonings' technology have led to the development of probabilistic knowledge-based models through Artificial Intelligence techniques. Examples of such models include Bayesian network, neural network, Markov chain models, fuzzy-neural models, etc[McCrea 2010].

However, these models are still unable to provide a full description of traffic features along road sections such as stop and go waves phenomena [McCrea 2010]. Another approach would be a transition matrix for the changing pedestrians flow at each junction. Garavello defined a transition matrix for each vertex as follows [Garavello 2009].

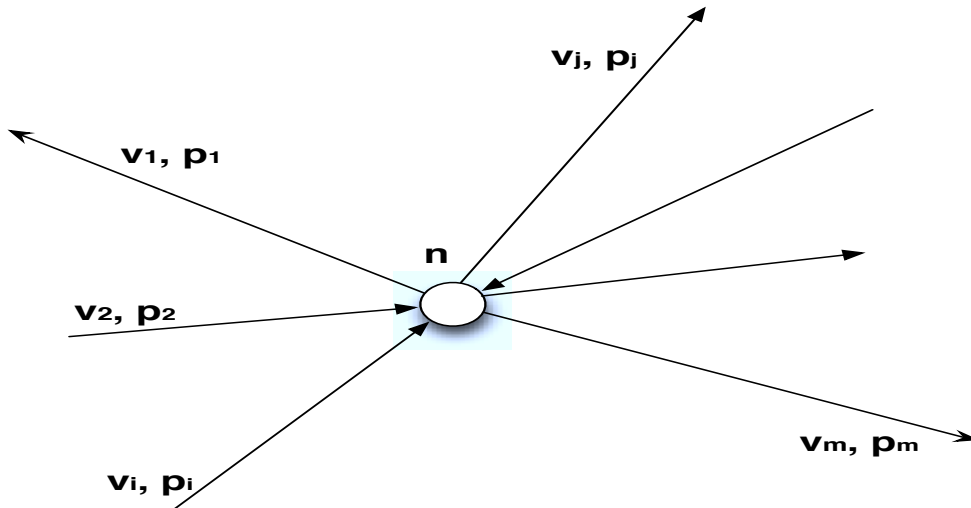


Figure 3.4: At a junction n , δ_n^- is set of outgoing roads and δ_n^+ are incoming roads. Each road has two variables $v_i(t, x), p_i(t, x)$ that are the velocity and density of pedestrians.

Garavello assumed that firstly the traffic from incoming roads is distributed on outgoing roads according to fixed coefficients. Second, pedestrians choose so as to maximize flow. To deal with the first assumption, he fixed a traffic transition matrix $A = (a_{ji})_{j \in \delta_n^-, i \in \delta_n^+}$ such that $0 < a_{ji} < 1$, for each $j \in \delta_n^-$ and $i \in \delta_n^+$, a_{ji} is the percentage of pedestrians arriving from the j incoming road that take the i outgoing road. Notice that with only the first assumption Riemann problems are still underdetermined. This choice represents a situation in which pedestrians have a final destination, hence distribute on outgoing roads according to a fixed law, but

maximize the flow whenever possible.

These matrix are fix parameters that make the models not true life and solve problem become complicated. Therefore, LWR model on a road network is only not flexible but also it raises another problem finding the set matrix A for all junctions in the road network.

Finally, the advantage of LWR model for a road network is found solution in suitable computational time. However, LWR model cannot represented pedestrians in detail. In addition, the assumption to solve problem is not flexible. To study a model that is more detail, we consider Agent-based model as follows.

3.2.3 Optimizing sign system in evacuation

Modeling agents' behaviors in Equation-based model

Let graph be $G = \{V, E\}$ representing the city in which $V = \{1, 2, \dots, n\}$ is a set of junctions and $E \subseteq V \times V$ is a set of edges representing roads connecting vertices. Each edge is associated with a weight c_{ij} representing the time required by an agent to move from vertex i to vertex j . Therefore, the set of neighbors of vertex i is referred to as $N(i) = \{j : (i, j) \in E\}$. Among all vertices, some of them are referred to as *Shelters*. Let $X \subset V$ denote the set of shelters (Fig. 3.5). We assume that all inhabitants are pedestrians that called agents. If an agent reaches a shelter, then it is considered out of danger.

To represent the behavior of the agents, we will use a Markov chain over the set of vertices. A Markov chain is composed of an initial distribution $\mu = \{\mu_i : i \in V\}$ where μ_i is the density of pedestrians at the junction i and a stochastic $n \times n$ matrix \mathbf{P} representing the transition probabilities from one vertex to another. Let us see how this Markov chain describes the behavior of the agents. At time $t = 0$, each agent is randomly placed on the graph with respect to the given distribution $\mu = \{\mu_i : i \in V\}$. At time $t > 0$, an agent positioned on vertex i will move towards vertex $j \in N(i)$ with probability P_{ij} , where \mathbf{P} is the stochastic matrix such that if $(i, j) \notin E$, then $P_{ij} = 0$ and such that $\sum_{j \in V} P_{ij} = 1$. Finally, if vertex i is a shelter, then $P_{ii} = 1$ (see Fig. 3.6). Thus shelters are absorbing states. To simplify the problem, we assume that the absorbing states have infinite capacity. Intuitively, this means that when an agent has reached a shelter, it will stay where it is. Technically, this is a slight generalization of Markov chains called *semi-Markov chains*, because the time required by an agent to cross the edge (i, j) is c_{ij} , which is not the same for all edges. Finally, for any agent, its probability distribution over V after m moves is given by $\mathbf{P}^m \mu$.

Formally, a quadruple (G, X, μ, \mathbf{P}) will completely define the territory and the behavior of agents when no signs are placed on the network. Let us introduce some

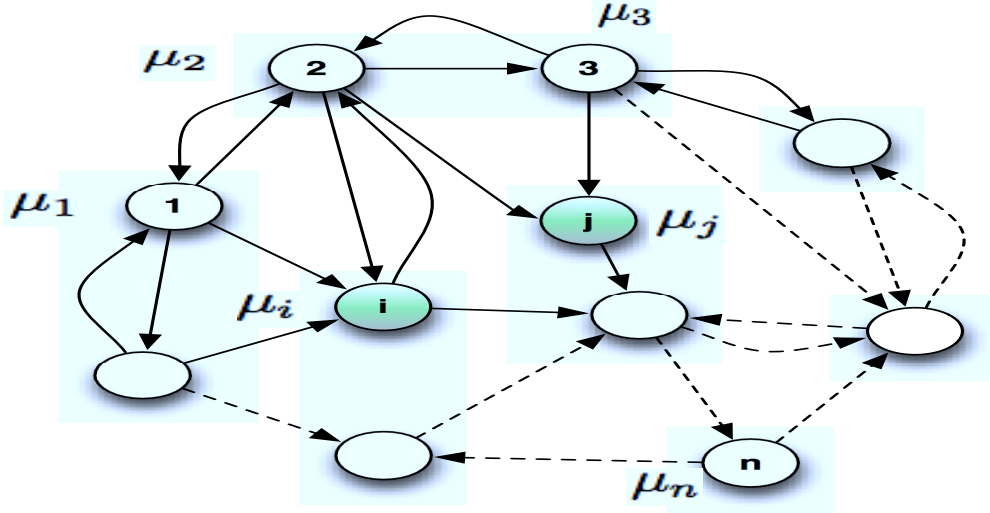


Figure 3.5: Among all vertices, some of them are referred to as *Shelters*. This figure, the shelters are green vertices. In each vertex i , there is an density of pedestrians μ_i represented for density of pedestrians near the junction i . Therefore, we have an initial distribution $\mu = \{\mu_i : i \in V\}$.

definition relative to sign placements.

Definition 3.1 A sign placement is a subset $S \subseteq E$ such that if $(i, j) \in S$ then for all $j' \neq j$, $(i, j') \notin S$. Informally, $(i, j) \in S$ means that we place a sign on the vertex i pointing towards the vertex j . Thus, $V(S) = \{i : \exists j, (i, j) \in S\}$ refers to the set of vertices on which signs are placed.

After some signs have been placed, the behavior of the agents will change. Intuitively, when an agent is on a signed vertex, it will always follow the sign. Formally, a set of signs induces a new stochastic matrix.

Definition 3.2 For a given sign placement S and a stochastic matrix \mathbf{P} , we define the induced stochastic matrix \mathbf{P}^S over the set of vertices as follows: for all $(i, j) \in S$ and for all $j' \neq j$, we have $P_{ij}^S = 1$ and $P_{ij'}^S = 0$. Also, for all $i \in V \setminus V(S)$ and all $j \in V$, we have $P_{ij}^S = P_{ij}$.

Given a sign placement S , the probability distribution of agents over V after m movements is given by $(\mathbf{P}^S)^m \mu$.

For example, the graph $G = \{V, E\}$ displays in the (Fig. 3.6) having $V = \{0, 1, \dots, 5\}$. We assume that agent positioned on vertex i will move towards vertex $j \in N(i)$ with the equal probability P_{ij} . Therefore, the transition stochastic matrix \mathbf{P} is given

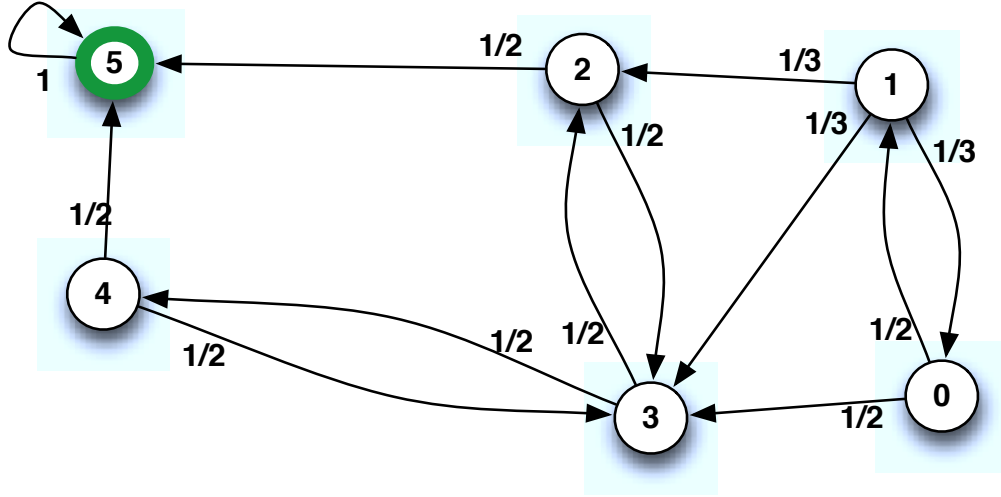


Figure 3.6: An agent positioned on vertex i will move towards vertex $j \in N(i)$ with probability P_{ij} such that if $(i, j) \notin E$, then $P_{ij} = 0$ and such that $\sum_{j \in V} P_{ij} = 1$. if vertex i is a shelter, then $P_{ii} = 1$.

$$\mathbf{P} = \begin{bmatrix} 0.0, & 1/2, & 0.0, & 1/2, & 0.0, & 0.0, \\ 1/3, & 0.0, & 1/3, & 1/3, & 0.0, & 0.0, \\ 0.0, & 0.0, & 0.0, & 1/2, & 0.0, & 1/2, \\ 0.0, & 0.0, & 1/2, & 0.0, & 1/2, & 0.0, \\ 0.0, & 0.0, & 0.0, & 1/2, & 0.0, & 1/2, \\ 0.0, & 0.0, & 0.0, & 0.0, & 0.0, & 1.0 \end{bmatrix}.$$

For given sign placement S (Fig. 3.7) the stochastic matrix \mathbf{P} , the induced stochastic matrix \mathbf{P}^S is given

$$\mathbf{P}^S = \begin{bmatrix} 0.0, & 1/2, & 0.0, & 1/2, & 0.0, & 0.0, \\ 0.0, & 0.0, & 1.0, & 0.0, & 0.0, & 0.0, \\ 0.0, & 0.0, & 0.0, & 0.0, & 0.0, & 1.0, \\ 0.0, & 0.0, & 0.0, & 0.0, & 1.0, & 0.0, \\ 0.0, & 0.0, & 0.0, & 0.0, & 0.0, & 1.0, \\ 0.0, & 0.0, & 0.0, & 0.0, & 0.0, & 1.0 \end{bmatrix}.$$

Formalizing sign placement as an optimization problem

Definition 3.3 Given a graph G , a stochastic matrix \mathbf{P} , a sign placement S , a set of shelters $X \subseteq V$ and an initial state $i_0 \in V$, the Average Evacuation Time

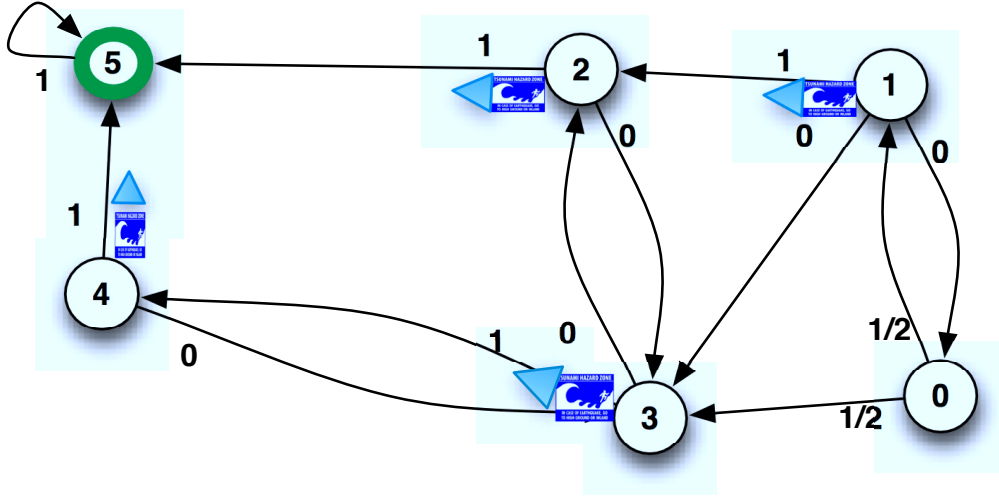


Figure 3.7: For a given sign placement S , the induced stochastic matrix \mathbf{P}^S over the set of vertices is as follows: for all $(i, j) \in S$ and for all $j' \neq j$, we have $P_{ij}^S = 1$ and $P_{ij'}^S = 0$.

$AET(S, i_0)$ is defined as the average time needed by an agent before it reaches a shelter, given that:

- At time $t = 0$, the agent is located on vertex i_0
- The behavior of the agent is dictated by the stochastic matrix \mathbf{P}^S .
- The time required by an agent to cross any edge $(i, j) \in E$ is c_{ij} .

In the case that agents are distributed randomly across the graph, we have the following definition:

Definition 3.4 Given a quadruplet (G, X, μ, \mathbf{P}) and a sign placement S , we define the Population Average Evacuation Time as $PAET(S) = \mathbb{E}_{i \sim \mu} [AET(S, i)] = \sum_{i \in V} \mu_i \cdot AET(S, i)$.

We note that $PAET(\emptyset)$ is the average rescue time without any sign. We can now formulate our optimization problem as:

Definition 3.5 *Minimization of Average Evacuation Time (MAET)*. Given a quadruplet (G, X, μ, \mathbf{P}) and an integer k , the MAET problem consists in finding the best sign placement S containing most k signs minimizing $PAET(S)$.

Unfortunately, unless $P=NP$ there are no polynomial time algorithms able to solve the corresponding decision problem. More precisely, we give a theorem but do not represent because of the length limit of the paper:

Theorem 3.6 *Given any number $s \in \mathbb{Q}$ and any instance of the MAET problem, checking if there exists a sign placement S of at most k signs such that $PAET(S) \leq s$ is NP-hard.*

Proof 3.1 *We will prove this by a reduction from the minimum vertex cover problem. For any graph $G = \{V, E\}$, a vertex cover of G is a set of vertices such that each edge of the graph is incident to at least one vertex of the set. Given a graph G and an integer k , the minimum vertex cover problem consists in checking whether there exists a vertex cover of G of size at most k . Assume $V = \{1 \dots n\}$. Let $G' = (V \cup \{0\}, E \cup \{(i, 0) : i \in V\})$ be the base graph for the MAET problem. Define the distribution over states as follows: Let $\mu_i = \frac{1}{n}$ for all $i \in V$ and $\mu_0 = 0$. The set of shelters is a singleton $X = \{0\}$. Let the transition matrix be defined as follows: $P_{i,0} = 0$ for all $i \in V$. Because the shelter is absorbing, we have $P_{0,0} = 1$. For all $(i, j) \in E$, we have $P_{i,j} = \frac{1}{N(i)}$. Because G is undirected, we have $(i, j) \in E \implies (j, i) \in E$, so there is always a non zero probability of going from i to j and back to i again. All other transitions not specified here have zero probability. Let $c_{i,j} = 1$ for all $(i, j) \in E$, and let $c_{i,0} = 0$ for all $i \in V$. Let $i_1 \dots i_k$ be the best set of vertices on which to place signs. Clearly, all signs should point towards 0, so the corresponding sign placement is $S = \{(i_1, 0) \dots (i_k, 0)\}$. If $i_1 \dots i_k$ is a vertex cover, then we have $AET(i, S) = 0$ if $i \in \{0, i_1 \dots i_k\}$, and $AET(i, S) = 1$ otherwise. Thus, $PAET(S) = \frac{n-k}{n}$. On the opposite, if $i_1 \dots i_k$ is not a vertex cover then there are two vertices $(u, v) \in E$ which have no sign placed on them. We still have $AET(i, S) = 0$ if $i \in \{0, i_1 \dots i_k\}$ and $AET(i, S) \geq 1$ if $i \in V \setminus \{0, u, v, i_1 \dots i_k\}$. For u and v , we now have $AET(u, S) > 1$ and $AET(v, S) > 1$. In fact, to reach the shelter, an agent starting on u must travel for at least one unit of time, and there is a non zero probability that the agent located on u will move towards v , in which case it will travel for more than one unit of time. Thus, we get $PAET(S) > \frac{n-k}{n}$.*

In conclusion, if we had a polynomial time algorithm to check if there exists a sign placement S such that $PAET(S) \leq \frac{n-k}{n}$, then we could solve the minimum vertex cover problem in polynomial time [Hassin 2003].

However, modeler using EBM cannot describe the agents' behaviors i.e each agent having many different behaviors. In below subsection, we show the ABM for evacuation on the road network.

3.3 Agent-Based Model

Modeler using ABM can take into account the heterogeneity of pedestrians' behaviors and the unspecified traffic conditions. For example, Tsai, Jason et al described a Agent-based model that incorporates four key features for the International

Terminal at Los Angeles International Airport: different agent types, emotional interactions, informational interactions, behavioral interactions [Tsai 2011].

ABMs [Gianluca Antonini 2006, Grimm 2006, Soteris 2004] are very flexible. However, they often require a lot more computation than their counterparts that may accommodate with very large populations. To model Agent-based for the tsunami evacuation, agents have many behaviors that depend on the factors such as psychology, emotion, age, family relationship, health, etc. In addition, ABM can represent and detail each pedestrian's behavior facing a tsunami signs. However, the ABM computation simulation is usually huge if we take in to account the complex and several agents behaviors. To reduce computation of the simulation using ABM for many agents in a large environment like a city, we have only considered two types of behaviors for agents who are knowledgeable agents and followers.

To present Agent-based model, we rely on the *Overview Design concepts Detail* (ODD) protocol [Grimm 2006, Grimm 2005] which is widely accepted as an agent based model template.

3.3.1 Overview

- Purpose

The purpose of this overview is to detail each pedestrian's behavior facing a Tsunami alert sign then to link the behavior to both the probability to survive and the global amount of time spend to evacuate. The simulation of the behaviors produces the emergence of pedestrians moving along the road networks. For the sake of simplicity we have only considered two kinds of behaviors, one that corresponds to an knowledgeable pedestrian (called a fox agent) and another one that is more a followers that do not have any idea how to respond to a Tsunami alert (called a sheep agent).

- Entities, state variables and scales

First, the pedestrians are entities. A *fox agent* is defined as a pedestrian who has been trained on evacuation procedures or has knowledge of how get to the safe place efficiently. The pedestrian evacuating randomly at junctions or following one fox agent is called *sheep agent*.

The state variables of pedestrian are their *position* and *velocity*. Each agent has his own behavior according to his goal and knowledge of the environment. His perception in the environment depends on space that the agent can observe. Position of the other agents around, road infrastructure can all be used by the agent to decide its move. His decisions are based on his perception of the environment and the information shared with the other agents. As agent moves, he adapts his speed to reach his desired speed. Indeed, if his speed is less than the desired speed, and if

there is enough space, he will try to accelerate.

Second, spatial scale in this model is meter and the unit time is minute. We consider the time that all the pedestrians move to the safe places and the specific area.

- Process overview and scheduling

The process movement of fox and sheep agents are:

- Agents follow road network from their position to the shelters following the behaviors of fox agent or sheep agent.
- The larger the width of the road, the faster agents' flow moves.
- The speed of an agent is controlled by road width and local density.
- Firstly, we assume that the road network has no alert signs. The fox agents are the agents who has been trained on evacuation procedures or has knowledge of how to get to the safe places efficiently or know one of the shelters, moves to the shortest path from their initial position to get there. Then, the fox agent will guide other sheeps to know their path [Anh 2011].
- Secondly, considering when the road network has an alert sign system. We investigate different behaviors of the fox agent. A fox agent is defined as a pedestrian goes following the alert sign system [Nguyen 2012] and (see Fig. 3.8). A fox agent moves to the end of a road then, he stays at the junction. If there is a tsunami warning sign, it follow the sign. Or else, he chooses randomly a road to move down on.
- sheep agent follows fox agent or chooses road randomly at a junction that is opposite direction to the tsunami [Anh 2011].

If he/she is a sheep agent, he/she choose a road randomly at a junction. If he/she is a fox agent, he/she moves to the direction that correspond to the shortest path to its objective position.

In panic situations, the pedestrians always want to escape from the dangerous place as quickly as possible. If there are no information available, they often move randomly or follow the crowd. The road networks is complex so the sheep agent finds it difficult to finding the safe place or reaching the safe place before its too late. Diagram (Fig. 3.8,3.9) is described the process of agents in evacuation.

3.3.2 Design concepts

- Basic principles

If the road network has not alert sign system, the fox agent chooses the shortest path and sheep agent moves randomly or follows one of the fox agents. Or else, a fox agent is defined as a pedestrian goes following the alert sign system.

- Emergence

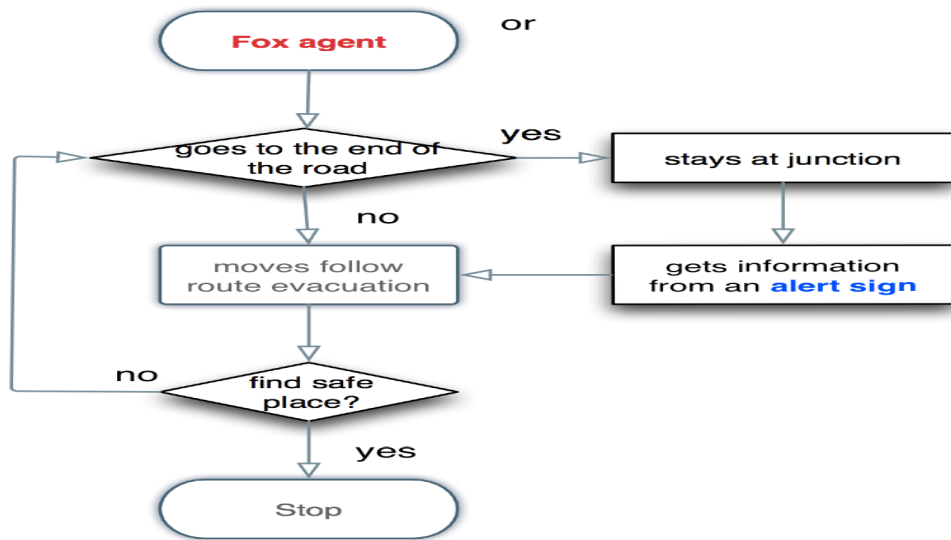


Figure 3.8: Processes a fox agent moving. A fox agent is defined as a pedestrian goes following the alert sign system [Nguyen 2012]. A fox agent moves to the end of a road then, he stays at the junction. If there is a tsunami warning sign, it follow the sign. Or else, he chooses randomly a road to move down on.

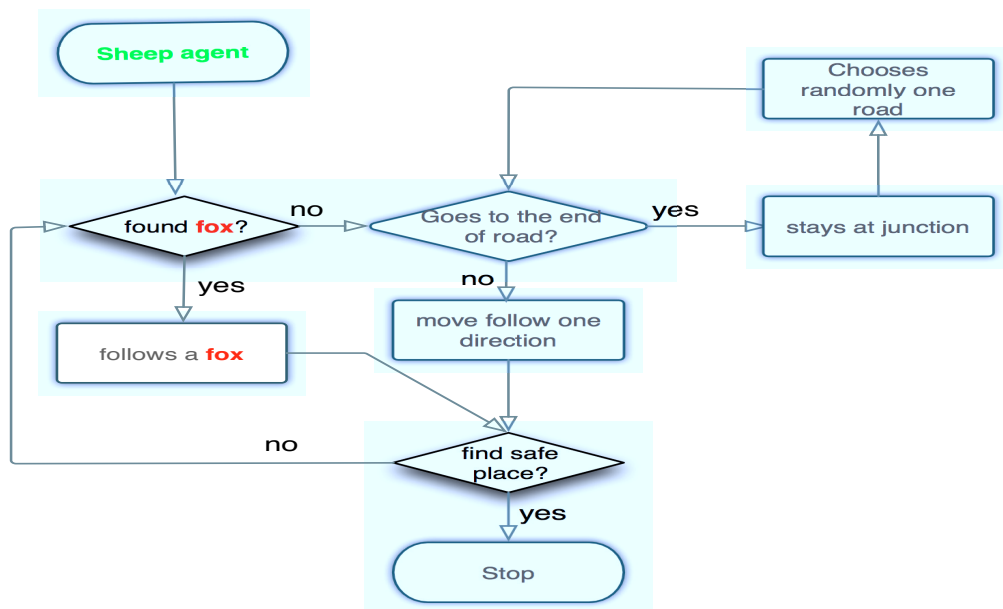


Figure 3.9: Processes a sheep agent moving. A sheep agent follows fox agent or chooses road randomly at a junction that is opposite direction to the tsunami.

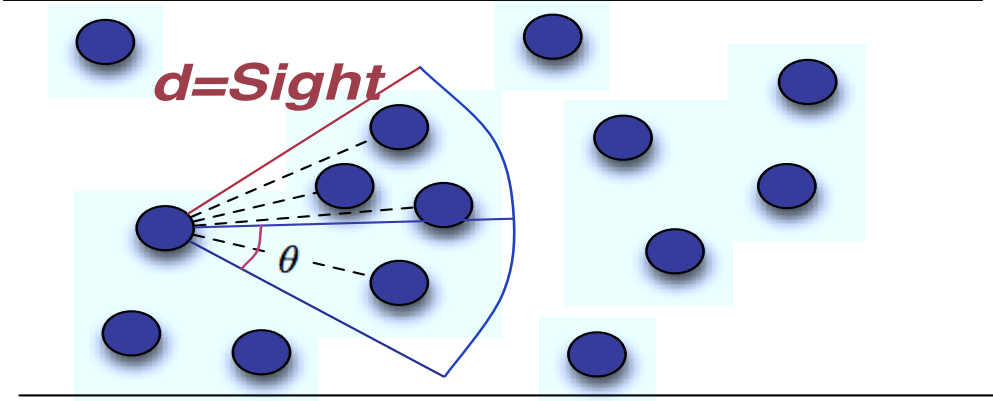


Figure 3.10: The set of all neighbors of the agent i is $Neighbors(i) = \{j : distance(i, j) < d \text{ and } j \text{ is front in the sight with the angle } \theta \text{ of agent } i\}$ and $N(i) = card\{j : j \in Neighbors(i)\}$.

The result shows that the more the number of fox agents in population, the lesser time spending of all agents.

– Adaptation

The Velocity of agents in the ABM is an issue that we need to study. The Velocities of agents has effect on the time of evacuation and the result of evacuation. However, they depend on many factors.

Normal pedestrians moved at a maximum of $1.5m/s$. (Fig. 3.11) shows the relationship between Velocity and local Density of agents. Velocity decreased with increasing local density, stopping at the maximum density $Density_{max} = 6persons/m^2$ [Goto 2012]. In this model, we assume that each agent has an effect radius d and it depends on the half forward circle of the agent.

Concretely, we consider that The set of all neighbors of the agent i is $Neighbors(i) = \{j : distance(i, j) < d \text{ and } j \text{ is front in the sight with the angle } \theta \text{ of agent } i\}$ and $N(i) = card\{j : j \in Neighbors(i)\}$.

The velocity of the agent belong the number of neighbors in front of i :

$$Velocity_{agent\ i}(t, x) = Velocity_{max,road\ k} \left(1 - \frac{N(i)}{N_{max,roadk}} \right)$$

where $N_{max,road\ k} = \pi d^2 \cdot Density_{max}$.

– Objectives

The fox agent's objective is to find the shortest path from current position to one of safe places and help the sheep agents. The objective of sheep agent is to find a fox agent and explore a safe place when he can not find any fox agent.

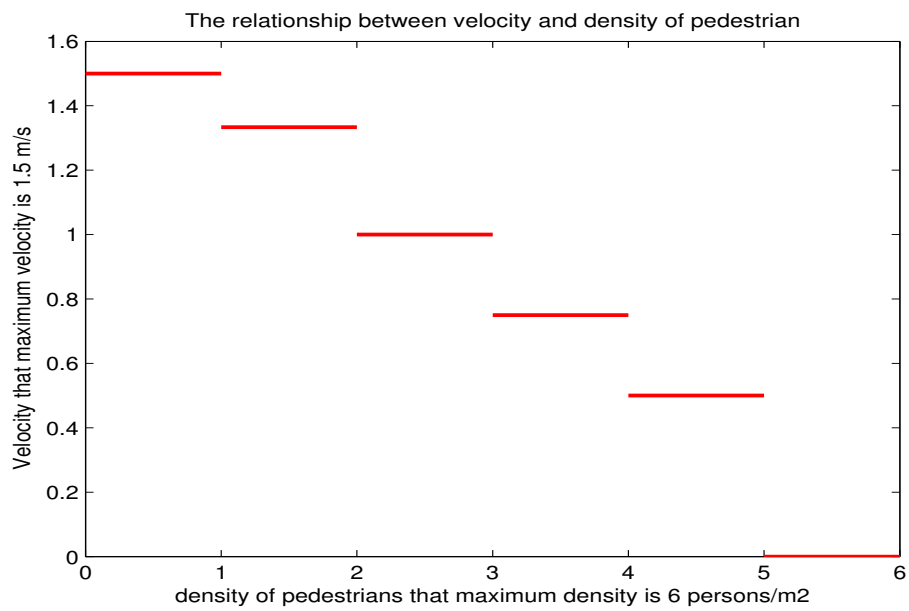


Figure 3.11: Normal pedestrians moved at a maximum of $1.5m/s$. This figure shows the relationship between Velocity and local density of agents. Velocity decreased with increasing local density, stopping at the maximum density $Density_{max} = 6persons/m^2$.

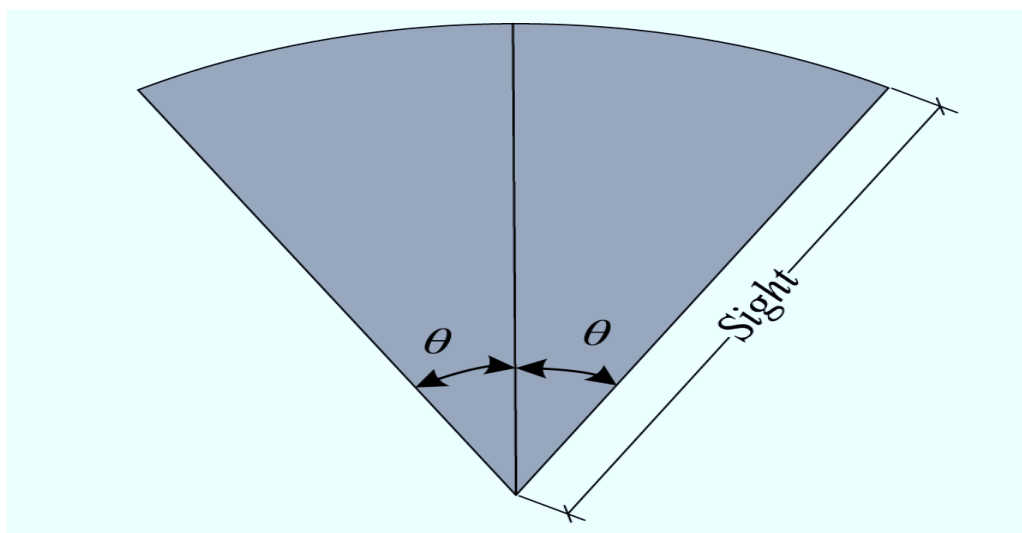


Figure 3.12: Sight means the agent's maximum distance of eye sight, and θ means half of the maximum angle the agent can see from its current position; the following two parameters are weight factors reflecting how the agent's behavior is affected by external factors from either crowd or environment issues [Xiong 2013].

- Prediction

The fox agent can predict the block of the traffic when he senses the crowd. The prediction of the fox agent helps him and the followers evacuate more effectively.

- Sensing

There are two levels in sensing the environment. The high level sensing of an agent is to know the sequence of roads from his/her position to one of destinations. The low level sensing of an agent is the local environment that helps him/her avoid the obstacles, the crowd and move efficiently on the road (Fig. 3.10, 3.12). A fox agent has both the high and the low levels. The high level sensing shows an fox agent the shortest path. On another hand, a sheep agent has only low level sensing or he/she tries to find an fox agent.

- Interaction

The sheep agent tries to find a fox agent is front in his/her sight with the angle θ and he/she follows. All agents impact each other by adapting their velocity.

- Collectives

The group includes a fox agent and all the sheep agents following the fox agent. The fox agent of each group is the leader that helps all the members of the group to escape danger to the safe place.

3.3.3 Detail

- Initialization

The initial data are the number of agents; the time in a day; the parameter tourist season is true or false; the rate of fox agent in the population.

- Input data

Input data are the pedestrians distribution that depend on the time in a day and the parameter tourist season; the number of shelters; the alert sign system; the GIS environment such as the road network, the buildings, the rivers, the beach, the wards,

When modelers use Agent-based models need to simulate the models, they need one or some tools supported Agent-based simulation. There are many Agent-based simulation tools such as DEFACTO, DRILLSIM, GAMA, etc [Schurr 2008, Khalil 2009, Massaguer 2006, Drogoul 2013a, Drogoul 2013b, Grignard 2013, Taillandier 2010] that we present detail in the next subsection.

3.3.4 Agent-based simulation tool

The DEFACTO system is a Agent-based simulation tool for training incident commanders for large scale disasters. The DEFACTO incorporates 3D visualization omni-viewer, and human-interaction reasoning into a unique high fidelity system. Human-interaction allows responders to interact with the coordinating agent team in a complex environment, in which the responder can gain experience and draw valuable lessons that will be applicable in the real world. While this system is currently used for the command of a disaster response scenario, the lessons learned and the methods used to approach this challenging domain apply directly to military applications such as the command and control of troops [Schurr 2008, Khalil 2009].

Architecture: DEFACTO is a multi-agent simulation and modeling system based on Machinetta proxy architecture. Architecture of DEFACTO is scalable ($\mathcal{O}(10,000)$ agents) and flexible. DEFACTO consists of simulator, 3D omni-viewer, Machinetta proxy based teamwork infrastructure, and analysis tool to analyze the impact of teamwork interaction strategies. Methodology: DEFACTO has modeled agent in proxy team formation (Machinetta). Machinetta proxies are responsible for transfer-of-control over a decision, managing local team beliefs communication between proxies, communication between proxy and a team member, coordination, and task allocation for the team. Each proxy provides all transfer-of-control strategy options. One of strategy options is selected based on current situation and agent role. An optimal transfer-of-control strategy balances the risk of high quality decision made by human against the risk of costs incurred due to a delay in getting the decision from agent. Each team implements team-oriented plans which describe

joint activities to be performed. Joint activities may include duplicate or conflicting tasks; hence Machinetta includes conflict resolution algorithms to remove conflicts [Schurr 2008, Khalil 2009].

A number of simulation systems have been developed based on Agent-based models such as DrillSim and GAMA. DrillSim is an augmented reality user-centric simulation environment for testing Information Technology solutions. The purpose of DrillSim is to play out a crisis response activity where agents might be either diverse roles (first responders, crisis managers, experts, etc.). An activity in DrillSim occurs in a hybrid world that is composed of the simulated world generated by a multi-agent simulator and a real world captured by a smart space.

Architecture: DrillSim is a multi-agent simulation and modeling system. DrillSim is based on scalable architecture ($\mathcal{O}(100,000)$ agents), and is extended by plug-and-play capability. System components include I/O interfaces, simulation engine, data management module, database server for spatial data, and the Virtual Reality/Augmented Reality modules.

Methodology: Each agent has a role and a profile (age, cognitive abilities, health, and knowledge). Simulation scenarios are created by binding roles and profiles to agents. DrillSim has modeled agent behavior as a discrete process where agents alternate between sleep and awake states. Agents wake up and take some action every t time units. For this purpose, an agent acquires awareness of the world around it, transforms the acquired data into information, and makes decisions based on this information using recurrent neural network. Then, based on the decisions, it (re)generates a set of action plans using A* and object avoidance algorithms. Action plans dictate the actions the agent attempts before going to sleep again. Agents share and disseminate information based on their relationships (represented in a social network) via their own communication devices [Khalil 2009, Massaguer 2006].

The GAMA (GIS & Agent-based Modeling Architecture) simulation platform aims at providing field experts, modelers, and computer scientists with a complete modeling and simulation development environment for building spatially explicit ABM simulations [Drogoul 2013a, Drogoul 2013b, Grignard 2013, Taillandier 2010]. The detail representation of the GAMA is in the Appendix A of this thesis.

Architecture: GAMA is a Agent-based simulation and modeling system. GAMA is based on scalable architecture ($\mathcal{O}(200,000)$ agents).

Methodology: The most important requirements of spatially explicit ABM simulations that GAMA platform fulfills are: the ability to transparently use complex GIS data as an environment for the agents; the ability to handle a vast amount of (heterogeneous) agents; the ability to offer a platform for automated controlled experiments.

The advantage of ABM is that modeler can take into account the heterogeneous

agent's behaviors. Because of the level of details described in ABM, the computational time is expensive so we investigate another model Hybrid-based model to speedup the simulation.

3.4 Hybrid-Based Models

3.4.1 Environment of the Hybrid Models

In a large scale environment such as a road network of a city, the importance of different areas are not equal. Indeed, there are some areas that are very important in evacuation whereas other areas can be ignored. Thus, the unimportant areas are represented by a directed graph and the important areas are represented by the GIS. In the environment of the hybrid model, each road is separated by three patches. At the begin and the end of each road, ABM is applied, whereas on the middle stretch of the road that is described by an edge of a directed graph is called a the tube, a EBM of the pedestrian flow is considered. The Hybrid environment described in (Fig. 3.13) combines a directed graph and GIS.

The tube has two special positions: its extremities that the first one correspond to the change from the begin of the road the tube and the position changing from the tube to the end of the road. The interface between two model is consider the aggregation and disaggregation procedure. It is the main idea and key point help speedup the Hybrid-Based simulation.

3.4.2 Aggregation and Disaggregation in Hybrid simulation

As mentioned above, one of the key issue in combining two such models ABM and EBM is the coherence of the results in terms of time, space (discrete/continuous) and behaviors. HBM will be built on the road network by each road, then would be divided into three patches that are the beginning, the ending of a road and the tube. Suppose we consider a road k , the length of the road k is denoted $LengthRoad_k$. The tube has two parameters that are the length of this patch $LengthRoad_k$ and capacity c_k of the road k (Fig. 3.13).

This road will be divided into three patches, the tube length is taken as $(1 - 2 \times \delta) \times LengthRoad_k$. The beginning and the ending of the road is taken as $\delta \times LengthRoad_k$. The parameter δ has value in interval $[0, 0.5]$. The value of δ is depended on the choice of modelers. If the modelers want to consider all the roads in ABM the $\delta = 0$. If the $delta = 0.5$, all the roads are considered in EBM. Or else, if $\delta \in (0.0, 0.5)$, ABM will be applied in the beginning and the ending of each road, EBM will applied in the tube. This analysis about the value of the parameter δ is

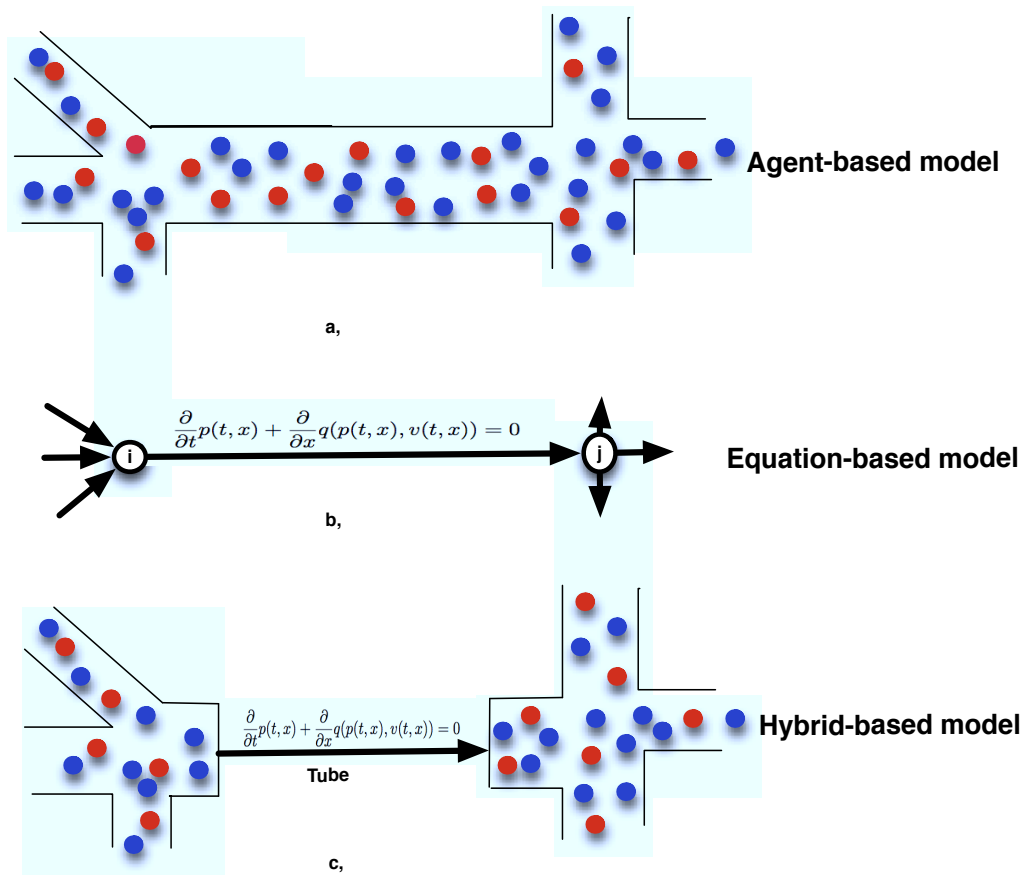


Figure 3.13: A blue/red dot is a sheep/fox agent. Modelers using Agent-based models can take into account the different agents' behaviors. b, Modelers using Equation-based model can compute the density of agent flow fast. c, In Hybrid-based model, Agent-based model and Equation-based model are combined on a road. The tube is considered an aggregated agent.

Parameter δ in Hybrid-based model			
δ	The beginning of a road	Tube	The ending of a road
0	ABM	ABM	ABM
(0.0,0.5)	ABM	EBM	ABM
0.5	EBM	EBM	EBM

Table 3.1: The proportion of the beginning, the ending of a road and the tube is $\delta \times LengthRoad_k$, $(1 - 2 \times \delta) \times LengthRoad_k$, $\delta \times LengthRoad_k$ respectively. The parameter δ has value in interval $[0, 0.5]$. The value of δ is depended on the choice of modelers.

given by (Table 3.1).

Then, trigger switches are built from ABM to EBM and from EBM to ABM from the ending and the beginning of the road to the tube and vice versa [Anh 2011].

3.4.3 The aggregation trigger switching ABM to EBM

The important issue of this hybrid-based model is built a trigger for switching ABM to EBM. The ideal for building aggregation trigger is displayed in (Fig. 3.15). It is not difficult to switch ABM to EBM because ABM contains much more information and parameters than EBM that is consider several values. Indeed, the ABM describes the agents in each individual pedestrians in detail such as sheep and fox behaviors, different velocity, etc. Meanwhile, EBM is only consider this problem with two values that are pedestrian density $p(t, x)$ and the average velocity $v(t, x)$ of the pedestrian density. First, let's choose one arbitrary road k and consider the road as hybrid-based environment that the beginning and the ending of this road is represented by GIS and the tube is represented by an edge of a directed graph. To simplify this problem, we assume that the agents move follow one direction from the beginning to the ending of the road k . There are two positions x_0, x_1 on the road that ABM is switched to EBM and EBM switched to ABM respectively. Pedestrians in ABM pass to the position x_0 where where $x_0 = \delta \times LengthRoad$ (Fig. 3.15). While, pedestrian flow in EBM is switched into the pedestrians in ABM at $x_1 = (1 - \delta) \times LengthRoad$. At x_0 the aggregation trigger changes the pedestrians in ABM to the pedestrian flow in EBM as follows:

- The interval of the time from t step to $t + 1$ step is called the time step t^{th} .
- The aggregation triggers changes the number of pedestrians of ABM at time step t^{th} to the pedestrian flow as the parameters

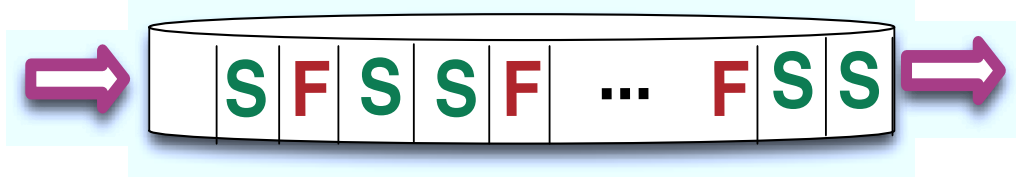


Figure 3.14: To keep two behaviors of fox agent or sheep agent in ABM, a token array is used to store two labels S for a sheep agent and F for a fox agent. If a sheep/fox agent moves to the tube, a label S/F is put into this token store.

$$q(p_k(t, x_0)) = \text{card}\{\text{Number of agents moves to tube at } t^{\text{th}} \text{ step}\}. \quad (3.18)$$

The average velocity of the number pedestrians at source gives the velocity of flow pedestrian in the tube

$$v_k(t, x_0) = \frac{\Sigma \text{Velocity of each agent moves to the tube}}{q(p_k(t, x_0))}. \quad (3.19)$$

– At the time step t^{th} the pedestrian density at time step t^{th} is given:

$$p(t, x_0) = \frac{q(p_k(t, x_0))}{v_k(t, x_0)}. \quad (3.20)$$

The disadvantage of this EBM is that modeler only describes agent flow with homogeneous behavior of agents. This EBM ignores all different behaviors of individual agent. While the ABM describes the pedestrians with different behaviors such as sheep and fox agents. To keep two behaviors of fox agent or sheep agent in this ABM, a token store is used to store two labels S for a sheep agent and F for a fox agent. If a sheep/fox agent moves to the tube, a label S/F is put to this token store (Fig. 3.14). They way to use the labels S/F of the token store is presented in the disaggregation trigger.

3.4.4 The disaggregation trigger switching EBM to ABM

The disaggregation trigger switching EBM to ABM is key of building Hybrid-based model. Unlike the aggregation trigger, the disaggregation trigger is more complicated because we need to rebuild ABM with many different behaviors for agents from EBM that contains only two values $p_k(t, x_0)$, $v_k(t, x_0)$. First, the relationship between time, velocity and pedestrian flow is given by a simple formula that the time pedestrian flow pass to the tube equals distance of the tube divided

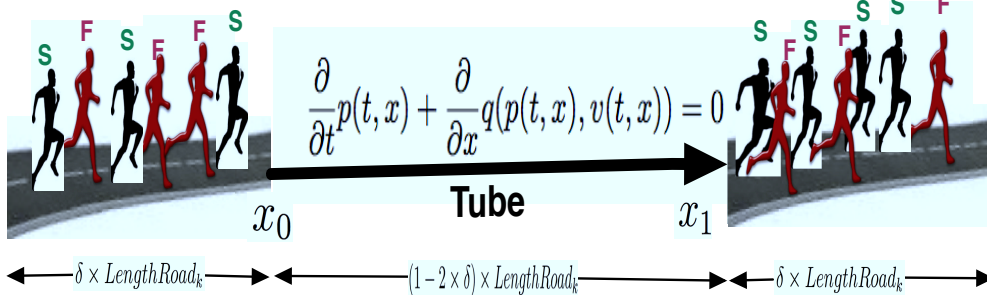


Figure 3.15: The EBM environment of the road k is described by a tube. The beginning and the ending of the road k are simulated by the ABM. At the beginning of the tube x_0 , the aggregation trigger switches ABM to EBM. At the ending of the tube x_1 , the Disaggregation switches from EBM to ABM.

by velocity of pedestrian flow. To switch EBM to ABM, The EBM values $p_k(t, x_0)$, $v_k(t, x_0)$ and token store are used for the initial value of EBM that is Cauchy problem of LWR model.

The average time of pedestrian flow passes to the tube of the road k is given:

$$T(t) = \frac{(1 - 2 \times \delta) \times LengthRoad_k}{v_k(t, x_0)}. \quad (3.21)$$

The pedestrian flow is aggregated at time step t^{th} will be disaggregated at the average time $t + T(t)$. The pedestrian flow at the time step $t + T(t)^{th}$ is solution of Cauchy problem of LWR model that we represented previous. Therefore, applying the solution of the formula of LWR (3.13), (4.6) and (4.7), at the time $t + T(t)^{th}$ gives results on the pedestrian density and velocity of pedestrian flow at the position x_1 $p_k(t + T(t), x_1)$, $v_k(t + T(t), x_1)$ where $x_1 = (1 - \delta) \times LengthRoad$. The pedestrian flow at $(t + T(t), x_1)$ is

$$q_k(t + T(t), x_1) = p_k(t + T(t), x_1) \cdot v_k(t + T(t), x_1). \quad (3.22)$$

These results $p_k(t + T(t), x_1)$, $v_k(t + T(t), x_1)$, $q_k(t + T(t), x_1)$ are the parameters of ABM for the ending of the road. First, we assume the flow of pedestrians that are released at the time $t + T(t)^{th}$ is a Poisson process [said EL HMAM 2008, MAGNE 2000, Ross 2006]. This process is characterized by a rate parameter $\lambda_{Poisson} = mean = q(p_k(t + T(t), x_1)$ at the x_1 generates the number of pedestrians.

The velocity of each pedestrian is generated by the normal truncated distribution with the $\mu_{velocity} = mean = v_i(t + T(t), x_1)$, at x_1 [said EL HMAM 2008, Ross 2006, MAGNE 2000]. Indeed, the velocity $V_{pedestrian}$ of pedestrian is assumed

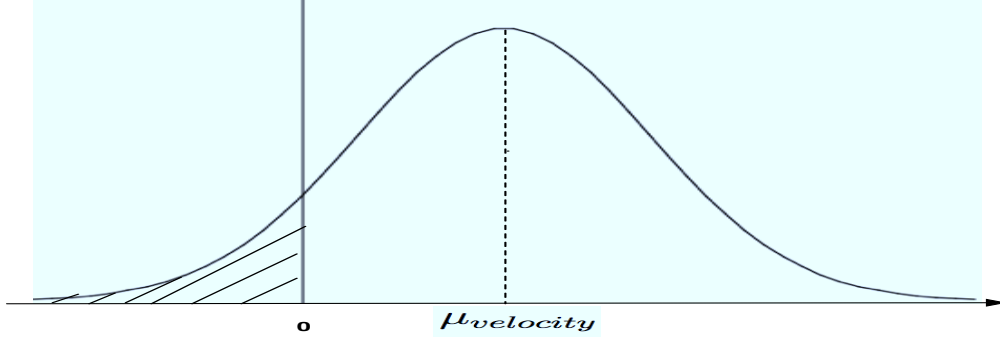


Figure 3.16: $V_{pedestrian} \sim \mathcal{N}(\mu_{velocity}, \sigma_{velocity}^2)$ and $V_{pedestrian} \geq 0$. Thus, the $V_{pedestrian}$ is considered normal truncated distribution.

followed normal distribution, i.e $V_{pedestrian} \sim \mathcal{N}(\mu_{velocity}, \sigma_{velocity}^2)$ and velocity is not smaller than 0 i.e the $V_{pedestrian} \geq 0$. Thus, the $V_{pedestrian}$ is considered normal truncated distribution (Fig. 3.16).

Gamma distribution is a distribution that arises naturally in processes for which the waiting times between events are relevant. It can be thought of as a waiting time between Poisson distributed events. The waiting time until the m^{th} Poisson event with a rate of change $\lambda_{Poisson} = q(p_k(t + T(t), x_1))$ has probability density function is given by

$$\frac{\lambda(\lambda_{Poisson}x)^{m-1}}{(m-a)!}e^{-\lambda_{Poisson}x} \quad (3.23)$$

for $X \sim Gamma(m, \theta)$ where $\theta = 1/\lambda_{Poisson}$ the gamma probability density function is as follows

$$\frac{x^{m-1}e^{-\frac{x}{\theta}}}{\Gamma(m)\theta^m} \quad (3.24)$$

where e is the natural number, m is the number of occurrences of an event, $\Gamma(m) = \int_0^\infty x^{m-1}e^{-x}dx$, if m is a positive integer, then $\Gamma(m) = (m-1)!$ is the gamma function and x is a random variable. This formula is based on the theory of Poisson process that we can read from [Ross 2006, MAGNE 2000]. The arrival time of agents order m^{th} follows Gamma distribution with parameter $\theta = 1/\lambda_{Poisson} = 1/q(p_k(t + T(t), x_1))$. $Gamma(m, \theta)$ distribution has the $mean = m\theta$.

Therefore, the time for one agent order m^{th} comes into the tube at the time t is released out of the tube to the the ending of the road:

$$t + T(t) - \frac{q_k(t + T(t, x_1)) \times [q_k(t + T(t, x_1)) + 1]}{2} + g(m, \theta). \quad (3.25)$$

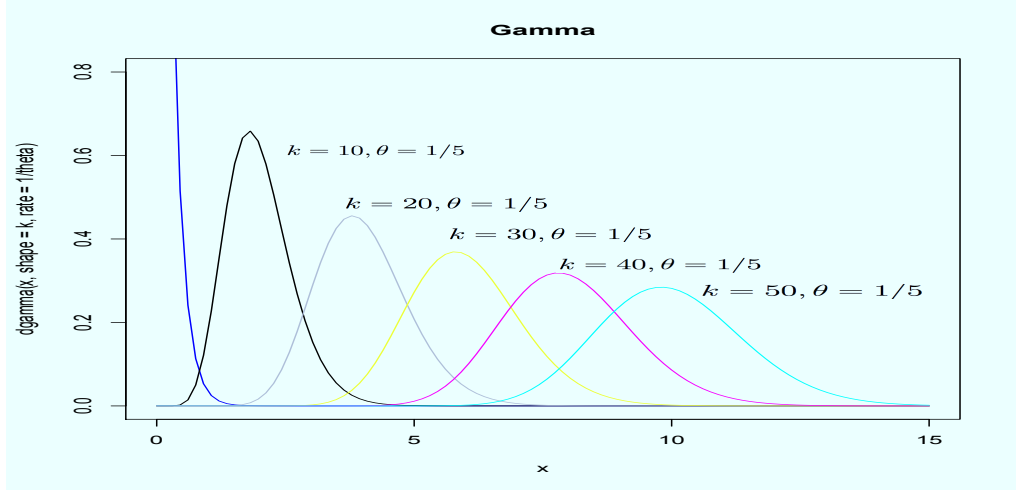


Figure 3.17: This figure shows the Gamma density distribution with two parameters (k, θ) where $\theta = 1/q_k(t + T(t, x_1)) = 1/5$ and $k = 1, 10, 20, 30, 40, 50$.

where $m = 0, 1, \dots$ and $g(m, \theta)$ is value of $Gamma(m, \theta = 1/q_k(t + T(t, x_1)))$ distribution (Fig 3.17).

All the pedestrians in the tube is consider one object of hybrid-based simulation. When the time for an pedestrians come, the disaggregate trigger will release the number of the pedestrians $q_k(t+T(t), x_1)$ out of the tube object to $q_k(t+T(t), x_1)$ separated objects with the behaviors take from token store.

The disaggregate trigger releases pedestrians in ABM as soap balls are blown from a pipe. Indeed, the number of pedestrians is followed the equation (3.22). The time of the pedestrian m^{th} is released from the tube by the equation (3.25). The velocity $V_{pedestrian}$ and behaviors of the pedestrian m^{th} is taken by the truncated normal distribution followed the equation (3.22) and the token store respectively.

Two triggers switching ABM to EBM and vice vera are the key of the hybrid-based model. Two triggers are represented detail above in order to build the hybrid-based model. Hybrid based model trade off the detail in the tube but speed up the computational time. However, because It takes modelers time to run the triggers in simulation, the hybrid-based model is not always faster than ABM.

The comparing the time of running ABM and HBM should be considered. We will show that in some certain conditions the HBM run faster than ABM, however, some special conditions the HBM is slower than ABM. One of limit conditions when using an hybrid-based model is the length of the roads on the road network. Indeed, we easily to see that If the road is too short, the time using for switching two models costs equally with the simulating time of the Agent-based model. Another problem

appear when hybrid-based model is used effectively. The analysis about this problem will be represented detail in the next chapter.

3.5 Conclusion

In this chapter, we presented the models for crowd evacuation with three level of detail that are Agent-based, Equation-based and Hybrid-based on a road network. In Equation-based model, we formula the sign placement problem then we described the pedestrian flow by LWR model. The advantage of EBM are possible to make an analytic study of the model and independence of the number of pedestrians in the system. However, EBM can not account the heterogeneity of the entities composing the system. Agent-based model is good method to consider the heterogeneity of entities of system.

Agent-based model is not only natural representation of the system but also accounting of the local interactions of entities. However, Agent-based model cost expensive computational time. The hybrid-based model are proposed to use advantages of both ABM and EBM. Two aggregated and disadvantage triggers are build to switch ABM to EBM and vice vera. The conditions to use hybrid-based model will be discussed in the next chapter.

On a hybrid-based simulation, we can use two-level models microscopic or macroscopic. Environment of the road network is classified based on the importance patches for each road. Two types of environmental are applied GIS and directed graph with two different models ABM or EBM respectively. Since, hybrid simulation can overcome the huge computational time required by ABMs. In the next chapter, we would discuss and display the ways to resolve the problems with these different models.

Chapter 4

Solving and Simulating Evacuation Models

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Foreword

Firstly, advantages of equation-based model are independence of the number of individual in the system and solving pedestrians evacuation problem on a road network in acceptable time. However, mathematical models are difficult to use in considering problems in detail with different realistic factors. Therefore, we choose EBMs to explore subproblem, that's used effectively to solve the Optimizing sign placement system.

ABMs close to reality with GIS data and the different behaviors of the pedestrians. Therefore, making it as practical and intuitive as possible. However, computation of Agent-based simulation cost expensively while the Agent-based simulation often require repeating experiments many times. The time simulation is real problem with many modeler using Agent-based simulation with large agents. We face the same problem with the other modelers so we investigate how to speeding up Agent-based simulation. We build hybrid-based model that combines Equation-based model and Agent-Based Model to obtain efficient simulations. This combination is shown in the diagram (Fig. 4.1). Simulation results are thereby combined, the optimizing sign placement system for different evacuation scenarios which can simulate multiple times with different behavior of the pedestrians to obtain optimal alternatives sign placement system.

The motivation of the research is the integrating of ABM simulations and *Minimization of Average Evacuation Time* (MAET). Integrated Mathematical Models with the simplest behaviors of each agent and ABM with different parameters and behaviors for each individual become more efficiency and realistic in finding the optimum sign placement for road networks. This paper represents the integrating(ed) simulations in schema (Fig. 4.1).

In general, the simulation of evacuation in road network has three loops (Fig. 4.1). First, GIS data is loaded that the data include a lot of spatial layers such as the roads, junctions, buildings, safe places, wards, etc. In our simulation, we use GIS spatial data that were provided by the Institute of Geophysics of Vietnam. Then, the second loop is to choose a sign placement system of the city to find the optimal configuration for evacuating. Next, the third loop picks up the spatial population distribution and the behaviors of pedestrians. The last loop is the running of simulation experiment using GAMA platform [Drogoul 2013a, Drogoul 2013b, Grignard 2013]. This loops affect the evaluation results of the simulation which includes the parameters that are described in the (Fig. 4.1). This scheme shows the steps that we solve the pedestrian evacuation problem in this thesis. To solve the problem, the solutions of Equation-based, Agent-based and Hybrid-based models are represented below.

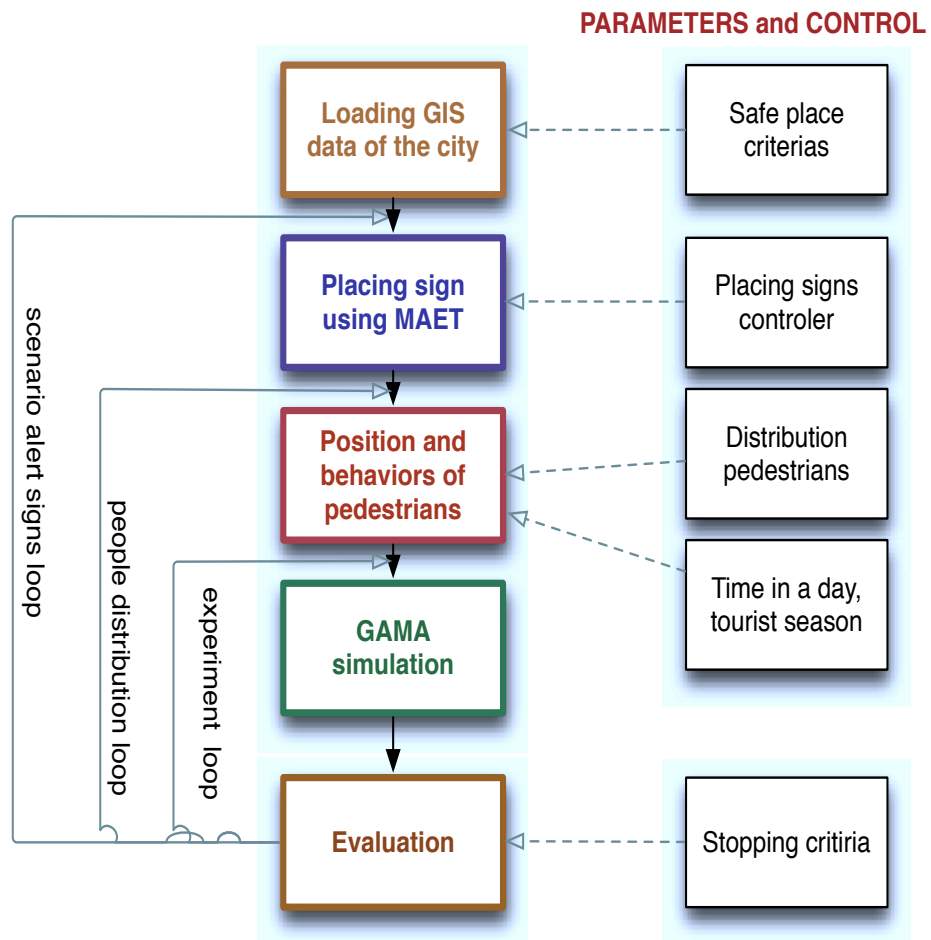


Figure 4.1: Detail of the scheme of the Emergency Evacuation Tsunami simulation. Firstly, the of loading GIS data of the Nhatrang city requires a lot of spatial data such as the roads, junctions, buildings, safe places, wards, etc. Then, the first loop is to choose a sign placement system of the city to find the optimal configuration for evacuating. Next, the second loop picks up the spatial population distribution and the behaviors of pedestrians. Lastly, the last loop is the running of simulation experiment using GAMA platform.

4.1 Mathematical solutions: Formulation of Sign Placement Optimization Problem

First, in this section, the sign placement optimization problem will be solve by Mixed Integer Linear Programming (MILP). This problem are proposed in the previous chapter and showed in the schema (Fig. 4.1). It is very importance work to plan the early warning evacuation before tsunami occurs. We find the alert sign placement for early warning tsunami plan to minimize the average time evacuation.

4.1.1 A Mixed Integer Linear Programming Formulation of the Minimization of Average Evacuation Time problem

In this section, we will study simple problems related to the MAET problem. These problems will help us to ultimately build a Mixed Integer Linear Programming (MILP) to solve the MAET.

Introduce to Mixed Integer Linear Programming and CPLEX

Mixed-Integer Programming is used in optimizing complex systems, such as those arising in biology, medicine, transportation, telecommunications, sports, and national security. Mixed-Integer Programming is a subset of the broader field of Mathematical Programming. Mathematical Programming formulations include a set of variables, which represent actions that can be taken in the system being modeled. One then attempts to optimize (either in the minimization or maximization sense) a function of these variables, which maps each possible set of decisions into a single score that assesses the quality of the solution. These scores are often in units of currency representing total cost incurred or revenue gained. The limitations of the system are included as a set of constraints, which are usually stated by restricting functions of the decision variables to be equal to, not more than, or not less than, a certain numerical value. Another type of constraint can simply restrict the set of values to which a variable might be assigned [Guignard-Spielberg 2005, M.Junger 2010, R. Bixby 2007].

Mixed Integer Linear Programming is NP-hard computational complexity. Our problem of interest is given by

$$\begin{aligned} & \min_{x \in X} c^T x && (4.1) \\ \text{satisfy} & Ax \leq b, \end{aligned}$$

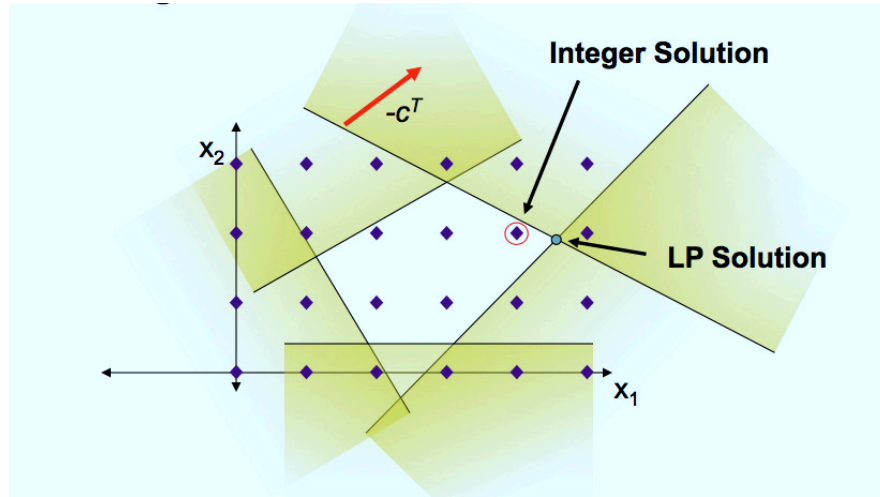


Figure 4.2: shows the integer solution and linear solution of an optimal integer linear programming problem.

where $X \subset \mathbb{Z}^n \times \mathbb{R}^m$, $c \in \mathbb{R}^{n+m}$ is a constant vector, $A \in \mathbb{R}^{n+m}$ is a constant matrix. The linear programming solution (LP solution) and integer solution of a Mixed Integer Linear Programming are represented in (Fig. 4.2).

The CPLEX optimizer was named for the simplex method as implemented in the C programming language, although today it also supports other types of mathematical optimization and offers interfaces other than just C. It was originally developed by Robert E. Bixby and was offered commercially starting in 1988 by CPLEX Optimization Inc., which was acquired by ILOG in 1997 [R. Bixby 2007]. ILOG was subsequently acquired by IBM in January 2009. CPLEX continues to be actively developed under IBM [IBM 2004]. In the fact that CPLEX is one of most powerful commercial solvers. Although, now CPLEX is free for academic purposes. Problem types that CPLEX can handle: linear programming, mixed integer programming, network flow problems, quadratic programming, and quadratically constrained programming problems. We formula the sign placement problem using MILP so CPLEX is chosen to solve this problem.

Evaluating the Population Average Evacuation Time

Before we tackle the full problem of minimizing the *Population Average Evacuation Time* (PAET), let us consider the problem of evaluating the PAET associated to a given sign placement.

Definition 4.1 *Evaluation of Average Evacuation Time.* Given a quadruplet

(G, X, μ, \mathbf{P}) and a sign placement S , compute $PAET(S)$.

Of course, the average evacuation time can be estimated by simulation, but it can also be computed exactly by solving a linear equation system, as shown here [Nguyen 2012].

For the sake of brevity, let us define $q_i = AET(S, i)$ for all $i \in V$. Recall that $PAET(S) = \sum_{i \in V} \mu_i q_i$. Observe that if $i \in X$, we have $q_i = 0$. Moreover, if there is a sign placed on i and pointing to j , we have $q_i = c_{ij} + q_j$. In all other cases, q_i is determined by the equations of the Markov chain. Finally, assuming that the Markov chain is an absorbing chain (that is, with probability one(1), all agents end up on a shelter), the following a linear equation system s uniquely determine the value of q_i which can then be used to compute $PAET(S)$:

$$\begin{aligned} \forall i \in X, \quad & q_i = 0 \\ \forall (i, j) \in S, \quad & q_i = c_{ij} + q_j \\ \forall i \in V \setminus V(S), \quad & q_i = \sum_{j \in N(i)} P_{ij} \cdot \{c_{ij} + q_j\} \end{aligned} \tag{4.2}$$

Of course, because it is formulated as a linear equation system, the evaluation of PAET can be done exactly in polynomial time [Lay 2005].

4.1.2 Optimizing the direction of the signs

Let us now focus on a more general problem than the evaluation of PAET, but still simpler than the MAET problem itself. Let us assume that we are *given* a set of vertices on which signs are placed which we still need to compute the optimal direction of each sign. Formally:

Definition 4.2 *Minimization of Average Evacuation Time with Fixed Sign locations.* Given a quadruplet (G, X, μ, \mathbf{P}) , a subset of vertices V' , find the best sign placement S minimizing $PAET(S)$ and such that $V(S) = V'$

Each sign located on $i \in V'$ points towards the vertex $j \in N(i)$ which minimizes the evacuation time. Thus for all $i \in V'$ we have $q_i = \min_{j \in N(i)} \{c_{ij} + q_j\}$. The following set of (non linear) equations uniquely define the value of q_i , which in turn allows us to compute $PAET(S')$. Again, note that this computation does not require the knowledge of S' but only of V' . In other words:

$$\begin{aligned}
 \forall i \in X, q_i &= 0 \\
 \forall i \in V', q_i &= \min_{j \in N(i)} \{c_{ij} + q_j\} \\
 \forall i \in V \setminus V', q_i &= \sum_{j \in N(i)} P_{ij} \cdot \{c_{ij} + q_j\}
 \end{aligned} \tag{4.3}$$

These equations are non-linear because they contain a *min* operator. They can however be linearized using a standard linear programming trick. Solving this linear program will allow us to compute both the optimal evacuation time given V' , and the optimal directions of the signs: a sign located on i should point towards j if $q_i = c_{ij} + q_j$.

Remark 4.1 Note that if we want to use meta-heuristics to solve the whole MAET problem, knowing that this intermediate problem is polynomial allows us to greatly reduce the search space: In fact, we can now simply search through the space of all sign locations (whose cardinality is at most $\binom{n}{k}$), as the optimal direction of each sign can be computed in polynomial time. Instead, a Naive metaheuristic approach would have been to search through the space of all sign placements, whose cardinality is $\binom{n\Delta}{k}$ where Δ is the degree of the graph.

4.1.3 The Mixed Integer Linear Program

Because the MAET problem is NP-complete, we either need carefully crafted heuristics to solve it in practice in a reasonable amount of time, or we can formulate this problem as a MILP problem which will allow us to use powerful MILP solvers such as CPLEX, to solve exactly or approximately our problem in a reasonable amount of time.

To formulate this problem as a mathematical programming problem, we need to introduce new variables a_{ij} which will be binary variables: For each edge (i, j) , the variable $a_{ij} \in \{0, 1\}$ indicates whether we should place a sign on edge (i, j) (in which case $a_{ij} = 1$) or not (in which case $a_{ij} = 0$). Variables a_{ij} naturally induce the sign placement $S = \{(i, j) \in E : a_{ij} = 1\}$. To ensure that there is at most one sign per vertex, we set the constraints $\sum_{j \in N(i)} a_{ij} \leq 1$ for all $i \in V$. To ensure that there are at most k signs in the whole network, we add the single constraint $\sum_{(i,j) \in E} a_{ij} \leq k$. So we get the following mathematical program:

$$\begin{aligned}
 & \min \sum_i \mu_i \cdot q_i && \text{such that} \\
 & \forall i \in X, q_i = 0 \\
 & \forall (i, j) \in E, q_i = C_{i,j} + q_j \text{ if } a_{ij} = 1 \\
 & \forall i \in V, q_i = \sum_{j \in N(i)} P_{ij} \cdot \{c_{ij} + q_j\} \text{ if } \sum_{j \in N(i)} \mathbf{a}_{ij} = \mathbf{0} && (4.4) \\
 & \forall i \in V, \sum_{j \in N(i)} a_{ij} \leq 1 \\
 & \sum_{(i,j) \in E} a_{ij} \leq k
 \end{aligned}$$

Domain constraints must be added to this set of constraints: for all $(i, j) \in E$, $a_{ij} \in \{0, 1\}$ and $q_{ij} \in \mathbb{R}_+$. Also, for all $i \in V$, $q_i \in \mathbb{R}_+$. If there exists a sign placement with at most k signs leading to finite average evacuation times (note that this is not always the case) then solving this program will yield the best one.

This set of constraints does not constitute a MILP, because there are conditional constraints (*if* operators). Our goal will thus be to convert these constraints into linear inequalities. For this purpose, let us define a constant Q_{max} with an arbitrary value at least as high as the highest average evacuation time. Then, we can replace $q_i = c_{ij} + q_j$ if $a_{ij} = 1$ by $q_i \geq c_{ij} + q_j - Q_{max} \cdot (1 - a_{ij})$. Note that if $a_{ij} = 0$, then this constraint roughly says that q_i is greater than a negative number. Because q_i is already constrained to be a positive real, this constraint is redundant. On the contrary, if $a_{ij} = 1$ then this inequality will be equivalent to $q_i \geq c_{ij} + q_j$, and because the objective is to minimize $\sum_i \mu_i \cdot q_i$, this will be equivalent to an equality constraint $q_i = c_{ij} + q_j$. The other conditional constraint are the same the equation system (4.4). Thus, the above mathematical program can be written as follows:

$$\begin{aligned}
 & \min \sum_i \mu_i \cdot q_i && \text{such that} \\
 & \forall i \in X, q_i = 0 \\
 & \forall (i, j) \in E, q_i \geq C_{i,j} + q_j - Q_{max} \cdot (1 - a_{ij}) \\
 & \forall i \in V, q_i \geq \sum_{j \in N(i)} P_{ij} \cdot \{c_{ij} + q_j\} - Q_{max} \cdot \sum_{j \in N(i)} \mathbf{a}_{ij} && (4.5) \\
 & \forall i \in V, \sum_{j \in N(i)} a_{ij} \leq 1 \\
 & \sum_{(i,j) \in E} a_{ij} \leq k
 \end{aligned}$$

Adding the same domain constraint as before, we get a MILP, whose solution gives us an optimal sign placement.

The modeler used Equation-based model cannot account the heterogeneous behaviors. These different behaviors of junctions are important for evacuating. In addition, the dynamics of pedestrian flow at junctions EBM are complex to solve. These limits of Equation-based model lead the modeler using Agent-based model.

4.2 Agent-Based Simulation

The advantages of Agent-based model are not only accounting the heterogeneous behaviors of individual pedestrians but also considering the local interactions of pedestrians. The environment in EBM is often homogeneous such as graph while environmental modeling of ABM can be GIS data.

4.2.1 A geographic information system and environmental modeling

A geographic information system (GIS) is a computer system for capturing, storing, checking, and displaying data related to positions on Earth's surface. GIS can show many different kinds of data on one map. This enables people to more easily see, analyze, and understand patterns and relationships [Ste 2013, Qiu 2008].

With GIS technology, people can compare the locations of different things in order to discover how they relate to each other. For example, using GIS, the same map could include sites that bounds, roads, rivers, buildings, shelters, tsunami alert signs, pedestrians.

GIS can use any information that includes location. The location can be expressed in many different ways, such as latitude and longitude, address. Many different types of information can be compared and contrasted using GIS. In this study a GIS-based a decision support system was built for tsunami evacuation by integrating the GIS and ABM. In evacuation problem, pedestrians' behaviors within space requires some sort of geographical information system (GIS) in order to identify spatial relationships. By linking ABM and GIS we have the ability to model the emergence of phenomena through individual interactions over space and time. However, there are few ABMs dedicated to studying the people who fail to evacuate, and such models tend not be overtly spatial or to study how the situation develops over time [Crooks 2013].

GAMA platform can integrate ABM and GIS. GIS data are bounds, roads, rivers, buildings, shelters, wards, etc sites. Some sites are generated from the available shape files (Fig. 4.3). Indeed, based on the shape file buildings, we get the

```

input : The direct graph of the Nhatrang city  $G = (V, E)$ , the cost
        matrix  $C$ , the transition probability matrix of each agent  $P$  and
        spatial population distribution  $\mu$ .
output: Positions of alert signs  $SI$  for optimizing the time evacuation of
        the city

1  $p = \text{MixedIntegerLinearProgram}(\text{maximization} = \text{True})$ 
   $\gamma \leftarrow 0.9999, \Omega \leftarrow 100000$ 
2 // Variables
3  $q = p.\text{new\_variable}(\text{real} \leftarrow \text{True})$ 
4  $a = p.\text{new\_variable}(\text{dim} \leftarrow 2, \text{binary} \leftarrow \text{True}, \text{name} \leftarrow 'a')$ 
5 for  $u \in V$  do
6 |  $p.\text{set\_max}(q[u], 0), p.\text{set\_min}(q[u], \text{None})$ 
7 end
8 for  $u \in V$  do
9 | for  $v \in \text{neighbor\_out\_iterator}(u)$  do
10 | |  $p.\text{set\_min}(a[u][v], 0), p.\text{set\_max}(a[u][v], 1)$ 
11 | end
12 end
13 // Objective to:
14  $p.\text{set\_objective}(\sum_{v \in V} (\mu[v] * q[v]))$ 
15 // Constraints:
16 for  $(u, v) \in E$  do
17 |  $p.\text{add\_constraint}(q[u] \leq -C[u][v] + \gamma * q[v] + \Omega * (1 - a[u][v]))$ 
18 end
19 for  $(u, v) \in E$  do
20 |  $p.\text{add\_constraint}(q[u] \leq$ 
21 | |  $\sum_{v \in \text{neighbor\_out\_iterator}(u)} (P[u][v] * (-C[u][v] + \gamma * q[v] + \Omega * (a[u][v])))$ 
22 end
23 for  $(u, v) \in E$  do
24 |  $p.\text{add\_constraint}((\sum_{v \in \text{neighbor\_out\_iterator}(u)} (a[u][v])) \leq 1)$ 
25 end
26 for  $u \in V$  do
27 |  $p.\text{add\_constraint}(q[u] \leq 0.0)$ 
28 end
29 for  $u \in SI$  do
30 |  $p.\text{add\_constraint}(q[u] \leftarrow 0.0)$ 
31 end
32 // Solve Mixed Integer Linear Program and get the results:
33  $p.\text{solve()} // \text{The result of the cost function}$ 
34 for  $u \in p.\text{get\_values}(a).\text{iteritems}()$  do
35 |  $\text{print } u // \text{Print the results of alert signs}$ 

```

Algorithm 1: shows the algorithm Mixed Integer Linear Programming

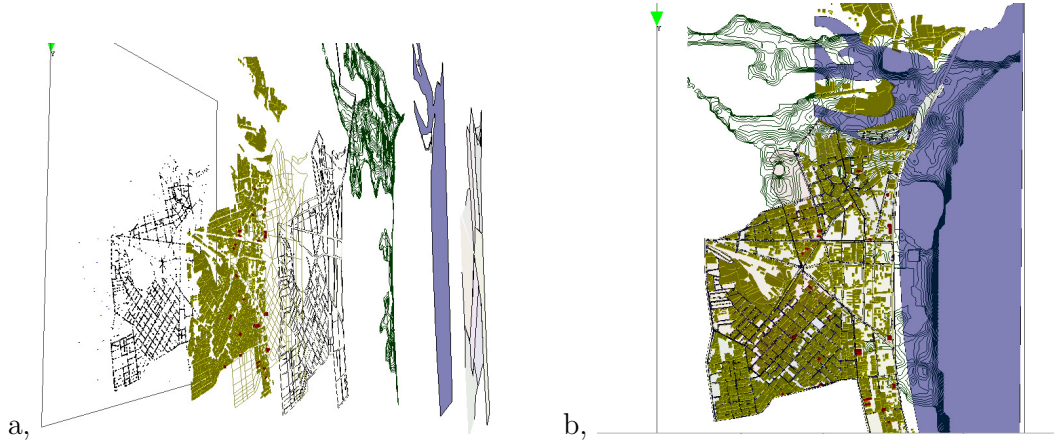


Figure 4.3: a, Nha Trang GIS data have many sites such as bounds, roads, rivers, buildings, shelters, tsunami alert signs, pedestrians. b, shows the Nha Trang GIS data merged all the sites together.

shelter system where the builds satisfy some condition such as the buildings are higher then 8 floors . Using the result of MAET model, a alert signs site is created also. The combination of GIS and ABM makes the simulation help for the decision support system much more realistic. However, while the use of GIS and spatial data in emergency evacuation is not new, applications often assume an unrealistically homogeneous population or address only one instant in time [Crooks 2013]. To avoid this problem, the initial of distribution and positioning of pedestrians will be described in the next subsection.

4.2.2 Distribution and Positioning

Nhatrang city is a famous city in Vietnam with beautiful beach and sites attracts tourist. During tourist time, the beach is crowded (Tourist season). The parameters t describing day time or night time and tourist season are considered. If it is day time in tourist season, the distribution of population on the beach is heavy and the wards Xuong Huan, Loc Tho. And when it's night time, the distribution of population follow the statistic data (Table 4.1). In the tourist season in each year, the number of tourists visiting Nha Trang is about 1200000. Let t be the time in the day $0 \leq t < 24$ and *Tourist – Season* be the tourist season variable that has two values $1 = true$ and $0 = false$.

Based on our observations of Nha Trang beach, we make a hypothesis that in the day time, the beach is available for the tourists and citizens from around 6:00 to 20:00. The people steadily increase from 6:00 to 9:00; then, the number of

people reduces from 9:00 to 15:00. However, people increase from 15:00 to 17:00 and decrease 17:00 to the 20:00. While, a Poisson process is a simple and widely used stochastic process for modeling the number of events. In addition, Poisson process is a special of an arrival process. A non-homogeneous Poisson process counts events that occur at a variable rate $\lambda(t)$. This rate may change over time [Doob 1953, Ross 2006]. This Poisson process is a case of the arrival process. Therefore, we assume non-homogeneous Poisson process [Ross 2006] for the people go out or come in the Nha Trang beach. The certain ward i has the counting process about the pedestrians go out from the ward i to the beach $\{N_{out}(i, t), t \geq 0\}$ said to be a non-homogeneous Poisson process with intensity function $\lambda_{out}(i, t), t \geq 0$ describing the average rate of people move out of the beach. Similarly, $\{N_{in}(i, t), t \geq 0\}$ said to be a non-homogeneous Poisson process with intensity function $\lambda_{in}(i, t), t \geq 0$ describing the average rate of people come into the ward i . The average rate of Poisson process for the ward i is represented:

$$\lambda_{in}(i, t) = \begin{cases} 0 & \text{if } 0 \leq t < 6 \\ a_{i,0} \cdot (t - 6) & \text{if } 6 \leq t < 9 \\ a_{i,1} & \text{if } 9 \leq t < 15 \\ a_{i,2} \cdot (t - 15) & \text{if } 15 \leq t < 17 \\ a_{i,3} & \text{if } 17 \leq t < 20 \\ 0 & \text{if } 20 \leq t \leq 24, \end{cases} \quad (4.6)$$

$$\lambda_{out}(i, t) = \begin{cases} 0 & \text{if } 0 \leq t < 6 \\ b_{i,0} & \text{if } 6 \leq t < 9 \\ b_{i,1}(t - 9) & \text{if } 9 \leq t < 15 \\ b_{i,2} & \text{if } 15 \leq t < 17 \\ b_{i,3} \cdot (t - 17) & \text{if } 17 \leq t < 20 \\ 0 & \text{if } 20 \leq t \leq 24, \end{cases} \quad (4.7)$$

and $\lambda_{out}(i, t) = \lambda_{out}(i, t)(t - 24)$ and $\lambda_{in}(i, t) = \lambda_{in}(i, t)(t - 24)$ for $t > 24$ where $a_{i,j}, b_{i,j}$ are parameters of the ward i .

If we let $m(i, t) = \int_0^t \lambda_{out}(i, s) ds$, then the probability of n people from the ward i go out to the beach in the interval $[t, t + s)$ it can be shown that

$$\begin{aligned} &Pro\{N_{out}(i, t + s) - N_{out}(i, t) = n\} = \\ &\exp^{-[m(i, t+s) - m(i, t)]} \frac{[m(i, t + s) - m(i, t)]^n}{n!}, n \geq 0. \end{aligned} \quad (4.8)$$

This hypothesis help us to estimate the pedestrian distribution in the city depend on the time t in a day and in the tourist season.

The data of the distribution population in Nha Trang city are given in (Table 4.1) that were published in the Vietnamese statistic yearbook [Nguyen Hong Phuong 2011]. A number of pedestrians are put randomly to each ward following the data in (Table 4.1). Then we use two parameter t and $Tourist_{season}$ to change the spatial population positions of Nha Trang city that follow the Poisson process presented above. The new spatial positions of pedestrians is taken the initial population distribution.

No	Ward name	Population
1	Vinh Phuoc	20 662
2	Vinh Tho	14 823
3	Van Thang	13 012
4	Xuong Huan	17 873
5	Phuong Sai	13 284
6	Phuoc Tan	13 103
7	Phuoc Tien	12 680
8	Phuoc Hoa	14 461
9	Tan Lap	16 242
10	Loc Tho	12 861
11	Van Thanh	14 884

Table 4.1: The population in the wards of Nhatrang city in 2009

The data in (Table 4.1) and the change of number of pedestrians depending on the tourist season and the time in a day make the initial population distribution more reality. It is reduce limit the initial population distribution in equation-based model. Modeler using ABM consider not only the detail initial population distribution but also the heterogeneous behaviors and local interaction of pedestrians.

4.2.3 Heterogeneous behaviors of pedestrians

As mentioned in the previous chapter, modelers using ABM can account the heterogeneous pedestrians' behaviors and the local interaction of the pedestrians. In ABM, modeler can define many different behaviors of agents in detail. To simplify the tsunami evacuation problem in a large environment and a large number of pedestrians and to reduce the complicated this problem, we consider two different agent types that are sheep agent and fox agent. A fox agent is defined as a pedestrian

who has been trained on evacuation procedures or has knowledge of how get to the safe place efficiently. A fox agent has a different behaviors such as his own velocity, his own shelter target, his own strategies in evacuating (choosing the shortest path or following alert sign system in junctions), etc. Meanwhile, a sheep agent has a different behaviors also such as his own velocity, evacuating randomly at junctions, following one fox agent, etc.

The fox agent evacuates through the shortest path

In our model, the fox agents are policemen, pedestrians trained evacuation before or pedestrian used smart phone to know the evacuation plan etc. He/she knows the shortest path from his position to the one of the shelters. Also, he guides the sheep agents to shelters. Sheep agent walks random in the junction or follow a fox agent. In our model, we assume that the fox agent knows the shortest path therefore, the Floyd-Warshall algorithm is used[Floyd 1962].

In computer science, the Floyd-Warshall algorithm is used to find the shortest paths in a graph that has positive edge weights. The definition of Floyd-Warshall algorithm is given:

Definition 4.3 *In a given digraph $G = (V, E)$ in which each edge $v \rightarrow u$ has a nonnegative cost $C[v, u]$, the Floyd-Warshall algorithm is to find for each ordered pair of vertices $\{v, u\}$, the smallest length of any path from u to v .*

This is an $O(n^3)$ algorithm, where n is the number of vertices in the digraph. It uses the principle of Dynamic Programming. Let $V = 1, 2, \dots, n$, the algorithm uses a matrix $A[1..n][1..n]$ to compute the lengths of the shortest paths. Initially,

$$A[i, j] \begin{cases} = C[i, j] & \text{if } i \neq j \\ = 0 & \text{if } i = j. \end{cases}$$

Note that $C[i, j]$ is taken ∞ as if there is no directed edge from i to j .

The algorithm makes n passes over A . Let A_0, A_1, \dots, A_n be the values of A on the n passes, with A_0 being the initial value. Just after the $(k - 1)$ th iteration, $A_{k-1}[i, j]$ = the smallest length of any path from vertex i to vertex j that does not pass through the vertices $k, k + 1, \dots, n$ (i.e that only passes through possibly $1, 2, \dots, k - 1$). The k^{th} pass explores whether the vertex k lies on an optimal path from i to j , $\forall i, j$

We use

$$A_k[i, j] = \min \begin{cases} A_{k-1}[i, j] \\ A_{k-1}[i, k] + A_{k-1}[k, j]. \end{cases}$$

The Floyd-Warshall algorithm is used to find the shortest path a pair of vertices $\{u, v\}$. The fox agent is programmed evacuating follow this shortest path. Moreover, this shortest path is a suggestion for pedestrians using smart phone. Evacuating the shortest path of the fox agent is only one of pedestrians' behaviors in this thesis. To observer a different behavior of fox agent, we will consider the fox agent following the alert signs.

The fox agent follows the alert signs

Firstly, we see that the pedestrians evacuate in the opposite direction away from the sea. Therefore, we assume all roads of a city has a beginning road and the ending road. The beginning road is one of two junctions where is shorter distance to the sea. The Gama platform has a command "goto" that has two parameters "target" and "speed". We use this command for the algorithm below to program the fox agent evacuating:

```

input : The position of fox agent
output: The time, the path and the survival status of the fox agent in
          evacuating
1 while the fox agent stop evacuating =false do
2   if the road that contains the fox agent has a shelter = true then
3     | the "target" is the position of the shelter, the fox agent stop
4     | evacuating =true
5   else
6     | the"target" is the end of the road
7   end
8   The fox agent goes to the end of the road that reaches a junction.
9   if the junction for alert sign =true then
10    | the new "target" is the end of the road that the sign pointing (the
11    | junction is consider the begin of the road)
12  else
13    | the "target" is one of the end of the roads that link with this
14    | junction
15  end
16 end

```

Algorithm 2: The algorithm is used to program the fox agent evacuating on the road network.

The sheep agent

The algorithm below is used to program the sheep agent evacuating: as following:

```
input : The position of sheep agent
output: The time, the path and the survival status of the sheep agent in
          evacuating

1 the sheep finds out a shelter =false, the “target” is shelter =false
2 while the sheep finds out a shelter =false or the “target” is shelter =false
  do
3   if the road that contains the sheep agent has a shelter = true then
4     | the “target” is the position of the shelter, the sheep finds out a
5     | shelter =true
6   else
7     | the “target” is the end of the road
8   end
9   The sheep agent goes to the end of the road that reaches a junction.
10  if The sheep agent stays in the junction =true then
11    | the “target” is one the end of a road in the list roads linking with
12    | this junction
13  end
14  if The sheep agent finds out a fox agent=true then
15    | the new “target” is the fox agent’s position
16  end
17  if The fox agent finds out a shelter then
18    | the “target” is shelter = true
19  end
20 end
```

Algorithm 3: The algorithm is used to program the sheep agent evacuating on the road network.

4.2.4 Agent-based simulation using GAMA platform

GAMA platform is good choice for modelers combining Agent-based simulation and GIS. GAMA is the object-oriented paradigm using GAML language [Drogoul 2007], where the notion of class is used to supply a specification for objects, agents in GAML are specified by their species, which provide them with a set of attributes (what they know), actions (what they can do), behaviors (what they

actually do) and also specifies properties of their population, for instance its topology (how they are connected) or schedule (in which order and when they should execute) [Drogoul 2007]. Any species can be nested in another species (called its macro-species), in which case the populations of its instances will imperatively be hosted by an instance of this macro-species. A species can also inherit its properties from another species (called its parent species), creating a relationship similar to specialization in object-oriented design. In addition to this, species can be constructed in a compositional way with the notion of skills, bundles of attributes and actions that can be shared between different species and inherited by their children. Given that all agents are specified by a species, simulations and experiments are then instances of two species which are, respectively, called model and experiment plan. Think of them as “specialized” categories of species. The relationships between species, models and experiment plans are codified in the meta-model of GAML in the form of a framework composed of three abstract species respectively called agent (direct or indirect parent of all species), model (parent of all species that define a model) and experiment (parent of all species that define an experiment plan). In this meta-model, instances of the children of agent know the instance of the child of model in which they are hosted as their world, while the instance of experiment plan identifies the same agent as one of the simulations it is in charge of. The agents that will belong to this species will only be provided with some built-in attributes and actions, a basic behavioral structure and nothing more. These elements are directly inherited from the default parent species called ‘agent’.

A species can contain several elements:

- Attributes: define the state of the agents.
- Actions: define a capability of the agents. An action is a block of instructions that are executed when the action is called.
- Inits and Reflexes: defines the default behavior of the agents. Both statements contain instructions that are executed, respectively, once when the agent is created for init statements, and at each simulation step (according to an optional condition) for reflex statements.
- Aspects: define how the agents can be displayed.
- Equations: define a set of differential equations that can be integrated when necessary.
- Micro-species: nested species can be described inside a species. See here? for more details on the relationships between macro- and micro-species. Note that all the elements previously defined are optional. It is totally possible to define an empty species without any attributes, actions, reflexes, aspects, equations or micro-species like in the example above.

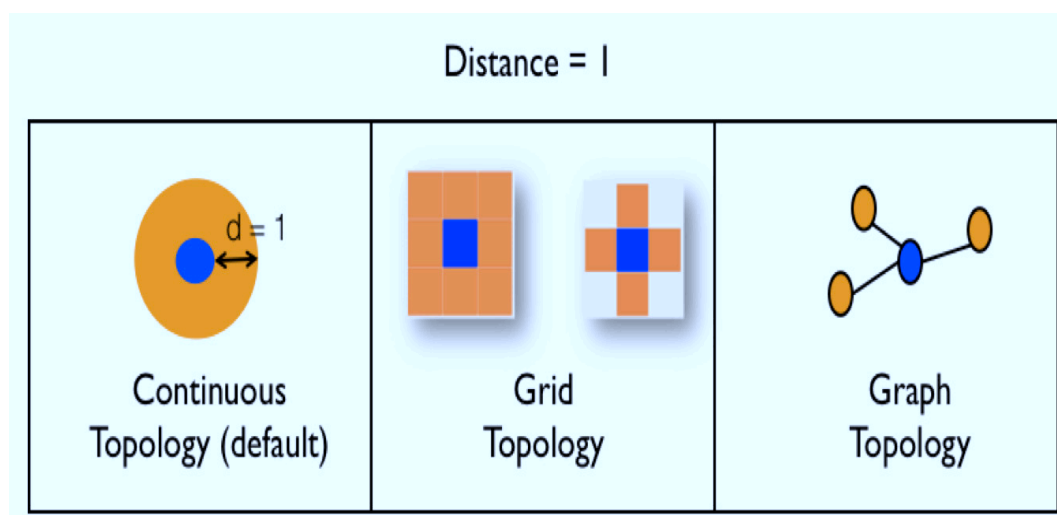


Figure 4.4: The topology describes the spatial organization of the species. This imposes constraint on the movement and perception (neighborhood) of the species' agents. GAMA supports three types of topology: continuous, grid and graph.

In addition to the regular inheritance mechanisms, modelers can attach skills and control architectures to species, which will provide their agents with new attributes, actions and behaviors. See here for how to define these capabilities.

Finally, some specific features concerning the interaction of users with agents can be added to any species. It is for example possible to define an action that will be executed by the user. See here for more details.

Scheduling Description The modeler can specify the scheduling information of a species. This scheduling information is composed of the execution frequency and the list of agent to be scheduled.

the execution frequency is the frequency which agents of the species are considered to be scheduled. "the list of agent to be scheduled" is an expression returning a list of agent dynamically evaluated at runtime

Topology Description The topology describes the spatial organization of the species. This imposes constraint on the movement and perception (neighborhood) of the species' agents. GAMA supports three types of topology: continuous, grid and graph (Fig. 4.4).

Types of Species Several types of species exist in GAMA:

- global species: The global species defines the model, i.e. the attributes, actions, behaviors and micro-species that describe the world agent.
- regular species: species of agents with a continuous topology by default.
- grid species: species of agents with a grid topology.

- graph species: species of agents with a graph topology.
- Mirror species: species of agents that mirror the population of another species

Example, one hand the pedestrians evacuate on the road network, the other hand there are many of vehicles such as cars, motorcycles, bicycles, etc. Pedestrians , motorcycles and cars,etc are different species in the GAMA platform. An pedestrian is atom agent. However, the carrying capacity of a motorcycle is three people, and the carrying capacity of car is from one to forty five people. The pedestrians and motorcycles can move in the small road but the car must move in the road more than 4 meters (Fig. ??).

Motorcycles evacuation

The relationship between the velocity of motorcycles and density of agents in front needs to consider. We assume that the velocity of motorbike depends on the density of agent in front that in are $L_m \times W$ where L_b is equal to 16.5 meters and W is wide of the road. The density of agents in front of a motorcycle i is defined that $\rho_{i,m} = N_i/L_b \times W$ where N_i is the number of agents in front of i . The article [Goto 2012] shows that the density $\rho_i \leq 0.17$ agents/ m^2 , the velocity at maximum is $30km/h(8.3m/s)$. The velocity of motorcycle decreases to 0 with increasing the density 0.9 agents/ m^2 .

Cars evacuation

In the simulation, the car agent and the other agents move in the same road. The velocity of a car at maximum is 40 km/h, and its velocity decreases to velocity of a pedestrian's velocity with the increasing the density 1 agents/ m^2 . The density of agents in front of a care is defined $\rho_{i,c} = N_i/L_c \times W$ with he length of the road $L_c = 11.1$ meters and the W is wide of the road.

4.2.4.1 Police agents

The police agents are identify the agent who know information of evacuation such as the shelters, the shortest path from a particular position to the shelters, etc. They announce the information of evacuees. We assume that all agents in the police agent effect know the shortest path from their position to a shelter. The velocity of police agent is equal to the motorcycle's velocity. Police agents share information to move all the roads of the city to give information to the other agents.

The species definition is basic and important element of GAMA platform. In this thesis, we only consider the pedestrians in the simulation. The other vehicles

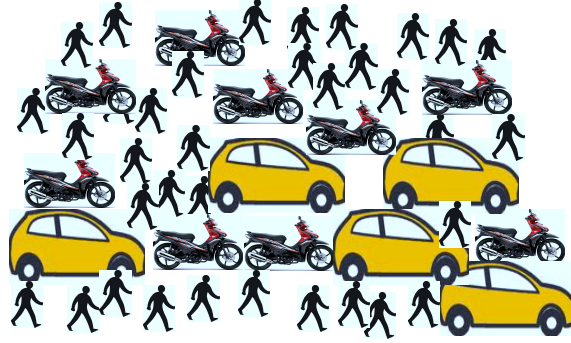


Figure 4.5: The pedestrians, motorcycles and cars on the road in evacuations.

can be assumed pedestrians with high velocities. In the next section, hybrid-based simulation is multi-level simulation so we identify several species that will be described.

4.3 Hybrid Simulation

On the complicated road network with many junctions and roads, the behaviors of agents at the junctions decide their survivor in evacuation. In order to study complicated behaviors of the agents at junctions, Agent-based model is used for the junctions and Equation-based model is used for the stretch road between two junctions in the Hybrid-based model. The objective of the Hybrid-based model is to speedup evacuation simulation on road network [Anh 2011, Abouaissa 2014].

4.3.1 The Consistency of Agent-based model and Hybrid-based model

First of all, it is obvious that each pedestrian has a effective area that he/she interacts with the other pedestrians thus this leads to the following definition.

Definition 4.4 *The disk of a given pedestrian i , denote $disk_d(i)$, is the disk with radius $d(d > 0)$ and the center point is where the pedestrian is.*

We define a disk graph for them

Definition 4.5 *A graph $G(V, E)$ of pedestrians is defined as follows:*

- Vertex set is the set of pedestrian: $V = \{1, 2, \dots, n\}$
- Edge set is the set of interactions between pedestrians. In detail, for two pedestrians $i, j : (i, j) \in E$ if and only if $distance(i, j) < d$.

The set of all neighbors of the pedestrian i is $Neighbors(i) = \{j : distance(i, j) < d \text{ and } j \text{ is front of } i\}$ and $N(i) = card\{j : j \in Neighbors(i)\}$.

The Velocity of the pedestrian belong the number of neighbors

$$Velocity_{agent\ i}(t, x) = Velocity_{max,road\ k} \left(1 - \frac{N(i)}{N_{max,roadk}} \right)$$

where $N_{max,road\ k} = \pi d^2 \cdot Density_{max}$.

Theorem 4.6 *The average velocity of the total pedestrians in ABM at the time t and the position x is equivalent with the velocity of pedestrian density in the EBM, i.e*

$$\overline{Velocity_{agent\ i}(t, x)} = Velocity_{max,road\ k} \left(1 - \frac{p}{p_{max}} \right) \quad (4.9)$$

Proof 4.1 *We consider the number of pedestrians in the Tube is n at the time t and around $(x, x + \Delta_x)$ and we assume n is larger,*

$$\overline{Velocity_{pedestrian\ i}(x, t)} = \frac{\sum_{i=1}^n Velocity_{pedestrian\ i}(x, t)}{n} = \frac{\sum_{i=1}^n Velocity_{max,road\ k} \left(1 - \frac{N(i)}{N_{max,roadk}} \right)}{n} \quad (4.10)$$

$$= Velocity_{max,road\ k} \frac{\left(n - \sum_{i=1}^n \frac{N(i)}{N_{max,roadk}} \right)}{n} = Velocity_{max,road\ k} \left(1 - \frac{1}{N_{max,roadk}} \frac{\sum_{i=1}^n N(i)}{n} \right) \quad (4.11)$$

Let us recall that, in [C.J.H 2005], McDiarmid et al showed that in a disk graph of n vertices, where two vertices's are neighbors if their distance is smaller than or equal to d , the average neighbors can be measured by the quantity nd^2 . That means, there exists a ratio ρ such that the average neighbors is equal to $\rho \cdot nd^2$. In addition, we denote the area $(x, x + \Delta_x) \times Width$ of the road in the tube is $Area$.

$$\overline{Velocity_{pedestrian}(x, t)} = Velocity_{max,road\ k} \left(1 - \frac{\rho nd^2}{N_{max,roadk}} \right) \quad (4.12)$$

We know that $p = \frac{n}{Area}$ and we set up $p_{max,road\ k} = \frac{N_{max,roadk}}{Area \rho d^2}$.

Substituting the formulas density in the (4.13), we have

$$\overline{Velocity_{agent}(x, t)} = Velocity_{max,road\ k} \left(1 - \frac{p}{p_{max,roadk}} \right) \quad (4.13)$$

This theorem is proved.

This theorem shows the consistency velocity of Agent-based model and Equation-based model. Therefore, the average velocity of pedestrians and velocity of pedestrian density are equivalent in hybrid-based model.

4.3.1.1 Hybrid-based simulation for a road

Because of the complicated road network, to easy for representing, we consider the hybrid-based simulation for a road. The Hybrid-based model for a road network is displayed in the next subsection. We introduce the aggregated agent in a tube. It is needed to take into account the interactions between the pedestrian agents and the aggregated agent. When a pedestrian agent touches somewhere within the area of the tube, the pedestrian is hibernated and not scheduled in the simulation anymore. The aggregated agent is based on a macroscopic model. The aggregated agent represents all pedestrians in the tube area it covers. In addition, aggregated agent decides the time to put the pedestrian back to the “active” mode (from the hibernated mode) in an appropriate position [An 2012].

We introduce the “*Tube*” agent in order to represent when a pedestrian moves into the tube. It is not scheduled in the simulation anymore, it is a micro-species of the “Road” species and a sub-species of the “pedestrian” species. We also declare that agents of this species are not scheduled in the simulation. The species structure of this model is displayed in the figure (Fig. 4.6).

Responsibilities of species in an experiment.

- The “pedestrian” species encapsulates the attributes and behaviors of “pedestrian” agents. Inside this species, we put the code to model how the pedestrian moves in the road network of the city to a set of predefined shelters.
- The “Road” species represents the “Road” agents. Each “Road” agent represents a road in the road network of the city. The road network is created from the GIS data.
- Being a Macro-Species of “*Tube*” species, “*Tube*” species is a sub-species of “pedestrian” species permits us to redefine the behaviors and variables of “pedestrian” in the definition of “*Tube*” species. It occupies $(1 - 2 \times \alpha)$ of the road, so “*Tube*” variable of each road is initialized automatically with a polygon occupying the tube of the road and covering $(1 - 2 \times \alpha)$ length of the road.

In the definition of “*Tube*” species, among other variables, we have two variables: “released_time” and “released_location”. They determine the moment and the location that a “*Tube*” agent is released from the “Road” agent. They are calculated by the “Road” agent based on the associated macroscopic model. A point to note here is that the organization of agents in which a “Road” can contain the “*Tube*” Micro-agents offer the modeler a framework to integrate a macroscopic model to control the dynamics of pedestrians in the tube. There is no constraint on the exact macroscopic model to use. Instead, the modeler has the freedom to test different macroscopic models. An important point is that the modeler has to assure an

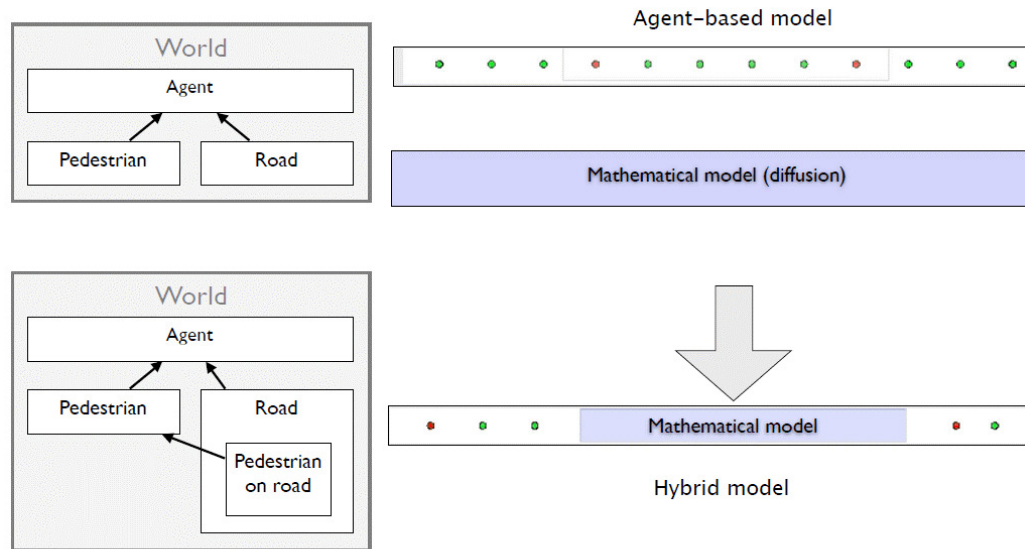


Figure 4.6: Species structure of Tsunami evacuation model's. In Agent-based and the Equation-based model, there are "pedestrian" agent and "Road" agent. In Hybrid-based model, an aggregated agent is defined.

"acceptable" consistency between two models: the model without the aggregated agent (pure ABM) and the model with the Aggregated agent (HBM).

4.3.2 Speed up simulation with certain conditions

When a "pedestrian" agent moves into the tube, the "Road" agent captures the pedestrian as an agent of the "*Tube*" species. In order to make the "Road" agent be capable of capturing the "pedestrian" agent, in the definition of the "Road". In each simulation step, the "Road" agent bases on the "released_time" of its Micro-agents ("*Tube*" agent) to release them in the appropriate location. If the "released_time" of a "*Tube*" agent is smaller than or equal to the current time of the simulation clock, it will be released as a "pedestrian" agent, Micro-agent of the "world" agent. The definition of in the "Road" species, illustrates how a "Road" agent releases its Micro-agents: The "capture" and "release" statements help to keep the identity and heterogenous information of pedestrians in the hybrid version of this models. These information will be used later in versions that need to take into account the fact that pedestrians move by groups (e.g: family, acquaintance). Currently, we use the LWR [Lu 2008, Friesz 2013, Wong 2002] as the Macroscopic model integrated in the

”Road” agent. The initial results of this work which prove the consistency between hybrid model and the pure ABM model the can be found in [Anh 2011].

4.3.3 Integrating ABM and MAET

In order to find the optimal sign placement for the road network, we integrate the Equation-based model and Agent-based model to benefit the advantages of both approaches. MAET being Equation-based model takes into account very simple Markovian behavior for pedestrians. Thus we want to integrate MAET with the Agent-based simulation that takes into account heterogeneous behaviors and GIS environment. To integrate MAET and Agent-based simulation, the results of MAET that is optimal sign placement is used to the input of Agent-based simulation. Agent-based simulation is run many times that give the new spending time of each road for the MAET. This information will be used as input in the next iteration of MAET in order to further optimize the sign placement (Fig. 4.7).

Concretely, when we solve the first time MAET the spending time of an agent C_{ij} that is based on the length of the road following this formula:

$$\frac{\text{length of the road}}{\text{average velocity of an agent}}. \quad (4.14)$$

However, the spending time C_{ij} is not only depend on the length of the road (i, j) . The spending time of an agent C_{ij} may depend on the width of roads, the velocity of pedestrians in the road (i, j) , the number of pedestrians on the road, etc. Thus to change the spending time $C_{i,j}$ using Agent-based simulation is better. Therefore, we integrate Agent-based simulation using GAMA and MAET.

This integration helps us get to further optimize sign placement. We not only find the optimal sign placement by MAET, but also consider the different behaviors of pedestrians by Agent-based simulation.

4.4 Visualization

To dress for visualization tsunami simulations, the simulations are represented not only in 2 dimensions (2D) space but also in 3 dimensions (3D). In the tsunami evacuation simulation using the GAMA platform, the representation of the shelters, the highlands, the terrain in 3 dimensions are importance for evacuees decide the safe places. The disadvantage of the simulations represented in 3D is slower than that in 2D because the simulations take time to compute the 3D data and the species. Otherwise, the simulations in 3 dimensions helps the modelers easily observe pedestrians dynamic. Moreover, the modelers easily watch the different scenarios

input : The direct graph of the Nhatrang city $G = (V, E)$, the cost matrix C , the transition probability matrix of each agent P and spatial population distribution $\{\mu_i, i = 1, \dots, n\}$, spending time $C_{i,j}$ of the edge (i, j) given by: $\frac{\text{length of the road}}{\text{average velocity of an agent}}$.

output: Positions of alert signs SI for optimizing the time evacuation of the city

```

1 The stop criteria=false
2 while The stop criteria=false do
3   Solving MAET to have optimal sign placement
4   Simulating evacuation in GAMA platform and assigning the new
   spending time  $C_{i,j}^{new} :=$  average velocity of all agent move on the road
    $(i, j)$ 
5   if  $\sum_{\forall(i,j) \in E} |C_{i,j} - C_{i,j}^{new}|^2 \leq \epsilon = true$  then
6     The stop criteria= true
7   else
8      $C_{i,j} := C_{i,j}^{new}$ 
9   end
10 end

```

Algorithm 4: Integrating simulations MAET and GAMA simulations to give an optimal sign placement.

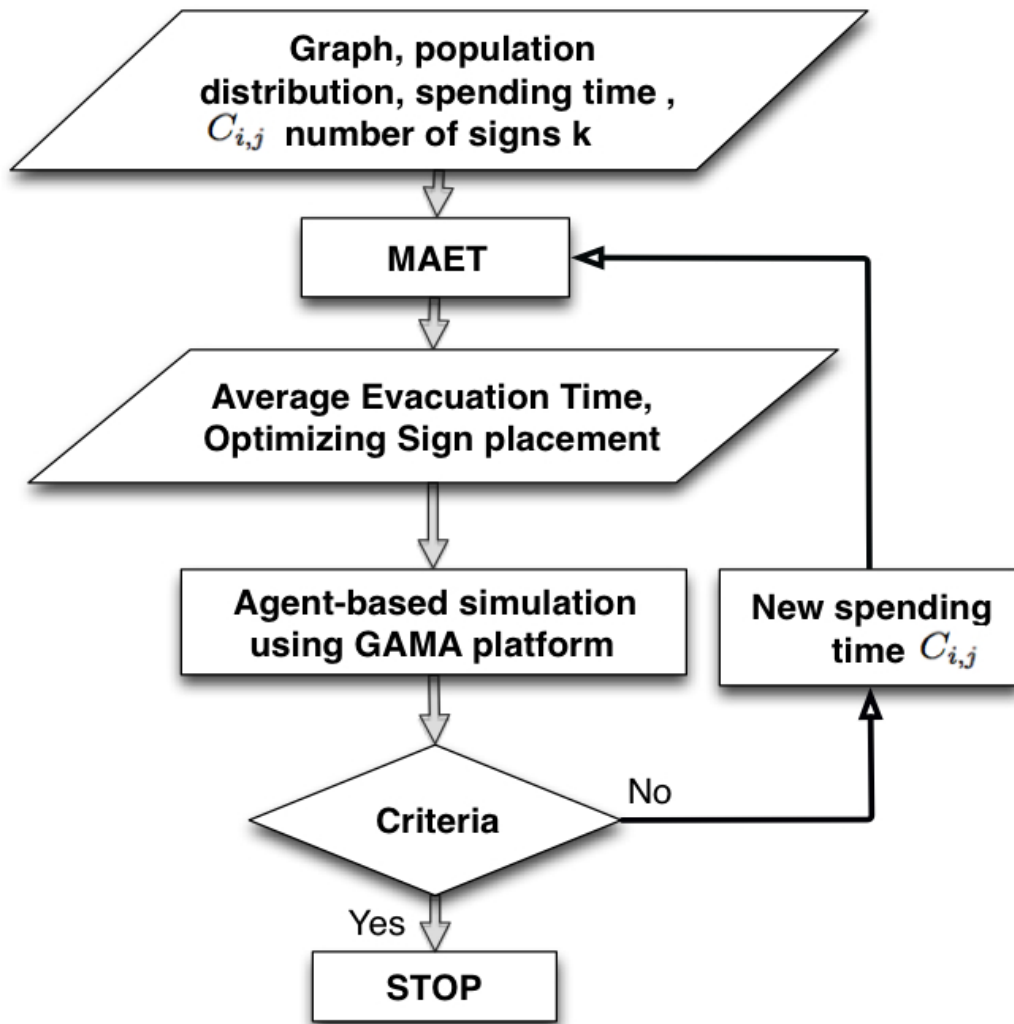


Figure 4.7: Integrating simulations MAET and Agent-based simulation to give an optimal sign placement. Agent-based simulation will give average spending time of each road $C_{ij}, (i, j) \in E$. This information will be used as input in the next iteration of MAET in order to further optimize the sign placement.

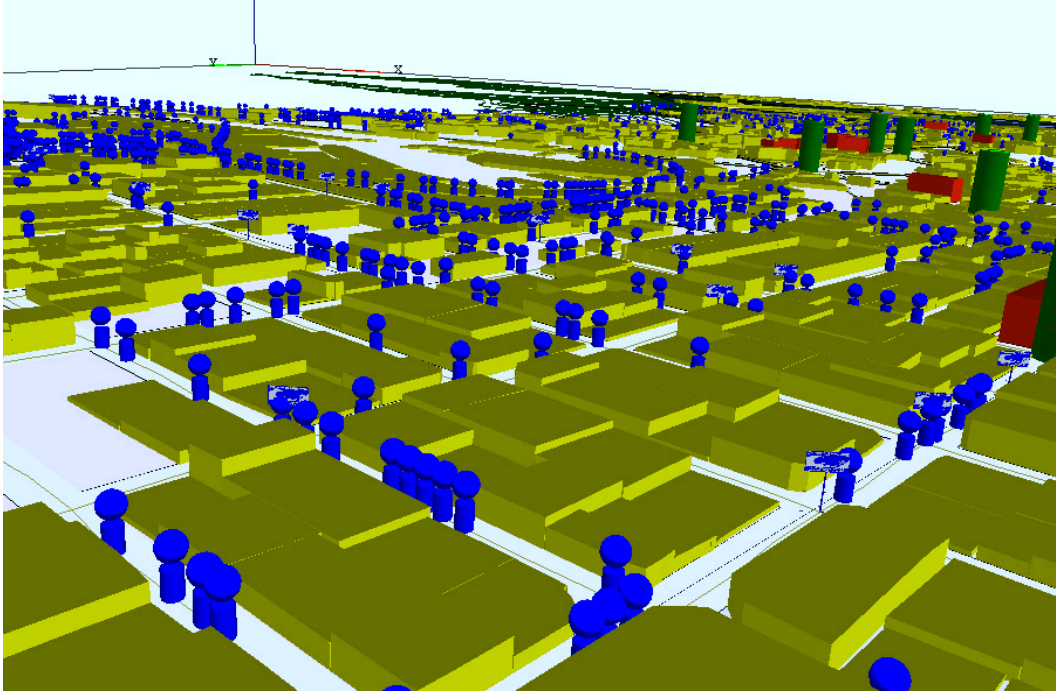


Figure 4.8: The simulation in the GAMA platform is represented in 3 dimensions that helps the modelers easily observe pedestrians dynamic and the real environment.

in evacuation that are useful in training for the evacuee in preparing tsunami ready (Fig. 4.8).

4.5 Conclusion

It is very important to plan early evacuation before tsunami occurs. The alert sign placement for early warning tsunami is considered. The sign placement that is minimized the average time evacuation is solved by Mixed Integer Linear Programming (MILP). The modeler used Equation-based model cannot take into account the heterogeneous behaviors. While the difference behaviors of pedestrians at junction decide to the survive of pedestrians. Thus, Agent-based model is used to study the different behaviors of pedestrians at the junctions.

The advantages of Agent-based model are not only accounting the heterogeneous behaviors of individual pedestrians but also considering the local interactions of pedestrians. The environmental modeling of ABM is GIS data that make the model is more realistic while the environment in EBM is often homogeneous and sim-

ple such as a graph, a simple building, etc. A geographic information system (GIS) can capture, store, check, and display many different kinds of data on one map. GIS makes the modelers easily analysis the data related the positions on Earth's surface. To avoid unrealistically homogeneous population or address randomly population, the initial of distribution and positioning of pedestrians is described.

In our model, the number of pedestrians in each ward is taken from the given data and then the positions of pedestrians are change following the Poisson process. The new positions of pedestrians are the initial spatial population for the Agent-based simulation. The advantage of Agent-based simulation is not only taken into account the initial spatial population but also the pedestrians' different behaviors.

To simplify the tsunami evacuation problem in a large environment and a large number of pedestrians and to reduce the complicated this problem, we consider two different agent types that are sheep agent and fox agent. A fox agent is defined as a pedestrian who has been trained on evacuation procedures or has knowledge of how get to the safe place efficiently. A fox agent has a different behaviors such as his own velocity, his own shelter target, his own strategies in evacuating (choosing the shortest path or following alert sign system in junctions), etc. Meanwhile, a sheep agent has a different behaviors also such as his own velocity, evacuating randomly at junctions, following one fox agent, etc. These behaviors are very important that decide the survive of pedestrians.

On the complicated road network with many junctions and roads, the behaviors of agents at the junctions decide their survivor in evacuation. In order to study complicated behaviors of the agents at junctions, Agent-based model is used for the junctions and Equation-based model is used for the stretch road between two junctions in the Hybrid-based model. The objective of the Hybrid-based model is to speedup evacuation simulation on road network. We introduce the aggregated agent in a tube. It is needed to take into account the interactions between the pedestrian agents and the aggregated agent. Then, we proved the consistency of the velocity of pedestrians in Hybrid-based model is equivalent with their velocity in Agent-based model.

In order to enhance optimal sign placement for the road network, we integrate the Equation-based model and Agent-based model to benefit the advantages of both approaches. MAET being Equation-based model takes into account very simple Markovian behavior for pedestrians. Thus we want to integrate MAET with the Agent-based simulation that takes into account heterogeneous behaviors and GIS environment. To integrate MAET and Agent-based simulation, the results of MAET that is optimal sign placement is used to the input of Agent-based simulation. Agent-based simulation is run many times that give the new spending time of each road for the MAET. This information will be used as input in the next iteration of MAET

in order to further optimize the sign placement.

The next chapter, we will present detailed results of each problem and the experiments that we carried out. The experiments applied to the Tsunami evacuation of the Nha Trang city, Vietnam.

Chapter 5

Experimentation and Analysis

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Foreword

This chapter presents the experiments for Nha Trang tsunami evacuation simulation. Concretely, we carried out Nha Trang tsunami evacuation simulations by three approaches Equation-based model, Agent-based model and Hybrid-based model. Firstly, we solve sign system problem based on EBM called MAET. Then, we used the results and apply it in the Agent-Based Simulations using the GAMA platform. Thirdly, Hybrid-Based simulations are do experiment because they are faster performance than the Agent-Based simulations do. Finally, MAET and Hybrid-Based simulations are integrated to find the further optimal sign placement.

5.1 Experimentations

When tsunamis occur, pedestrians must be quickly informed of the oncoming danger in order to begin the evacuation. For coastal areas of central Vietnam, whether the source of the tsunami is located offshore or near shores, evacuation time is often short. Getting ready for tsunami warning means each coastal city needs to prepare to evacuate the area as promptly as possible. One important part of the tsunami response is the design of evacuation maps and other specific scenarios in coastal areas prone to tsunamis.

We chose to focus on the urban areas of the coastal Nha Trang city, which is composed of 11 wards, 163,885 inhabitants and a total surface area of $7.9km^2$ in 2009 [Nguyen Hong Phuong 2011]. Nha Trang city is displayed a map in (Fig. 5.2). In Nha Trang city, Vietnamese researchers in Vietnamese Institutes of Geography Physic proposed two cases that the sources of the tsunamis are located offshore or near shores. They also proposed two scenarios in evacuation. According to the literature, an earthquake of 8.4 Richter magnitude occurring in the deep-sea near Manila can yield a 1.9 m high tsunami in Nha Trang and up to 4 m if an earthquake with Richter magnitude 8.8 appears in the same area [Phuong 2012]. Thus, the shelters are buildings thereby have to satisfy some critical requirements. More generally, shelters must meet some specific criteria with regards to their height, structural foundations and purpose of the building(schools, government buildings or military buildings). The researchers In the next Subsection, MAET is applied to two scenarios; Warning signs are placed according to the solution from the MAET problem for the road network.

In general, the evacuation Nha Trang tsunami evacuation models on road network have three loops in the scheme (Fig. 4.1). In the first loop, the different equation-based simulations using MAET are carried out to find optimal sign placement in city. The second loop picks up the distribution of people and the behaviors

of agents. The last loop displays the experiment of the simulation using the GAMA platform [Taillandier 2010]. These loops affects the results and the evaluation of the simulation. We represented the experiments following this scheme (Fig. 4.1).

To simulate evacuation for pedestrians in Nha Trang city, the algorithm is created as following:

- Step 1: Loading the GIS environment and the initial parameters.
- Step 2: Optimizing the alert signs system.
- Step 3: Choosing parameters for the time, the tourist season, the rate of fox agents in pedestrians.
- Step 4: Running the Agent-based simulation using the GAMA platform.
- Step 5: Counting the number of Survivors and estimate the average time an agent spends.
- Step 6: Testing stopping criteria.
- Step 7: If the stopping criteria does not satisfy then choosing other parameters and return to Step 4.

Each loop involves to solve a subproblem for the entire tsunami evacuation simulation. In the the first loop, sign placement for tsunami evacuation is found. The second loop, initial spatial population distribution based on time of day and season of travel factors is considered. Then, the different behaviors of the pedestrians in the evacuation are investigated. In the third loop, simulates evacuation process based on the HBM or ABM.

Application for Evacuation of Nha Trang city

In Nha trang city, the tsunami sources located offshore or near shores cause two levels of emergency that relates with the time eevacuation. The tsunami propagation time from the source region to the sea near Nha Trang is about 2 hours [Phuong 2012, Nguyen Hong Phuong 2011]. Based on these studies, the two following levels of emergency were selected as the basis for building evacuation plans:

- Scenario 15 minutes (evacuating the part of Nha Trang city which is less exposed to the tsunami): Allows pedestrians to evacuate in time: $t \leq 30 \text{ minutes}$ (Fig. 5.1).
- Scenario 90 minutes (evacuating the whole Nha Trang city): Allows pedestrians to evacuate in time: $30 \text{ minutes} \leq t \leq 2h$ (Fig. 5.2)

Based on these two evacuation scenarios, the tsunami evacuation was classified into two types. For scenario 15 minutes, the evacuation time for implementation is only 30 minutes, the time evacuation is very short so the shelters have to stay in the city where has crowd population. Thus, the high buildings with solid structures near to the coast are selected as shelters in the study area (Fig. 5.1). The shelters in city

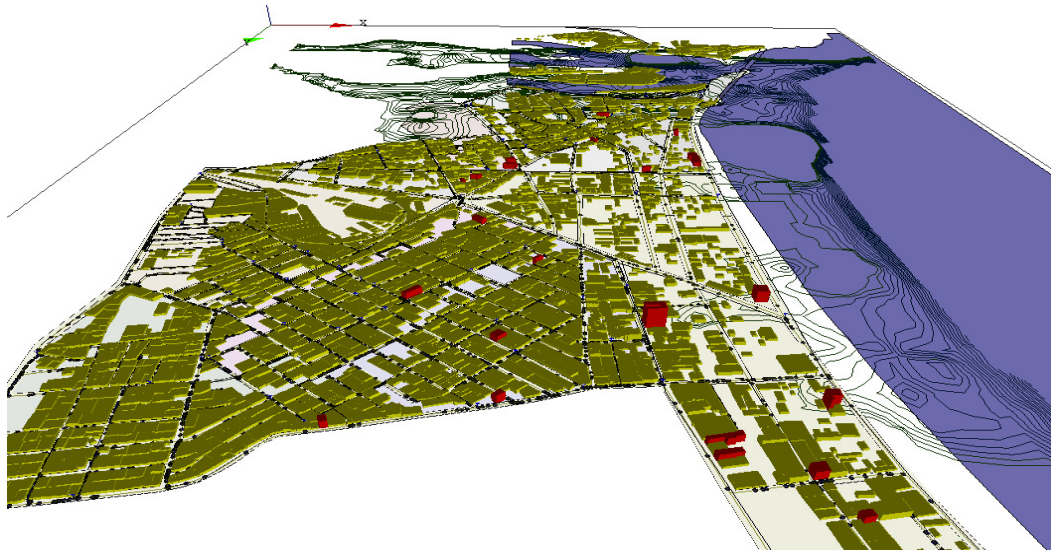


Figure 5.1: The shelters in Agent-based simulation are high buildings with solid structures and are not close to the coast.

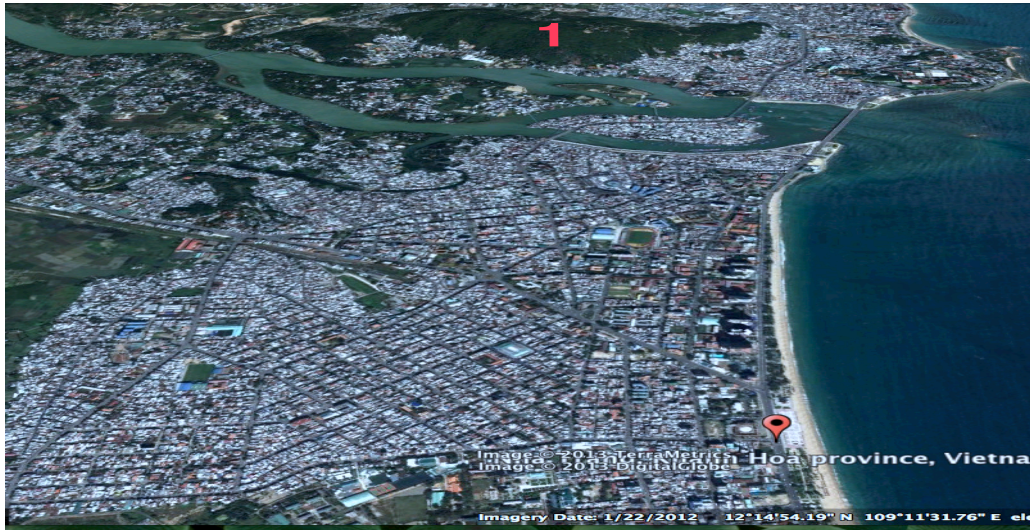


Figure 5.2: Scenario 90 minutes: Allows pedestrians evacuate in time: $30 \text{ min} \leq t \leq 2h$. The evacuation time is longer, up to two hours, so the evacuation of selected areas may be located further inland on the condition that the terrain is high enough to avoid the impact of the tsunami such as position 1

help pedestrians evacuating in short time. However, the shelters may be impact of the forces of tsunami waves that pull down the high buildings. So if the evacuating time evacuating for this city is longer, the researcher chose the other shelters. For scenario 90 minutes, the evacuation time is up to 2 hours, so the shelters may be located further inland that their terrains are high enough to avoid the impact of the tsunami waves. In the study of Institute of Physical Geography Vietnam IGP researchers, the mountains whose position 1 in (Fig. 5.2) are proposed to be the shelter for the scenario 90 minutes [Phuong 2012, Nguyen Hong Phuong 2011].

Load the GIS environment

The GAMA platform is used for spatially explicit Multi-Agent simulations. It integrates ABMs and GIS that can interact: identity, causal, temporal and topological. Thus, its ability to use complex GIS data as an environment for the agents. The commands of GAMA platform to obtain information GIS data are easy.

Many Agent-Based simulation softwares are available but they don't support GIS data strongly. The GAMA platform is considered easier and more effective using GIS for Agent-Based simulations.

5.2 The experiments for Equation-based simulation MAET

To easily understanding MAET model, we present MAET model in a small environment with a few roads.

Experiments MAET in a small environment

For these first experiments, we chose a small part of Nha Trang city (Fig. 5.3). There are 8 roads and 6 junctions numbered 0, 1, 2, 3, 4, 5. The junction 5 has a high building that satisfies all the requirements of a shelter, so the junction 5 is considered a shelter. We assumed the one-way or two-way roads as shown in the figure (Fig. 5.4). The problem is finding sign placement using MAET model.

We use the GAMA platform [Taillandier 2010] to transfer GIS data to the direct graph $G = (V, E)$ and applying the results of MAET to the GIS to simulation evacuation [Anh 2011, Anh 2012].

Let a graph $G = (V, E)$ represent the city in which $V = \{0, 1, \dots, 5\}$ is a set of junctions and $E \subseteq V \times V$ is a set of edges representing roads connecting vertices. Each edge is associated with a weight c_{ij} representing the time required by an agent

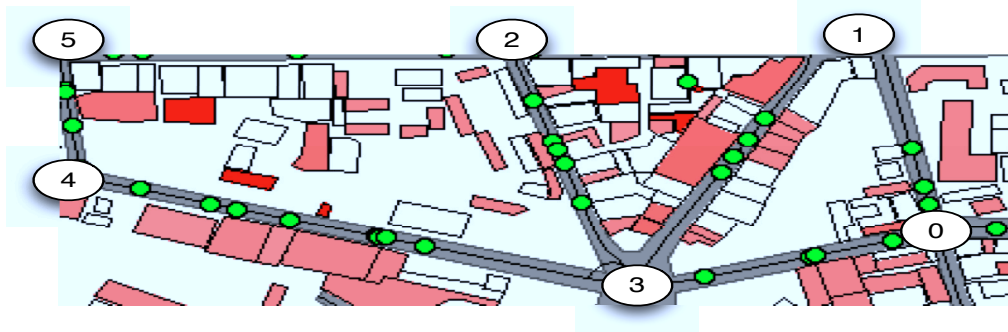


Figure 5.3: One part of the road network in Nha Trang city. GIS data are buildings, roads, junctions, agents, rivers, shelters.

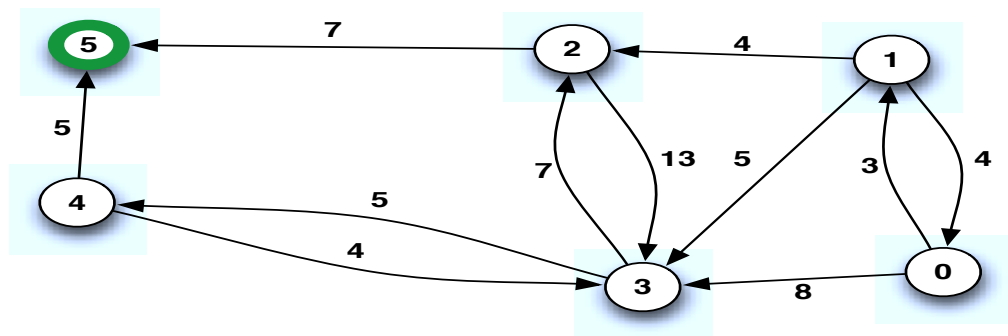


Figure 5.4: The GIS data is converted to a directed graph. There are 8 roads and 6 junctions numbered 0, 1, 2, 3, 4, 5. The junction 5 is a shelter. The figure also shows the one-way or two-way roads.

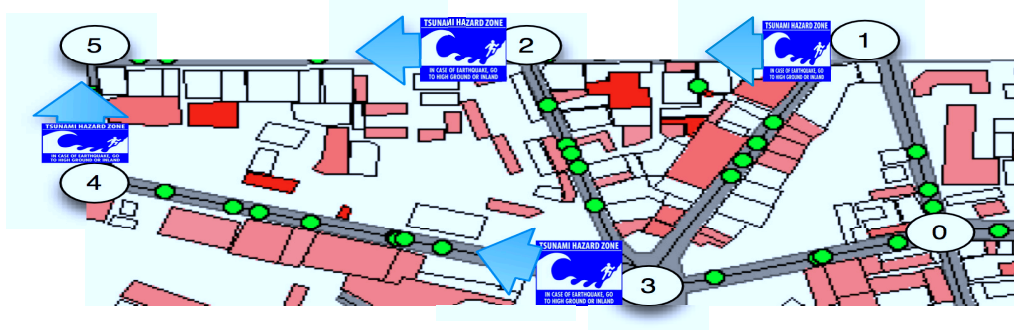


Figure 5.5: The sign placements are set up based on the MAET results. $k = 4$ the tsunami signs place at $V = \{1, 2, 3, 4\}$ and the direction are $\{(2, 5), (4, 5), (1, 2), (3, 4)\}$.

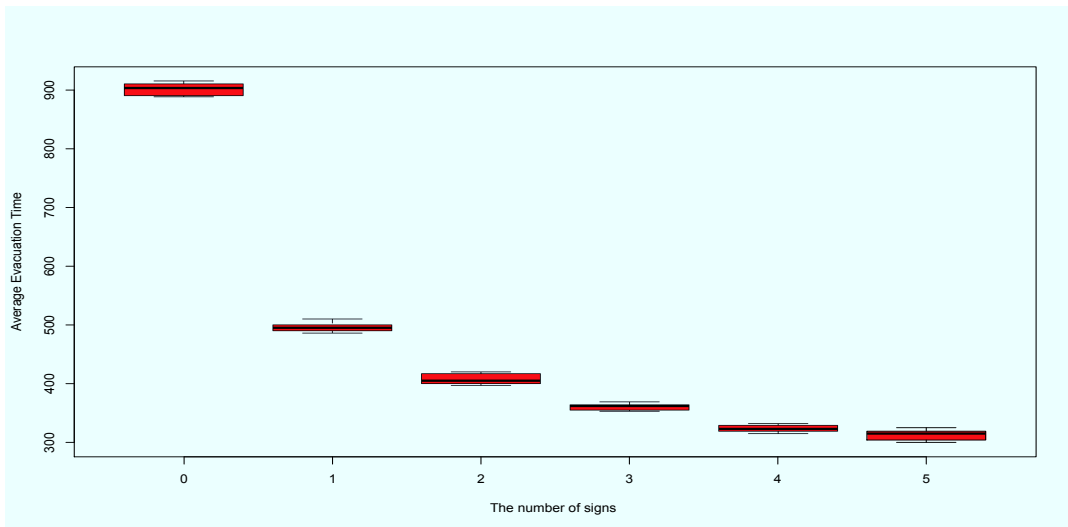


Figure 5.6: The Average evacuation time of pedestrians w.r.t. the number of signs.

to move from vertex i to vertex j . Also, the set of neighbors of vertex i is referred to as $N(i) = \{j : (i, j) \in E\}$. The vertex 5 is a *shelter*.

To represent the behavior of the humans, we will use a Markov chain over the set of vertices. A Markov chain is composed of an initial distribution $\mu = \{\mu_i : i \in V\}$ and a 6×6 stochastic transition matrix \mathbf{P} representing the transition probabilities from one vertex to another. Let us see how this Markov chain describes the behavior of the agents. At time $m = 0$, each agent is randomly placed on the graph with respect to the given distribution μ . At time $m > 0$, an agent positioned on vertex i will move towards vertex $j \in N(i)$ with probability P_{ij} , where \mathbf{P} is the stochastic matrix such that if $(i, j) \notin E$, then $P_{ij} = 0$ and such that $\sum_{j \in V} P_{ij} = 1$. Finally, because the vertex 5 is the shelter so $P_{55} = 1$. Technically, this is a slight generalization of Markov chains called *semi-Markov chains*, because the time required by an agent to cross the edge (i, j) is c_{ij} , which is not the same for all edges. Finally, for any agent, its probability distribution over V after t moves is given by $\mathbf{P}^m \mu$.

We made the assumption that the behavior of all agents can be represented by a stochastic matrix \mathbf{P} . When we do experiments, we further assumed that an agent located on vertex i has an equal probability to reach any vertex $j \in N(i)$.

To have a road network as a graph for EBM, We use the GAMA platform [Taillandier 2010] that support GIS and program a code to transfer GIS data that has road network site to the direct graph [Anh 2011, Anh 2012]. This graph is represented by a weight matrix $\mathbf{C} = \{C_{ij}\}$ that C_{ij} is average spending time of an agent given by: $C_{ij} = \text{length of the road from } i \text{ to } j / \text{average velocity of an agent}$. The weight matrix given by:

$$C = \begin{bmatrix} 0.0, & 3.0, & 0.0, & 8.0, & 0.0, & 0.0, \\ 4.0, & 0.0, & 4.0, & 5.0, & 0.0, & 0.0, \\ 0.0, & 0.0, & 0.0, & 13.0, & 0.0, & 7.0, \\ 0.0, & 0.0, & 7.0, & 0.0, & 5.0, & 0.0, \\ 0.0, & 0.0, & 0.0, & 4.0, & 0.0, & 5.0, \\ 0.0, & 0.0, & 0.0, & 0.0, & 0.0, & 0.0 \end{bmatrix}$$

The stochastic transition matrix \mathbf{P} representing the transition probabilities from one vertex to another given by:

$$\mathbf{P} = \begin{bmatrix} 0.0, & 0.5, & 0.0, & 0.5, & 0.0, & 0.0, \\ 1/3, & 0.0, & 1/3, & 1/3, & 0.0, & 0.0, \\ 0.0, & 0.0, & 0.0, & 0.5, & 0.0, & 0.5, \\ 0.0, & 0.0, & 0.5, & 0.0, & 0.5, & 0.0, \\ 0.0, & 0.0, & 0.0, & 0.5, & 0.0, & 0.5, \\ 0.0, & 0.0, & 0.0, & 0.0, & 0.0, & 1.0 \end{bmatrix}$$

Number of signs k	Optimal sign placement	Average Evacuation time
0		904
1	$\{(2, 5)\}$	507
2	$\{(2, 5), (4, 5)\}$	413
3	$\{(2, 5), (4, 5), (1, 2)\}$	358
4	$\{(2, 5), (4, 5), (1, 2), (3, 4)\}$	329
5	$\{(2, 5), (4, 5), (1, 2), (3, 4), (0, 1)\}$	319

Table 5.1: The optimal sign placement and the average evacuation time with different k are the results of MAET problem.

$$\mu = ([5.0, 6.0, 7.0, 12.0, 3.0, 12.0])$$

The optimal sign placement is solved by MAET as follows:

$$a = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

We ran the CPLEX which is a well known MILP solver. The solution of optimal sign placement problem using MAET that is represented in (Table 5.1) for various values of $k = 1, 2, \dots, 5$. The MAET simulations are run 30 times with each different k . The results of MAET are not only the optimal sign placement but also the average evacuation time responsively k .

Experiments MAET in Nha Trang city environment

The simulation results of MAET are an optimal sign placement and the average evacuation time. At Initiation, the GIS road network of the Nha Trang city is converted into a road network graph with 394 vertices that's described by an adjacency. Then, we do evacuation simulation with the road network graph of Nha Trang city, two scenarios (15 minutes and 90 minutes) and the different number of signs k . Each scenario, we run 150 experiments. Based on many times we run experiments for the scenario 90 minutes, we observe that there are not much different simulation results when a number of signs are greater than 150. Thus, we test the simulations with $k = 0, 30, 60, 90, 150$. We did experiments 30 times with each $k = 0, 30, 60, 90, 150$. The graph is described by an adjacency list corresponding to the 394 elements. The complexity of MAET algorithm depends on the graph structure such as the number of vertices, the way that edges link together. However, this complexity does not depend on the scenarios or the number of signs k

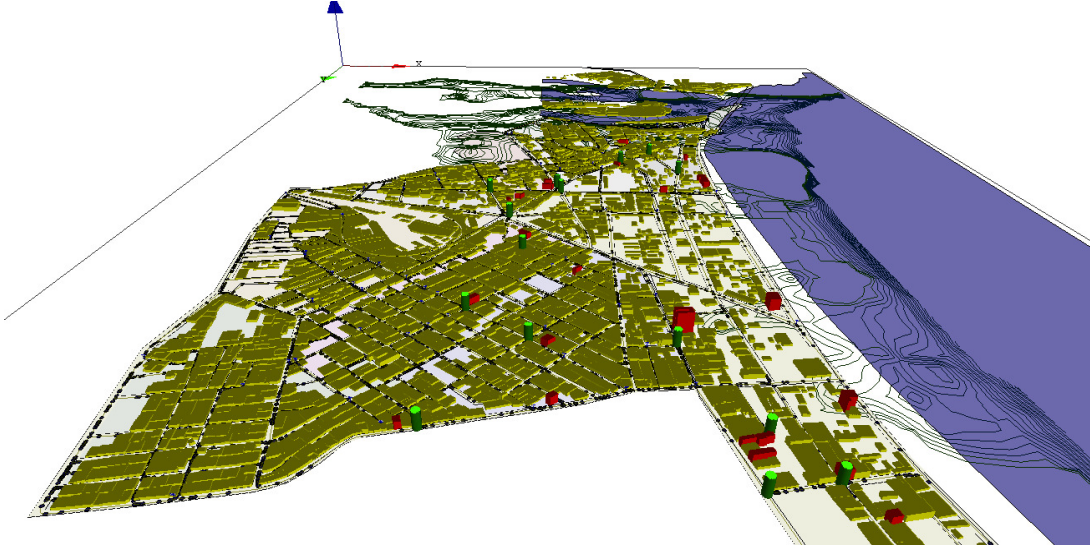


Figure 5.7: Evacuation Simulation using the GAMA platform have a sign placement that is result of MAET with $k = 150$. The shelters are the green cylinders that locate in the junctions of the road network.

($k \neq 0$). Indeed, When we run the MAET with two scenarios (15 minutes and 90 minutes) and with different number of signs $k = 0, 30, 60, 90, 150$, each simulation step is 1 second, the simulating time is stable with the different number of signs k for the Scenario 90 minutes (see Fig(??)). The figure presenting simulation time of the scenario 15 minute is similar with Figure ?? so it's not shown. It takes us an average of 420 seconds for each simulation.

The scenario 15 minutes, the MAET results describe in (Fig. 5.8). The Average evacuation time of an agent depends on the number of signs k . The Figure (Fig. ??) shows that the more number of signs k , the less the average evacuation time of an agent. We observe that the MAET of the scenario 15 minutes is stable as distribution follows the number of signs (Fig. 5.8).

However, the average evacuation time of an agent of the scenario 90 minutes does not follow the rule that's the more the number of signs k , the lesser the evacuation time of the scenario 15 minutes. The reason of this result is the long evacuation paths. These paths have many intersections without sign placement. Thus, pedestrians have to choose randomly a road several times. The MAET of the the scenario 90 minutes is not stable in distribution (see Fig. 5.9).

The result of the MAET simulation for the scenario 15 minutes in Nha Trang city are shown in (Fig. 5.10). Because the city is too large and the signs are small for representation, we choose one part of Nha Trang city. The sign system is placed at the junctions of the road network on Nha Trang city following the MAET result.

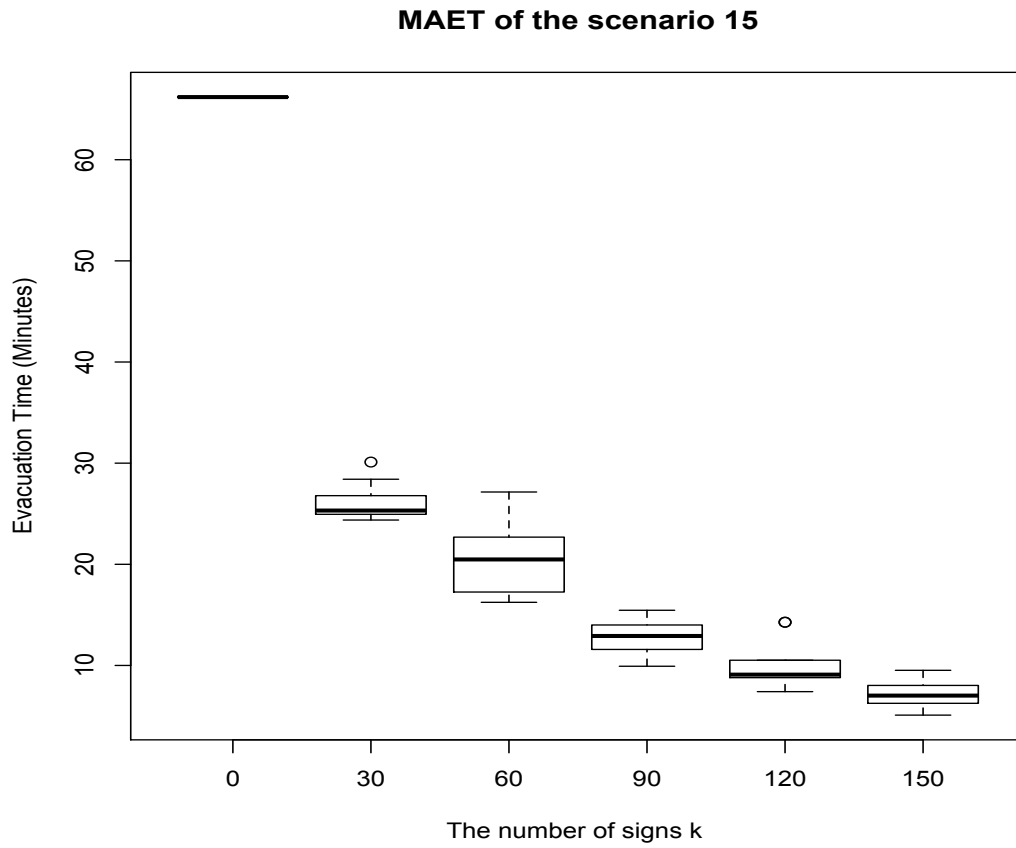


Figure 5.8: The scenario 15 minutes, Each scenario, we run 150 experiments. We do experiments 30 times with each $k = 0, 30, 60, 90, 150$. We see that the more the number of signs k , the less the average evacuation time of an agent.

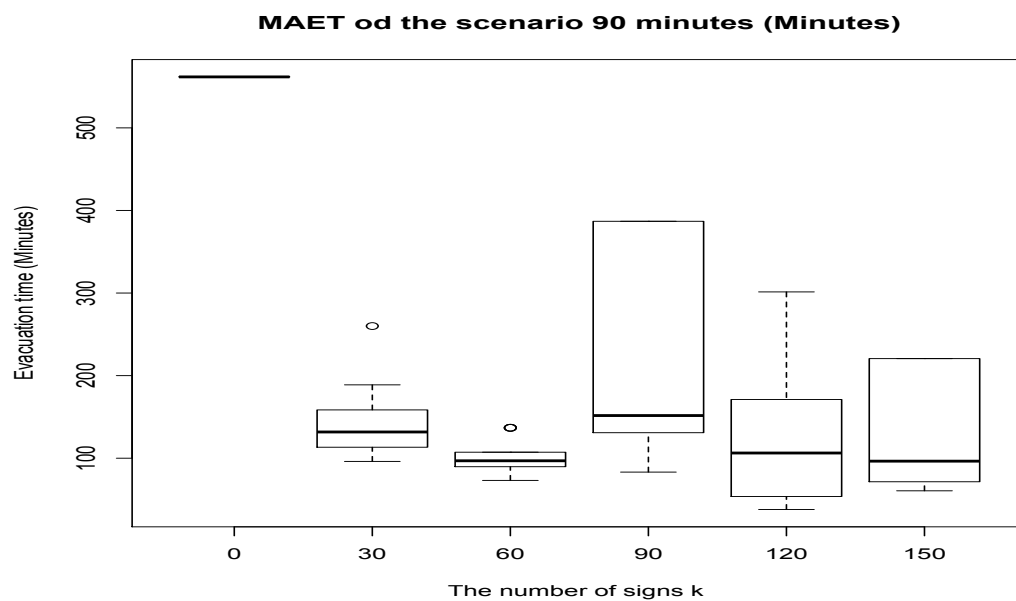


Figure 5.9: The average evacuation time of an agent of the the scenario 90 minutes is not stable in distribution with different $k = 0, 30, 60, 90, 150$.

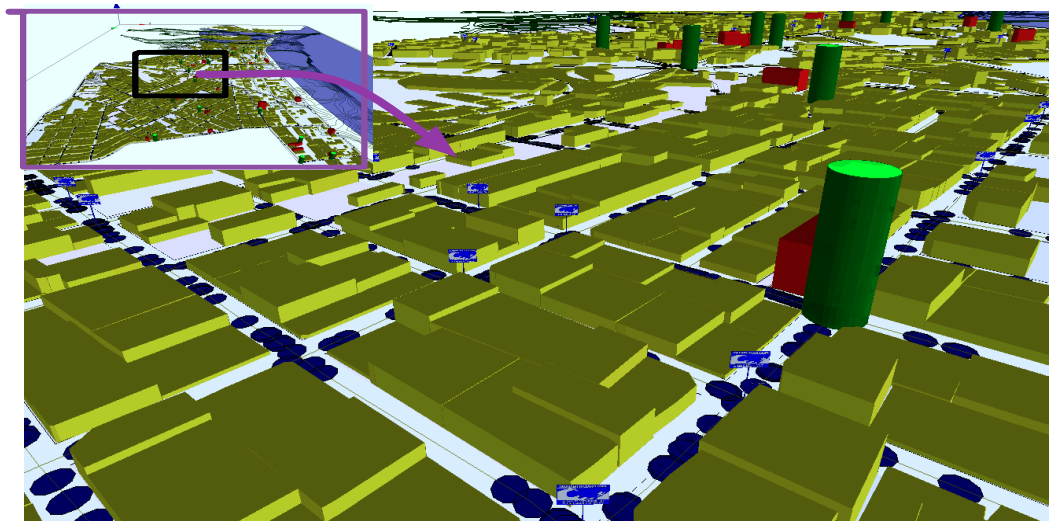


Figure 5.10: The optimal sign system of the simulations for MAET in Nha Trang city environment. This figure shows details of one part of Nha Trang city. The dots are pedestrians. The signs are placed at the junctions.

The results of MAET that are applied in small part and two scenarios for Nha Trang city have been represented. However, MAET is EBM so we can not take into account the heterogeneous behaviors of pedestrians. Thus, we do experiments using Agent-based simulations that overcome the EBM limitations.

5.3 Positions and behaviors of pedestrians

Initial positions of pedestrians

Based on the observation of the Nha Trang, we hypothesize that in the day time, the beach is available for the tourists and citizens which begin at about 6:00 and stop at 20:00. The people steadily increase from 6:00 to 9:00; then, reduces gradually from 9:00 to 15:00. However, people increase from 15:00 to 17:00 and decrease in similar order from 17:00 to the 20:00. The population visiting the Nha Trang beach are assumed Poisson process [Ross 2006]. Firstly, we have basic habitants data based on (Table 4.1). When parameters t and *Tourist – Season* have input data, we count the number of habitants changing position from a ward to the beach and vice versa. Finally, we have an initial population distribution, results for the population distribution are represented in the figures (Fig. 5.12a, Fig.5.12b):

The code is programed for the Initial distribution depending on time of the day and the Tourist season as following

To run simulation, the parameters are setted with difference values. The initial time on the day that a tsunami occurs is an important parameter to determine the population distribution and the rate of fox agents in population. The initial time to run simulation and the rate of fox agents in population.

<i>Time</i>	8.5	13.5	18.5
Rate of fox agents	0.2	0.5	0.8

The (Fig. 5.12) shows the relative average time that agents spends to arrive safe place with the different parameters of initial time and rate of fox in population. The minimum and maximum time step simulation of all parameter are 285 and 290 respectively. The average times all survivors spend with many parameters are not different. The simulation shows that the high rate of fox agents in population does not made the average time of survivors reduce.

The (Fig. 5.14) represents the number of Survivors with different parameters, the higher the rate of fox agents in population, the higher the rate of survivors. The result on the number of survivors shows that the initial time effects is small and depends on the rate of fox agents in population. This determines the efficient of the evacuation.

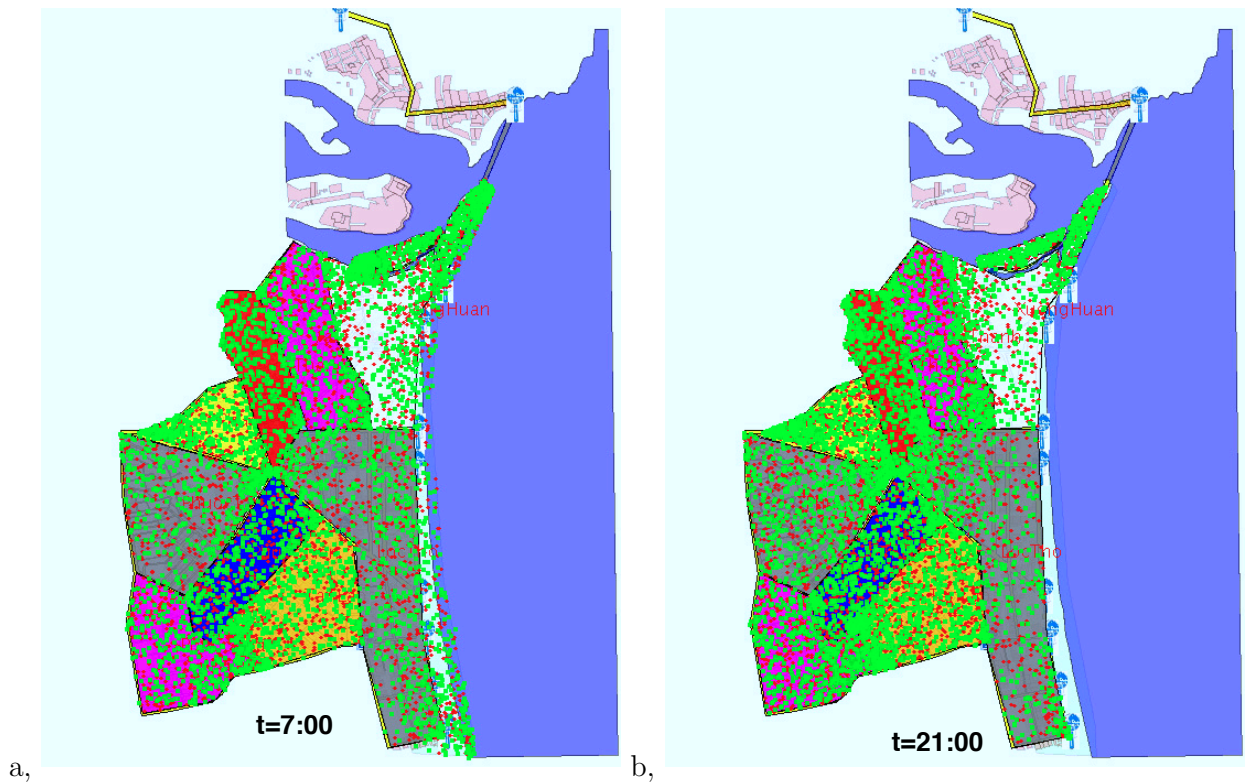


Figure 5.11: a, A fox agent is a red circle, a sheep agent is a green square. a) The distribution of the people in Nha Trang city is described at the time $t = 7 : 00$ in the tourist season. The beach contains many pedestrians. b, The distribution of the people in Nha Trang city is described at the time $t = 21 : 00$ in the tourist season, when the beach contains few pedestrians.

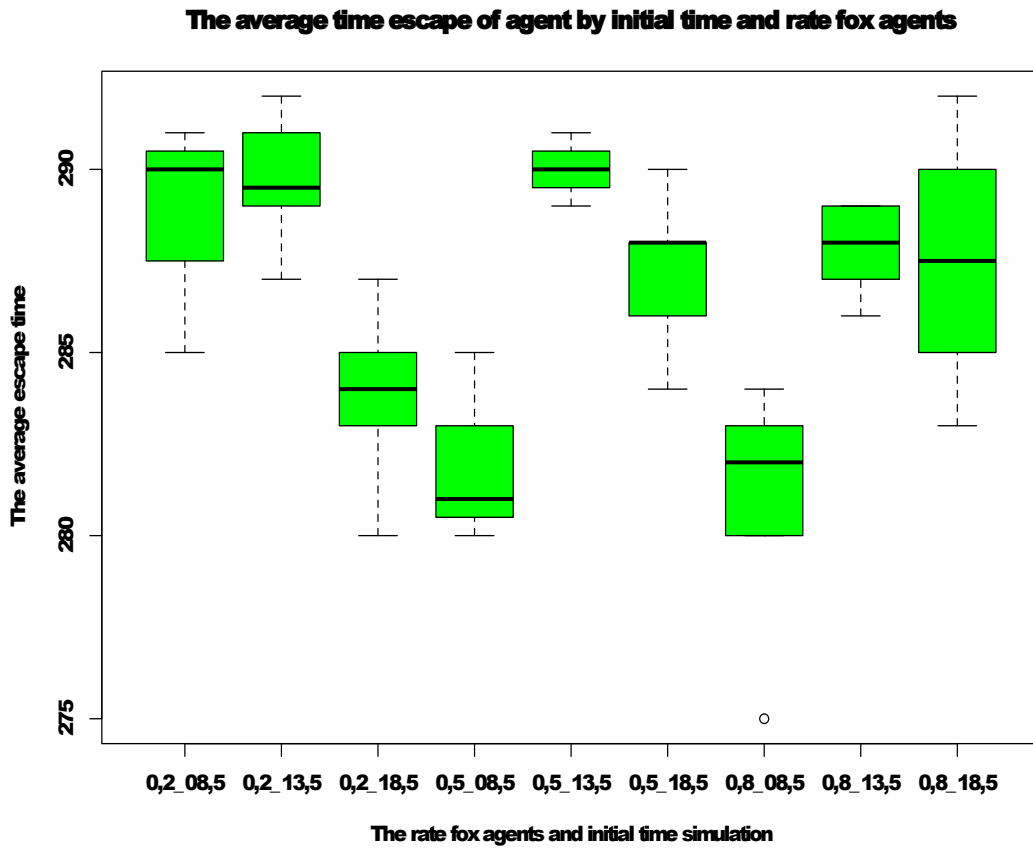


Figure 5.12: The average escape time that the time for an agent spends from the starting evacuation to shelters depends on the initial time in the day $\{8 : 30, 13 : 30, 18 : 30\}$ and the rate of fox agents in population 0.2, 0.5, 0.8.

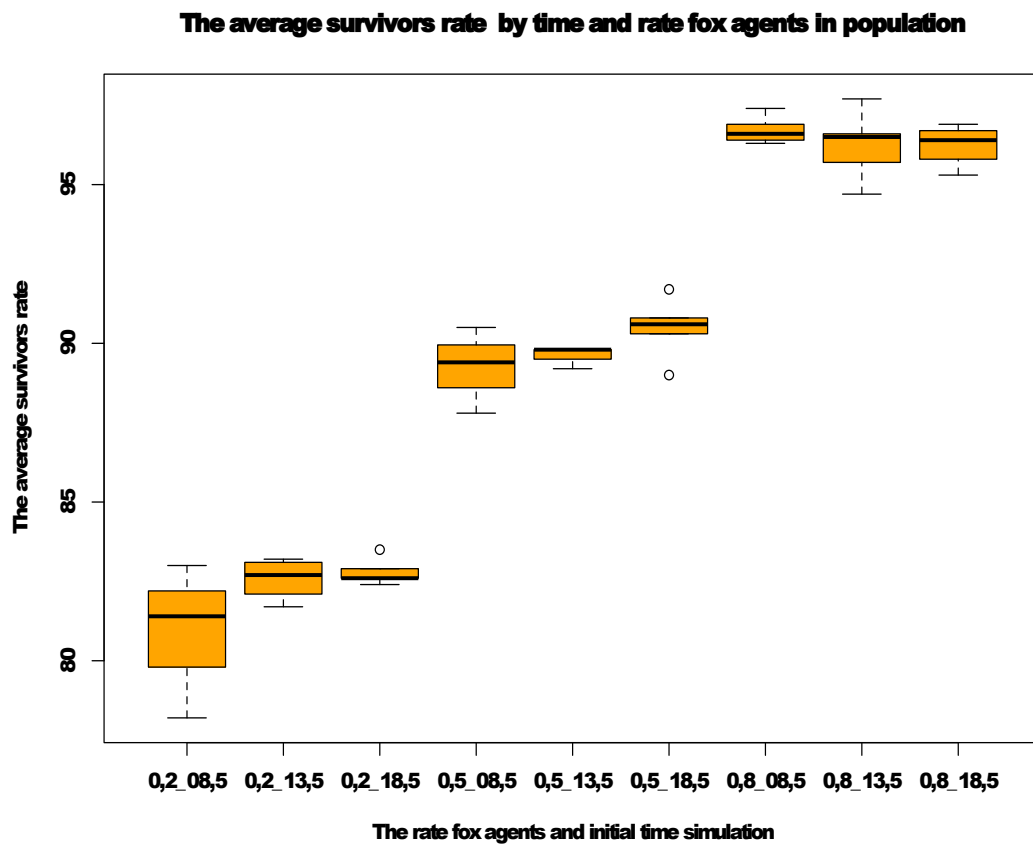


Figure 5.13: Survivors rate in the population with different parameters: the initial time in the day {8 : 30, 13 : 30, 18 : 30} and the rate of fox agents in population 0.2, 0.5, 0.8.

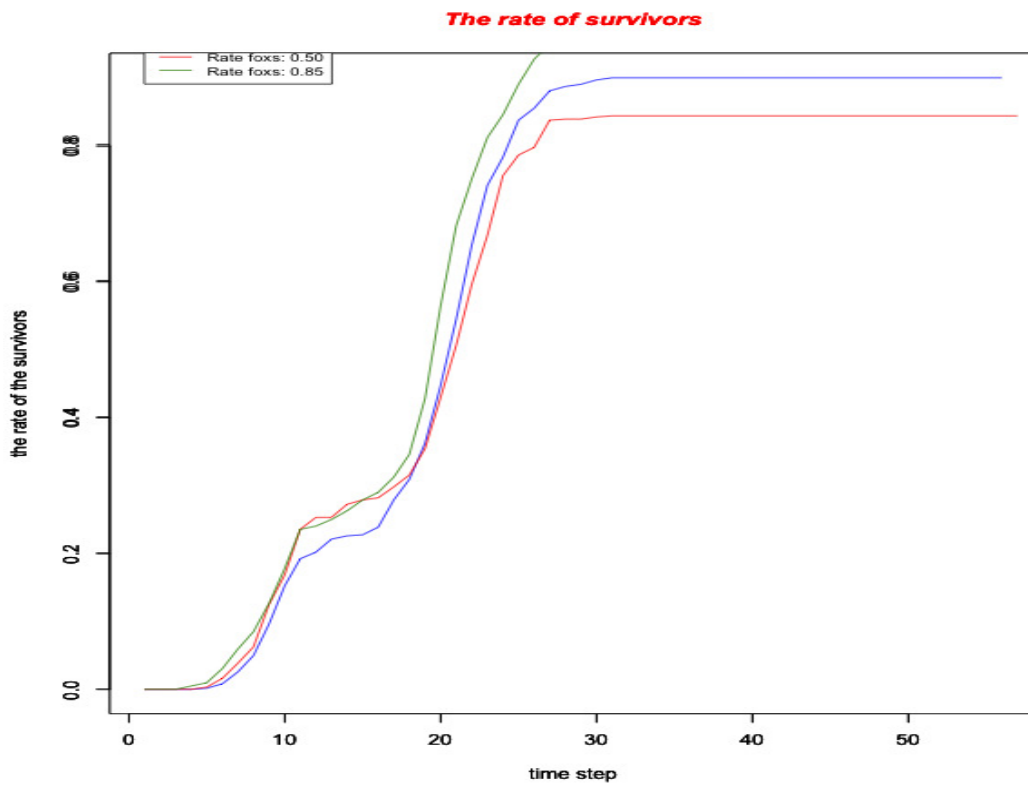


Figure 5.14: The rate of survivors depends on the rate of fox agents in population 0.2, 0.5, 0.8. The x-axis is the time of evacuation in simulation that count in time steps, the y-axis is the rate of survivors.

Behaviors of pedestrians

ABM can take into account many different behaviors of pedestrians. To simplify in experimenting, we consider two behaviors called fox and sheep that we publish in [Anh 2011]. Each pedestrian has his own *position* and its *velocity*. Each agent has his own behaviors according to its goals and knowledge of the environment as well as its perception of the environment, which depends on the space that the agent can observe. The position of the other agents around and road infrastructure can all be used by the agent to decide its move. Decisions are based on his perception of the environment and the information shared with the other agents. As the agent moves, it adapts his speed to reach its desired speed. Indeed, if his speed is less than the desired speed, and if there is enough space, it then accelerates to attain its maximum. We choose fox agent and sheep agent as

- A pedestrian moves to the end of a road. Next, he stays at the junction. If there is a tsunami warning sign, he will follow the sign else, he will choose randomly a road to move down.

The velocity of normal pedestrians is maximum at 5.4 km/h . The slow velocity of pedestrians such as infant, old or handicapped is maximum at 2.7 km/h . Moreover, a pedestrian's velocity depends on their neighborhood density. It decreases when the local density increases and vice-versa. A pedestrian stops when local neighbors are 6.0 person/m^2 .

- In the different experiments, a fox agent is defined as a pedestrian who has been trained on evacuation procedures or has knowledge on how to get to the safe place efficiently or following the alert signs system. We use the command *goto* in the GAMA platform that has two parameters; road network and targets. The road network does not change, we use GIS data.
- Sheep agents follow fox agents or choose randomly the road at the junction that is opposite to the direction of tsunami occurrence [Anh 2011].

5.3.1 Integrated Equation-based simulation for MAET and Agent-based simulation using the GAMA platform

The figure (Fig. 5.15) represents the relationship between the average evacuation time of Equation-based simulation for MAET and Agent-based simulation using the GAMA platform. When the average evacuation time of the two simulations is the same, we stop the loop finding the optimal sign placement by integrating simulations.

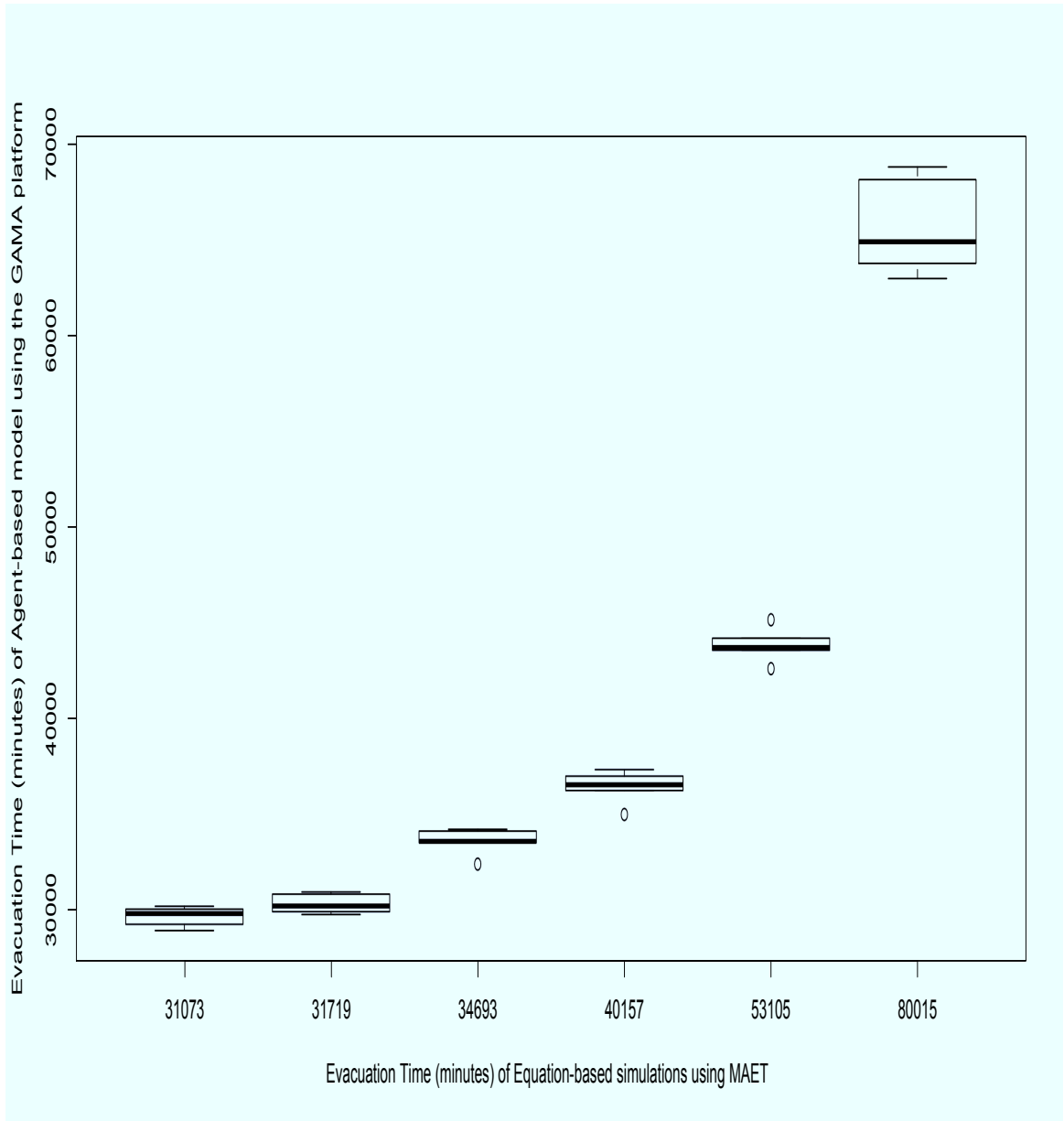


Figure 5.15: Relationship of evacuation time using the GAMA platform and using Equation-based model MAET. The Equation-based simulations using MAET are performed with a different the number of signs k . Each result are simulated 30 times in the GAMA platform. The x-axis displays the average evacuation time of an agent (second) using MAET, the y-axis displays the average evacuation time of an agent that is the result of simulations using the GAMA platform(second).

5.4 Agent-based simulation and Hybrid-based simulation using the GAMA platform

After setting input such as GIS environment, initial position and behaviors of pedestrians, sign placement system, we carry out simulations using the GAMA platform. The data from Nha Trang including the road networks, buildings, beach, rivers, sea and safe places called targets. Parameters of the model are the numbers of fox, sheep agents and Average, variance velocity of pedestrians. The Hybrid-based simulation is improved the simulation time that run faster than Agent-based simulation. Indeed, the Hybrid-based simulation does not only have fast computation speed but also supports larger number of agents compared to the Agent-based simulation. In our program in the GAMA platform, there is an option for running program in Agent-based simulation or Hybrid-based simulation. The Agent-based simulation shows the pedestrians evacuating detail on the whole road network while Hybrid-based simulation show pedestrians evacuating only at the junctions.

5.4.1 Hybrid-based simulation for one road

We compare the performance gain of the hybrid model compared to the pure ABM model. The result shows that the hybrid simulation runs faster than the pure ABM simulation in all the experimental scenarios. The acceleration ratio varies from 2 to 5 times. This variation depends on various parameters (e.g: the size of tube, the organization and the number of shelter, ...). For example, the larger the size of tube, the bigger the acceleration ratio is. The longer the distance between the pedestrians and the shelters, the bigger the acceleration ratio [An 2012]. The result shows the effective speed of HBM. The simulation time depends on the number of pedestrians. In Nha Trang city, the population is 163885. Comparing Agent-based simulation time and Hybrid-based simulation time are carry out. Simulations are run on the MacbookPro OSX with Processor 2.53 GHz Intel Core 2 Duo. The number of pedestrians in the simulations is 1%, 5% and 10% of population respectively 1638, 8190 and 16388 pedestrians.

Then we evaluate the speed of Hybrid-based simulation and Agent-based simulation for one road. The simulation time step of Hybrid-based simulation is evaluated in millisecond that shows (Fig. 5.18a)). The vertical axis is numbers of millisecond units. The horizontal axis is time step of simulation. The highest time step of Hybrid-based simulation is 300 milliseconds. The average time step is 150 milliseconds.

We compare two Agent-based simulation and Hybrid-based simulation. The time step that is evaluated in millisecond of ABM simulation is increased to more

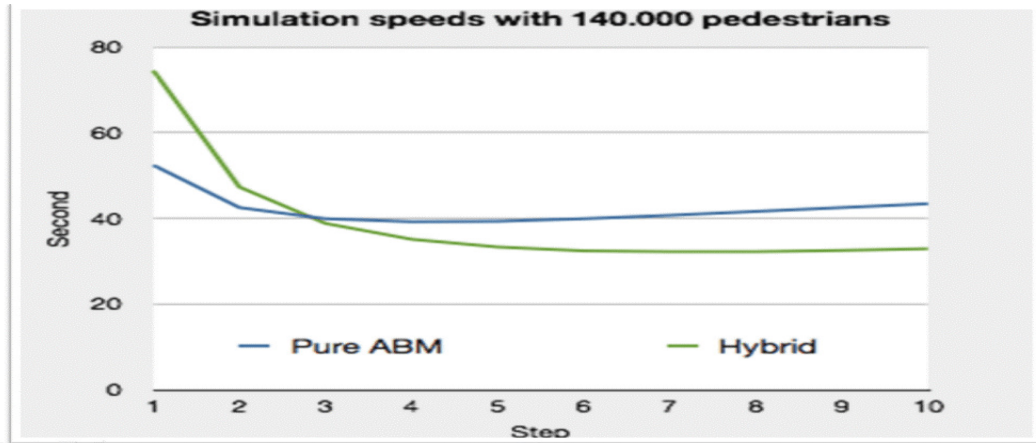


Figure 5.16: Comparing the speed of Hybrid-Based simulation and pure Agent-Based simulation and ABM evacuation simulations on one road with 160000 agents. Speed of HBM simulation is increased at approximately 200%. The speed increases only 25% for doing aggregation including captures and releases.

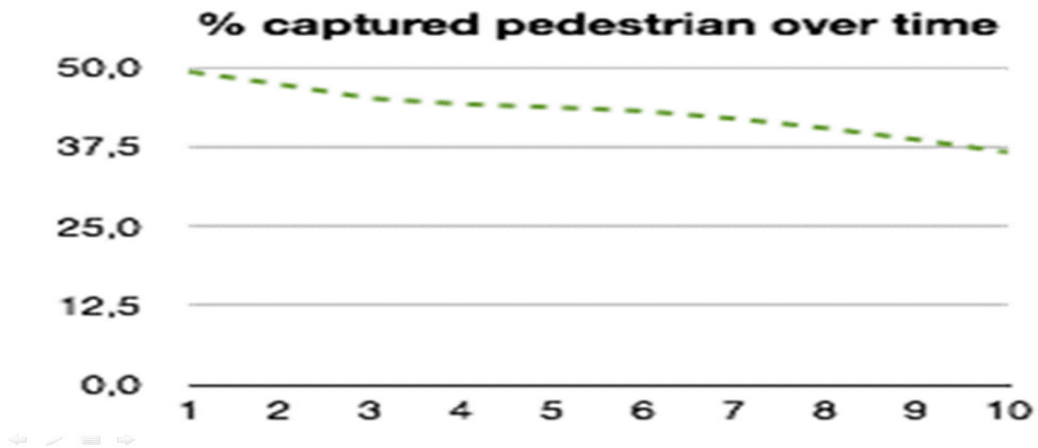


Figure 5.17: Capture pedestrians over time get the speed increased 25%.

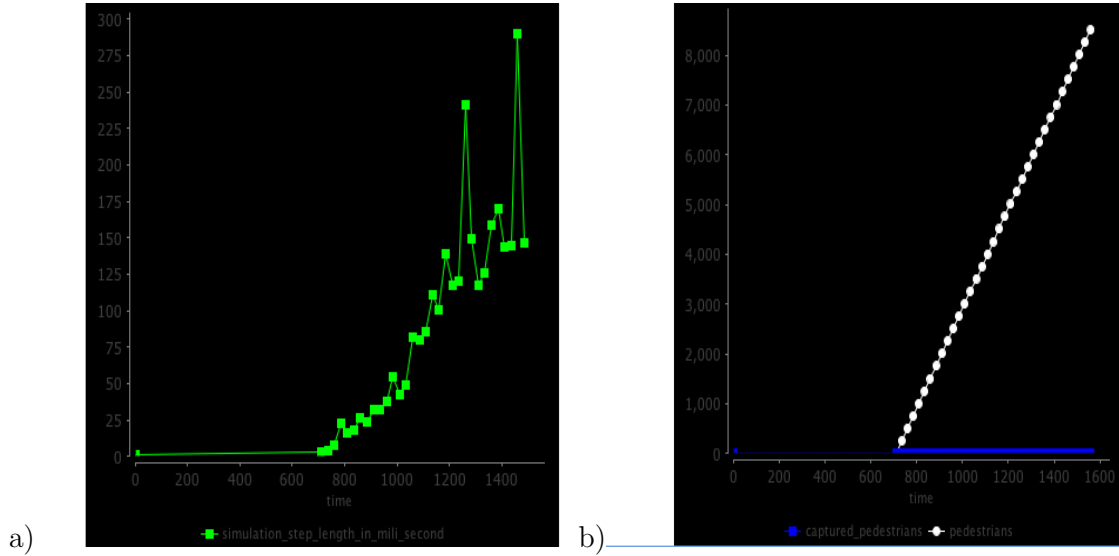


Figure 5.18: a) The simulation time step of Hybrid-based simulation is evaluated in millisecond. b) Comparing the two simulations Agent-Based Model and Hybrid Model.

than 9000 milliseconds when we carry out experiment. While, the time step of HBM simulation does not change fast as shown in the figure (Fig. 5.18b)) because its around 150 milliseconds.

5.4.2 Hybrid-based simulation for the road network of Nha Trang city

Hybrid-based simulation for road network of Nha Trang city in order to speedup Agent-based simulation. The tube in each road is used Equation-based model and the the junctions is used Agent-based model (Fig. 5.19). Each experiment for Nha Trang pedestrian evacuation, a number of pedestrians reaching the shelters are counted and they are represented (Fig. 5.21). In addition, the average velocity of pedestrians at the time t is counted by the velocities of all agents are evacuating divide by the number of agents that are showed (Fig. 5.20). Otherwise, we compare the CPU computing time for two simulations Agent-based and Equation-based that counted in millisecond. The figure (Fig. 5.28) displays that the blue curve shows the time for computing the agents in the tubes of all roads and the green curve shows the time for the agents in the junctions.

Agent-based simulation and Hybrid-based simulation are run 30 times for each different the number of pedestrians. Because the limit of number agents in simu-

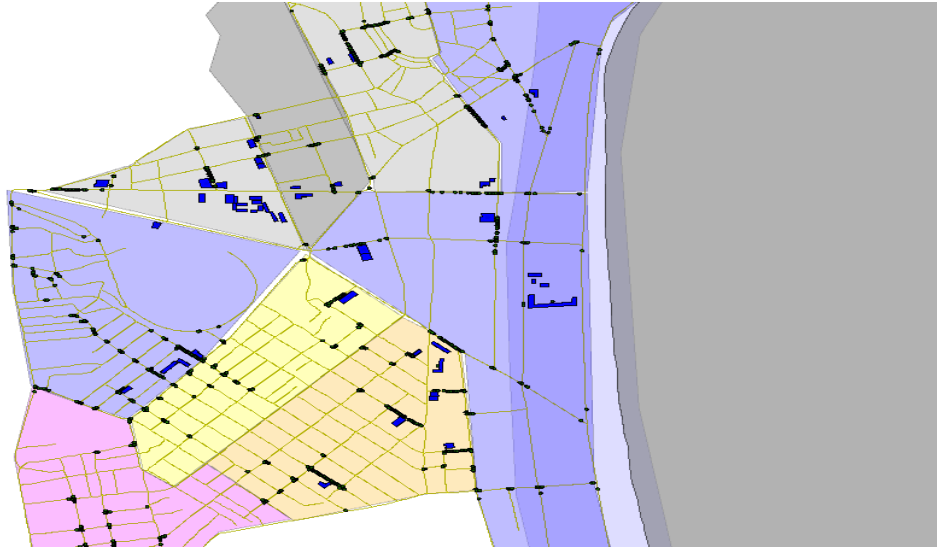


Figure 5.19: Hybrid-based simulation for road network of Nha Trang city in order to speedup Agent-based simulation. The tube in each road is used Equation-based model and the the junctions is used Agent-based model.

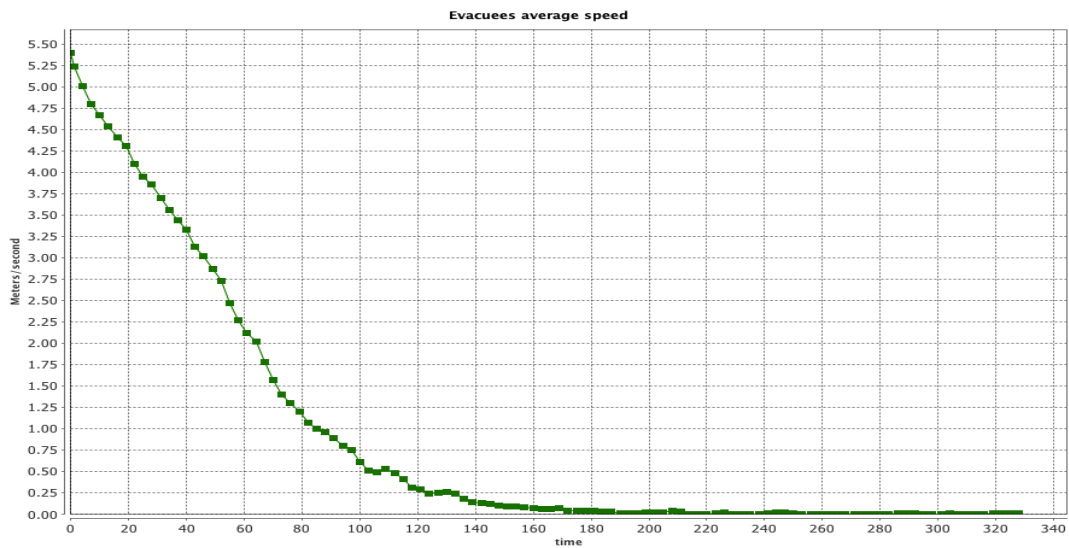


Figure 5.20: The Evacuees average velocity at the time t is counted by the velocities of all agents are evacuating divide by the number of agents. The x-axis displays the time step in simulation, the y-axis displays the velocity counted (meter/second).

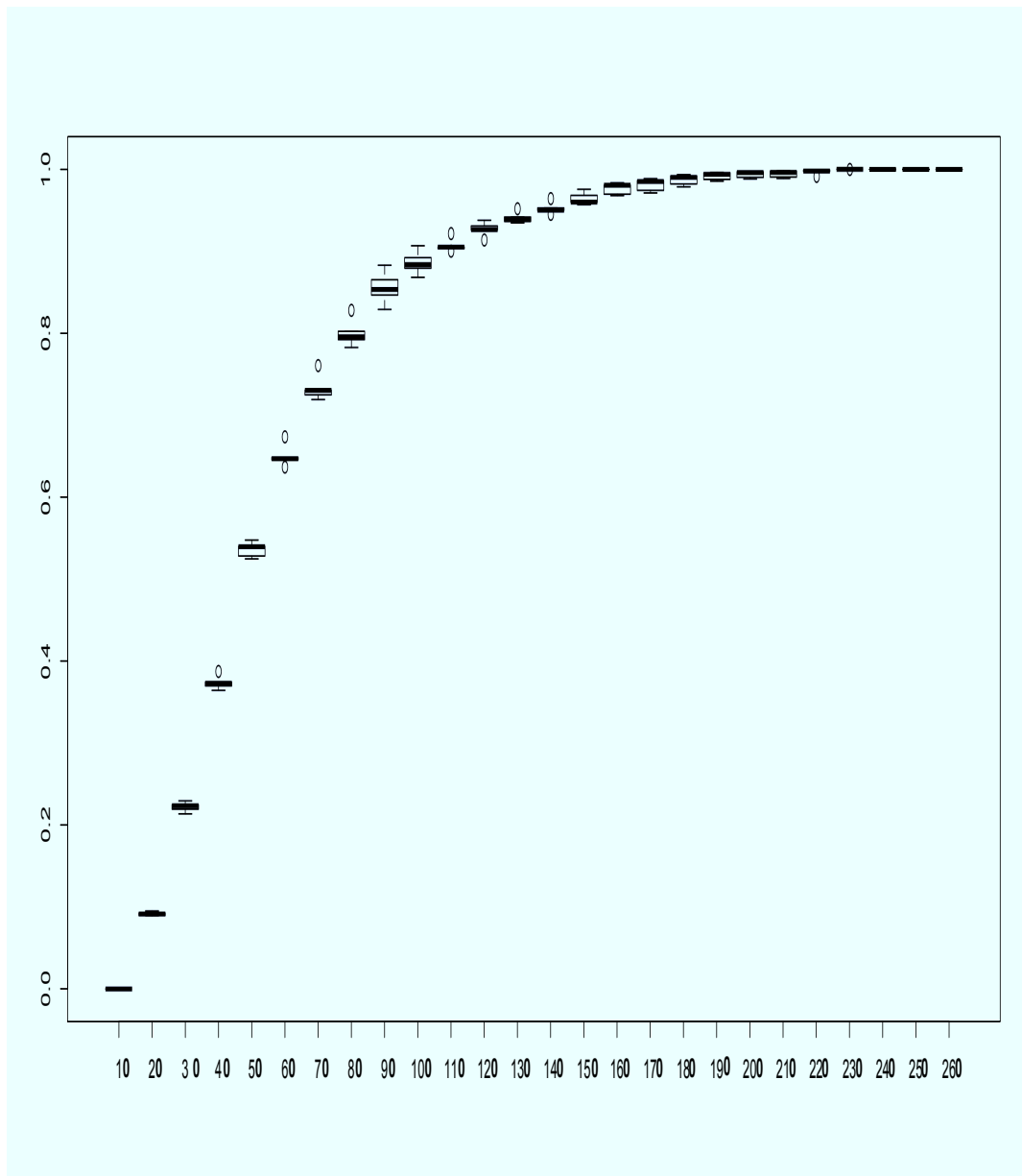


Figure 5.21: The x-axis displays the time step in the simulation (minutes). The y-axis displays the rate of survivors that we run simulations 30 times. This figure shows the survivors rate e.g. the rate of the number of pedestrians reaching the shelters in the whole pedestrians in Nha Trang city.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.3607	50.4100	74.3100	93.9800	116.6000	730.5000

Table 5.2: The summary data for the lengths of the roads in Nha Trang

Percent	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Threshold	0.4	24.1	39.7	55.4	63.1	74.1	85.5	112.0	125.0	173.4	598.2

Table 5.3: Using the 10 break points of the lengths of roads to be the thresholds that for optimizing the Hybridization.

lations, we only consider the number of pedestrians in in the simulation is 1%, 5% and 10% of population. Then, we comparing Agent-based simulation time and Hybrid-based simulation time. All simulations are run on the MacbookPro OSX with Processor 2.53 GHz Intel Core 2 Duo.

The number of pedestrians in in the simulation is 1%, 5% and 10% of population, Hybrid-based simulation time is faster 24.769%, 61.29526% and 80.69089% than that of Agent-based simulation respectively (Fig. 5.22), (Fig. 5.23), (Fig. 5.24).

Hybrid-based simulation is not always effective in simulation. Indeed, hybrid-based simulation spends the computing time for switching ABM to EBM and vice versa for each road. Hybrid-based simulation applied to a long road takes less computing time than the ABM. However, in a short road, the computing time of the aggregated and the disaggregated trigger may be greater than the Agent-based simulations. On the other hand, in a road network, if all roads are applied the HBM, computing time of Hybrid-based simulation is not always effective. Indeed, if there are many the number of small roads, the computing time spends for the aggregated and the disaggregated trigger of all roads may be greater than the Agent-based simulations . So we propose a threshold β for the length of the roads. If the length of a road is greater than β . HBM is used for the that road. The goal the threshold β is to find when Hybrid-based simulation achieves the best simulation in speed. We see that If the threshold β is equal to the maximum length of the road, all the road are not used HBM. Therefore, we use the pure ABM for all the roads. If the threshold β is equal to the minimum length of the road, all the roads are greater than the threshold β , all roads use the HBM. The range of the threshold β :

The threshold $\beta \in$ (the minimum length of the roads, the maximum length of the roads) Therefore, we can find the threshold β that the HBM achieve the highest simulation speed. To test the threshold β . We analysis the lengths of all roads in Nha Trang (Table. 5.2)

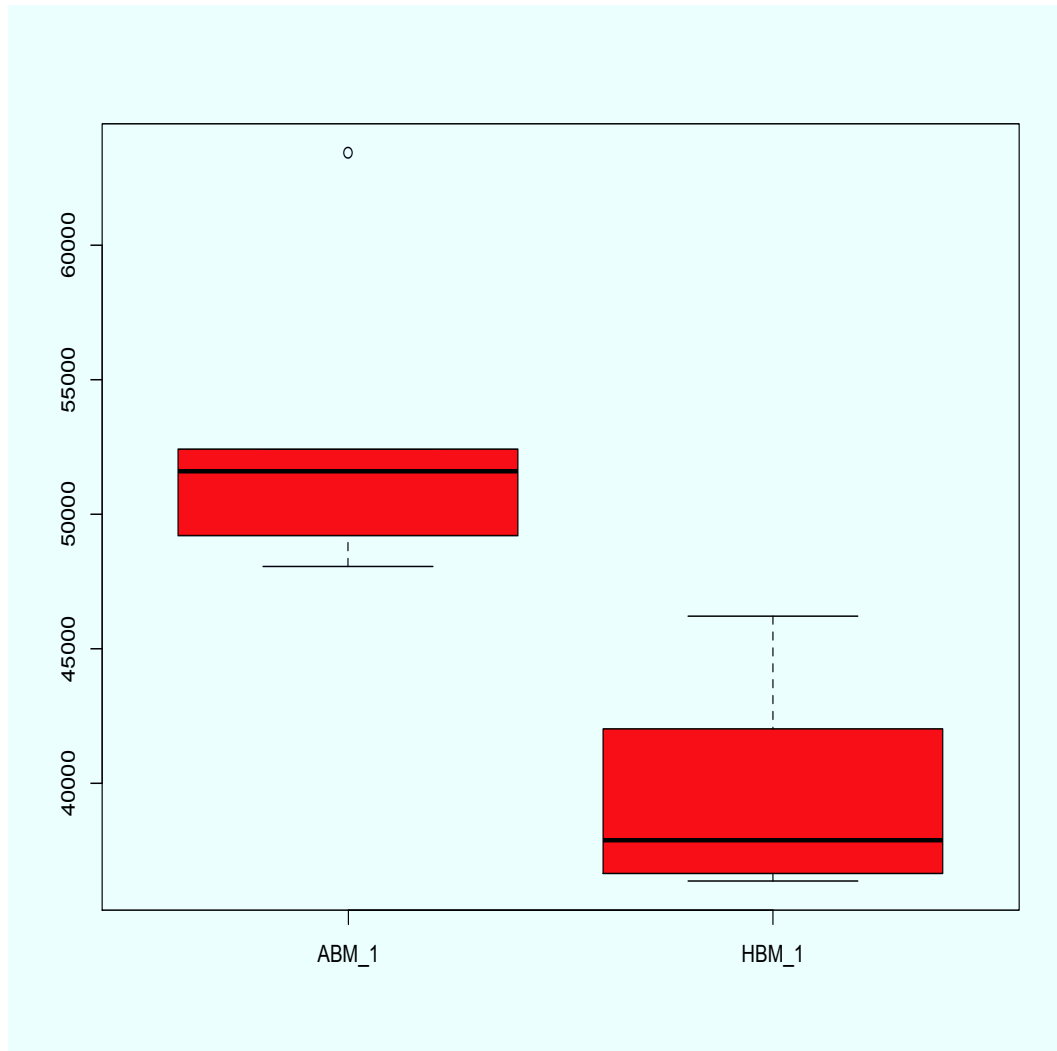


Figure 5.22: Comparing Agent-based simulation time and Hybrid-based simulation time. Agent-based simulation is faster 24.769% than Hybrid-based simulation time. Simulations are run on the MacbookPro OSX with Processor 2.53 GHz Intel Core 2 Duo. The number of pedestrians in the simulation is 1% of population. X-axis displays the two data groups of ABM and HBM, y-axis shows the simulation time counted in millisecond.

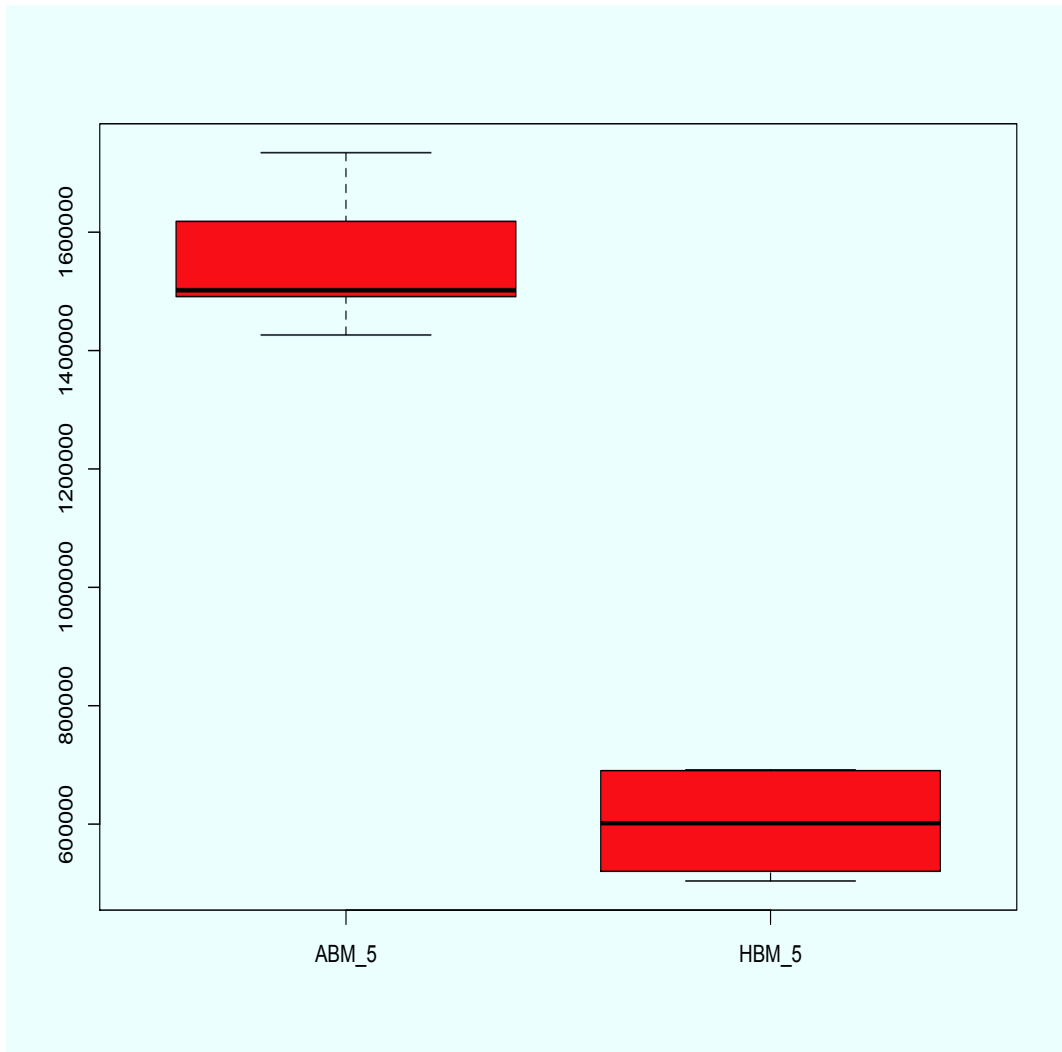


Figure 5.23: Agent-based simulation is faster 61.29526% than Hybrid-based simulation time. The number of pedestrians in in the simulation is 5% of population. X-axis displays the two data groups of ABM and HBM, y-axis shows the simulation time counted in millisecond.

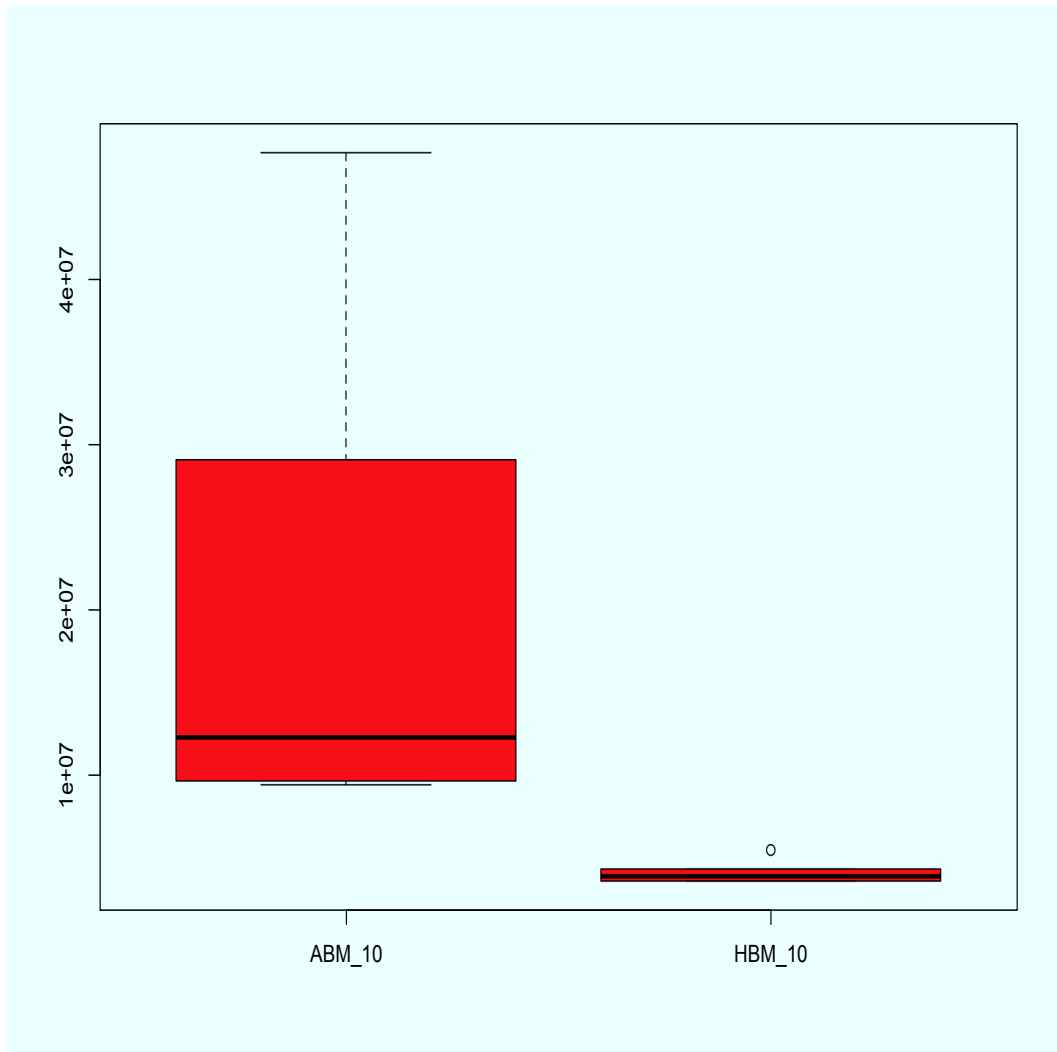


Figure 5.24: Agent-based simulation is faster 80.69089% than Hybrid-based simulation time. The number of pedestrians in the simulation is 10% of population. X-axis displays the two data groups of ABM and HBM, y-axis shows the simulation time counted in millisecond.

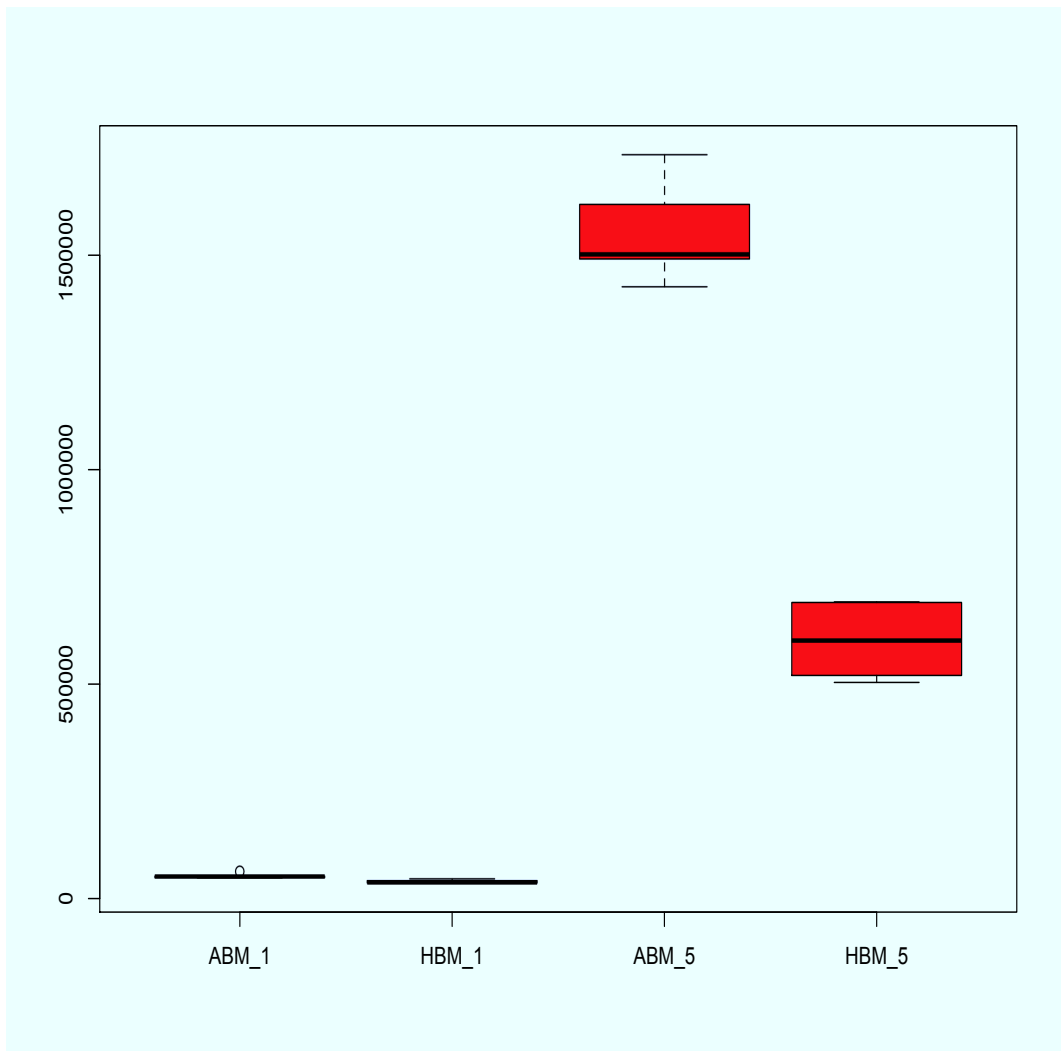


Figure 5.25: X-axis displays the 4 data groups of ABM and HBM with the number of pedestrians in the simulation is 1% and 5% of population, y-axis shows the simulation time counted in millisecond.

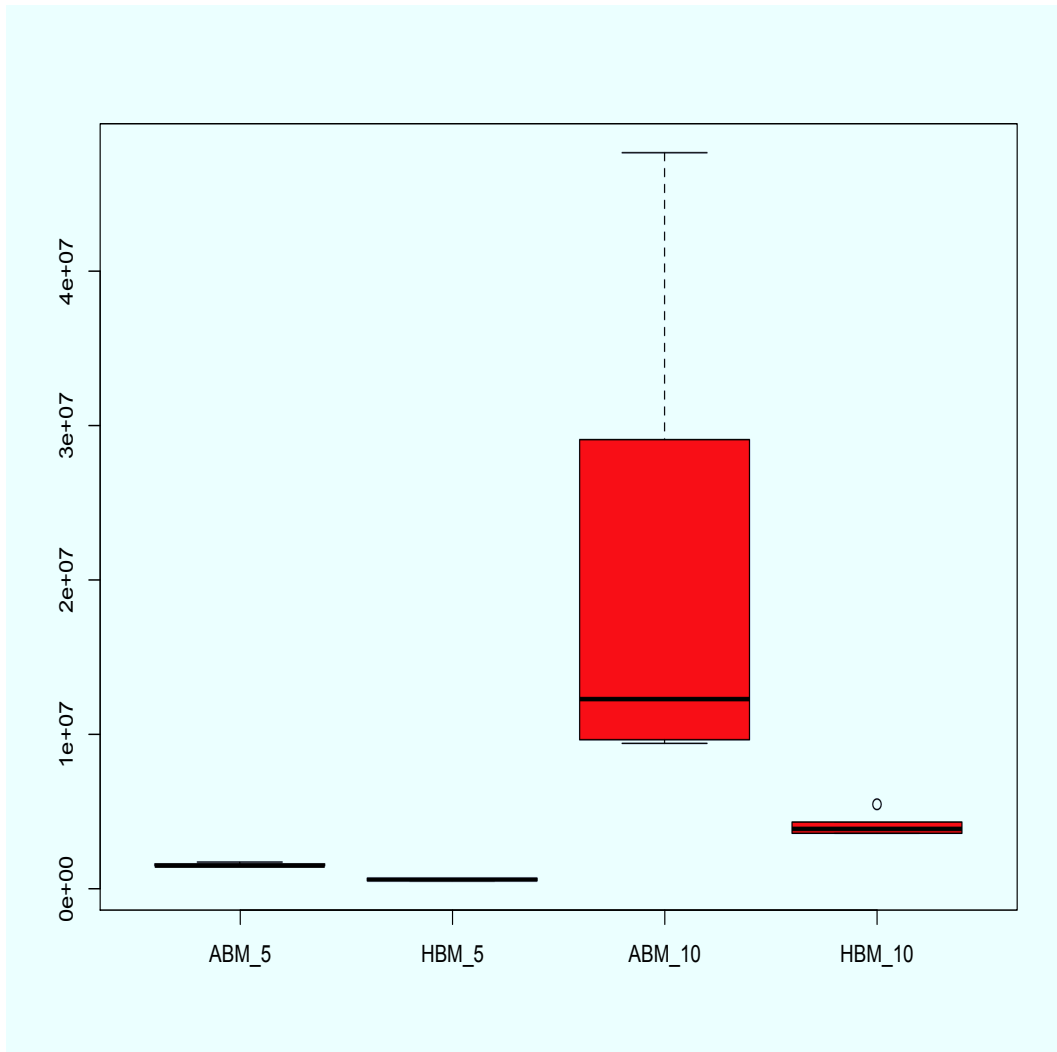


Figure 5.26: X-axis displays the 4 data groups of ABM and HBM with the number of pedestrians in in the simulation is 5% and 10% of population, y-axis shows the simulation time counted in millisecond.

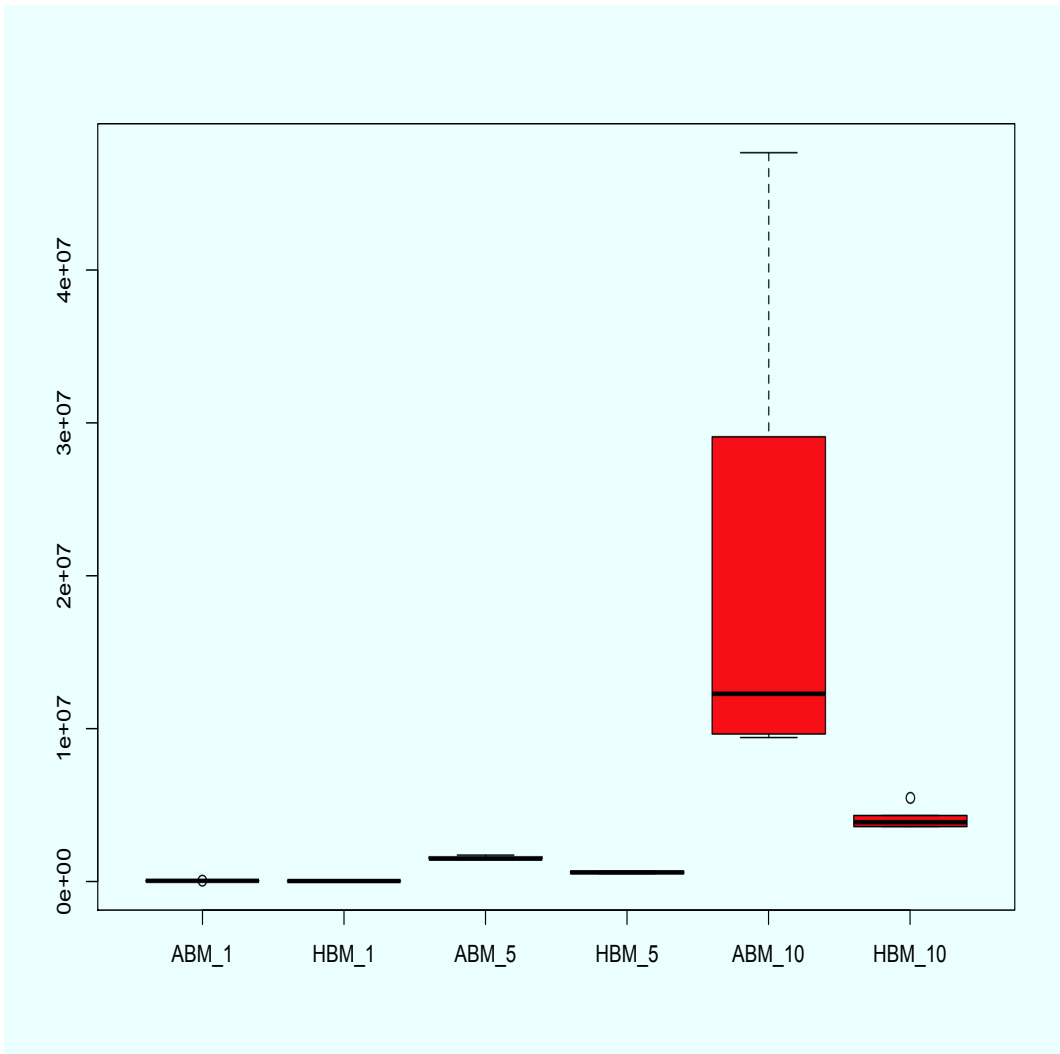


Figure 5.27: X-axis displays the 6 data groups of ABM and HBM with the number of pedestrians in the simulation is 1%, 5% and 10% of population, y-axis shows the simulation time counted in millisecond.

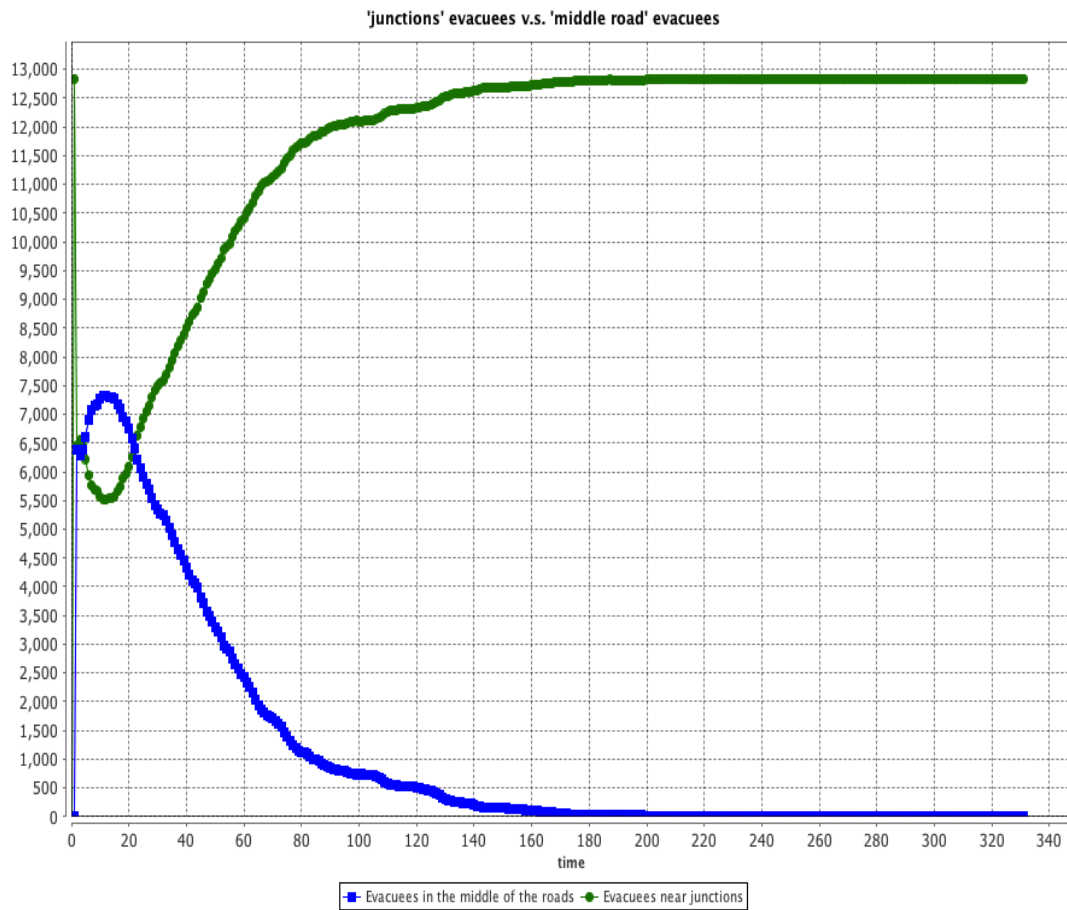


Figure 5.28: The x-axis displays the CPU time counted in millisecond, the y-axis displays the time step in simulation. The blue curve shows the agents in the tubes of all roads. The green curve shows the agents in the junctions.

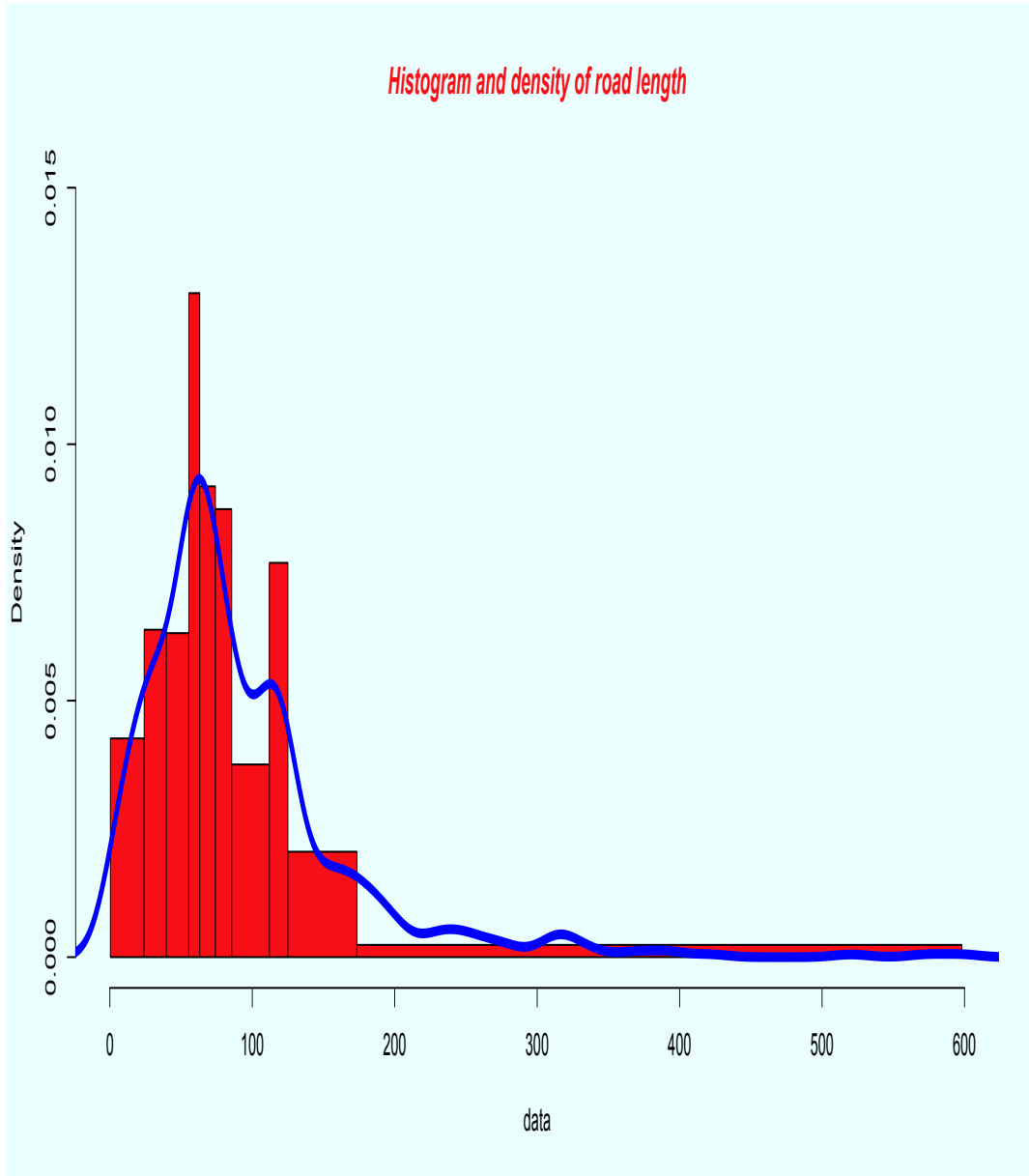


Figure 5.29: Histogram of the lengths of road that are separated by 10 break points that show in the table (5.3).

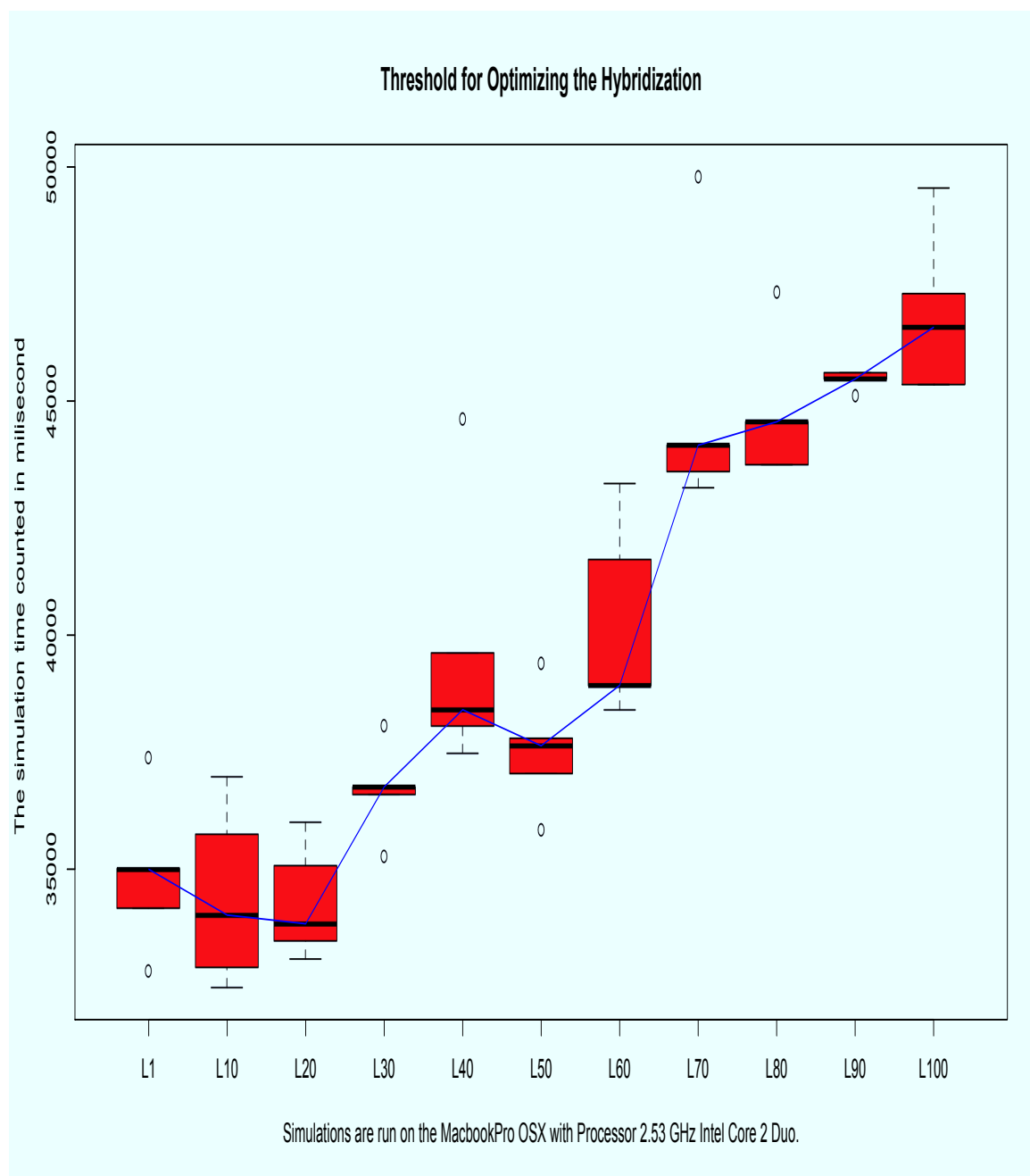


Figure 5.30: This figure shows the results of different thresholds for optimizing the Hybridization. 10 thresholds in the table (5.3) are used to simulated hybrid-based simulation. The length of the road $\beta = 39.7$ meter respectively with the threshold $L20$ that 20% of road have not used hybrid-based simulation is the best threshold for optimizing the Hybridization of Nha Trang road network.

5.5 Conclusion

In the experiments chapter, Equation-based model using MAET is applied for the two directed graphs that are small graph with 6 vertices for easily representing and Nha Trang road network graph. Considering the Equation-based model using MAET in orders to find the optimal the tsunami sign placement by minimizing the average evacuation time. The advantage of Equation-based model using MAET is that the complicated does not depend on the number of pedestrians in the model.

First, in the small graph with 6 vertices, it is easily to describe the weight matrix $\mathbf{C} = \{C_{ij}\}$ that C_{ij} is average spending time of an agent given by: $C_{ij} =$ length of the road from i to j is divided to average velocity of an agent and the stochastic transition matrix \mathbf{P} representing the transition probabilities from one vertex to another vertices. Otherwise, the population distribution depending on the vertices of this graph $\mu = \{\mu_i, i = 0, 1, \dots, 5\}$ is considered the initial data. This representation helps us more intuitive our Equation-based model using MAET.

Second, the direct graph for road network of Nha Trang city that is complicated with nearly 400 vertices. With the large graph, it is very difficult to represent the weight matrix C , the stochastic transition matrix \mathbf{P} or the vector population distribution for all the vertices $\mu = \{\mu_i, i = 0, 1, \dots, n\}$. In the fact that, Equation-based model can only consider the population distribution in all the vertices and the shelters in some of vertices in the graph. However, in the real, the pedestrians' position often in the buildings, roads, grounds, etc and the shelters are some of the buildings that are not the same positions of the junctions. The limitation of Equation-based model using MAET is not possible to take into account the complicated population distribution or the shelters' position in the real. Therefore, each vertex is grouped all the pedestrians around. The vertex is considered the shelter if there is a shelter that is nearest this vertex. The next limitation of Equation-based model using MAET is that the average spending time $\{C_{ij}, (i, j) \in E\}$. Specially, Equation-based model using MAET only carried out with very simple pedestrians' behavior that is Markovian. Meanwhile, some roads are congestion and some road pedestrians can move with maximum velocity.

To reduce the limitations of Equation-based model using MAET, Agent-based models are used that modelers cannot only take into account the heterogeneous pedestrians' behaviors but also the heterogeneous environment. To find better optimal sign placement, integrating Equation-based model and Agent-based model to is carried out by changing average spending time $\{C_{ij}, (i, j) \in E\}$ in each iteration of Agent-based simulation. The relationship between Agent-based model and Equation-based model to finding optimal sign placement show in this chapter. The Agent-based simulation is used the result optimal sign placement of the Equation-

based model using MAET. The average evacuation time using ABM and EBM has strong relationship. The Agent-based simulation help the optimal sign placement more reality and better. However, the disadvantage of Agent-based model is the computational cost that depending on the number of agents. If we want to simulate more than 16 000 pedestrians in Agent-based simulation for Nha Trang road network, it may take us 12 hours running in the laptop MacbookPro OSX with Processor 2.53 GHz Intel Core 2 Duo. The time of Agent-based simulations with the larger number of agents is a big problem. Thus, Hybrid-based simulations are chosen to speed up the simulation time.

Hybrid-based simulation for road network of Nha Trang city in order to speedup Agent-based simulation. The tube in each road is used Equation-based model and the the junctions is used Agent-based model. Otherwise, we compare the CPU computing time for two simulations Agent-based and Equation-based that counted in millisecond. Agent-based simulation and Hybrid-based simulation are run 30 times for each different the number of pedestrians. Because the limit of number agents in simulations, we only consider the number of pedestrians in in the simulation is 1%, 5% and 10% of population. Then, we comparing Agent-based simulation time and Hybrid-based simulation time. All simulations are run on the MacbookPro OSX with Processor 2.53 GHz Intel Core 2 Duo. The number of pedestrians in in the simulation is 1%, 5% and 10% of population, Hybrid-based simulation time is faster 24.769%, 61.29526% and 80.69089% than that of Agent-based simulation .

Hybrid-based simulation is not always effective in simulation. Indeed, hybrid-based simulation spends the computing time for aggregated and disaggregated triggers switching ABM to EBM and vice versa for each road. Hybrid-based simulation applied to a long road takes less computing time than the ABM. However, in a short road, the computing time of these aggregated and disaggregated triggers may be greater than the Agent-based simulations. The results of different thresholds for optimizing the Hybridization are done in this chapter. We propose 10 thresholds are used to simulated hybrid-based simulation. The length of the road 39.7 meter respectively with the threshold that 20% of road have not used hybrid-based simulation is the best threshold for optimizing the Hybridization of Nha Trang road network.

The two scenarios for tsunami evacuation simulation on road network of Nha Trang city are considered with different approaches that are equation-based , agent-based or hybrid-based simulations. These experiments give the meaning results about the optimal sign placement, the average evacuation time, the rate of survivors. These results help the researchers in IGP analyzing and giving the property decisions in early tsunami warning.

Chapter 6

Conclusion

6.1 Conclusion

The important research problems in this thesis are combining two approaches, Agent-based models and Equation-based model, to early planning for tsunami evacuation on a road network. First, modelers using Agent-based models can describe naturally real problems with many different behaviors of agents and consider the local interaction of agents. In addition, modelers can integrate agents with dynamic heterogeneous environments. However, Agent-based simulations are very expensive in computation so they require huge time in running experiments. In order to speed up the computation time of Agent-based simulations, Equation-based models are used to integrate with Agent-based models. The integration creates new models that called Hybrid-based models. Hybrid-based models are a trade-off between the level of detail and efficiency of two models Agent-based and Equation-based.

This thesis, the Hybrid-based model is built for a road network of a city. On the road network, the junctions are the important parts where pedestrians have many different behaviors related their survival in evacuation while in the middle of a road, the pedestrians do not have much behaviors relating their survival. The strong point of Equation-based simulations is whose complexity does not depend on the number of agents, but its weak point is that Equation-based model can not represent heterogeneous behaviors of agents and environments. Thus, Equation-based models are applied to these parts that reduce the level of detail to be faster computing. The keys to building the Hybrid-based model are two triggers in purpose switching the Agent-based model to Equation-based model and vice versa. The Agent-based model has many agents that are separated objects with many different behaviors. An aggregated trigger abstracts these objects to one object in Equation-based model. This aggregated trigger kept the agents in Agent-based model into a token store and hibernated them. Then, this trigger computes two parameters that

are the numbers of agent and the average velocities of the number of agents. These parameters are the input for Equation-based model. The Equation-based model use these parameters for the disaggregated trigger that computes the time for these agents released out the token store. In the fact that, this disaggregated trigger reverses the role of the aggregated trigger that switches Equation-based model to Agent-based model. It releases one object in Equation-based model to many objects in Agent-based model. The solutions of Equation-based model are used for the disaggregated trigger to decide the number agents will released in the token store into Agent-based model with their velocities respectively the results of Equation-based model. The important factor of the disaggregated trigger is that the behaviors of agents still respectively with them when they put to the token store. The time for computing two triggers are often smaller than that for computing the number of agents in Agent-based simulation moving in the middle of roads. Therefore, Hybrid-based simulation is often faster than Agent-based simulation. When Hybrid-based model is applied to evacuation tsunami simulation the middle of roads. Therefore, Hybrid-based simulation is often faster than Agent-based simulation. When Hybrid-based model is applied to evacuation tsunami simulation on the road network of Nha Trang city. The time of Hybrid-based simulations are shown that they are faster 20%, 60% 80% than that of Agent-based simulations respectively the number of agents are 1%, 5%, 10% population of Nha Trang city.

However, Hybrid-based simulation is not always more effective than Agent-based simulation. Beside Hybrid-based simulation computes Agent-based model in junctions and Equation-based model in the middles of roads, Hybrid-based simulation still need the time to compute the aggregated and disaggregated triggers switching ABM to EBM and vice versa for each road. If Hybrid-based simulation is applied to a long road, the time for computing two triggers takes less than that of Agent-based simulation. Thus, Hybrid-based simulations are faster than that of Agent-based simulation. However, in a short road, the computing time of these aggregated and disaggregated triggers may be greater than that of the Agent-based simulation. Thus, the thresholds for hybridization are proposed. Only the roads whose lengths are longer than the threshold are applied Hybrid-based simulation. Otherwise, the roads are applied Agent-based simulation. We propose 11 thresholds 0%, 10%, 20%, . . . , 100% proportions of the lengths of the roads on the road network. These thresholds are used to simulate Hybrid-based simulation. We do 30 experiments for each thresholds. By experiment results, in the 11 values of the thresholds, there is a best threshold that is chosen from 11 thresholds because its average simulation time is the smallest. Concretely, when we test the Hybrid-based simulations with 100% percent of the roads are hybridized, the average time of these simulations is faster 25% than that of Agent-based simulations. When the best threshold is used

for the Hybrid-based simulations, their average time of these simulations is faster 15% than that of the simulations with 100% the roads hybridization. Therefore, using the best threshold for Hybridization, the Hybrid-based simulations are faster 40% than that of the Agent-based simulations. Eventually, the best threshold for optimizing the Hybridization of Nha Trang road network is one of the new results that we achieve in this thesis that make Agent-based simulations more faster.

In this thesis, one hand, we investigate speed up the Agent-based simulation, on the other hand, we study problems about early planning for tsunami evacuation on a road network. Thus, the sign placement for tsunami evacuation on a road network is put forward. The the sign placement for tsunami evacuation is carried out by optimized for the average evacuation time and the causalities. First, we formulated this problem using Mixed Integer linear programming, a Equation-based model, that called MAET. Then, we gave the algorithm to find the solution by using CPLEX software. Finally, this theory is applied for the tsunami evacuation on the road network of Nha Trang city. This optimal sign placement for tsunami evacuation on the road network of a city is also the new result that we gain in this thesis. Beside optimization the sign placement problem for early planning for tsunami evacuation is solved in acceptable time, it still has some limits. In the fact that, Equation-based model using MAET to find the sign placement have some limits that are the initial density of pedestrians and the shelters must stay in the vertices of a road network. Moreover, the spending time of the pedestrians on each road from one vertex to the other vertex are computed by a very simple formula that is the length of road is divided by the average velocity of all agents. Thus, integrating Equation-based model using MAET and Agent-based model will help us to find better sign placement. Concretely, we iterate two simulations MAET and Agent-based. First iteration, MAET simulation runs with the spending time of an agent depend on the length of the road and the average velocity of an agent. However, the spending time does not only depend on the length of the road, but also depend on the width of roads, the interaction between an agent with the other agents on the roads, the agents' position on the roads, etc. Otherwise, the spending time in the Agent-based simulation is considered the different behaviors of agents and heterogeneous environment. Thus the next iteration of MAET, MAET simulation changes the spending time by the spending time of Agent-based simulation. The iteration between MAET simulation and Agent-based simulation is repeated until the spending time is stable. Therefore, integrating Agent-based simulation and MAET simulation in order to further optimize and be true to life the sign placement for tsunami evacuation on a road network.

We do modeling Agent-based for the tsunami evacuation simulation for pedestrians with heterogeneous behaviors and Geographic Information System environ-

ment. Modelers using Agent-based model can take into account complicated and different behaviors of human. To simplify in modeling, some important behaviors in evacuation are considered such as moving follow tsunami alert signs, going follow the shortest path. The agents have these behaviors called fox agents. Otherwise, the agents move follows the fox agents or random walk called sheep agents. Moreover, we describe the initial population distribution of pedestrians in the city at different time in a day and different season such as the tourist season. In this thesis, we have done the modeling and simulating Agent-based for the tsunami evacuation simulation on the road network in Nha Trang city.

The visualization of evacuation simulation is help for training. The simulation is not only visual in the 2 dimensions (2D) but also visual in the 3 dimensions (3D). In the tsunami evacuation simulation using the GAMA platform, the pedestrians and environment such as shelters, the highlands, the terrain is represented in 3D. The disadvantage of the simulations represented in 3D is slower than that in 2D because the simulations take time to compute the 3D data and the species. The visualization in 3D helps modelers easily observe pedestrians dynamic, the safe places, the dangerous areas under the water and the trainers easily visualize the real evacuation. Moreover, the modelers easily watch the different scenarios in evacuation that are useful in training for the evacuee in preparing tsunami ready.

Eventually, this thesis has theoretical and practical issues. Theoretical approaches are using mathematical and informatics models to describe the tsunami evacuation on the road network of a city. Thus, we investigate building Hybrid-based model combining ABM and EBM. Hybrid-based model for Tsunami readiness reveals more efficient execution than Agent-based model, as well as, an improved simulation quality. In addition, we integrate the MAET simulations and Agent-based simulations on road networks for optimizing sign placement. Then, we also apply these studies to verify the validation of scenarios in Nha Trang city.

6.2 Discussion

This thesis is a part of the project that has cooperation between the Institute of Physical Geography Vietnam and UMI 209, UMMISCO, IRD (UMMISCO). In fact, many coastal cities in Vietnam need to be prepared for Tsunami disasters in order to mitigate losses. The early planning for tsunami evacuation in coastal cities in Vietnam was proposed by the researchers at the Institute of Physical Geography Vietnam. Thus, the researchers of UMMISCO and Institute of Physical Geography Vietnam give some tsunami evacuation problems and their solutions. The Agent-based models and Equation-based models are used to study these problems. In the fact that many researchers in the world often use Agent-based models for small

environment such as a building, a metro station, a ship, a junction of a road and small number of agents. However, the real problems require the large environments and the huge number of agents. The researchers in UMMISCO want to extend the application of Agent-based model not only for larger environments using Geographic Information System but also the large number of agents. This thesis is a case study of this project that speed up the simulations in a large environment and the number of agents.

Concretely, one major problem would be to find the best evacuation procedure in coastal city so as to minimize the number of casualties in the time available. In this thesis, we address the problems that involved scaling up simulations for evacuating pedestrians on a road network of a city. We formulate these problems in two models Agent-based and Equation-based. Then we build the Hybrid-based model that the key idea is to exploit the advantages of both Agent-based model and Equation-based model. A case study to prepare Nha Trang city Tsunami-Ready based on Hybrid-based model shows a more efficient execution than Agent-based model, as well as an improved simulation quality when compared with Equation-based model. In the evacuation simulation, dynamic environment includes various parts having different levels of importance. On the road network, the junctions are important because many complex behaviors lead to the different decisions of agents. Agent-based model is used for junctions and Equation-based model is used for the stretch road between two junctions. This methodology in this thesis applied to the city of Nha Trang can be used for preparing other coastal cities.

In addition, we propose and solve the sign placement problem in order to minimize average evacuation time called MAET problem. Solving MAET problem by EBM requires unrealistic conditions. Otherwise, solving sign placement problem by ABM requires running a lot of simulations. Thus, we integrate these two models to obtain better optimization results. However, we have not compared the differences between MAET with the other methods solving the sign placement problem.

In fact that, to solve the tsunami evacuation on the road network, there are many issues that need to learn. For instance, there are various transportation vehicles such as motors, bicycles, cars, buses beside pedestrians on evacuation roads. In the large environment like a city, Agent-based modeling with many types of transportation vehicles make the problems much more complicated. To simplify the model in this thesis, pedestrians are considered with two types fox agents and sheep agent while pedestrians have many different behaviors such as their behaviors with family members or relatives, psychology, ages, habit, etc. Otherwise, this thesis has some limitations such as we cannot consider the different capacity of the shelters, the validation of the evacuation simulations with the real evacuation, etc. These limitations are the perspective works.

6.3 Perspective

As the previous limitations, future works would involve: Exploring various behaviors of Pedestrians, Finding the way to validate the evacuation simulations, Finding the threshold factor for effective Hybrid-Based simulations, Using more models for different important parts of a road network, Building a model takes into account the capacities of the Shelters, etc.

First, there are many different vehicles with the other pedestrians such as cars, buses, taxis, motorbikes, bicycles, etc. Each vehicle type has the different capacity in carrying the number of agents and different maximum velocity. The different velocity of vehicle lead to their differences in decision choosing shelters and evacuation path. In addition, the different traffic ruler with big vehicles such as cars or buses and small vehicles, bicycles, motorbikes or pedestrians. While small vehicles can move in any roads, they can move from big roads to mall roads and vice versa, while big vehicles require move on the roads that all of them are larger than 2.5 meters. So the big vehicles may have different plan with small vehicles. Modeling Agent-based model with many vehicles is much more complicated than that with pedestrians so it is still the roads that all of them are larger than 2.5 meters. So the big vehicles may have different plan with small vehicles. Modeling Agent-based model with many vehicles is much more complicated than that with pedestrians so it is still an open issue for us to analysis and solve.

Second, the various behaviors of pedestrians such as the way they react, related to family members or relatives, psychology, ages, habit, etc. Their reactions to Tsunami when they have knowledge on evacuation procedures and vice-versa should be considered in the future.

Third, in order to ensure the correctness of the model, validation of the simulation also should be included in future work. In the fact that validation of the simulation is the most difficult even that the simulation applies to the small environment. The researchers need the pedestrians to drill evacuation when the tsunami siren warns. Then, comparing the evacuation simulations and drill evacuation is analyzed. Drilling evacuation of the population in a city is hard so the validation of the simulation still a open problem.

Four, the capacities of the shelters in the model should be taken into account, as this is an important factor to the survival of pedestrians. In deed, if a shelter cannot contain agents so the agents have to find the other shelters. To find out the new shelter, the pedestrians need the information of a shelter being available from a decision support system. It appears new problem for the future that we need to build a decision support system about information available status of the shelters.

Conclusion, the results of this thesis are the cooperation between the Institute

of Physical Geography Vietnam and UMMISCO. Theoretical and practical issues represented in this thesis have applied to Nha Trang city. After that, we expect that they can apply to the other coastal cities in the world.

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Appendix A

Introducing the GAMA platform

A.1 GAMA platform

GAMA (Gis & Agent based Modeling Architecture) simulation platform is aimed at providing field experts, modelers, and computer scientists with a complete modeling and simulation development environment for building spatially explicit Multi-Agent simulations [Drogoul 2013a, Drogoul 2013b, Grignard 2013]. The most important requirements of spatially explicit multi-agent simulations that our platform fulfil are: the ability to transparently use complex Geographical Information System (GIS) data as an environment for the agents; the ability to handle a vast number of (heterogeneous) agents; the ability to offer a platform for automated controlled experiments (by automatically varying parameters, recording statistics, etc.); the possibility to let non-computer scientists design models and interact with the agents during simulations.

GAMA is a simulation platform, which aims at providing field experts, modelers, and computer scientists with a complete modeling and simulation development environment for building spatially explicit agent-based simulations. It is being developed by several French and Vietnamese research teams under the umbrella of the IRD/UPMC International Research Unit UMMISCO since 2007.

GAMA provides the modeler with:

The ability to use arbitrarily complex GIS data as environments for the agents. The possibility to run simulations composed of vast numbers of agents (up to millions). A way to conduct automated controlled experiments on various scenarios, with a systematic, guided or "intelligent" exploration of the space of parameters of models. The possibility to let users interact with the agents in the course of the simulations.

GAMA relies on: A modeling language, GAML, for specifying agents and environments An extensible library of agents architectures, statistical and spatial

analysis functions. A cross-platform reproducibility of simulations A user interface based on the Eclipse platform, with flexible plotting and graphical views GAMA is an open-source project hosted on this site. Its latests stable version can be freely downloaded from here (and used without additional requirements on MacOS X, Windows and Ubuntu). It comes pre-loaded with several models, tutorials and a complete on-line documentation.

Spatially explicit Agent-Based simulations, like the ones that are being developed in GAMA, are at the heart of modern EDSS (Environmental Decision Support Systems) that support deciders and stakeholders in the management of environmental problems (flood control, mitigation of natural catastrophes, land-use and land-planning, plant pests invasions, and so on). Specifically, these simulations allow to couple social, institutional, economical, ecological or biophysical models in a seamless way, and to take into account their influences and interactions on multiple forecasting scenarios.

The different teams also offer training and courses on Agent-Based Modeling and GAMA (please contact the project owners on this subject).

GAMA is developed on Eclipse, and profiled using YourKit Java Profiler. YourKit is a kindly supporting open source projects with its full-featured Java Profiler. YourKit, LLC is the creator of innovative and intelligent tools for profiling Java and .NET applications. Take a look at YourKit's leading software products: YourKit Java Profiler and YourKit .NET Profiler.

A.2 GAMA source code for evacuation on road network

A.2.1 code for Hybrid evacuation on road networks

```
model evacuation_HybridModel
global {
float simulated_population_rate <- 0.1 const: true;

file shape_file_road <- shapefile('../gis/roads.shp');
string shape_file_roadlines <- '../gis/roadlines.shp';
string shape_file_rivers <- '../gis/rivers.shp';
string shape_file_beach <- '../gis/beach.shp';
string shape_file_bounds <- '../gis/bounds.shp';
string shape_file_shelters <- '../gis/edu_gov.shp';
string shape_file_ward <- '../gis/wards.shp';
```

```

float insideRoadCoeff <- 0.1 min: 0.01 max: 0.4;
rgb evacuee_color <- rgb('green') const: true;
float evacuee_max_speed <- 5.4 min: 0.1;
float local_density_window_length <- 2.0;
float max_density <- 5.0 min: 1.0 max: 10.0;
int macro_patch_length_coeff <- 5;
bool is_hybrid_simulation <- false;
list<rgb> ward_colors <- [rgb('black'), rgb('magenta'), rgb('blue'),
rgb('orange'), rgb('gray'), rgb('yellow'), rgb('red')] const: true;
topology road_graph_topology;
list<road> nearest_roads_to_shelters <- [];

rgb shelter_color <- rgb('blue') const: true;
rgb road_color <- rgb('black');
rgb road_width_color <- rgb('yellow') const: true;
rgb beach_color <- rgb('blue') const: true;
rgb river_color <- rgb('gray') const: true;

float evacuees_average_speed -> { self compute_average_speed [] };
int evacuees_reach_shelters ->
  {length(list(evacuee) where each.reach_shelter)};

list<evacuee> not_reach_schelters <- list(evacuee) update:
list(evacuee) where !((evacuee(each)).reach_shelter);

int captured_evacuees update: sum(road collect (length((each.members))));
int not_captured_evacuees update: length(evacuee);

action compute_average_speed type: float {
list<evacuee> not_reach_target_evacuees <-
  list(evacuee) where !(each.reach_shelter);
if (empty(not_reach_target_evacuees)) { return 0; }
return ( sum(not_reach_target_evacuees collect each.speed) /
  length(not_reach_target_evacuees) );
}

init {
loop road_geom over: (shape_file_road.contents) {

```

```
create road with: [ shape :: geometry(road_geom),
  width :: (geometry(road_geom) get ('WIDTH')) ];
}

create road_width from: shape_file_roadlines;
create shelter from: shape_file_shelters;
create beach from: shape_file_beach;
create river from: shape_file_rivers;
loop s over: list(shelter) {
add item: ( road closest_to (s) ) to: nearest_roads_to_shelters;
}

nearest_roads_to_shelters <- (remove_duplicates(nearest_roads_to_shelters));
create ward from: shape_file_ward with:
id :: read('ID'), wardname :: read('Name'), population :: read('Population')]
{
do init_overlapping_roads;
}

road_graph_topology <- topology(as_edge_graph (list(road)));

if (is_hybrid_simulation) {
create road_initializer;
road_initializer ri <- first (road_initializer);
loop rd over: (road as list) {
ask ri { do initialize the_road: rd; }
}
}

loop w over: list(ward) {
if (!(empty(w.roads))) {
create evacuee number:
int ((w.population * simulated_population_rate) ) {
location <- any_location_in (one_of (w.roads));
}
}
}
}
}
```

```
environment bounds: shape_file_bounds;

species ward {
  int id;
  int population min: 0;
  string wardname;
  rgb color <- one_of(ward_colors);
  list<road> roads;

  action init_overlapping_roads {
    roads <- road overlapping shape;
  }

  aspect base {
    draw shape color: color;
  }
}

species shelter {
  aspect base {
    draw shape color: shelter_color;
  }
}

species road_width {
  aspect base {
    draw shape color: road_width_color;
  }
}

species beach {
  aspect base {
    draw shape color: beach_color;
  }
}

species river {
  aspect base {
```

```
draw shape color: river_color;
}
}

species road {
float width;
geometry extremity1;
geometry extremity2;
geometry macro_patch;
geometry macro_patch_buffer;
species evacuee_in_middle_road parent: evacuee schedules: [] {
int released_time;
point released_location;
aspect default {}}
}

reflex capture_evacuees when: ( (is_hybrid_simulation)
and (macro_patch != nil) ) {
list<evacuee> to_be_captured_evacuee <-
(evacuee overlapping (macro_patch_buffer)) where !(each.reach_shelter);
if !(empty(to_be_captured_evacuee)) {
to_be_captured_evacuee <- to_be_captured_evacuee where (
(each.current_road = self)
and (each.last_macro_patch != self)
and (each.previous_location != nil)
and (each.speed > 0));
}

if !(empty (to_be_captured_evacuee)) {
capture to_be_captured_evacuee as:
evacuee_in_middle_road returns: c_evacuees;
loop cp over: c_evacuees {
geometry road_source_to_previous_location <-
(shape split_at (cp.previous_location))
first_with ( geometry(each).points contains (cp.previous_location) ) ;
geometry road_source_to_current_location <- ( shape split_at (cp.location) )
first_with ( geometry(each).points contains cp.location);

float skip_distance <- 0;
```

```

if (road_source_to_previous_location.perimeter <
road_source_to_current_location.perimeter)
{
skip_distance <- geometry( (macro_patch split_at cp.location)
last_with (geometry(each).points contains cp.location) ).perimeter;
cp.released_location <- last (macro_patch.points);
} else { // agent moves towards extremity1
skip_distance <- geometry( (macro_patch split_at cp.location)
first_with (geometry(each).points contains cp.location) ).perimeter;
cp.released_location <- first (macro_patch.points);
}
cp.released_time <- time + (skip_distance / cp.speed);
}
}
}

reflex release_captured_evacuees when: (macro_patch != nil) {
list<evacuee_in_middle_road> to_be_released_evacuees <-
(members) where ( (evacuee_in_middle_road(each).released_time) <= time );
if !(empty (to_be_released_evacuees)) {
loop rp over: to_be_released_evacuees {
point r_position <- rp.released_location;
release rp in: world as: evacuee returns: r_evacuees;
evacuee(first (list (r_evacuees))).last_macro_patch <- self;
evacuee(first (list (r_evacuees))).location <- r_position;
}
}
}

aspect base {
draw shape color: road_color;
}
}

species macro_patch_viewer {
aspect base {
draw shape color: rgb('red');
}
}

```

```
}

species evacuee skills: [moving] {

bool reach_shelter <- false;
float local_density <- 0.0;
float speed <- evacuee_max_speed;

road last_macro_patch;
road current_road;
point previous_location;

geometry window_viewer;
float local_density_window_area;
shelter goal;

action compute_speed type: float {
current_road <- road closest_to self;
local_density_window_area <-
  local_density_window_length * (current_road.width);

int obstacle_evacuees <-1 +
length ((evacuee at_distance local_density_window_length)
where ( ( evacuee(each).current_road = current_road)
and !( evacuee(each).reach_shelter ) ) ) );

if (obstacle_evacuees = 0) {
local_density <- 0;
return evacuee_max_speed;
}

local_density <- ( float (obstacle_evacuees) ) / local_density_window_area;

if (local_density >= max_density) { return 0; }
else { return evacuee_max_speed * ( 1 - (local_density / max_density) );}
}

reflex move when: !(reach_shelter) {
previous_location <- location;
}
```



```
speed <- self compute_speed [];
goal <- shelter closest_to self;

do goto target: goal on: road_graph_topology speed: speed;

if (location = goal.location) {
  reach_shelter <- true;
  speed <- 0;
}
}

aspect base {
  draw circle(5) color: evacuee_color;
}
}

species road_initializer skills: [moving] {
  action initialize {
    arg the_road type: road;

    bool should_build_macro_patch <- empty( list(shelter) overlapping (the_road) );
    should_build_macro_patch <-
    should_build_macro_patch and !(nearest_roads_to_shelters contains the_road);

    if (should_build_macro_patch) {
      geometry inside_road_geom <- the_road.shape;
      speed <- (the_road.shape).perimeter * insideRoadCoeff;
      point point1 <- first(inside_road_geom.points);
      point point2 <- last(inside_road_geom.points);
      location <- point1;
      do goto target: point2 on: road_graph_topology;
      list<geometry> lines1 <- list(inside_road_geom split_at location);
      the_road.extremity1 <- lines1 first_with (geometry(each).points contains point1);
      inside_road_geom <- lines1 first_with (!(geometry(each).points contains point1));
      location <- point2;
      do goto target: point1 on: road_graph_topology;
      list<geometry> lines2 <- list(inside_road_geom split_at location);

      the_road.extremity2 <- lines2 first_with (geometry(each).points contains point2);
```

```
inside_road_geom <- lines2 first_with (!(geometry(each).points contains point2));

if (inside_road_geom.perimeter >
    (macro_patch_length_coeff * evacuee_max_speed)
    {
the_road.macro_patch <- inside_road_geom;
the_road.macro_patch_buffer <- inside_road_geom + 0.01;
}
}
}
}

experiment 'ABM (10% population)' type: gui {
parameter 'Hybrid simulation' var: is_hybrid_simulation <- false;

output {
display ward_road_network refresh_every: 3 {
species ward aspect: base transparency: 0.8;
species road aspect: base transparency: 0.5;
species road_width aspect: base transparency: 0.5;
species beach aspect: base transparency: 0.9;
species river aspect: base transparency: 0.5;
  species evacuee aspect: base transparency: 0.1;
  species shelter aspect: base transparency: 0.1;
}
}

monitor total_evacuees value: length(list(evacuee));
monitor average_speed value: evacuees_average_speed;
monitor evacuees_reach_shelters value: evacuees_reach_shelters;
monitor stuck_evacuees value: length( list(evacuee)
where ( (each.speed = 0) and !(each.reach_shelter) ) );
monitor average_local_density value: (sum (list(evacuee)
  collect (each.local_density))) / (length(evacuee));
monitor average_step_duration value: average_duration;

monitor all_evacuees value: length(world.members of_generic_species evacuee);

display evacuees_average_speed {
```

```
chart "Evacuees' average speed" type: series {
data "Meters/second" value: evacuees_average_speed color: rgb('green');
}
}

display evacuees_reach_target {
chart "Evacuees reach shelters" type: series {
data "Number of evacuees" value: evacuees_reach_shelters color: rgb('blue');
}
}
}
}

experiment 'Hybrid (10% population)' type: gui {
parameter 'Hybrid simulation' var: is_hybrid_simulation <- true;

output {
display ward_road_network refresh_every: 6 {
species ward aspect: base transparency: 0.8;
species road aspect: base transparency: 0.5;
species road_width aspect: base transparency: 0.5;
species beach aspect: base transparency: 0.9;
species river aspect: base transparency: 0.5;
  species evacuee aspect: base transparency: 0.1;
  species shelter aspect: base transparency: 0.1;
}
}

monitor captured_evacuees value: captured_evacuees;
monitor not_captured_evacuees value: not_captured_evacuees;

monitor average_speed value: evacuees_average_speed;
monitor evacuees_reach_target value: evacuees_reach_shelters;
monitor stuck_evacuees value: length( list(evacuee)
where ( (each.speed = 0) and !(each.reach_shelter) ) );

monitor average_local_density value: !(empty(list(evacuee))) ?
(sum (list(evacuee) collect (each.local_density))) / (length(evacuee)) : 0;
monitor average_step_duration value: average_duration;
```

```
monitor roads_WITH_macro_patch value: length( (list(road)
where (each.macro_patch != nil)) );
monitor roads_WITHOUT_macro_patch value: length( (list(road)
where (each.macro_patch = nil)) );
monitor nearest_roads value: length(nearest_roads_to_shelters);

monitor all_evacuees value: length(world.agents of_generic_species evacuee);

display evacuees_average_speed refresh_every: 3 {
chart "Evacuees average speed" type: series {
data "Meters/second" value: evacuees_average_speed color: rgb('green');
}
}

display evacuees_reach_target {
chart "Evacuees reach shelters" type: series {
data "Number of evacuees" value: evacuees_reach_shelters color: rgb('blue');
}
}

display captured_vs_not_captured_pedestrians {
chart "'junctions' evacuees v.s. 'middle road' evacuees" type: series {
data "Evacuees in the middle of the roads"
value: captured_evacuees color: rgb('blue');
data "Evacuees near junctions" value: not_captured_evacuees color: rgb('green');
}
}
}
}
```

A.2.2 code for integrating MAET and GAMA

```
model edestrian_MAET_GAMA

global {
file shape_file_road <- file('../includes/gis/roadlines.shp');
file shape_file_bounds <- file('../includes/gis/bounds.shp');
file shape_file_rives <- file('../includes/gis/rivers.shp');
file shape_file_wards <- file('../includes/gis/wards.shp');
```

```
file shape_file_builds <- file('../includes/gis/buildr.shp');
file shape_file_roads<- file('../includes/gis/roads.shp');
file shape_file_contour<- file('../includes/gis/ngaplut_city_contour.shp');

file panel_MAET <- file('../includes/MAET2_a_TD/TDSce15k120.txt');
file safe_places_data <- file('../includes/safe_places_15minutes.txt');

float pedestrian_max_speed <- 5.4 parameter:
'Max speed (m per s)' category: 'Pedestrian';
float max_density <- 6.0 min: 1.0 max: 10.0 parameter:
'Max density (people per m2)' category: 'Pedestrian';

int number_of_pedestrian <- 5000 parameter: 'Number of pedestrians';
bool model_shelters <-true parameter:
'MAET Shelters in the junctions/ GAMA shelters';
list<build> list_shelters update: build where (each.stage>8);

graph road_graph ;
list<pedestrian> moving_pedestrians update:
pedestrian where !(each.reach_target);
float average_speed update: !(empty(moving_pedestrians)) ?
  mean(moving_pedestrians collect each.speed) : 0;
list<pedestrian> pedestrians_reach_target update:
pedestrian where (each.reach_target);
int total_reach_target_duration update:
sum( pedestrians_reach_target collect each.reach_target_time );
float average_reach_target_duration update:
  !(empty(pedestrians_reach_target))?
  (total_reach_target_duration / length (pedestrians_reach_target) ): 0;
file ShapeSign <- file('../includes/sign.jpg') const:true;
list<rgb> ward_colors <-[rgb('green'),rgb('magenta'), rgb('blue'), rgb('orange'),
rgb('gray'),rgb('yellow'),rgb('red'),rgb('white'),rgb('black')] const:true;
geometry shape <- envelope(shape_file_bounds);
list<point> safe_places_location;
init {
create road from: shape_file_road;
road_graph <- as_edge_graph (road);
do generate_panels;
if (model_shelters){
```

```

do generate_safe_places;
}else{
do generate_safe_places1;
}
create pedestrian number: number_of_pedestrian;
create rive from: shape_file_rives;
create ward from: shape_file_wards with:[id :: int(read('ID'))];
create build from: shape_file_builds with:[stage :: int(read('STAGE'))];
create contour from:shape_file_contour with:[altitude :: int(read('CONTOUR'))];
}
action generate_panels {
loop i from: 0 to: ( length(panel_MAET) - 1 ) {
list<point> MAET_2_points <- read_panel_info (panel_MAET[i]);
point v1_ <- MAET_2_points[0];
point v2_ <-MAET_2_points[1];
point v1 <- point(road_graph.vertices with_min_of (point(each) distance_to v1_));
point v2 <- point(road_graph.vertices with_min_of (point(each) distance_to v2_));
if (road_graph contains_edge ( v1 :: v2 )) {
create panel with: [ location :: v1, target_vertex :: v2];
}
}
}
list<point> read_panel_info (string panel_info) {
list tokenized <- panel_info split_with ' ';
point panel_location_ <- { float(tokenized[0]), float(tokenized[1]) };
point panel_target_ <- { float(tokenized[2]), float(tokenized[3]) };
point panel_location <- point(road_graph.vertices with_min_of
(point (each) distance_to panel_location_));
point panel_target <- point(road_graph.vertices with_min_of
(point (each) distance_to panel_target_));
list<point> retval <- [ panel_location, panel_target ];
return retval;
}
action generate_safe_places {
loop i from: 0 to: (length(safe_places_data) - 1) {
list safe_place_line <- string((safe_places_data[i])) split_with ' ';
point a_safe_place_location_ <-
{ float(safe_place_line[0]), float(safe_place_line[1])}
point a_safe_place_location <- point(road_graph.vertices with_min_of

```

```
(point (each) distance_to a_safe_place_location_));

create safe_place with: [ location :: a_safe_place_location ] {
safe_places_location << location;
}
}
}
action generate_safe_places1 {
loop i from: 0 to: (length(list_shelters) - 1) {
create safe_place with: [ location :: list_shelters[i].location ];
}
}
reflex stop_sim when: empty(pedestrian where !(each.reach_target)) {
write 'Simulation stops at: ' + (string(time));
do halt;
}
}
entities {
species contour {
float altitude;
aspect base {
draw shape color: rgb('green') at:{location.x,location.y,-altitude*2};
}
}
species build {
int stage;
rgb color;
file texture<- textures[rnd(9)];
aspect base {
if (stage>8){
color <-rgb('red');
}
else{
color <-rgb('yellow');
}
draw shape color: color border:color depth: (1 + stage*2);
}
aspect textured {
draw shape texture:[roof_texture.path,texture.path] depth: (1 + stage*2) ;
```

```
}
}
species road {
aspect base {
  draw shape color: rgb('yellow');
}
}
species ward {
int id;
aspect base {
  draw shape color: ward_colors[id-1];
}
}
species rive {
aspect base {
  draw shape color: rgb('blue');
}
}
species panel {
var target_vertex type: point;
aspect base {
draw box(0.1,0.1,10) color:rgb("blue") border:rgb("blue");
draw box(10,0.1,5) color:rgb("blue") border:rgb("blue") at:
{location.x,location.y,10} texture:[ShapeSign.path];
}
}
species safe_place {
aspect base {
  draw cylinder(10,50) color:rgb("green") border:rgb("green");
  //draw circle(20) color: rgb("green");
}
}
species pedestrian skills: [moving] {
point end_road ;
bool reach_target <- false;
float speed <- pedestrian_max_speed;
int reach_target_time ;
rgb color <-rgb('blue');
init {
```



```

location <- any_location_in(one_of(road));
road current_road <- road closest_to self;
end_road <- flip(0.5) ? first((current_road.shape).points) :
last((current_road.shape).points);
}
action compute_speed {
int obstacle_pedestrians<- 1 + length ( ( pedestrian at_distance speed )
where ( !( each.reach_target ) ) ) ;
if (obstacle_pedestrians = 0) { speed <- pedestrian_max_speed; }
float local_density <- obstacle_pedestrians / (3.14 * speed * speed);
if (local_density >= max_density) { speed <- 0.0; }
else { speed <- pedestrian_max_speed * ( 1 - (local_density / max_density));}
}
reflex move_around when: !(reach_target) {
if !(model_shelters){
loop i from: 0 to: (length(list_shelters) - 1)
{
if (location distance_to list_shelters[i].location <40)
{
reach_target <- true ;
location <- list_shelters[i].location;
color <- rgb('red');
}

}

if (reach_target) {
reach_target_time <- cycle;
}
}else{
loop i from: 0 to: (length(safe_places_data) - 1)
{
if (location distance_to safe_places_location[i] <40)
{ reach_target <- true ;
location <- safe_places_location[i];
color <- rgb('red');
}
}

if (reach_target) {
reach_target_time <- cycle;
}
}
}

```

```

}
}
if !(reach_target) and (location = end_road) {
panel available_panel <- one_of(panel where (each.location = location));
if (available_panel != nil) {
end_road <- available_panel.target_vertex;
} else {
list<road> possible_next_roads<-
  road where (end_road in ((each.shape).points));
road next_road <- one_of(possible_next_roads);

if (location = point( first((next_road.shape).points) ) ) {
end_road <- last((next_road.shape).points);
} else {
end_road <- first((next_road.shape).points);
}
}
}
do compute_speed;
do goto target: end_road on: road_graph speed: speed;
}
aspect base {
draw shape color: color;
}
aspect real {
draw cylinder(2,6) color: color border:color;
draw sphere(3) at:{location.x,location.y,10} color: color;
}
}
}

experiment Pedestrian_MAET type: gui {
output {
display road_panel_display type:opengl
ambient_light:30 diffuse_light:255 tessellation:false{
species panel aspect: base refresh:false;
species pedestrian aspect: base;
species safe_place aspect: base transparency: 0.1 refresh:false;
species build aspect: base refresh:false;
}
}
}

```

```

species road aspect: base transparency: 0.3 refresh:false;
image gis: shape_file_roads color: rgb('yellow') transparency: 0.9;
species contour aspect: base;
species rive aspect: base transparency: 0.5 refresh:false;
species ward aspect: base transparency: 0.9 refresh:false;
}
monitor panels value: string(list(panel));
monitor pedestrians_reach_target value: pedestrian count (each.reach_target);
monitor average_speed value: average_speed;
monitor total_pedestrian_duration value: total_reach_target_duration;
monitor average_pedestrian_duration value: average_reach_target_duration;
}
}

```

A.2.3 The program is represented by the Floyd's algorithm

```

void Floyd (floatC[n - 1][n - 1], A[n - 1][n - 1])
{ int i, j, k;
  { for(i = 0, in - 1;i ++
    for(j = 0;jn - 1, j ++
      A[i, j] = C[i, j];
    for(i = 0;in - 1;i ++
      A[i, i] = 0;
      for(k = 0;kn - 1;k ++);
      {
        for(i = 0;in - 1;i ++
          {
            for(j = 0;jn - 1, j ++
              if(A[i, k] + A[k, j] < A[i, j])
                A[i, j] = A[i, k] + A[k, j]
            }
          }
        }
      }
    }
  }
}

```


Appendix B

Mathematic models

B.1 MILP model

B.1.1 Introduction

As regarding MILP in the Chapter 4, MILP is used to solve in the NP-hard time. What are the implications of complete enumeration techniques on processing time? Suppose that there exist n variables, each of which can take on a value of zero or one. Furthermore, suppose that each configuration of these variables can be evaluated (tested for feasibility to the problem constraints and scored) using n computer operations. Since there are 2 choices for each variable, there are 2^n configurations. Even if we are using a computer capable of processing 10 trillion operations per second (or 10 teraflops, and at the time of this writing, only 58 of the world's top 500 supercomputers are capable of such a feat), if $n = 50$, the computer will take 1.5 hours to finish enumerating all possibilities. One might be tempted to simply let the computer run all night if need be for important problems, and while this is indeed valid for the case in which $n = 50$, the computational growth rate for these problems is astounding: for $n = 60$, the computer will require 80 days to terminate, and for $n = 70$, the computer will require 262 years. Another question regards the evolution of computing speed, noting that faster computers are constantly emerging. If the program must be finished within two hours, the current 10 teraflop machine will permit the solution of problems with $n = 50$. If a quantum leap is discovered that results in the invention of 10,000 teraflop machine, this fictional computer would only be able to handle problems with $n = 60$ within two hours. Computer speedups, however impressive, are simply no match for exponential enumeration problems [Guignard-Spielberg 2005, M.Junger 2010, R. Bixby 2007]. Therefore, a more efficient technique is required to solve problems containing discrete variables. Mixed-integer programming techniques do not explicitly examine every possible

combination of discrete solutions, but instead examine a subset of possible solutions, and use optimization theory to prove that no other solution can be better than the best one found. This type of technique is referred to as implicit enumeration.

B.1.2 Modeling Principles

Firstly, we present the general form of a linear programming problem. Linear programming problems (usually called linear programs) contain a set of decision variables, which are the unknown quantities or decisions that are to be optimized. In the context of linear and mixed-integer programming problems, the function that assesses the quality of the solution, called the objective function, should be a linear function of the decision variables. A linear programming will either minimize or maximize the value of the objective function. Finally, the decisions that must be made are subject to certain requirements and restrictions of a system. We enforce these restrictions by including a set of constraints in the model. Each constraint requires that a linear function of the decision variables is either equal to, not less than, or not more than, a scalar value. A common condition simply states that each decision variable must be nonnegative. In fact, all linear programming problems can be transformed into an equivalent minimization problem with nonnegative variables and equality constraints [Guignard-Spielberg 2005, M.Junger 2010, R. Bixby 2007]. Thus, suppose we denote x_1, \dots, x_n to be our set of decision variables. Linear programming problems take on the form:

Minimize or maximize

$$c_1x_1 + c_2x_2 + \dots + c_nx_n \text{ such that}$$

Subject to:

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n & (\leq, =, \geq) b_1 \\ a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n & (\leq, =, \geq) b_2 \\ & \dots \\ a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n & (\leq, =, \geq) b_m \\ & x_i \geq 0, \quad \forall i = 1, \dots, n. \end{aligned}$$

B.2 Program of MAET using CPLEX in Python

To solve MAET, we code program in Python. First, we input the weigh graph $G = \{V, E\}$. Then, the safe places X are inputed. Final, we solve MAET that can use CPLEX.

```

import networkx as nx
import matplotlib.pyplot as plt
import sys
import cplex

def build_weighted_graph():
    data = {1:{197:22.799922616894747,300:134.1806059521864,307:67.84566903004063},
           G = nx.Graph()
    for i in data:
        for j in data[i]:
            G.add_weighted_edges_from([(i,j,data[i][j])])
    return G

def build_test_graphs():
    G = nx.Graph()
    G.add_weighted_edges_from([(1,2,12.0),(2,3,23.0),(3,4,34.0),(4,1,41.0)])
    Safe = [3]
    return G, Safe

def cplex_build_MIP(G, SafePlaces, k, mu=None, Qmax=500.0, verb=False, timelimit=10.0):
    n = len(G)

    Unsafe = [i for i in G if i not in SafePlaces]
    # variables: q1..qn, a1..am
    q = {i:("q"+str(i)) for i in G}
    a = {(i,j):("a"+str(i)+","+str(j)) for i in Unsafe for j in G.neighbors(i) }
    if mu == None:
        mu = [1.0/n]*n

#####

    my_obj = mu+[0.0]*len(a)
    my_colnames = q.values()+ a.values()
    my_lb = [0.0]*len(q)+[0.0]*len(a)
    my_ub = [cplex.infinity]*len(q)+[1.0]*len(a)
    my_types = "C"*len(q)+"B"*len(a)

    # Constraints: safeplaces
    my_rownames = ["SafePlaces_"+str(i+1) for i in range(len(SafePlaces))]

```

```
A =[
    [ [q[i]] , [1.0] ]
    for i in SafePlaces
    ]
my_rhs = [0.0] * len(SafePlaces)
my_senses = "E"*len(SafePlaces)

# Constraints:  $q_i - q_j - Q_{max}.a_{ij} > C_{ij} - Q_{max}$ 
for i,j in a:
    my_rownames += ["signs_"+a[i,j]]
    #print "qi=",q[i]
    #print "qj=",q[j]
    #print "aij=",a[i,j]
    A += [
        [ [q[i],q[j],a[i,j]] , [1.0,-1.0,-Qmax] ]
        ]
    my_rhs += [ G[i][j]['weight'] - Qmax ]
    my_senses+= "G"

# constraint  $q_i - \sum(P_{ij}.q_j) + \sum(Q_{max} a_{ij}) > \sum(P_{ij}.C_{ij})$ 
for i in Unsafe:
    Pij = 1.0 / G.degree(i)
    my_rownames += ["markov_chain"+q[i]]
    A += [
        [
            [q[i]]+[q[j] for j in G.neighbors(i)]+[a[i,j]
            for j in G.neighbors(i)],
            [1.0] +[-Pij for j in G.neighbors(i)]+
            [Qmax for j in G.neighbors(i)]
        ]
    ]
    my_rhs += [sum([ Pij*G[i][j]['weight']
    for j in G.neighbors(i) ])]
    my_senses += "G"

# constraint for each i,  $\sum(a_{ij}) \leq 1$ 
for i in Unsafe:
    my_rownames += ["only_one_sign_per_node"+q[i]]
    A += [
```



```

        [
            [a[i,j] for j in G.neighbors(i)],
            [1.0      for j in G.neighbors(i)]
        ]
    ]
    my_rhs += [1.0]
    my_senses += "L"
# constraint sum(aij) <= k
my_rownames += ["at_most_k"]
A += [
    [
        [a[i,j] for i,j in a] ,
        [1.0      for i,j in a]
    ]
]
my_rhs += [k]
my_senses += "L"

prob = cplex.Cplex()
prob.objective.set_sense(prob.objective.sense.minimize)

prob.variables.add(obj = my_obj, lb = my_lb, ub = my_ub,
names = my_colnames , types = my_types)

prob.linear_constraints.add( lin_expr = A, senses=my_senses,
rhs=my_rhs,names=my_rownames)

if verb == False:
    prob.set_results_stream(None)
    prob.set_log_stream(None)

prob.parameters.timelimit.set(timelimit)

prob.solve()

if prob.solution.get_status_string() == "integer infeasible":
    return [], [], prob.solution.get_status_string(), None

q_sol = (prob.solution.get_values())[0:n]

```

```
a_sol = [(i,j) for i,j in a if prob.solution.get_values(a[i,j])==1]
#prob.write("montest.lp")
return q_sol,a_sol,prob.solution.get_status_string(),
prob.solution.get_objective_value()

#####

def test_cplex_build_MIP():
    G,SafePlaces = build_test_graphs()
    q_sol,a_sol,sol_status,sol_val = cplex_build_MIP(G,SafePlaces,k=3)
    print q_sol
    print a_sol
    print sol_status
    print sol_val

#####

def cplex_find_directions(G,SafePlaces,SignLocations,mu=None,verb=False):
    n = len(G)

    UnsafeUnsigned = [i for i in G if (i not in SafePlaces) and
(i not in SignLocations)]
    # variables: q1..qn
    q = {i:("q"+str(i)) for i in G}
    if mu == None:
        mu = [1.0/n]*n

    #####
    my_obj = mu
    my_colnames = q.values()
    my_lb = [0.0]*len(q)
    my_ub = [60000.0]*len(q)

    # Constraints: safeplaces
    my_rownames = ["SafePlaces_"+str(i+1) for i in range(len(SafePlaces))]
    A = [
        [ q[i] , [1.0] ]
        for i in SafePlaces
```

```

    ]
my_rhs = [0.0] * len(SafePlaces)
my_senses = "L"*len(SafePlaces)

# Constraints:   $q_i - q_j < C_{ij}$ 
for i in SignLocations:
    for j in G.neighbors(i):
        my_rownames += ["signs_"+str(i)+"_"+str(j)]
        A += [
            [ [q[i],q[j]] , [1.0,-1.0] ]
        ]
        my_rhs += [ G[i][j]['weight'] ]
        my_senses+= "L"

# constraint  $q_i - \sum(P_{ij}.q_j) + \sum(Q_{max} a_{ij}) > \sum(P_{ij}.C_{ij})$ 
for i in UnsafeUnsigned:
    Pij = 1.0 / G.degree(i)
    my_rownames += ["markov_chain"+q[i]]
    A += [
        [
            [q[i]]+[q[j] for j in G.neighbors(i)],
            [1.0] +[-Pij for j in G.neighbors(i)]
        ]
    ]
    my_rhs += [sum([ Pij*G[i][j]['weight'] for j in G.neighbors(i) ])]
    my_senses += "L"

prob = cplex.Cplex()
prob.objective.set_sense(prob.objective.sense.maximize)
prob.variables.add(obj = my_obj, lb = my_lb, ub = my_ub,
names = my_colnames)
prob.linear_constraints.add( lin_expr = A,
senses=my_senses,rhs=my_rhs,names=my_rownames)

if verb == False:
    prob.set_results_stream(None)
    prob.set_log_stream(None)
prob.solve()
q_sol = (prob.solution.get_values())[0:n]

```

```
prob.write("montest2.lp")
return q_sol,prob.solution.get_status_string(),
prob.solution.get_objective_value()

#####

def test_find_directions():
    #G,SafePlaces = build_test_graphs()
    G = build_weighted_graph()
    SafePlaces = [1,40,80,120,160,200,240,280,320]
    q_sol,sol_status,sol_val =
    cplex_find_directions(G,SafePlaces,range(22,60),verb=True)
    print q_sol
    print sol_status
    print sol_val

#test_find_directions()
```

The algorithm MAET is coded by Python that use CPLEX. when we want to do many experiments MAET with different $k = \{3, 30, 60, 90, 120, 150\}$, the procedure was written.

```
import networkx as nx
import matplotlib.pyplot as plt
import sys
import cplex
from cplex_placement import *

G = build_weighted_graph()
SafePlaces = [1,40,80,120,160,200,240,280,320]

for k in [3,30,60,90,120,150]:
    q_sol,a_sol,sol_status,sol_val =
    cplex_build_MIP(G,SafePlaces,k,Qmax=60000.0,verb=False,timelimit=240.0)
    print q_sol,a_sol,sol_status
    print "for ",k," signs, the average evacuation time is " , sol_val
    print ""
```

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