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Optimization Models for Pedestrian Emergency Evacuation Planning

A THESIS SUBMITTED FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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A dream doesn't become reality through magic; it takes sweat, determination and hard work.

Abstract

The cell transmission model (CTM) proposed by Carlos F. Daganzo in 1994 and used by Ziliaskopoulos to formulate the Single Destination System Optimal Dynamic Traffic Assignment (SD-SO-DTA) model has been widely applied to such situations as mass evacuations in a transportation network. Although the model is formulated as a linear program (LP), a network representation that embeds multi-period cells would yield an extremely large problem for real-size cases. As a result, most of these models are applied in the literature to small scale network sizes only.

This doctoral research aims at developing innovative algorithms that overcome both computational efficiency and solution applicability issues. We first developed a network transformation and conversion (NTC) model to convert any transportation infrastructure into a cell-based network. NTC enables the application of different formulations to large-scale real-world networks for SO-DTA analysis employing cell transmission models. We then propose the Dynamic Cell Transmission Evacuation Planning model (DyCTEP), a modification of CTM by Arbib et al. [23, 24], to incorporate city-level networks under extreme and undesirable conditions. The formulation of DyCTEP model allows its use as a practical tool to dynamically approach pedestrian emergency evacuation, providing an optimal solution in terms of destinations, route, time, flow-staging and flow distributions. The model also approximates non-linear arc capacities to manage congestion phenomena. We also propose a heuristic algorithm for optimal route assignment that takes into consideration the whole time-dynamics of solutions.

We also implemented three new approaches, namely Dynamic Earliest Arrival Flow (DEAF), Extended CTM and Multiple Cells, designed to cope with inconveniences in the DyCTEP model: in fact, single-size cells may lead to unacceptable imprecision if too large or, if too small, to an excessive amount of constraints and variables in the optimization model, demanding in computational terms but in fact unnecessary to meet the desired operation accuracy. In order to formulate DEAF, we modified the Time Expanded Graph (TEG), showing that there is no need to explicitly partition and embed the underlining evacuation network into elementary cells, as the network can be converted using travel time information. We also verified and validated the equivalence of DEAF and DyCTEP model. The other two approaches are extension of the DyCTEP model to simplify the choice of the optimum cell size. Different analyses were carried out to determine the effects of these models on problem complexity, solution accuracy, and computation time.

We proposed the Priority Multi-Party Capacity Constrained Route Planning method (PMP-CCRP), a heuristic algorithm which extends the CCRP method by Shekhar et al. [311]. The proposed PMP-CCRP method incorporates the ability of planning the evacuation of different parties with different objectives (e.g., a situation where evacuees are directed from endangered sources to safe locations, while emergency rescuers go the other way round), therefore seeking for optimal paths for both incoming emergency units and evacuees. PMP-CCRP ensures that, during evacuation, priority is given to high risk areas; that is, evacuees in highly endangered zone are evacuated before those in less risky areas.

The feasibility and applicability of our modeling framework was investigated with the help of real case studies: the emergency evacuation of the historical centres of L'Aquila and Sulmona (Abruzzo, Italy). The models were customized with respect to several parameters, and re-scaled to the network by several orders of magnitude. In the Sulmona case study, we solved a problem with over 2,000,000 nodes. And there was a significant improvements in the computational complexity and time of the first approach. Still, the results obtained were definitely encouraging in terms of approach viability.

Keywords: No-notice Evacuation, Cell Transmission Model, Capacity Constrained Route Planning, Pedestrian Evacuation, flow, Disaster Management, Dynamic Optimisation Modelling, Time Expanded, large-scale urban area, model validation.

Declaration

I, Evans Etrue Howard, hereby declare that this thesis titled, Optimization Models for Pedestrian Emergency Evacuation Planning and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- I have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date: 22/ 05/ 2022

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Evans Etrue Howard, L'Aquila, June 2022

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Evans Etrue Howard, L'Aquila, June 2022

Dedication

To my dad, Alex Ofoli Nortey and my mum, Olivia Ofori (blessed memory, 2018) and Janet Kwakye for their unconditional love and support.

Contents

Abstracts ii

Declaration iv

Funding v

Acknowledgements vi

Dedication vii

List of Figures x

List of Tables xii

Nomenclature xiv

Acronyms xv

1 Introduction 1
- 1.1 Background . . . 1
- 1.2 Motivating Scenario: Disaster Management . . . 3
- 1.3 Problem Statement . . . 6
- 1.4 Research Scope/ Objective . . . 9
- 1.5 Contribution . . . 10
- 1.6 Thesis Outline . . . 11

2 Pedestrian Emergency Evacuation Models: A State of the Art 13
- 2.1 Introduction . . . 13
- 2.2 Data Source . . . 15
- 2.3 Conceptualisation . . . 21
- 2.4 Domains of pedestrian evacuation approaches . . . 26
  - 2.4.1 Architectural methods of evacuation optimisation . . . 26
  - 2.4.2 Mathematical programming methods of evacuation optimisation . . . 28
  - 2.4.3 Behavioural modification methods of evacuation optimisation . . . 31
- 2.5 Problem type, objective function measures, and decisions considered. . . . 35
- 2.6 Model realism . . . 37
  - 2.6.1 Empirical research on pedestrian and crowd dynamics . . . 38
  - 2.6.2 Implications for modelling . . . 40
- 2.7 Modelling and solution techniques . . . 41
  - 2.7.1 Macroscopic models . . . 42
  - 2.7.2 Microscopic models . . . 43
- 2.8 Discussion and conclusion . . . 45

3 Network Generation and Conversion **48**
3.1 Introduction . . . 48
3.2 Cell Transmission Model - Daganzo's traffic simulation model . . . 49
3.3 Network Transformation and Conversion (NTC) Model . . . 52
3.3.1 Network Transformation . . . 53
3.3.2 Cell-Connector conversion from Node-Arc Network . . . 55
3.4 Concluding Remark . . . 56

4 Automatic Generation of no-notice large-scale Evacuation plans **59**
4.1 Introduction . . . 59
4.2 Related Work . . . 60
4.3 Mathematical Model . . . 62
4.3.1 Dynamic Cell-Transmission-based Evacuation Planning Model (DyCTEP) . . . 62
4.3.2 Incorporating Arc-Congestion into Model . . . 65
4.3.3 Pedestrian-Holding Cell Property . . . 67
4.3.4 Static Evacuation Route Plans: Paths generation on maps . . . 68
4.3.4.1 Analysis of Algorithm 1 . . . 70
4.3.5 Model Parameter Settings . . . 70
4.4 Numerical Experiments . . . 72
4.4.1 Base Case Example . . . 73
4.4.2 Real-Size Network Case Implementation . . . 80
4.5 Summary . . . 81

5 Modified Dynamic Pedestrian Evacuation Planning **83**
5.1 Introduction . . . 83
5.2 Related Work . . . 84
5.3 Updated Mathematical Models . . . 85
5.3.1 Dynamic Earliest Arrival Flow (DEAF) . . . 85
5.3.1.1 The setting . . . 85
5.3.2 Modified Optimization Model . . . 89
5.4 Extension of the Dynamic Cell-Transmission Evacuation Planning (DyCTEP) Model 92
5.4.1 Approach 1: Extended CTM Approach . . . 93
5.4.2 Approach 2: Multiple Cell Sizes . . . 95
5.5 Numerical Experiments . . . 96
5.5.1 Base Case Example . . . 96
5.5.1.1 Impact of Modification on Problem Size . . . 97
5.5.1.2 Comparison of Model Performance . . . 97
5.5.2 Real-Size Network Case Implementation . . . 99
5.6 Summary . . . 101

6 Towards an Emergency Evacuation Planning Service **103**
6.1 Introduction . . . 103
6.2 Related Work . . . 104
6.3 Proposed Approach . . . 105
6.4 Implementation . . . 108
6.5 Experimentation . . . 108
6.6 Discussion . . . 111
6.7 Conclusion . . . 111

7 Summary, Conclusions and Future Research **114**
7.1 Summary and Conclusions . . . 114
7.2 Research Contribution . . . 116
7.3 Research Publications . . . 117
7.4 Future Research . . . 117

Bibliography **119**

List of Figures

1.1 Timeline for the various operations performed before and after disasters. 3
1.2 Geographical representation of natural disaster occurrences for various European countries. 4
1.3 Geographical representation of technological disaster occurrences for various European countries. 6
1.4 A summary of the occurrences of disasters in Italy from 1990 to 2022 based. 8

2.1 The trend of published articles in pedestrian emergency evacuation studies. 17
2.2 Number of publications published per year based on methodology 19
2.3 Overview of publications per journal and per year. 20
2.4 The number of published articles in the ten (10) main categories. 20
2.5 Overview of publications per journal and per methodology. 21
2.6 Overview of publications according to journal types per year and per research objectives. 21
2.7 Conceptualisation of the descriptive (observational) vs prescriptive (interventional) domains of pedestrian studies. 24
2.8 Conceptualisation of numerical simulations and experimentation of pedestrian evacuations. 24
2.9 Identification of sub-domains related to each of the three major evacuation optimisation approaches. 25
2.10 Overview of descriptive modelling techniques. 42

3.1 Fundamental Diagram in the CTM Model 50
3.2 Illustration of the various types of cells used in the cell transmission model 51
3.3 Depiction of Merging and Diverging Cells in the CTM 52
3.4 A bi-directional sample network to illustrate the CTM 53
3.5 A uni-directional sample network to illustrate the CTM 53
3.6 Transformed Evacuation Scenario Network for both bi-and uni-directional networks in Figures 3.4 and 3.5 54
3.7 Representation of intersection and u-turn nodes with their various connectors. 57
3.8 Complete transformed bi-directional cell-connector network using CTM 57
3.9 Complete transformed uni-directional cell-connector network using CTM 58

4.1 Linearization of a congestion curve. 66
4.2 Illustrative example of how Algorithm 1 works 69
4.3 Time and Space complexity analysis of Algorithm 1 71
4.4 Transformed Test Network 73
4.5 Transformed Test Network 74
4.6 Network associated with Figure 4.5 75
4.7 Optimal stagging and flow distributions at the source cells for each time slot τ for base model. 76

4.8 Comparison of the model performance on the various networks (the original network, the network generated by the heuristics and the shortest path network). 77
4.9 Illustration of optimal route assignment using the Heuristic Algorithm 1). 78
4.10 Optimal stagging and flow distributions at the source cells for each time slot τ for model with arc-congestion. 79
4.11 Number of people safely evacuated in CTM Model 4.4 vs CTM Model with non-linear arc congestions 4.5 at every time slot τ. 79
4.12 L'Aquila Network used for Real-Life case study 80
4.13 Optimal distribution of flow at the destinations. 81
4.14 Optimal route assignment using Heuristic Algorithm 1. 82

5.1 Representation of a Static Network G of a simple street layout 86
5.2 Constructed Time-Expanded-Dynamic Network G_T of the static network G of figure 5.1 with $T = 4$ 87
5.3 Dynamic Network G_T of the static network G of figure 5.1 with $T = 4$ by Deleting Inessential Arcs and Nodes 88
5.4 A section of a road network. 93
5.5 Network representation using multiple cell sizes. 93
5.6 Constructed Dynamic Time Expanded Network for Figure 4.4 96
5.7 Comparison of model performance. 98
5.8 Number of people safely evacuated in each Model at every time slot τ. 99
5.9 Comparsion of Optimal destination flow distribution for models DyCTEP and Dynamic Earliest Arrival Flow (DEAF). 100
5.10 Optimal route assignment applying Heuristic Algorithm 1 on the model dynamics obtained by DyCTEP (in red, yellow and blue) and DEAF (in green). 101

6.1 Network Model for a multi-party evacuation route planning. 105
6.2 Network Model representation of CCRP vs PMP-CCRP. 106
6.3 Object Oriented Programming procedure for the proposed Algorithm 2 109
6.4 The graph on the left shows the population before evacuation while the graph on the right shows the population after evacuation and response. 110
6.5 Comparison of the total egress time for CCRP and PMP-CCRP. **Top Left:** Histogram comparing CCRP Evacuation vs PMP-CCRP Total Time. **Top Right:** CCRP Response vs PMP-CCRP Total Time. **Bottom Left:** CCRP Total Egress Time vs PMP-CCRP Total Time. **Bottom Right:** Total Time Saved using PMP-CCRP on a trial by trial basis. 112

List of Tables

1.1 Global (European) Occurrences from Disasters (Natural and Technological from 1990 - 2022) . . . 5
1.2 Summary of disasters in Italy from 1990 to 2022 based on Disaster category and type 7

2.1 Types of retrieved documents in pedestrian emergency evacuation studies. . . . 16
2.2 Sub-domains under architectural methods of pedestrian evacuation . . . 27
2.3 Sub-domains under Mathematical programming methods of pedestrian evacuation . 30
2.4 Sub-domains under Behavioural modification methods of pedestrian evacuation . . . 35
2.5 Problem type. Evacuation planning consists of determining the optimal way to evacuate pedestrian facilities as quickly and safely as possible. Some studies focus on a specific type of facility, such as a building or a room. Design of bottlenecks considers the optimal lay-out that maximises flow or minimises egress time. Crowd management decides on control policies to ensure the safety and comfort of people at mass-crowd events. In timetabling, the problem is to minimise people flows resulting from the timing and location of events. . . . 36
2.6 Objective function measure and problem type. . . . 37
2.7 Decisions considered and problem type. . . . 38
2.8 Parameters for speed-density and flow-density relationship from literature. . . . 39
2.9 Model Realism . . . 41
2.10 Modelling and solution techniques . . . 47

3.1 Embedding static network into grids with time-step = 7 secs . . . 56

4.1 Notations and Parameters . . . 63
4.2 Pedestrian free flow velocity. . . . 71
4.3 Arc widths of the street networks . . . 73
4.4 Optimal staging of flow units at source cells – base case . . . 75
4.5 Optimal distribution of flow units for source cell connectors – base case . . . 76

5.1 Additional Parameters . . . 94
5.2 Model size comparison . . . 97
5.3 Comparison of model performance . . . 98

6.1 Possible parameters for all nodes for each party . . . 109
6.2 Results of the comparative analysis performed of Figure 6.5 . . . 111

Nomenclature

δ_i^t The ratio $\frac{w}{v}$:= The traffic flow parameter for cell i at time t

$\hat{y}_i$ Initial occupancy of cell i

$\lambda_{ij} = \lambda_{ji}$ The travel time, i.e. the time needed to travel from node i to node j.

$\mathfrak{T}$ Set of discrete time intervals $T = \{0, 1, \cdots, \tau\}$

c_{ij} The capacity of the connector between cell i and cell j: this is the maximum nominal amount of people that can traverse the passage in the unit time.

n_i The maximum nominal capacity of cell i

q_i Total number of evacuees to be evacuated from cell i

$Q_i^t = Q_i$ The maximum number of people that can pass in and/or out of cell i at time t

$x_{i(k,k+1)}^t$ An auxiliary flow which displays the number of people moving from sub-cell k to subcell $k+1$ in cell i at time step t

x_{ij}^t The flow of people from cell i to adjacent cell j in the time $(t, t+1]$. This gives the average speed at which pedestrian move from cell i to cell j.

y_i^t The state of cell i at time t i.e the number of persons contained in cell i at time t, in particular, $\sum_i q_i \leq n_0$.

z_i^{t+1} Flows from node i at time t to the same node with travel time $\lambda_{ii} = 1$ represent the number of evacuees who prefer to stay in node i at time t for at least one unit time.

0 A collection of all the sink nodes of graph G or the super-sink node

D Set of sink/destination nodes in graph G

S Set of source nodes of graph G

V Set of nodes or cells of graph G

v Free-flow walking velocity.

w Backward propagation of speed

Acronyms

CA Cellular Automata

CCG Capacity Constrained Graph

CRED Center for Research on the Epidemiology of Disasters

CTM Cell Transmission Model

DEAF Dynamic Earliest Arrival Flow

DM Disaster Management

DSO Dynamic System Optimal

DTA Dynamic Traffic Assignment

DUE Dynamic User Equilibrium

DyCTEP Dynamic Cell-Transmission Evacuation Planning

EAF Earliest Arrival Flow

EM-DAT Emergency Events Database

EMA Emergency Management Agencies

ERP Evacuation Route Planning

FEMA The US Federal Emergency Management Agency

GIS Geographical Information System

IFRC The International Federation of Red Cross and Red Crescent Societies

NFPA National Fire Protection Association

NTC Network Transformation and Conversion

OOP Object Oriented Programming

PMP-CCRP Priority Multi-Party Capacity Constraint Route Planning

SCIE Science Citation Index Expanded

SO-DTA System Optimum Dynamic Traffic Assignment

SSCI Social Science Citation Index

TEG Time Expanded Graph

UN-ISDR United Nations Internationals Strategy for Disaster Reduction

WHO World Health Organization

WOS Web of Science

Chapter 1

Introduction

1.1 Background

Every day, natural or artificial (that is, technological) disasters, all around the world fill the reports of newspapers, radio, TV and other media. Over the past three decades, the number of reported disasters has risen more than threefold. Roughly, five billion people have been affected by disasters in this period, with an estimated damages of about 1.28 trillion dollars [115]. Although most of these disasters could not have been avoided, a significant relief in death counts and property losses could have been made by an efficient distribution of supplies and services: by this term we here mean – for example – personnel, medicine, food and all sort of resources and actions which play a critical role in emergency situations. The supply chains involved in providing emergency services in the wake of a disaster are referred to as humanitarian relief supply chains. Humanitarian relief supply chains are formed within short time period after a disaster with the government and the NGO's being the major drivers of the supply chain. Supranational organisations typically define disaster according to their line of work. For the World Health Organization (WHO), a disaster is an occurrence disrupting the normal conditions of existence and causing a level of suffering that exceeds the capacity of adjustment of the affected community [368]. According to the United Nations Internationals Strategy for Disaster Reduction (UN-ISDR), a disaster is "a serious disruption in the functioning of the community or a society causing wide spread material, economical, social and environmental losses that exceed the ability of affected society to cope using its own resources [241]." The The International Federation of Red Cross and Red Crescent Societies (IFRC) [159] defines a disaster as a natural or man-made phenomenon such as a hurricane, earthquake, flood, nuclear accident and terrorist attack which disrupts the functioning of a community in such a way that the widespread losses incurred exceed the community's capacity to cope with it. IFRC [159] defines disaster management as the organization and management of resources and responsibilities for dealing with all humanitarian aspects of emergencies, in particular preparedness, response and recovery in order to lessen the impact of disasters. Gunns [117] focuses more on causes than on consequences, and defines a disaster as the result of a vast ecological breakdown in the relations between man and environment. Three conditions should occur in an event to render it a disaster: it must disrupt the normal conditions of life, exceed the local capacity of recovery, and affect a relevant amount of people (without people, there would be no disaster but just a physical phenomenon [368]).

Every year, more than 500 disasters are estimated to strike our planet, killing around 75,000 people and impacting more than 200 million others [356]. Among recent disasters, either natural (earthquakes, volcanic eruptions, landslides, floods, tsunamis, hurricanes, typhoons) or provoked by man (terrorist attacks, chemical or nuclear leakages etc.), the most remarkable losses were recorded in: the earthquakes of Nepal (April 2015), Japan (March 2011), Haiti (January 2010), Chichi (Taiwan, September 1999), Bam (Iran, December 2003), Kashmir (Pakistan, October 2005), and Chile (May 1960); various tsunamis in Japan and the Indian Ocean; the major hurricanes Katrina, Rita, and Sandy in the US; and the 9/11 attacks in US [281]. Recent examples are the Australian bushfires [2, 277] killing at least 34 people between June 2019 and May 2020; Hurricane Eta, November 2020, killing at least 150 people in Central America [5, 6]; flash floods killing more than 150 people in Afghanistan in August 2020 [4, 116]; earthquake and tsunami killing a total of 117 people in Greece and Turkey in October 2020 [3] (not to mention animals). These and many more examples identify the need for developing good crowd management and *emergency evacuation procedures*.

A disaster is the result of a vast ecological breakdown in the relations between man and his environment [117]. It can be both natural (earthquakes, floods, hurricanes) and man-made (terrorist attacks, chemical leakages). Disasters result in massive demands that often exceed resources. The process of planning, managing, and controlling the flow of those resources to provide relief to affected people is called emergency logistics [316]. However, the systematic planning of emergency logistics is oftentimes neglected. Fritz Institute [91] observed that logistics planning during the 2004 Indian Ocean tsunami was conducted manually without the presence of logistics experts. As of today, the situation remains unchanged and the 2010 Haiti earthquake provides an excellent example of this lack of expert planning. In January 2010, after the first seismic shocks in Haiti, various on-field journalists [28, 129, 136, 257] reported that relief efforts were stalling in the logistics web and that, therefore, much aid remained undelivered.

Disaster Management (DM) aims at reducing, or possibly avoiding, potential losses from hazards, and at assuring prompt and appropriate assistance to the victims. According to Mansourian [244], DM can be undertaken by operations that include *preparedness*, *response*, *recovery*, and *mitigation* as shown in Figure 1.1. *Preparedness* encompasses all the planning activities performed by various Government organizations, NGO's, businesses and other national and international organizations to quickly respond to disaster, in anticipation of its occurrence. *Response* refers to the immediate activities and efforts which seek to address the immediate and short term effects of disaster, focusing primarily on the actions necessary to save lives and protect properties, e.g.: efforts to minimize hazards induced by the disaster, rescue and relief operations, fire fighting, medical aids, shelters, evacuation, law enforcement and security. *Recovery* indicates all those activities (like reconstruction of buildings, exemption in taxes and long term medical care/counseling) which brings back the community to its normal condition. Along with prevention, *mitigation* requires all those activities that minimize the effects of the disaster, for example building codes and zoning, vulnerability analysis and public education [190].

There are four phases of an adequate disaster management program: mitigation, preparedness, response and recovery [39, 40, 112, 247]. The US Federal Emergency Management Agency (FEMA) [112], Bullock and Haddow [39], Altay and Green [17] and Bumgarner [40] list the typical activities involved in these phases and Caunhye et al.[46] summarize the framework for the emergency logistics activities. To protect people from the possible impact of a disaster, the foremost used strategy is the evacuation of the disaster region [144]. Evacuation planning and management are included in the preparedness and response phases of disaster management activities respectively (Figure 1.1). In the literature, facility location, pre-positioning of recovery stocks and short-notice evacuation are drafted as the main pre-disaster operations, while relief distribution and casualty transportation are categorized as post-disaster. According to this categorization, the operation timeline is structured into three main parts: facility location, relief distribution and casualty transportation (see Figure 1.1). In particular, *pre-disaster operations* are carried out prior to disaster occurrence and play an instrumental role in strategic planning (facility location and stock pre-positioning) or disaster mitigation (evacuation); *post-disaster operations* are done after disaster occurrence and serve to react to disaster impacts.

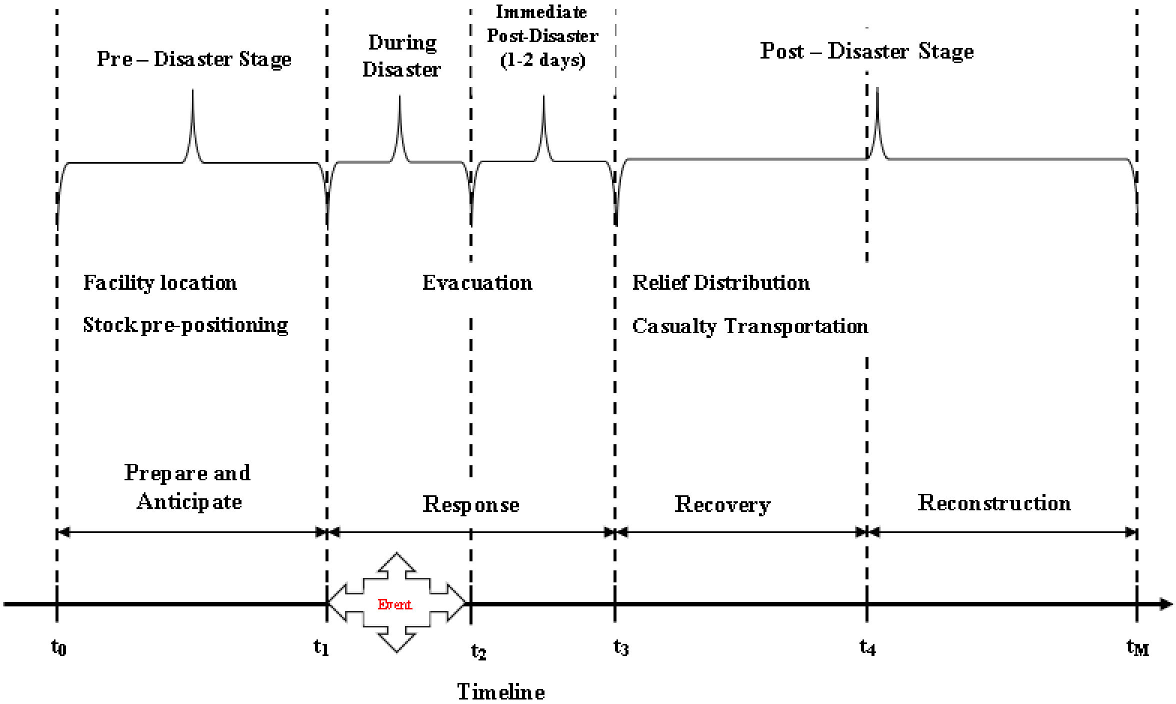


Figure 1.1: Timeline for the various operations performed before and after disasters.

1.2 Motivating Scenario: Disaster Management

Almost all of us have sometimes found ourselves in a situation where a large number of people gathered together in a particular place: spectators at concerts or sports events, students in school premises, commuters in railway and metro stations, employees in large office buildings. To ensure people safety and comfort, not only a careful design of pedestrian facilities is required, but also effective strategies for crowd management. In particular, strategies for an efficient facility evacuation are of paramount importance in case of emergency, be it natural (earthquakes, tsunamis, hurricanes) or caused by human activities (fire, gas leak, bomb threat etc.). The study of pedestrian and evacuation dynamics is very complex, especially due to the nonlinear interactions among the (large) number of people involved. Those interactions also include, in general, hardly predictable psychological factors influencing human behavior, and also such external factors as the layout of pedestrian passageways is to be taken into account.

The Center for Research on the Epidemiology of Disasters (CRED) [1] has kept the record all international emergency disaster database since 1900 in which various governments and international organisations had to declare the state of emergency. Table 1.1 reports the occurrences of disasters, both natural and technological, for European countries from 1990 to 2022. In the Emergency Events Database (EM-DAT), the natural disaster listed include but not limited to wildfire, earthquake, volcano, flood, landslide and storm while the technological disasters include: industrial explosion, collapse, explosion, fire, transportation disasters (air, rail, road and water) and other miscellaneous disasters. The columns of Table 1.1 reports on the number of occurrences of each of the two disaster categories, together with the total number of affected people and total deaths recorded for every country through the year.

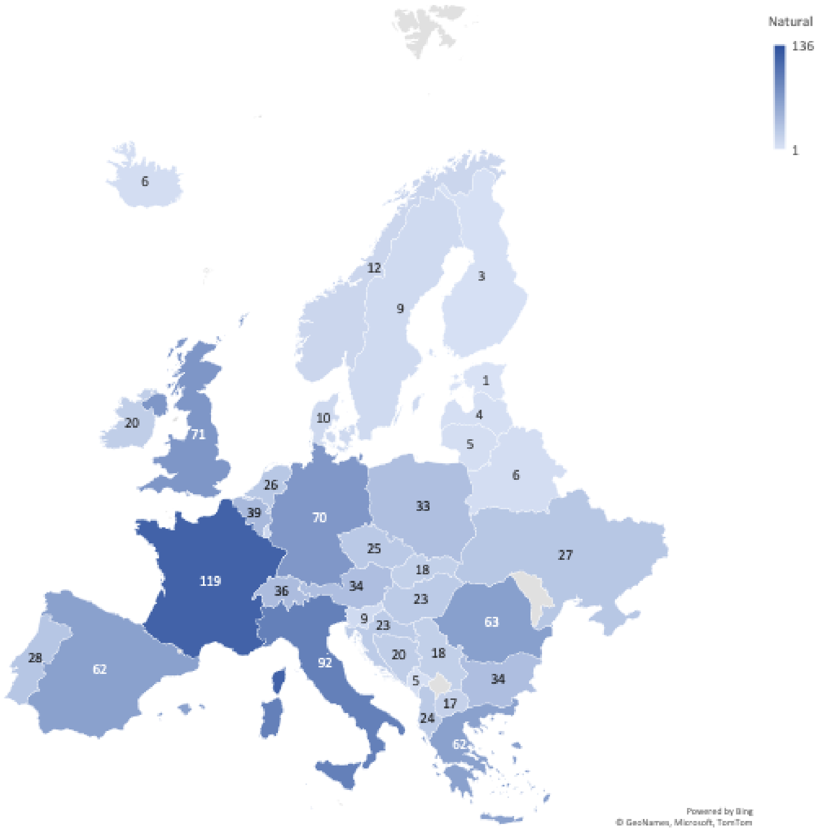


Figure 1.2: Geographical representation of natural disaster occurrences for various European countries.

Figures 1.2 and 1.3 is the overview of the geographical presentation of occurrences of natural and technological disasters respectively in the EU zone. From Figure 1.2, The Federal Republic of Russia and France recorded the highest occurrences of natural disasters in the time span respectively

Table 1.1: Global (European) Occurrences from Disasters (Natural and Technological from 1990 - 2022)

Country	Natural	Tech.	Natural: Affected People	Natural: Total Deaths	Tech: Affected People	Tech: Total Deaths
Albania	24	6	940820	82	10357	140
Austria	34	7	72246	121	229	284
Azores Islands	3	1	1215	39	1011	35
Belarus	6	2	113390	7	109	85
Belgium	39	12	7903	89	719	151
Bosnia and Herzegovina	20	3	1596592	40	11	67
Bulgaria	34	6	67945	96	71	129
Canary Is	6	7	8023	42	72	129
Croatia	23	5	249467	28	100	131
Czech Republic	25	7	1626170	117	149	112
Denmark	10	3	2000	15	2172	1
Estonia	1	3	100	26	170	944
Finland	3	2	400	78	48	35
France	119	45	4123871	637	21727	847
Germany	70	36	577431	503	2575	501
Greece	62	42	280096	497	4426	1375
Hungary	23	11	406263	66	7388	200
Iceland	6	2	282	34	200	29
Ireland	20	2	4900	24	700	29
Italy	92	68	294323	1249	4953	2748
Latvia	4	1	1040	6	29	54
Lithuania	5	2	780000	12	700007	35
Luxembourg	11	1	1519	15	2001	20
Macedonia	17	8	1335026	35	89	433
Moldova	9	10	2677537	64	31	434
Montenegro	5	1	8086	59	30	11
Netherlands	26	2	265125	40	832	13
Norway	12	16	7860	16	3362	237
Poland	33	10	358887	217	42	460
Portugal	28	16	163994	258	621	307
Romania	63	10	415192	506	232	258
Russia	136	17	2909869	3670	219	325
Serbia	18	232	132768	60	10049	6484
Serbia	12	10	134260	15	705	171
Slovakia	18	7	59569	76	284	89
Slovenia	9	2	18405	11	17509	13
Soviet Union	16	13	346216	434	168	350
Spain	62	48	56246	382	49229	1066
Sweden	9	3	13500	19	184	76
Switzerland	36	11	7712	95	5220	172
Ukraine	27	56	2756684	128	10636	1454
United Kingdom	71	30	767132	323	4157	363

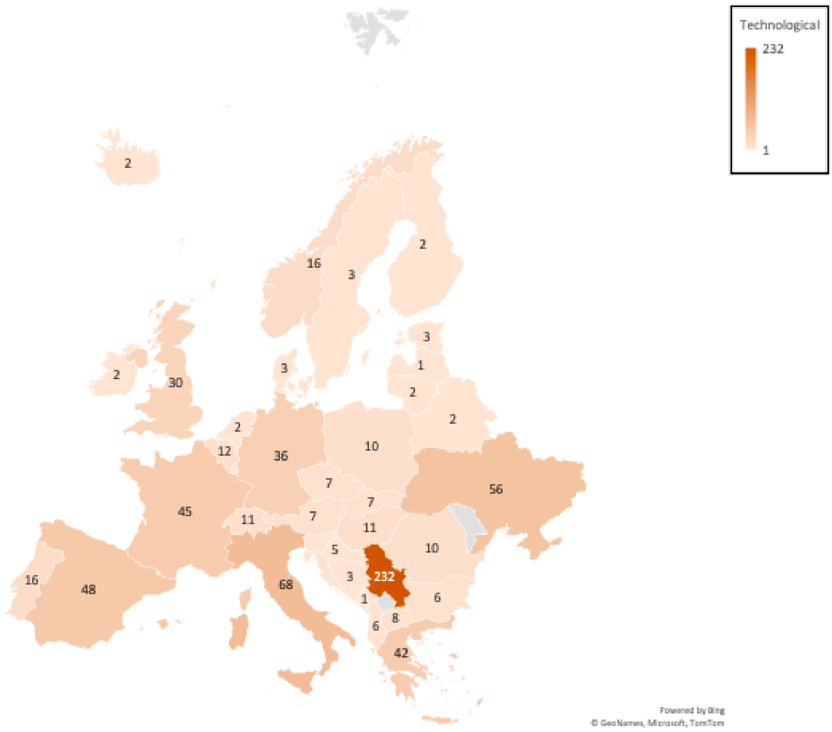


Figure 1.3: Geographical representation of technological disaster occurrences for various European countries.

with total records of 136 and 119 disasters, which resulted in 2,909,869 people been affected in Russia killing 3690 people. In the case of France 4,123,871 people were affected of which 637 died. Similarly, Figure 1.3 reports the technological disasters with Serbia and Italy recording the highest cases. Which affected a total of 10049 people in Serbia of which 6484 people died. Table 1.2 and Figure 1.4 gives an overview of the summary of occurrences of disasters based on the disaster category and the type. Relatively limited in space, yet mostly concentrated on an urban area, the 2009 L'Aquila earthquake (Italy) unveiled unprecedented challenges for logistics planners. The earthquake caused vast damages to the town and to its infrastructures, which crumbled, and existing emergency response systems were destroyed. This resulted in a very grim situation: besides 309 casualties [16], approximately 1,500 people were injured and over 65,000 lose their homes [149].

1.3 Problem Statement

Understanding how the flow and evacuation of crowds can be safely facilitated is important to growing cities worldwide. Urban populations are increasing faster than ever and mass gatherings are becoming more frequent [328]. Knowing how to facilitate the flow and discharge of people in crowded spaces is an essential element in ensuring public safety. Facilitation of crowd flows becomes of far greater significance in cases of crises and emergencies where the ability to rapidly discharge a crowd can mean the difference between life and survival. From this perspective, evacuation preparedness is of utmost importance to public safety.

Unpredictability and the uncertain nature of disasters are the key challenges of designing emergency

Table 1.2: Summary of disasters in Italy from 1990 to 2022 based on Disaster category and type

Disaster Group	Disaster Type	Total Deaths	Total people affected	Count
Natural	Wildfire	14	11900	7
	Earthquake	714	165721	16
	Volcano	28	7328	3
	Flood	256	99519	40
	Landslide	171	11624	6
	Storm	94	5731	20
Technological	Industrial-explosion	10	590	1
	Collapse	132	696	3
	Explosion	27	7	1
	Fire	30	7	2
	Other	34	1500	3
	Transport-air	195	293	4
	Transport-rail	99	470	7
	Transport-road	166	550	11
	Transport-water	2055	1430	36

evacuation plans. Evacuation can be mandatory, recommended or voluntary; besides, it may differ by scale, objects of relocation, and levels of control by the authorities. Evacuation plan is very essential and very necessary for those areas which are highly vulnerable and susceptible to disasters. An emergency evacuation plan assigns evacuees to fixed routes and directions before the disaster, and defines evacuation policies for the occupants of areas subject to the risk of a disaster [42]. Disaster operations can be performed before or after disaster occurrence, and emergency logistics consists of the process of planning, managing, and controlling the flow of resources to provide relief to the people affected. Its planning presents key challenges that do not normally occur in ordinary business logistics [316]. Kovács, Spens et. al [188], stress that the importance of logistics is quite underestimated in pre- and post-disaster operation, being that the relevant organizations typically more concerned with fundraising. Still, a large number of researches addressed those challenges via statistical or probabilistic models [64, 377], queuing theory [25], simulation [155, 286], decision theory [66, 335], fuzzy methods [85, 165], and most commonly, optimization models and algorithms. Optimization modeling has become a powerful tool to tackle emergency logistics problems since its first adoption in maritime disaster situations in the 1970s [30]. The Fritz Institute [91] reported that logistics planning during the 2004 Indian Ocean tsunami was conducted with no computer support and without the presence of logistics experts. Systematic plans of emergency logistics are however very often neglected. The persisting threat of disasters of this type results in a massive safety demand that, however, unfortunately exceeds the resources available to make houses and infrastructures intrinsically safe: therefore, effective emergency plans to cope with disasters will continue to be a need worldwide. Also, most impacts of catastrophes can be mitigated by planning in advance and adopting specific measures of disaster management [15].

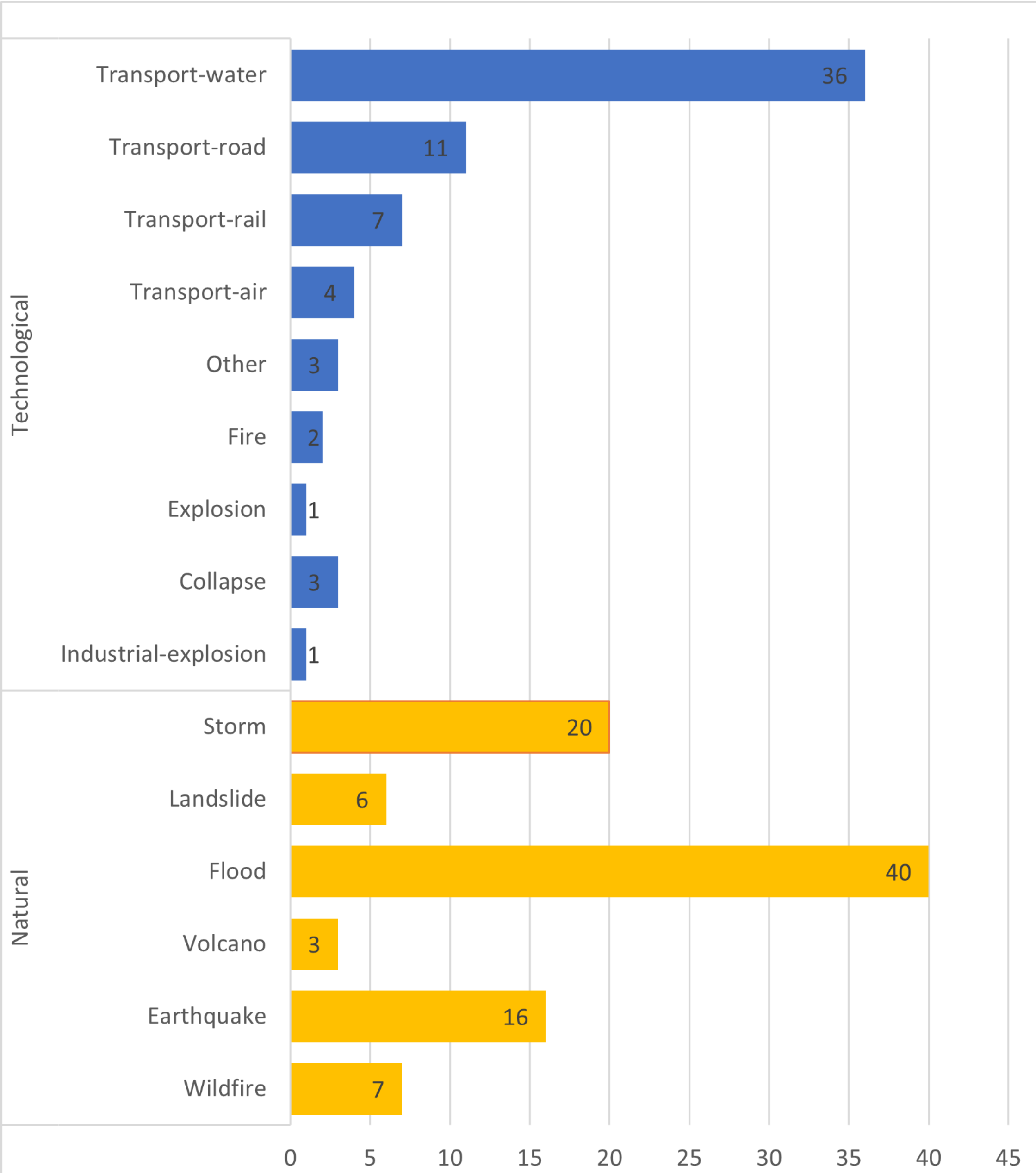


Figure 1.4: A summary of the occurrences of disasters in Italy from 1990 to 2022 based.

There can never be a way that we can avoid the possibility of disasters striking our planet. But there can be a way or a strategy with which we can reduce the impact of such disasters. A proper emergency evacuation planning and operation is the key in minimizing the impact and saving people's lives and properties. Due to the exceedingly "abnormal demands" at a given city road network during disasters, this generates bottlenecks at intersections followed by queues of evacuees and freezes the traffic flow on links. Hence, it becomes crucial to have a proper planning and operation strategy in advance to mitigate the impact of such disasters. System optimal time, entry queue time, network clearance time, optimal flow-staging at origins, optimal flow distribution at intersections, optimal routes followed by the evacuees and optimal destinations are the major decisions that dictates the efficiency of an evacuation operation during an extreme event. Network

Optimisation and Transportation researchers have developed some models that analyses the impact of such high demand. However such models have not been efficient enough to give optimum solutions which could be the reliable basis for planners to make decisions during the extreme events. Thus, there is a need for the efficient evacuation model that solves the problems related to evacuation.

1.4 Research Scope/ Objective

An emergency evacuation plan is developed by consecutive steps, simulation and revision carried out following domain-specific rules. Basic steps require the definition: of safe areas at nearby locations, of safe routes to reach those areas, and of a correct partition of the evacuees proceeding to safe areas. Modeling the plan is a formal process that starts from all the relevant documents (population and census, maps, regulations etc.) and ends up with structured data and software tools to access and use them. In an emergency management information system, one of the key research objects obviously consists of the event itself. According to the $5W$ principle (When, Where, Who, What, hoW), event-related information contains time, place, features, task, and estimated resource needs. Pre-arranged emergency plans contain these five information types, formulated by emergency response units of whatever kind. The emergency management information system has to meet the issue of data abstraction, reflecting in this way the special nature of all the emergency units involved [376]. Designing an evacuation plan should then envisage the following actions:

- *Determination of safe areas.* There are two ways to find out safe areas in a city. One way is to take advantage of the ones built in the GIS file(s) of land use. Another way is to use satellite imagery. For a planned city, the former method is more efficient than the latter because land utilization (mapped by organizations like transportation, municipalities) is already known.

- *Determination of paths.* A most important design action in the definition of an evacuation plan is to find out the safest (not necessarily the shortest paths) for providing the routes to evacuate people from the danger zones to the safe locations.

- *Ramification of people.* Disaster management authority, police, army, and other government or non-government organization that works either voluntarily or non-voluntarily during disasters can provide better humanitarian services provided they have a good coordination and synchronization according to the situation. Prior to evacuation, gather all the information about the capacity of crowd, census data of inhabitants and exit points of incident area so that easy ramification of people could take place. Disaster managers command all the organizations working in search and rescue operation and make co-ordination among them. Soldiers and volunteers take the instructions from disaster managers and help evacuees by indicating towards the safe areas and by helping them to evacuate. There is no certain rule or algorithm which is applicable in efficient and effective distribution of people because the moment when disaster triggers it creates havoc at that place. So ramification of people should be done by accurate analysis and inspection of situation.

In this dissertation, we focus on developing new techniques and framework for an automated emergency evacuation operations and planning that deals with optimising the flow of people and maximising safety thereby ensuring reducing in the lost of lives and properties. We limit ourselves to three main objective functions measurements that are common in literature (see Chapter 2) and the most relevant for our problem settings using the Cell Transmission Model (CTM) proposed by Carlos F. Daganzo [71, 72] .

1. The first objective function concerns the minimisation of network clearance time using the dynamic network generated in Chapter 3. We then propose the Dynamic Cell Transmission Evacuation Planning model (DyCTEP), a modification of CTM, to incorporate city-level networks under extreme and undesirable conditions. The formulation of DyCTEP model allows its use as a practical tool to dynamically approach pedestrian emergency evacuation, providing an optimal solution in terms of destinations, route, time, flow-staging and flow distributions. The model also approximates non-linear arc capacities to manage congestion phenomena. We also propose a heuristic algorithm for optimal route assignment that takes into consideration the entire time-dynamics of optimal solutions.

2. A second objective function attempts at measuring how safe is the evacuation plan. Since embedding the spatial network into the CTM network generated results in an exponential size of the spatial network, a new network (see Chapter 5), Time Expanded Graph (TEG), is generated using arc travel times. We then minimize the evacuation (or egress) time, that is the time taken for the last person to be brought to safety. Two additional modifications of the models are also formulated.

3. Finally, a third objective is to safely migrate most of the people (in a multi-party scenario, that is, including both evacuees and responders) to one or more safe locations while minimizing the total egress time. This is achieved by a scalable Dijkstra's algorithm with weight criteria indicating node priorities and edge travel times.

1.5 Contribution

The main contribution of this work is the advancement of mathematical optimisation modelling of dynamic network flows in a no-notice or short-notice large scale pedestrian emergency evacuation. The proposed cell transmission based system optimal linear evacuation model has become a bridge to link with the mathematical linear optimization world and thus use the advance solvers developed so far in getting global optimal solutions. The development of the network conversion technique (in Chapter 3) is useful to generate cell network of any large scale real network. The proposed approach the adaptation of the dynamic optimization model developed by Arbib et al. [23] to outdoor scenarios, that calculates the safest paths citizens should follow to reach pre-identified safe locations. While the network is computed off-line at design time, the optimization model, or one of its reductions, can be embedded in a real-time system that, recomputing it several times, can guide citizen after a natural disaster even in case of high dynamic scenario. Also, the dynamic model is then validated on a real case study. Different experiments were carried out to analyse the trade-off between the number of safe places and the total evacuation time. Based on the dynamics of the resulting optimal solution, a heuristic was then developed to generate a set of paths for evacuees with certain attributes to follow from the danger zone to the safe locations.

We also proposed and implemented three new approaches, namely Dynamic Earliest Arrival Flow (DEAF), Extended CTM and the Multiple Cells Approaches (see Chapter 5) to cope with the inconveniences associated with the Dynamic Cell-Transmission-based Evacuation Planning (DyCTEP) model in the sense that, usage of cells with fixed single size may lead to a too many number of cells (imply an excessive number of constraints and variables in the optimization model), unnecessary to meet the required level of network and operation accuracy which may turn out to be unpractical for real use.

We developed the network transformation and conversion (NTC) model to convert any sized node-arc network into the cell network. The NTC model enabled the application of all the different model formulations to large-scale real-world networks for SO-DTA analysis employing cell transmission models. The feasibility and applicability of the modelling procedures was tested on large-scale real-life networks, and the customisation of these models with several parameters in literature to reflect reality.

We proposed an approach which provides a better total egress time for multiple parties emergency evacuation taking into consideration node priorities in the underlying network. Moreover, because almost all arrangements of evacuee and rescuer source and destination overlaps are possible, such as rescuers and evacuees sharing the same source location, or evacuees having the same destination as a rescuers' source and vice versa, additional precautions are necessary to ensure that fictitious paths that backtrack down one party sub-source and up another that provide a teleportation-like behavior across the real transportation network are not utilized. Such an approach will be the core engine of a novel smart city service that is able to guide evacuees and rescuers after a disaster to bring safely as much people as possible out the risky places. The service must be fed by real-time information (which roads are safe enough, which are damaged by the disaster, how many people are in a specific area, and so on). Starting from our proposed algorithm, we are able to specify, design and implement a smart city infrastructure and connected mobile app able to collect all the needed data. These together with the proposed algorithm will realize the rescue and evacuation service for smart cities of the future.

1.6 Thesis Outline

Each of the three main research scopes listed above constitute a chapter which has its own introduction, modeling framework, method, application and conclusion and stand independently on its own. The thesis contains seven (7) chapters.

The background of the study is given in Chapter 1.

Chapter 2 provides a review of optimisation models for pedestrian evacuation and design problems. It starts with the classification of different articles based on the problem type, objective function

measures, and decisions that are considered. Then, there is a discussion on the relevant empirical research and their implications for modelling pedestrian evacuation behaviour. Finally, we compare modelling techniques used in optimisation models with techniques used in descriptive models.
Chapter 3 deals with the conversion and generation of static networks into dynamic networks using the CTM.
Chapter 4 focuses on the adaptation of the dynamic optimization model developed by Arbib et al. [23] to outdoor scenarios, that calculates the safest paths citizens should follow to reach pre-identified safe locations. The model takes into account the congestion, that will approximate the non-linearity of the arc capacities. This in turn affected the speed the system empties modelled as a decreasing function of the cell occupancy. Then, we aimed to make a trade-off analysis between the number of safe places and the total evacuation time. Finally, a heuristic was developed to help generate a set of paths for pedestrians to follow from the danger region to the safe locations. Two articles based on this chapter have been published as: *Definition of an enriched GIS network for evacuation planning* [154] and *Toward Effective Response to Natural Disasters: a Data Science Approach* [252].
Chapter 5 focuses on handling the weakness (that is, the exponential size of the resulting network after embedding the it into elementary cells to meet network requirements and operational accuracy) of the dynamic optimisation model discussed in previous chapter by proposing three approaches to cope with this weakness.
Chapter 6 uses a heuristics approach based on the capacity constrained route planning (CCRP) to proposes a scalable algorithm, called priority multi-party capacity constrained route planning (mpccrp) to safely migrate maximum evacuees, in a multi-party scenario, to a set of safe locations while minimizing the total egress time using a modified Dijkstra's algorithm with weight criteria as the node priorities and edge travel times. The goal of the proposed approach is to estimate the total evacuation time for multiple parties involved in an emergency evacuation process, where each of these parties have separate objectives such that, evacuees may start from a source in danger and migrate to a safe location while inversely rescuers may start anywhere with the goal to migrate to a destination in danger. An article based on this chapter has was presented at a conference as: *Towards an Emergency Evacuation Planning Service* [153].
Finally, in Chapter 7, we conclude this dissertation with summary and future research directions.

Chapter 2

Pedestrian Emergency Evacuation Models: A State of the Art

2.1 Introduction

In recent times, unexpected emergencies have occurred frequently around the world. In addition to traditional emergencies caused by natural disasters such as hurricanes, earthquakes and floods, new types of events such as terrorist attacks, stampedes and fires are also emerging; these catastrophic events have caused great harm to mankind, human life and property, and other losses are incalculable [105]. Examples of which include the "9/11" (United States) terrorist attacks in the in 2001 [220], the 2004 Indian Ocean tsunami [246], the 2005 Hurricane Katrina (US) [134], the 2006 Hajj pilgrimage stampede in Mecca [322], the 2008 Wenchuan (China) earthquake [383] and the 2010 Fukushima nuclear power plant leakage caused by the earthquake in Japan [237]. The increasing losses caused by various disastrous events to human society, illustrates the need for developing good crowd management and emergency evacuation procedures. In the event of a disaster, emergency evacuation is a process of rapidly evacuating people from danger zones to safe locations [169]. Although the impact of a sudden event may be small at the beginning of the event, if the situation spreads, it is likely to cause greater impact and casualties. Therefore, it is extremely necessary to evacuate people in the area immediately after an emergency [83]. Emergency evacuation research is a complex and systematic problem involving personnel behavior and organization, traffic management and control, rescue response and logistics support, etc. [223, 255]. Effective emergency evacuation is of great significance for mitigating disaster or accident losses and ensuring the safety of people's lives and property [369]. Undoubtedly, emergency evacuation is an interdisciplinary scientific problem in engineering, operational research, transportation and social sciences [271, 338]. At present, scholars have contributed abundant research in the field of emergency evacuation. The existing research mainly involved pedestrian evacuation models, group simulation technology, intelligent evacuation management systems and emergency evacuation planning. In recent years, most scholars have proposed pedestrian evacuation models that including pedestrian dynamics, paying more attention to the calibration and implementation of models [358].

The study of pedestrian and evacuation dynamics is very complex, due to the large number of people involved and the non-linear interactions between them, psychological factors influencing human behaviour, and the influence of external factors such as the layout of a pedestrian facility. As a consequence, the topic has received attention from researchers in different fields, including psychologists, sociologists, physicists, computer scientists, and traffic scientists [140]. Four distinct, yet interrelated, research streams can be distinguished. The first stream focuses on the empirical study of pedestrian behaviour and crowd dynamics, whilst the second is concerned with the development of mathematical models to describe the movement and interactions of pedestrians as realistically as possible [342]. The third focuses mainly on simulation-based approaches which integrates microscopic crowd-simulation methods that models the behaviour of each individual person from which collective behaviours can then emerge [355]. Finally, the fourth stream of research uses an optimisation-based methodology to develop models which determine optimal evacuation plans or design solutions [9]. Most of the research falls under the first three categories. Several review articles discuss the empirical research on and modelling of pedestrian and evacuation dynamics. Schadschneider et al. [297, 300] provide a summary of the empirical studies and theoretical modelling that has been done and give two examples of possible applications of this research. Helbing and Johansson [140] give a similar overview, and additionally discuss research into situations of panic and critical crowd conditions. Schadschneider and Seyfried [299] investigate the quantitative data on pedestrian dynamics for the calibration of evacuation models. They focus on the fundamental diagram,i.e. the density-dependence of the flow or density (see Section 2.6.1) and consider the implications for cellular automata models (see Section 2.6.2). Papadimitriou et al. [266] assess two different topics of research, namely route choice models and crossing behaviour models, which study how pedestrians cross the street under different traffic conditions. Gwynne et al. [120] classify 22 evacuation models based on the nature of the model application, the enclosure representation (that is, how the building is or the representation of the area been analysed in the model), the population perspective (that is, are the agents modelled as separate entities or are the modelled together and described using average quantities), and the behavioural perspective (that is, what assumptions and rules are used to describe the behaviour of pedestrians). Zheng et al. [403] distinguish seven methodological approaches: cellular automata, lattice-gas, social-force, fluid dynamics, agent-based, game-theoretic models, and experiments with animals. (An overview of these approaches in is given in Section 2.4.) They also look at the possibility of modelling heterogeneous individuals, the scale of representation, whether time and space are discrete or continuous, whether a normal or an emergency situation is assumed, and the typical phenomena that the model can represent. Additionally, Duives et al. [82] identify eight motion base cases and six self-organising crowd phenomena which a simulation model should be able to reproduce. Furthermore, they look at ten other model characteristics, such as the ability to simulate pressure in crowds and the computational requirements of the model, in order to assess the models' applicability. Their classification distinguishes between cellular automata, social-force, activity-choice, velocity-based, continuum, hybrid, behavioural, and network models. Vermuyten et al. [358] reviewed the use of optimisation models for pedestrian evacuation and design problems including pedestrian dynamics, paying more attention to the calibration and implementation of models. Van Toll and Pettre [355] analyzed how the research on microscopic crowd simulation has advanced since the year 2010, focusing on the most popular research area within the microscopic paradigm, which is local navigation, and most notably collision avoidance between agents. They also discussed the four most popular categories of algorithms in the area (force-based, velocity-based, vision-based, and data-driven). Haghani's [122, 123] work on the systematic review of optimisation methods for pedestrian evacuations focuses is on interventional approaches that seek to improve evacuation efficiency rather than efforts to purely describe/predict evacuations. Three major evacuation optimisation approaches are identified: architectural design and infrastructure adjustment, mathematical programming and optimisation of path/departure-schedule planning and behavioural modification, training and active instructions. Dong et al. [79] reviewed pedestrian and evacuation dynamics so as to comprehensively understand the motion behaviors of pedestrians from observations to simulation aspects. Shiwakoti et al. [323] investigated the performance of an obstacle near an exit and found that although there is a general consensus on the beneficial effect of an obstacle, there is a large uncertainty on the situations on which the positive effect of obstacle could be observed. Stating that there is no clear established relationship between the exit width, obstacle distance and obstacle size/shape. Chen et al. [54] proposed a social force modelling framework in terms of assessment criteria for pedestrian models considering pedestrian attributes, motion base cases, self-organisation phenomena presented from the perspectives of description ability, parameter calibration and flexible application in a complex environment. Gao-qi et al. [135] addressed two concerns: What are the intrinsic reasons behind human behavior? How do we model and exhibit human behavior? Spearpoint and MacLennan [329] examined the possible effects of gender, age and obesity and uses a Monte Carlo network evacuation model to examine whether these changes will significantly increase the total evacuation time from an exemplar high-rise building. Yuan et. al. [388] presented an approach that integrates both network approaches for efficient and detailed assessment of evacuation in large and complex buildings. Stanton and Wanless [330] considered a number of factors affecting the flow of pedestrians, and reviews the available data for the appraisal of existing facilities and the design of new facilities. Kalakou and Moura [173] present a general overview of models from different research areas to analyse the design of pedestrian facilities, whilst Lee et al. [196] focus on models for the evacuation of ships. Finally, Bellomo et al. [31] focus on the mathematical properties of models for pedestrian behaviour. The fourth category of research has received less attention in the literature. Moreover, to the best of our knowledge, the works of Hamacher and Tjandra [131] and Vermuyten et al. [358] are the only review that focuses on optimisation models for evacuation problems. However, most of the models they discuss are network models with constant (i.e. density-independent) travel times.

2.2 Data Source

We first searched for literature reviews and articles that discuss general topics related to pedestrian dynamics or evacuation and design problems from the overview articles above [31, 54, 79, 82, 120,

Table 2.1: Types of retrieved documents in pedestrian emergency evacuation studies.

Rank	Type of document	Frequency	Proportion
1	Article	252	64.45012788
2	Proceedings Paper	85	21.73913043
3	Review	31	7.928388747
4	Meeting Abstract	15	3.836317136
5	Editorial Material	8	2.046035806
Total		391	100

122, 123, 131, 140, 173, 196, 266, 299, 323, 324, 329, 330, 355, 358, 388, 403] and checked the references therein. Next, we used the Web of Science (WOS) database to find relevant articles. We used combinations of the keywords "optimisation", "problem", "evacuation", "pedestrian", "crowd", "model", "movement", and "flow" and "not vehicle". No a-priori cut-off date was used, since no previous review articles exist that follow our perspective, apart from the works of Hamacher and Tjandra [131] and Vermuyten et al. [358]. Articles on the traffic assignment problem and articles on evacuation and design problems which do not focus on pedestrian traffic and crowd dynamics, are not included, also the category of medical surgery was removed from the search, so that the search is designed to collect more accurate data. This resulted in a broad, but not exhaustive, overview of the current literature on optimisation models for crowd and evacuation dynamics. The data was retrieved from the core collection database in the WOS comprehensive bibliographic database, including Science Citation Index Expanded (SCIE), Social Science Citation Index (SSCI) and other citation index databases. In particular, the past decade has been the fastest period of emergency evacuation development. Haghani and Sarvi [123] used existing data retrieval techniques to analyze the literature distribution of pedestrian crowds and emergency evacuation, and the study show that the volume of literature on crowd model is on the rise after 2008. There was a total of 391 retrieved document records covering 5 types of documents with the following composition: 64.5% Articles, 21.8% Conference Proceedings Paper, 7.9% Review papers, 3.8% Meeting abstract and 2.0% Editorial materials (see Table 2.1). The focus was mainly on the first 3 items (Article, Proceedings Paper, Review) throughout the entire study.

A statistical analysis of the published years of literature in a certain field can be used to understand the development of the research in the field of research from the time distribution. Preliminary search found that records in the core collection database of the WOS had only records after 1985s. To understand more comprehensively the emergency evacuation development process, we selected data from all the databases in the WOS for analysis. As we can see from Figure 2.1, the entire course of development can be divided into the following three stages: the initial growth stage, the steady growth stage and the rapid development stage.
Initial growth stage (1985 - 1995): In all the databases in the WOS, the documentation on emergency evacuation studies began as early as 1985. Prior to 1995, there were very few articles on relevant studies. In this initial stage, there was no lack of high-quality literature in this field. For

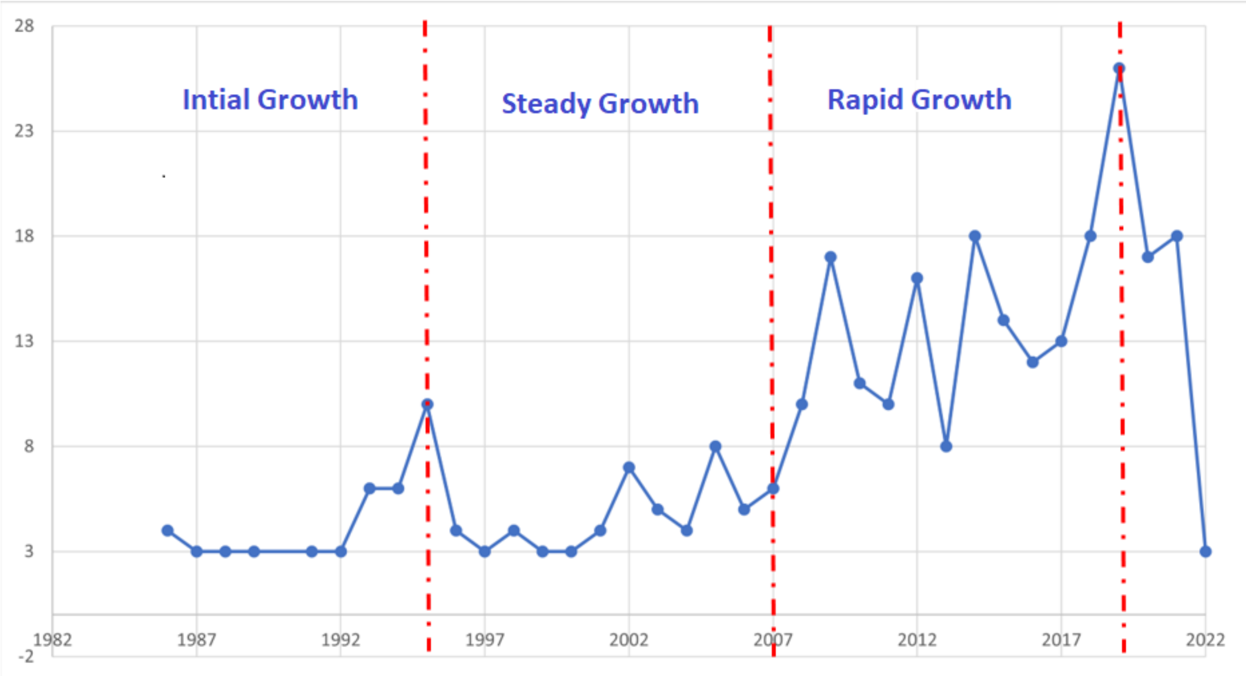


Figure 2.1: The trend of published articles in pedestrian emergency evacuation studies.

example, in 1985, Kisto and Francis [183] developed a user-friendly interactive computer program called EVACNET+ which allows the modeling of emergency building evacuations. Later in 1994 Galea and Galparsoso [104] developed the EXODUS computer program, an egress-prototype model designed to simulate the evacuation of large number of individuals from an enclosure. The model tracks the trajectory of individuals as they make their way out of the enclosure, or are overcome by fire hazards such as heat and toxic gases. These explorations laid the research foundation for the subsequent development.

Steady growth stage (1996–2007): Although there were few papers on relevant research before 2008, the number of publications has been stabilizing year by year. With the rapid development of computers, the research methods in this stage range from statistical investigation to simulation. In 2002, Gwynne et al. [120] classify 22 evacuation models based on the nature of the model application, the enclosure representation (that is, how the building is or the representation of the area been analysed in the model), the population perspective (that is, are the agents modelled as separate entities or are the modelled together and described using average quantities), and the behavioural perspective (that is, what assumptions and rules are used to describe the behaviour of pedestrians). In 2004, Isobe et al. [161] studied the evacuation process of students in a room filled with smoke by combining experiments and a lattice gas model simulation, which is of great significance for the reference of emergency evacuations of buildings.

Rapid development stage (2008–2020): After 2007, the number of papers increased drastically for the first time, and since then, the volume of publications on emergency evacuation research has basically shown a multiple growth trend; this stage belongs to the rapid development stage. At this stage, the increasing trend of literature quantity is most obvious, and the research contents begin to be more abundant and include the crowd evacuation model of buildings, optimization of evacuation path, post-disaster operation management and emergency rescue and evacuation (Zheng et al., [403]; Stepanov and Smith, [331]; Galindo and Batta, [105]; Gelenbe and Wu, [108]). In 2008, Johansson et al. [168] used video to study crowd behaviors under a large number of basic conditions, thus improving the maximum capacity of pedestrian evacuation facilities to ensure crowd safety. The steady growth period in the field of emergency evacuation research (the number of articles in 2018 has not been counted yet) spans from 2015 until now, and the accumulation of articles continues to increase, although at a smaller growth rate. As seen from the variation trend of the number of published papers, with the development of new technologies, the number of publications on emergency evacuation presents an in- creasing trend year by year, indicating that the attention level of this field shows an increasing trend year by year.

Research efforts in the field of pedestrian evacuation dynamics can be categorized in two general domains:

1. Studies whose primary aim is to assess, explore, describe or predict the likely evacuation behaviour either through experimentation or numerical simulation, i.e. the descriptive or observational domain; and

2. The body of research that seeks to identify useful interventions or prescriptive solutions whose main aim is to improve efficiency of evacuation processes as opposed to purely predicting them, i.e. the prescriptive or interventional domain.

There appears to be notable degrees of imbalance between the amount of research produced in these two general domains. Observational studies further our understanding of crowd's likely behaviour and produce predictive models. Descriptive knowledge is essential in enabling researchers and practitioners to improve the accuracy of prediction models. The interventional solutions and the extent of their effectiveness are often derived from descriptive models, hence adding yet more emphasis on the importance of having access to accurate prescriptive knowledge and models. Despite significant advancements in the field of crowd dynamics in terms of both modelling and experimentation (Gibelli and Bellomo [111]; Haghani [121]), more work seems necessary to:

1. Determine how occupants should respond to emergencies (Lin et al. [212]) as opposed to how they are likely to respond

2. How the physical infrastructures should be prepared to accommodate fast evacuations, and

3. How pre-designed evacuation plans could be devised to assist efficient management of evacuation processes

Considering that the end goal of the evacuation research is optimisation, these possible avenues would constitute essential steps in translating the evacuation knowledge into tangible practical outcomes and well-established codes and guidelines for evacuation management. The various codes and standards for fire safety developed by National Fire Protection Association (NFPA) [175, 288, 366] may be a prime example of how the scholarly literature on evacuation research could contribute to establish a scientific and evidence-based approach in evacuation planning practices. However, it appears that the scholarly knowledge on evacuation optimisation is rather scattered and fragmented [358], the literature is not well organised, different approaches in evacuation optimisation of pedestrians have not been distinctly differentiated and the extent of their relative effectiveness and practicality are yet to be evaluated.

In our review, we distinguish between optimisation and non-optimisation articles. The optimisation category consists of all papers that use a methodology to obtain an optimal or a good solution to a specific problem involving crowd dynamics, such as the efficient evacuation of a building. All articles that describe empirical results or descriptive models for the movement of pedestrians that do not use an optimisation methodology, belong to the non-optimisation category. We only take the optimisation articles into account in our classification process. However, we summarise the empirical research and descriptive modelling approaches in our text in order to give the reader the necessary background information for the discussion of the optimisation models.

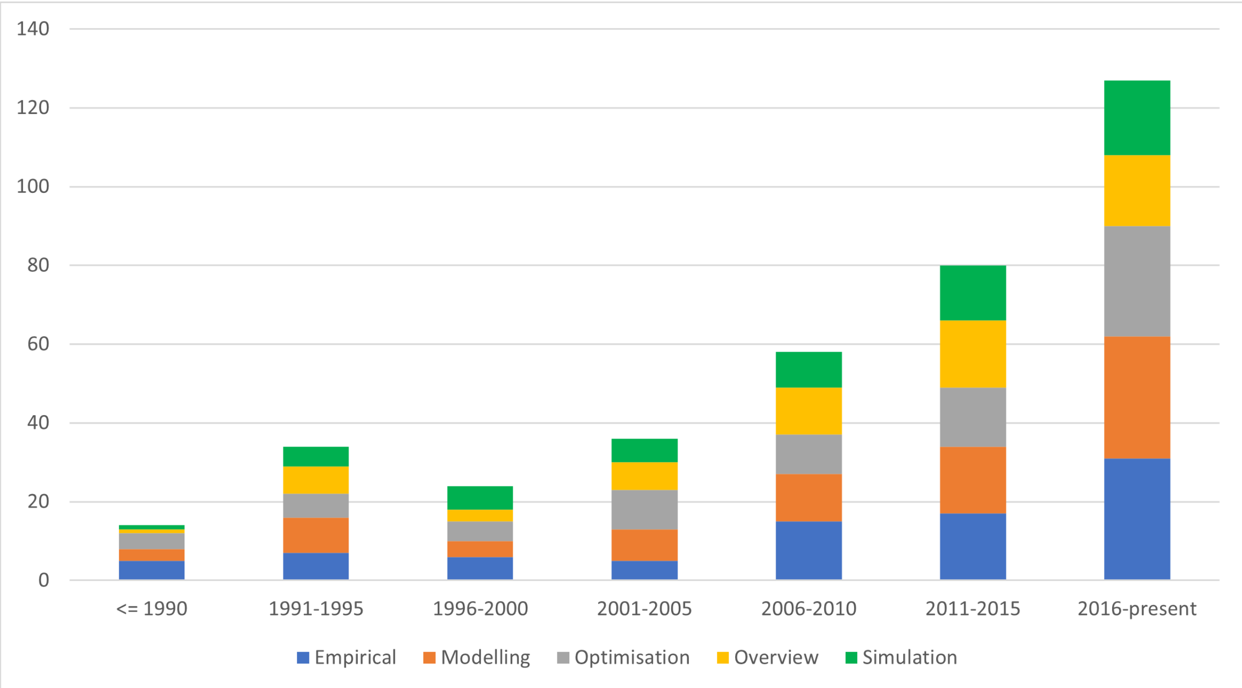


Figure 2.2: Number of publications published per year based on methodology

Figure 2.2 gives information on different types of articles (empirical, descriptive, optimisation, overview and simulation) published across the years. All articles published before the 1990s were aggregated, and after 1990, the aggregation was done on 5-year basis. It is clear that pedestrian emergency evacuation has received increasing attention in the last decade. Figure 2.3 lists the top-10 journals in which most of the articles in this chapter have been published across the time-span. Taking the different types of articles (empirical, descriptive, optimisation, overview) together, Safety Science, Transportation Research Part B: Methodological and European Journal of Operations research are the three journals that publish most of the articles related to pedestrian emergency evacuation and behaviour research.

Furthermore, Figure 2.4 shows the annual output of each major discipline in recent decade. There are about 161 published papers, accounting for 40.12% of the total literature reviewed in

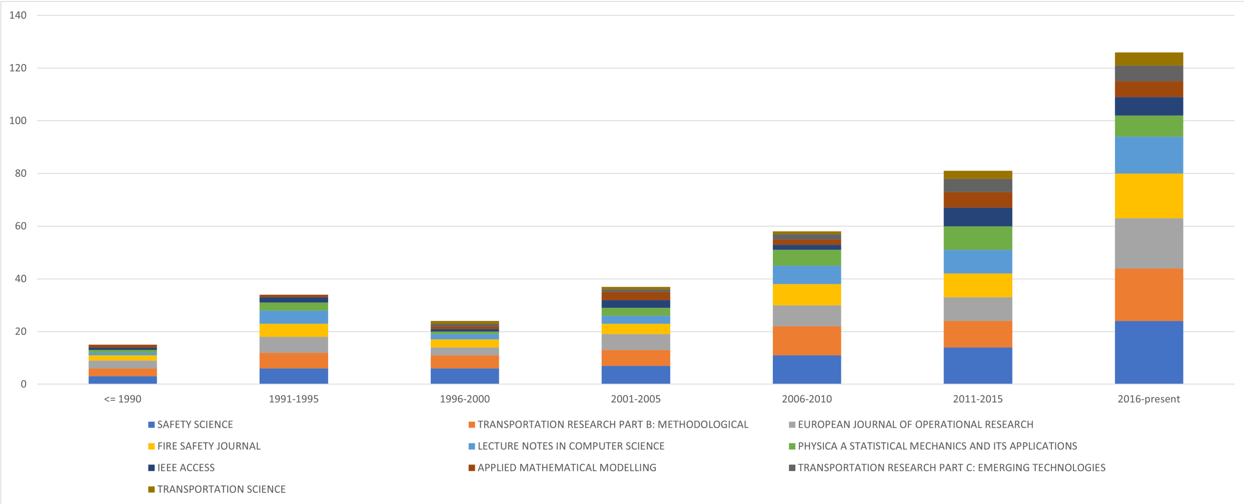


Figure 2.3: Overview of publications per journal and per year.

this chapter. In the figure, it is evident that, engineering displicine has the highest share of the published articles considered. It is followed by operations research management science, computer science, applied mathematics and transportation, for these five disciplines, in addition, a number of published papers are also distributed in the fields of geology, social sciences, environmental sciences ecology, physics and material science. Finally, figure 2.5, gives an over of the number of articles published by the top-ten journals based on the methods/approaches considered. In all these journals, empirical studies has been given vast majority of the attention, followed by modeling and simulation.

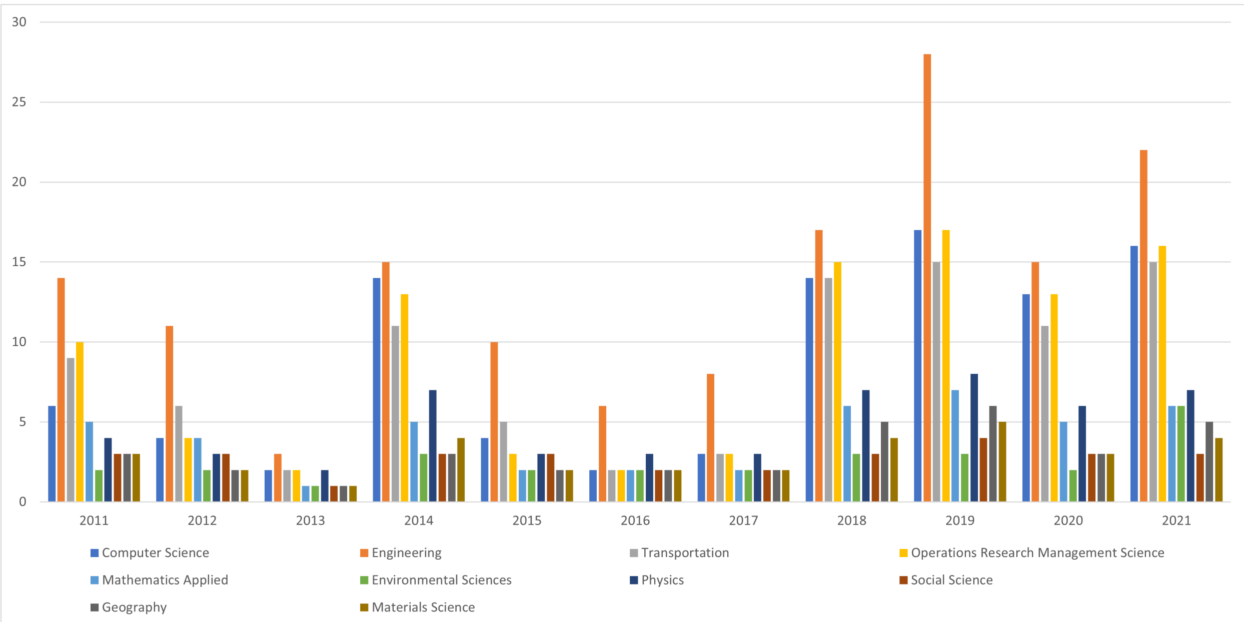


Figure 2.4: The number of published articles in the ten (10) main categories.

We use different perspectives for organising the literature. Each section discusses a specific perspective and presents detailed tables in which the relevant articles are categorised. Section 2.3 discusses the different problem types that are studied in the literature, the criteria used to assess

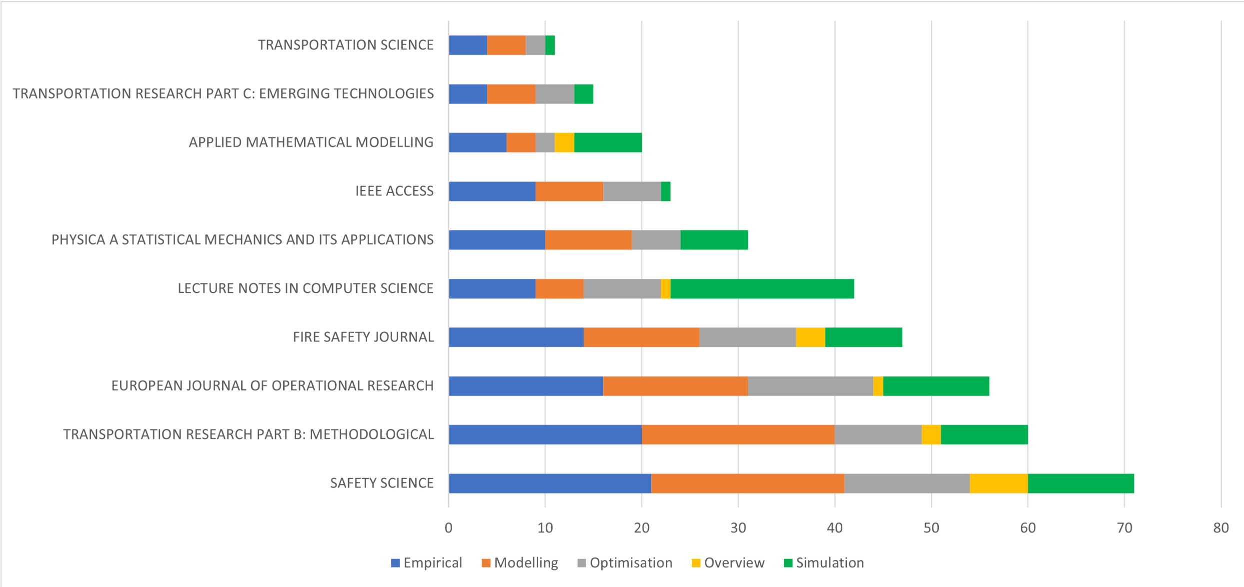
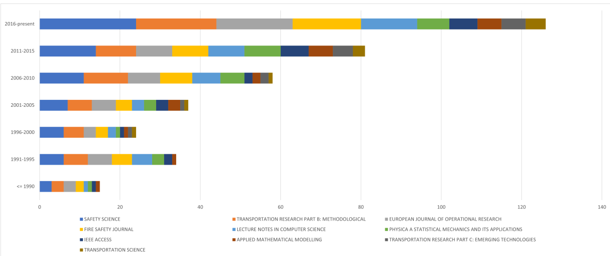
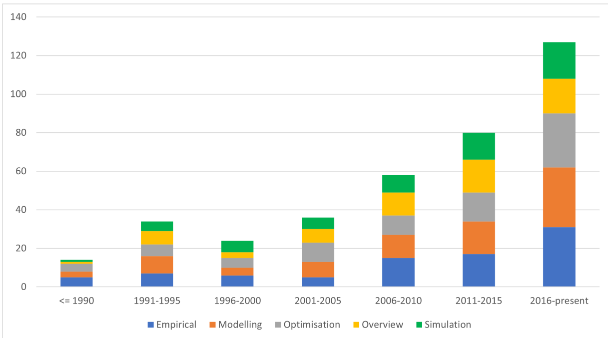


Figure 2.5: Overview of publications per journal and per methodology.



(a) Overview of publications per year and per journal.



(b) Overview of publications per year and per research objectives.

Figure 2.6: Overview of publications according to journal types per year and per research objectives.

the quality of the resulting solutions, i.e. the objective function measures, and the types of decisions that are considered in the model. The domains of pedestrian evacuation approaches is discussed in section 2.4. Sections 2.5 and 2.7 analyses the modelling and solution techniques employed to solve the different models. The realism of the proposed models and their conformity to empirical results on pedestrian dynamics is investigated in Section 2.6. The paper concludes with the main findings and perspectives for future research in Section 2.8.

2.3 Conceptualisation

According to a glossary for research on human crowd dynamics [11], evacuation refers to *moving individuals or a crowd to a (safe) location due to a threat or warning or due to safety reasons.* Adrian et al [11] distinguished between various categories of crowd evacuations including inevacuation, immediate evacuation, phased evacuation, and non-immediate evacuation . Studies of crowd evacuation, whether experimental (empirical) or numerical, can be generally attributed to one of the two general approaches. Descriptive or observational studies whose purpose is to learn how the crowds behave during emergencies, what the likely response of individuals are, how their likely behaviour can be modelled into mathematical formulations and how these computational methods can be used for predicting evacuation processes and their relevant metrics such as evacuation time, density distribution, bottleneck identification etc. [82, 212]. On the other side, prescriptive or interventional studies of pedestrian evacuation aim to employ the knowledge and the mathematical models obtained from descriptive studies in order to come up with solutions that can facilitate or optimise evacuation processes. The two approaches are interconnected as the prescriptive methods rely directly on descriptive models and borrow important inputs from them [217, 290, 296]. Informed by descriptive models, interventional approaches establish methods that facilitate/optimise evacuation processes. In other words, the effectiveness of the interventional solutions for crowd evacuation, especially when conducted in the numerical domain, as opposed to the experimental domain, depends heavily on the accuracy of the underlying computational tool. Therefore, values of the knowledge and prediction capabilities gained from descriptive models are undeniable as there is absolute benefit in being able to predict evacuation processes and obtain useful descriptive statistics. A reasonably accurate estimate of the likely evacuation time for a venue could in and of itself be of great value to evacuation managers. However, it should be noted that the potential of this descriptive knowledge will not fully materialise unless it can be translated to practical solutions for evacuations. The question that arises is that what general approaches can be explored in order to achieve this goal, i.e. optimising pedestrian evacuations.

After surveying the relevant literature, it became apparent that the research efforts in evacuation optimisation can be categorised in three general sub-domains:

1. architectural design and infrastructure adjustment;
2. mathematical programming and optimisation of path/ departure-schedule planning, and
3. behavioural modification, training and active instructions.

The key elements of distinction between these three methods are as follows. The architectural design approach includes any solution that seeks to facilitate crowd flows through making alterations to the physical space of the movement, i.e. the infrastructure. These studies may by all means resort to mathematical programming techniques to find the optimum design solution, but the key distinction here between this method and the second category is whether or not the solution concerns the physical design of the infrastructure. The details of the literature survey will make it clear that this has been so far the dominant approach in the literature.

The mathematical programming approach is one that generally seeks to find the optimum path planning or departure schedule planning solutions for a fixed given design of the infrastructure and the environment. The general premise underlying this approach, which is comparable to finding the social optimum solution in urban traffic studies or even car traffic evacuation optimisation of (sub)urban areas [158, 255], is that, assuming we can control the path/exit choice or departure time of the crowd, what would the optimum path/departure-time solution be. These studies are

generally based on network-type formulation of evacuations that represent the evacuation space through nodes and links (similar to the methods used in urban network analysis and vehicular traffic models Shahhoseini et al., [304]) although optimisation studies based on agent-based simulations have been emerging recently as well.
With the behavioural studies however, the general premise is that an infrastructure design is given, and that people are free to choose their own path or departure time during the evacuation process, and that those aspects are not to be controlled through a central decision- making unit for the entire crowd. Rather, decisions of evacuations are made individually by the occupants. The main question within this approach would be how one can provide effective instructions or advice or training guides to the individuals in order to influence/modify their behaviour in a way that, if followed and complied with [81], it leads to a more efficient evacuation process collectively. The key distinction here with the mathematical programming approach is that, here, the solution does not concern the path finding or the departure scheduling of the entire crowd, rather, individual actions and strategies are to be influenced in order to enhance the evacuation efficiency. The survey of the relevant literature in this paper will make it clear that this is a rather emerging method in the literature and one that has only recently been gaining attention and momentum. This could be claimed as the most tangible knowledge gap that can be currently pointed out in the domain of crowd evacuation optimisation studies. Figure 2.7 is an illustration of the above discussions. Figure 2.7 differentiates between the two general approaches and identifies the main sub-categories within each approach. For developing descriptive models, the analyst needs to be able to model and reproduce the locomotion behaviour, way-finding behaviour and pre-evacuation behaviour of the occupants, often referred to as operational, tactical and strategic layers of the behaviour, respectively [147]. To optimise an evacuation process however, three general solutions (which are not mutually exclusive and can be utilised in combination with each other) can be followed: making adjustments to the physical design of the infra- structure, optimising path/schedule schemes for the entire crowd, or influencing individuals' behaviour and strategies through peacetime training, education or active instructions on the site (during the emergency). The third approach, here referred to as the behavioural modification approach, was identified as a major knowledge gap and one that has been generally overlooked in this domain. The dashed line indicates the fact that that approach has not been explored to its full potential this far. Both descriptive and prescriptive studies can be followed through numerical simulation 2.8a or experimentation 2.8b (see Figure 2.8).

Figure 2.8a makes it clear that the use of numerical simulation as computational behavioural laboratories (Gwynne and Hunt, [120]) where effectiveness of various behavioural strategies can be tested has not been fully explored compared to other application of numerical models (e.g. architectural adjustment). Same goes with regard to the experimental efforts 2.8b, where the general focus of the crowd evacuation experiments has, thus far, been on making observations, or calibrating/validating numerical models. Whereas, experiments designed for the purpose of evacuation training and establishing its effectiveness have remained largely scarce.

The main sub-domains of each of the three major optimisation approaches were also identified (See Figure 2.9 for detailed overview). Studies that explored the literature in infrastructure and

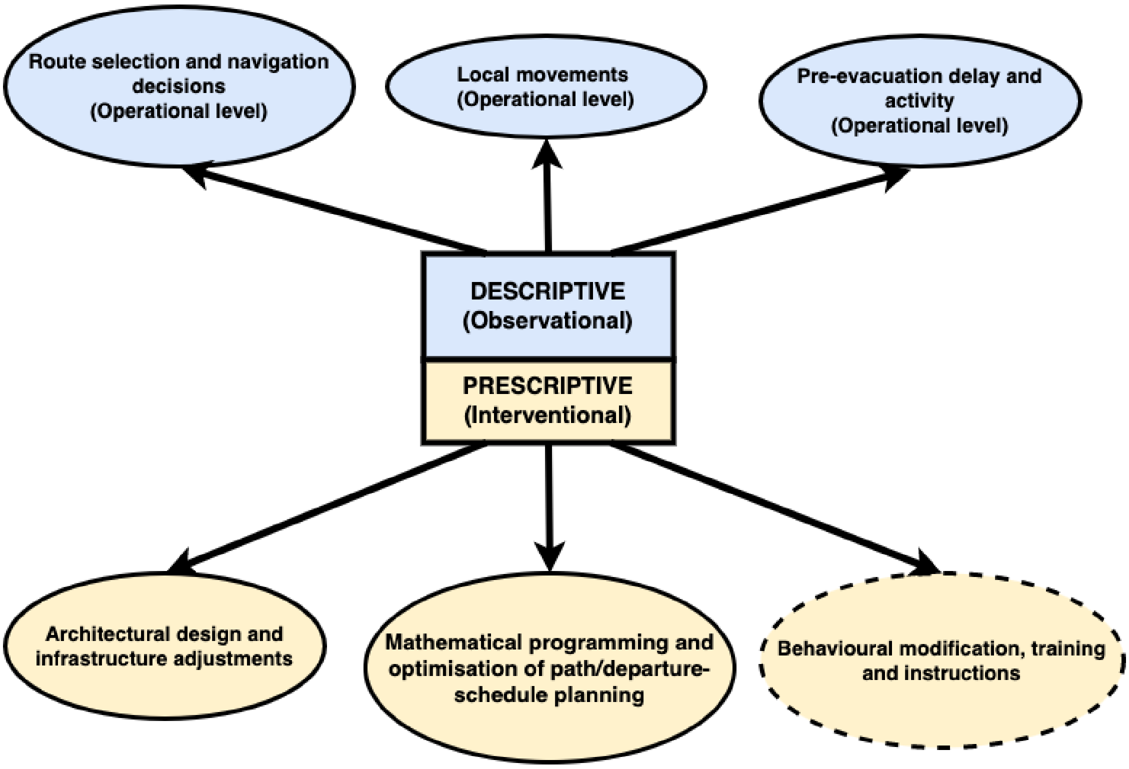
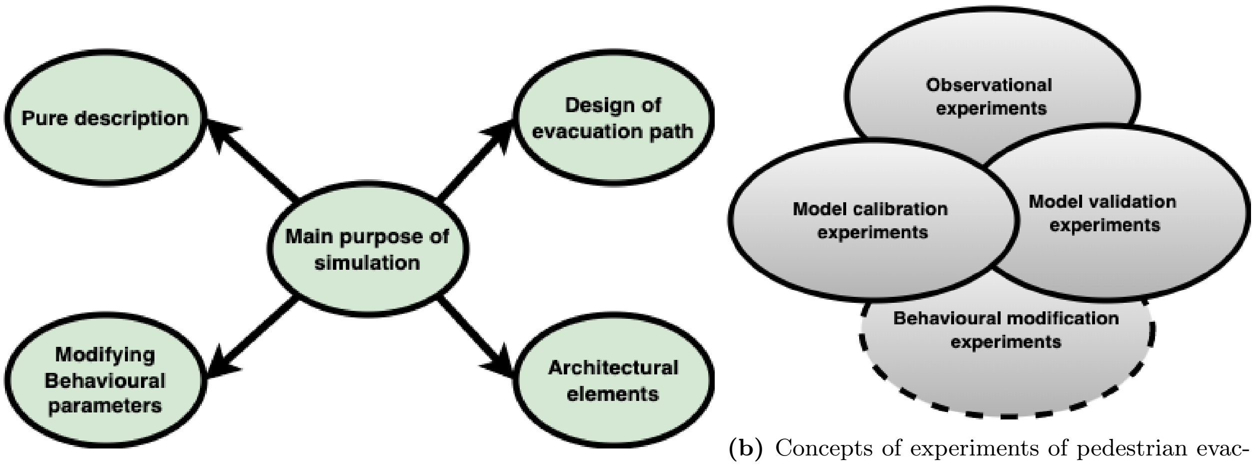


Figure 2.7: Conceptualisation of the descriptive (observational) vs prescriptive (interventional) domains of pedestrian studies.



(a) Concepts of numerical simulation of pedestrian evacuations.

(b) Concepts of experiments of pedestrian evacuation.

Figure 2.8: Conceptualisation of numerical simulations and experimentation of pedestrian evacuations.

architectural adjustment are grouped into five important elements of the architectural design. These include: include (I) optimising flow through partial obstruction of exits (i.e. obstacle optimisation), (II) optimising the location of the exits, (III) optimising the physical configuration of exits, (IV) optimising the physical configuration of corridors and staircases, and (V) optimising the placement of the exit signs within the building.

Studies that employed mathematical programming methods have considered: (I) path planning optimisation, (II) optimisation of the departure schedule, (III) optimisation of the exit assignments, and (IV) optimisation of the evacuation strategies specific to tall buildings, e.g. the use

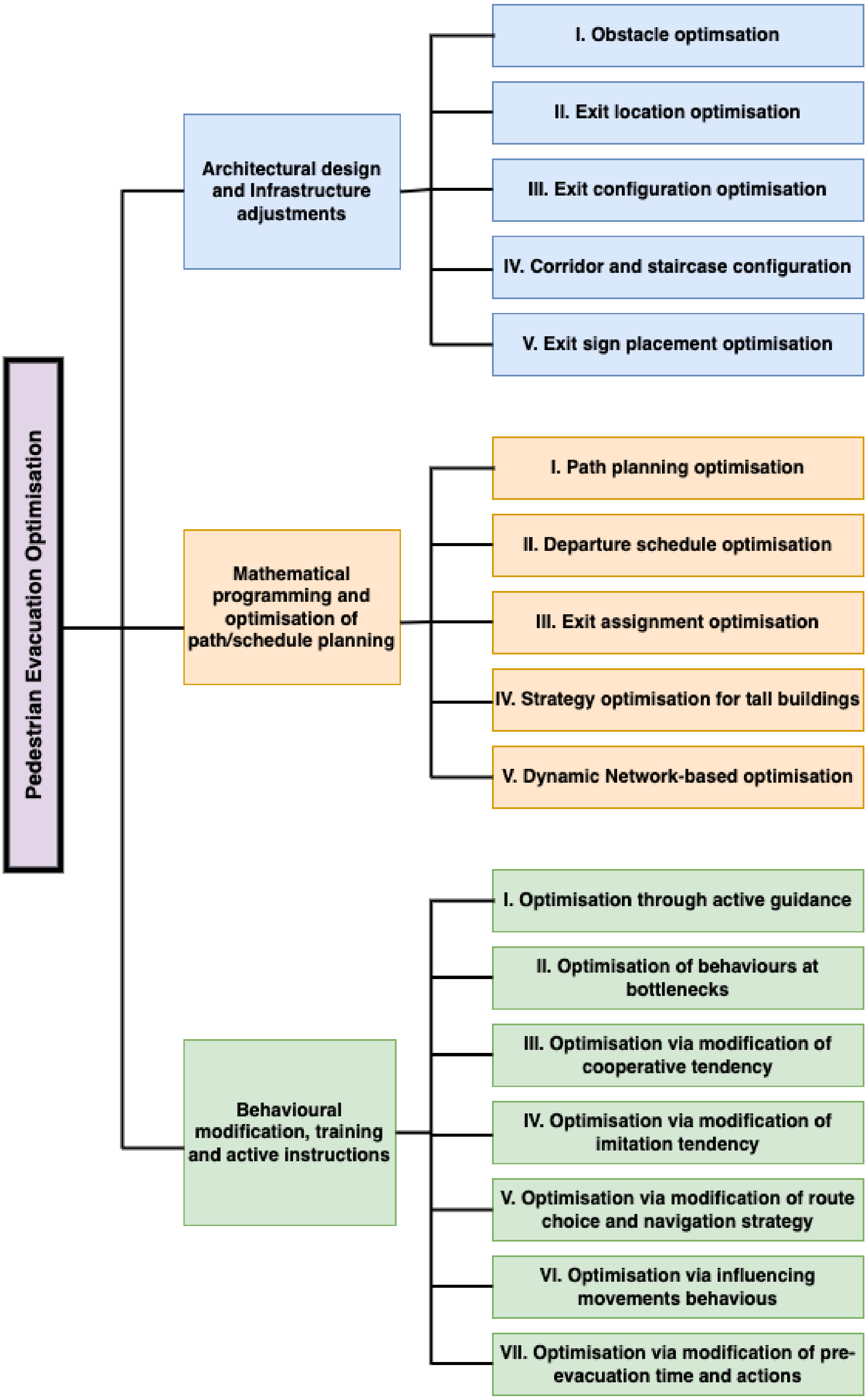


Figure 2.9: Identification of sub-domains related to each of the three major evacuation optimisation approaches.

of elevators, stairs and refuge floors. The existing efforts in behavioural optimisation were more scattered. Seven categories are differentiated here, each of which concerning a certain aspect of the evacuee behaviour that could be potentially optimised (according to the current literature). These include (I) optimisation approaches that explored the effectiveness of on-site instructions and advice through leaders and authority figures within the crowd (almost exclusively based on numerical simulation), (II) optimisation of the behaviour at bottlenecks, (III) optimisation through modifying the patience, cooperation and selfishness tendency of the evacuees (again, exclusively based on numerical analyses), (IV) optimisation through modifying the tendency of evacuees to imitate peers, (V) optimisation through influencing exit/route choice and navigation strategies of evacuees, (VI) optimisation through influencing locomotion behaviour of pedestrians in (heavy) flows, and (VII) optimisation through modifying the waiting or pre-movement time strategies of individual evacuees, or through giving instructive advice for the optimum pre-evacuation strategies that may enhance the chance of survival, e.g. taking shelter etc.

2.4 Domains of pedestrian evacuation approaches

2.4.1 Architectural methods of evacuation optimisation

The creation of congestion and bottleneck at exit points is a common feature of pedestrian evacuation scenarios, particularly when the rate of occupancy is relatively high compared to the capacities. Arguably, the most popular idea in the domain of architectural optimisation is the counter-intuitive assumption that partial obstruction, e.g. via a column or a panel-shaped obstacle, could improve the efficiency of the flow and the total egress time at exit points. This is an important assumption given that exit bottlenecks are often critical points of evacuations where the efficiency of movement can have a major impact on the total evacuation time, in addition to the fact that these spots can themselves be likely locations of injury and fall due to crowd pressure. The research on this aspect has been initiated through computational numerical models [139, 167] and then has been in recent years further tested by multiple experiments with mice, ants and human crowds [323]. Table 2.2 gives an overview of the articles published in the five sub-domains in the architectural methods of pedestrian evacuation optimisation. In order to factor obstacles into pedestrian emergency evacuation, Jiang et al. [164] suggested that appropriately placing two pillars on both sides but not in front of the door can maximize the escape efficiency. The findings of Zhao et al.[397] indicated that panel is more robust than pillar to guarantee the enhancement of pedestrian outflow. The findings of some studies have gone as far as suggesting placing a column can be effective by more than 90% in decreasing the evacuation time (Shiwakoti and Sarvi [321]), whereas there are studies that have reported much smaller numbers in their observations of efficiency improvement (Wang et al., [361]).

Another aspect that has been suggested by several studies to be a potential influential factor during evacuations is the spatial positions of exits. This includes both the absolute positions of exits inside a room and the relative position of exits in multi-exit spaces. The study of Tavares [341] contributed substantially to this very topic by revisiting a criterion in a British regulatory standard for determining exit locations. The criterion to which they referred utilises the maximum travel

Table 2.2: Sub-domains under architectural methods of pedestrian evacuation

Obstacle	Berseth et al. [34]; Cristiani and Peri [67, 68]; Frank and Dorso [98]; Garcimartín et al. [107]; Haghani and Sarvi [126]; Helbing et al. [138, 139]; Jiang et al. [164]; Johansson and Helbing [167]; Karbovskii et al. [176]; Kirchner et al. [182]; Li et al. [199, 202]; Lin et al. [215]; Rodriguez et al. [289]; Shao and Yang [309]; Shi et al. [318]; Shiwakoti and Sarvi [321]; Wang et al. [361]; Yanagisawa et al. [379]; Yano [385]; Zhao et al. [397]; Zheng et al. [401]; Zuriguel et al. [410, 411];
Exit location	Berseth et al. [34]; Chen et al. [52]; Gao et al. [106]; Jianyu et al. [166]; Khamis et al. [178]; Kurdi et al. [191]; Lei and Tai [197]; Li et al. [200]; Shi et al. [318]; Shiwakoti and Sarvi [321]; Sticco et al. [333]; Tavares [340, 341]; Wu et al. [374, 374]; Xie et al. [375]; Yanagisawa and Nishinari [380]; Zhao et al. [398]
Exit configuration	Adrian et al. [12]; Haghani and Sarvi [128]; Li and Xu [204]; Liu [222]; Tavana and Aghabayk [339]; Wang et al. [362]; Zhang et al. [394];
Corridor and staircase	Adrian et al. [12]; Lei and Tai [197]; Li et al. [200]; Lian et al. [205]; Liao et al. [206]; Shahhoseini et al. [307, 308]; Shahhoseini and Sarvi [305, 306]; Shiwakoti et al. [320];
Exit sign	Liu et al.[221]; Ma et al. [238]; Shao and Yang [309]; Zhang et al. [395];

distance as a key factor for determining escape routes. Their results showed that the maximum travel distance values required to be used for code compliance does not necessarily produce the minimum egress times. They proposed an alternative approach to this based on the notion of relative distance between exits and show that this impacts evacuation efficiency particularly in densely populated environments. It has been suggested by Shao and Yang [309] that multiple exits will slow down the evacuation process, however, this findings has not been re-confirmed by any other study to the best of the author's knowledge. In terms of optimising the exit configuration, some studies have considered how optimising the physical design of exits can be used to enhance evacuation efficiency. Adrian et al. [12] established experimentally how a physical guiding system in front of an entrance can reduce pushing, and thereby, the density at entrances. Zhang et al. [394] also experimentally investigated the required width of exit at which the pushing behaviour at bottleneck does not lead to slower evacuations, i.e. the so-called faster-is-slower effect. They found that when the exit is wide enough to accommodate two agents passing through at the same time, then the faster-is-slower effect will not occur and pushing will not delay the evacuation.

Another aspect that could be considered in conjunction with the infrastructure optimisation design for evacuations is the case of corridors and stairs where architectural adjustments could be made to enhance flow efficiency. Within this category, Shiwakoti et al. [320] investigated the influence of merging architectural features on pedestrian crowd movement by examining different merging angles and different desired speeds. Lian et al. [205] also studied pedestrian merging behaviour under various architectural configurations and observed that the branch width has a significant impact on the density of the flows at the corners. The experiments reported by Shahhoseini and Sarvi [306] examined a broad range of merging angles and three different speed regimes in more than 50 high-density experimental scenarios. Based on these sets of experiments they observed the dependency of the flow efficiency on merging angels and that, delay and momentary blockages are more likely in asymmetrical merging layouts. They also concluded that the difference between symmetric and asymmetric layouts is more pronounced at elevated level of speed, although the patterns of influence of the geometric constraints on traffic efficiency were by-and-large common across all three speed regimes. The study of Lei and Tai [197] suggested that buildings should be designed with exits facing the staircase and that large staircases should be replaced with two identical sets of staircases. Liao et al. [206] employed a multi-agent system to simulate the pedestrians and used Bayesian-Nash Equilibrium to model their decision-making process in a tunnel. They observed that expanding the tunnel width by one meter will allow the safe pedestrian flow rate to increase by about 3 pedestrians per second. See Table A1 for a full list of studies in this category. Finally, exit signs are critical components of indoor evacuations and their proper instalment can make a real difference in leading people through quickest evacuation routes. Although exit signs can be regarded as means for evacuation guidance, but it also can be argued that they are also part of the building infrastructure and therefore, the location of exit signs could be considered as part of the infrastructure design and a component that could also be optimised for efficient evacuations. For example, Liu et al. [221] argued that "determination of the effective distance of emergency evacuation signs is a basic requirement for optimising and improving emergency sign systems". In their study, they proposed a computational methodology for calculating the effective distance, a method that takes into account multiple factors including the inertia effect. Zhang et al. [393] studied the optimal number and location planning of evacuation signage in public spaces. They proposed a calculation method to determine the guidance efficiency of signage and applied that method to optimally determine the location of an evacuation signage in a hall. Ma et al. [238] also studied the effect of escape signs on pedestrian evacuation and demonstrated that there are optimal positions for escape signs for a certain range of view radios. They also suggested that the optimal position of escape signs is independent of the degree of the building occupancy and the number of evacuees.

2.4.2 Mathematical programming methods of evacuation optimisation

Table 2.3 gives an overview of the articles published in the five sub-domains in the mathematical programming methods of pedestrian evacuation optimisation. The vast majority of the studies in the category of mathematical programming have addressed the path planning problem. These studies are also predominantly based on macroscopic network-based models for evacuations (i.e. abstract modelling of the space using links and nodes) similar to those used in vehicular traffic assignment. Studies of path planning optimisation based on agent-based models have also emerged in recent years [9] as will be discussed here. Pursals and Garzón [280] modified the initial network-model formulation of the building evacuation problem as a mathematical programming problem made by (Chalmet et al.[49]; Francis [97]). They generalised the evacuation function to incorporate evacuation routes. Fang et al. [87] argued in their study that "The central challenge in evacuation planning is to determine the optimum evacuation routing". They described an evacuation network of a stadium as a hierarchical directed network and proposed a multi-objective optimisation to solve the routing problem. These objectives include minimising total evacuation time, total evacuation distance and cumulative congestion degrees. They employed an ant colony algorithm to solve this optimisation problem. Kou et al.[187] similarly considered multi-objective optimization of evacuation routes in a stadium using a potential field network. Their three criteria in the objective function are consistent with that of Fang et al. [87]. Teknomo and Fernandez [343] argued that "If the number of occupants in the building is only small, then the shortest paths to the exits may enable all the occupants to evacuate in minimum possible time". They applied an optimisation search on a mesoscopic multi-agent pedestrian simulation to determine the minimum egress time in densely crowded scenarios. They showed that the difference between the shortest-path egress time and their optimisation solution increases rapidly as the crowding level increases. Feng and Miller-Hooks [90] proposed a network optimisation based approach, formulated as a bi-level integer programming problem for crowd management in large public gatherings. The program at the upper level seeks a layout configuration that minimises the total travel time of users and the lower level produces a pure Nash Equilibrium for the collective behaviour of the crowd. Taneja and Bolia [337] also investigated the problem of network redesign for efficient crowd flow and evacuation. They also formulated the problem as a bi-level network-based problem and also investigated the robustness of the optimal solution to the evacuation demand level. The study of Verbas et al. [357] also proposed an integrated optimisation and simulation framework for large-scale crowd management considering the formation, scheduling and path assignment of the crowd. They applied this framework to the Jamarat process during the Hajj season in Saudi Arabia. Noh et al. [260] formulated the evacuation routing problem that considers a partially dedicated evacuation strategy to the high-speed sub-population and the sub-population with limited mobility. They used a time-expanded network flow model and a simulation-based optimisation approach to solve the problem. The study of Zhang et al. [393] put forward four key performance indicators to assess evacuation performance within different route planning strategies in a metro station. Liu et al. [222] examined a path planning approach for crowd evacuation in buildings based on bee colony algorithm which uses the evacuation times of individuals as the evaluation metric. Shin et al. [319] presented mathematical models and a heuristic algorithm, based on network model, that address simultaneous evacuation and entrance planning, providing optimal route for evacuees and responders.

Relative to the dominant approach of path planning optimisation, a more limited number of studies have considered optimisation of departure time scheduling as another alternative to improve evacuation efficiency. In many of these cases, the problem has been formulated as a joint path and departure-schedule planning optimisation. Among those studies, Cepolina [48] investigated the notion of phased evacuation that aims to find the route-alarm-time schedule plan that minimises the building evacuation time. Their underlying static movement model, embedded into the optimisation

Table 2.3: Sub-domains under Mathematical programming methods of pedestrian evacuation

Path planning	Aalami and Kattan [7]; Cassol et al. [44]; Cepolina [48]; Chu [63]; Ding [76]; Fang et al. [88]; Feng and Miller-Hooks [90]; Kisko and Francis [183]; Kou et al. [187]; Li et al. [203]; Liu et al. [218]; Lu et al. [235]; Luh et al. [236]; Noh et al. [260]; Pursals and Garzón [280]; Rozo et al. [292]; Shin et al. [319]; Taneja and Bolia [336, 337]; Teknomo and Fernandez [343]; Verbas et al. [357]; Wang et al. [365]; Wong et al. [373]; Zhang et al. [393];
Departure schedule	Abdelghany et al. [9]; Fang et al. (2011a) [87]; Lin et al. [213]; Shende et al. [314, 315]; Verbas et al. [357];
Exit assignment	Lin et al. [213]; Abdelghany et al. [9]; Kang et al. [174]; Liu et al. [223]; Galán [102] ;
Strategic optimisation for tall buildings	Aleksandrov et al. [14]; Ding et al. [77]; Nguyen et al. [259]; Noh et al. [260];

algorithm, estimates the building evacuation time for any given route and alarm time optimisation plan and assesses the evacuation efficiency, while considering the capacity drop phenomenon. The study of Fang et al. [88] also proposed a waiting-time strategy for improving space–time use efficiency in stadium evacuation scenarios. The authors claimed that the waiting-time strategy is essentially a mean for avoiding the so-called faster-is-slower effect during evacuations, which is itself a debatable topic in crowd dynamics [121, 122, 128, 305]. Their study also introduces a space–time use efficiency measure for evaluating the utility of both space and time resources during evacuations. The aim of their proposed algorithm is essentially to mitigate the level of congestion at bottlenecks "by virtue of the strategically timed moving-waiting-rerestarting" patterns of evacuation. The study of Abdelghany et al. [9] also proposed a simulation-optimisation framework for evacuation of large-scale crowded pedestrian facilities with multiple exits. Their method integrates a genetic algorithm (for finding the optimal solution) with a microscopic agent-based simulation framework (for generating the underlying behaviour). Their method can be described as a joint optimisation of exit gates and evacuation start times and it has been shown to outperform the "nearest-gate immediate" evacuation strategy.

Some of the mathematical programming studies formulated the problem of path planning as a question of exit/gate assignment. Some of these methods are also often join optimisation problems considering gate assignment and departure scheduling at the same time. Therefore, some of these studies have been already covered in previous sections. Among the remaining, one can point out to the study of Kang et al. [174] who formulated an optimal facility–final exit assignment algorithm for complex building evacuations. In their formulation, facilities are assigned to gates in a way that it minimises the evacuation time of the last evacuee. They formulated the problem both as a linear programming and as an integer programming problem with different constraints, realism and applicability characteristics. They demonstrated that the proposed optimal evacuation plan outperforms the facility–nearest exit assignment solution using a simulated numerical experiment on a shopping mall. Similarly and in another study, Galán [102] constructed a floor field optimisation method by assigning pedestrians to exits such that the estimated time for complete evacuation is minimised.

Four studies were identified offering specific optimisation strategies tailored to the evacuation of high-rise buildings. This includes the study of Noh et al. [260] with partially dedicated strategy for the sub-population with and without mobility limitation, that was discussed earlier because of its relevance to path planning optimisation. Ding et al.[77] studied the case of ultra-high-rise building where they argued that "the evacuation strategy of using stairs and evacuation elevators should be optimised". They utilise a bi-level simulation-based optimisation method for this purpose. In their formulation, evacuation elevators can arrive at the refuge floors, and the scheduling of the elevators is optimised based on the GA algorithm. The study of Aleksandrov et al. [14] also focused on the finding optimal evacuation strategy for tall buildings and proposed an optimisation method that takes into consideration the probabilistic nature of occupants' response. They considered in their strategy formulation the use of stairs, evacuation lifts, and refuge floors and defined the problem as a multi-objective optimisation that includes total evacuation time as well as the number of people waiting in their floors to start the evacuation. The study of Nguyen et al. [259] is another case whose focus is on evacuation strategies of tall towers. They also proposed a new approach of planning for overall emergency occupant egress through evacuation elevators using numerical modelling techniques and applied their method to a case study of a 350 m tall tower.

2.4.3 Behavioural modification methods of evacuation optimisation

Table 2.4 gives an overview of the articles published in the seven sub-domains of the behavioural modification methods of pedestrian evacuation optimisation.

- *Leadership guidance*: There is a group of studies in the field of crowd evacuation that have investigated, how the presence of leaders could potentially improve the efficiency of evacuations (solely based on numerical simulations). Wang et al. [363] showed that if a subset of exits becomes partially clogged due to congestion, the evacuation becomes more efficient by adding a virtual leader that can regulate the process. In their model specification, each agent updates its direction of action in each step and the virtual leader factors were considered in the update rule. Ma et al. [240] also studied potential benefits of effective leadership for crowd evacuation. According to their findings, just a few of leaders could guide a large evacuee crowd in a room to the exit. They also observed that the effectiveness of the leadership is linked to the room visibility condition. They suggested that when the room is visible enough, the leadership effect may become negative. They also argued in their study that properly selecting the number and position of evacuation leaders is important particularly when evacuees are not familiar with the internal layout of the building. Along the same lines, Song et al. [326] investigated the effect of authority figures for pedestrian evacuation at metro stations.

They also studied factors influencing the effectiveness of authority figures during evacuations, including their number and locations and the spread of their directions. They observed that too many authority figures could have adverse effect on the evacuation process.

- *BOTTLENECKS*: As discussed earlier, the efficiency of the egress flow at the bottlenecks and exits is a major component of evacuation optimisation and a topic researched immensely in literature. In addition to the studies that have explored architectural methods for flow optimisation at bottlenecks, as discussed in sections 2.4, there are a considerable number of studies that have investigated the effect of the behavioural conduct at the bottlenecks and its impact on the flow efficiency. These studies are predominantly related to whether or not pushing at bottlenecks is detrimental to the crowd flow rate referred to as the "faster-is-slower" effect.The literature on this topic traditionally supported the idea of faster-is-slower being a universal phenomenon [334]. However, recent studies have increasingly suggested evidence that questions the universality of the phenomenon, with the term "faster-is-faster" having appeared increasingly in recent studies [128, 317, 332]. The numerical study of Sticco et al. [332] concluded from the force balance condition that "friction was the key feature for the faster is faster instance to take place. As the crowd pushing force increases, the compression between individuals in the blocking structure will not be enough to provide a slowing down in the moving pedestrian. Thus, the faster is slower instance switches to a faster is faster instance". In the experimental domain also, comparisons between empirical testings conducted by Pastor et al. [269] and Haghani et al. [126], have suggested that the faster-is-slower effect will not be observed unless the door is extremely narrow and unless the amount of force exerted by the crowd members amounts to aggressive and explicit shoving. In other cases, the intuitive faster-is-faster effect seems to remain in place. These findings challenges the previously established idea that instructing people not to rush at the exits could have a positive effect on evacuation time. Recent findings suggest that such advice would have a counterproductive effect, when considering the evacuation time as the main objective of the optimisation. The extent to which the answer to this question is moderated by the size of the crowd is yet to be systematically investigated [126]. While the literature in this category is mostly dominated by studies on the faster-is-slower phenomenon, new studies have also emerged lately looking at different aspects of the bottleneck behaviour on flow efficiency such as the body orientation effect. The study of Parisi et al. [267] brings attention to this new dimension, investigating active particles with desired orientation flowing through a bottleneck, by performing numerical simulations of the flow of anisotropic self-propelled particles through a constriction. The authors observed that "when particles propel along the direction of their long axis (longitudinal orientation) the flow-rate notably reduces compared with the case of propulsion along the short axis (transversal orientation)". The authors further suggested that this finding explains why the variation of flow rates when changing competitiveness were significantly lower for pedestrians than for sheep (as originally observed in [269]).

- *COOPERATION*: A body of studies on evacuation dynamics have explored, exclusively via mathematical formulations and numerical simulation experiments, how modifying the level of impatience or selfishness or cooperative behaviour can influence evacuation efficiencies. Zheng and Cheng [400] developed a theoretical game model to study evacuees' cooperative and competitive behaviours. Their analyses demonstrated that imitation effect enhances cooperation among evacuees, but reduces evacuation efficiency, which is consistent with the computational observations of Haghani and Sarvi [125]. The study by Song et al. [326] suggested that selfish behaviour has an adverse effect on total evacuation time. Using an integrated Cellular Automata (CA) and theoretical game modelling framework, Cheng and Zheng [57] investigated the emergence of cooperation during emergency evacuations. They examined the relationship between escape aspiration and cooperation and observed that high escape aspiration promotes cooperation. Cheng and Zheng [56] raised the question as to whether cooperative behaviour can promote evacuation efficiency and observed the highest evacuation efficiency for the intermediate levels of cooperation. Using numerical simulations Dossetti et al. [80] also studied various profiles of behavioural effects and observed that neither fully cooperative nor fully egoistic attitude is optimal. Instead, an intermediate behaviour results in lowest evacuation times. Also, Zou et al. [409] suggested that neither the presence of too many co-operators nor too many defectors are beneficial for the evacuation process. The cost is minimum when there are equal numbers of co-operators and defectors. The study of Kirchner et al. [182], however, links the effect of cooperative versus competitive behaviour to the door width. They showed that when the doors are narrower than a critical width, competitive behaviour increases the evacuation time. But for wider doors, the effect is reversed.

- *IMMITATION*: Some studies have investigated whether modifying (i.e. increasing or decreasing) the imitation tendency of evacuees could have a positive effect on evacuation performance. Three studies could be identified on this topic [124, 125, 127]. The studies of Haghani and Sarvi [124, 125] raised the question in relation to the exit-choice behaviour, respectively for homogenous and heterogeneous crowds. And their study [127] raised the question in relation to the exit-choice adaptation behaviour. All three studies have been based on numerical simulations. and the author is not aware of any empirical study conducted so far in this domain. These studies have collectively shown that peer imitation in exit choice is almost invariably detrimental, whereas the crowd could benefit from intermediate degrees of peer imitation tendencies for exit choice changing (or adaptation). When considering a case of double-class heterogeneous crowd, increasing the proportion of agents with follow-the-majority exit-choice strategy increased the evacuation time, whereas increasing the proportion of agents with the opposite strategy (i.e. follow-the-minority direction) reduced the evacuation time. However, it was observed that the detriments of increasing the follow-the-majority tendency is much more noticeable than the benefit of increasing the follow-the-minority concentration [125]. Most importantly, simulation results showed that most benefit of the system was realised at about 50% concentration of the desired strategy. This has important implications for evacuation training purposes as it suggests that for obtaining the benefits of the training, not all individuals in the crowd need to have been trained. If half the crowd members apply the desired strategy (possibly instructed to them via training) then the system will still gain most of its potential efficiency benefits. In relation to the exit-choice adaptation, neither of the zero imitation nor extreme degrees of imitation appeared to be the optimal strategy. Rather, the optimum resided at an intermediate degree [127].

- *ROUTE CHOICE*: A number of predominantly numerical studies have investigated how way-finding and route choice strategies of pedestrians can be improved to optimise evacuations. The study of Wang and Cao [361] investigated pedestrian evacuation strategies under limited visibility by examining different navigational strategies such as walking along the wall, following the average movement direction or the average position. They investigated the efficiency of these strategies under various contextual conditions such as visibility levels, density levels, and exit widths using a modified social force model. Various observations were made regarding the effectiveness of the strategies under different conditions. For example, walking along the wall was more effective at low densities and following the average movement direction was more effective at high density. The latter is rather at odds with the observations of Haghani and Sarvi [128] based on a different set of numerical testing. Similarly, Zhou et al. [404] also compared five evacuation route choice strategies using social force model applied to simulating a large-scale public space. They observed that the strategy that considers density and capacity factors had the best performance. Delcea and Cotfas [73] used an agent-based evacuation simulation model, as an educational tool, to increase awareness in classroom evacuation situations. They observed that the acquired knowledge using this method of training reduced evacuation time by more than 20%.

- *LOCOMOTION*: Optimisation via influencing locomotion behaviour in heavy flows Only two studies have looked at strategies that could improve the locomotion aspects of pedestrian flow from a behavioural perspective [381, 392]. Both studies explored the possibility of influencing pedestrians walking behaviour in directional flows using rhythm and investigated its potential impact on the flow efficiency. Both studies presented major experimental components also Yanagisawa et al. [381] included analytical solutions. They observed that slow-rhythmic walking achieves larger flow in the high-density regime.

- *PRE-EVACUATION ACTIONS*: Three studies were identified to have explored the pre-evacuation activities and pre-evacuation delays [127, 180, 230]. The study of Lovreglio et al. [230] prototyped a virtual reality serious games method for earthquake preparedness and evacuation actions in buildings and applied the method to a case study of a hospital building. Another influential and pioneering study in this very domain was conducted by Kinateder et al. [180] investigating the effect of information and behavioural training during road tunnel evacuations. Their experiments demonstrated that the virtual-reality behavioural training was more effective compared to pure information. The authors also raised the question on the durability and the long-term benefit of the acquired training knowledge to be investigated in future research. Haghani et al. [127] revisiting the long-held assumption that staged evacuations or waiting strategies are more efficient than a case where the entire crowd shows an instant response to the evacuation cue. They investigated various degrees of waiting strategies and pre-evacuation time variability on a continuum and observed that, an instant response resulted in shorter evacuation times and was therefore a more efficient strategy in that sense. Even though the instant-response strategy created denser and longer lasting bottlenecks, relative to the waiting strategy, the elevated density formation did not translate to longer evacuation times.

Table 2.4: Sub-domains under Behavioural modification methods of pedestrian evacuation

Active guidance	Li and Han [198]; Ma et al. [239, 240]; Song et al. [327]; Wang et al. [363]; Yang et al. [384]; Zhou et al. [405];
Behaviour at bottlenecks	Haghani et al. [126]; Lin et al. [214]; Parisi et al. [267]; Pastor et al. [269]; Sticco et al. [332]; Suzuno et al. [334];
Cooperation	Cheng and Zheng [56, 57]; Dossetti et al. [80]; Heliövaara et al. [143]; Kirchner et al. [181]; Li and Han [198]; Lin and Wong [210]; Shi et al. [317]; Song et al. [326]; Zheng and Cheng [400]; Zou et al. [409] ;
Immitation	Haghani and Sarvi [124–126]; Yanagisawa et al. [381];
Exit/Route choice	Delcea and Cotfas [73]; Haghani and Sarvi [124–127]; Kinateder et al. [180]; Lin et al. [211]; Shen et al. [312]; Wang and Cao [364]; Zhou et al. [404];
Locomotion	Zeng et al. [392]
Pre-evacuation action	Catal et al. [45] ; Haghani et al. [126]; Kawai et al. [177]; Lovreglio et al. [230];

2.5 Problem type, objective function measures, and decisions considered.

Optimisation models are used to tackle different types of problems related to pedestrian dynamics. As can be seen from Table 2.5, by far the most attention has been devoted to the development of optimal evacuation plans for pedestrian facilities. Many articles specifically focus on a certain type of pedestrian facility, as this enables researchers to tailor models to the specifics of the environment (e.g. Cepolina, [47]). Most models focus on the evacuation of buildings or large rooms with multiple exits. One of the first articles that studied the building evacuation problem was written by Chalmet et al. [49] in 1982. A second type of problem is studied by Johansson and Helbing [167], who look at the problem of finding designs that improve the flow through a bottleneck. Flow is the number of pedestrians who pass through a line segment per metre per second. The study of the influence of design on flow was prompted by the observation that placing an obstacle in front of the exit can reduce the magnitude of clogging. A genetic algorithm is used to find the configuration that maximises the outflow. Finally, Howard et al. [154], and Mudassir et al. [252] applied the CTM for no-notice emergency evacuation of a large city.

Table 2.5: Problem type. Evacuation planning consists of determining the optimal way to evacuate pedestrian facilities as quickly and safely as possible. Some studies focus on a specific type of facility, such as a building or a room. Design of bottlenecks considers the optimal lay-out that maximises flow or minimises egress time. Crowd management decides on control policies to ensure the safety and comfort of people at mass-crowd events. In timetabling, the problem is to minimise people flows resulting from the timing and location of events.

Evacuation planning	
Building	Arbib et al. [22–24], Borrmann et al. [37], Cepolina [47, 48], Chalmet et al. [49], Chen and Feng [53], Choi et al. [61], Deng et al. [74], Fahy [86], Georgoudas et al. [110], Hoppe and Tardos [151], Kang et al. [174], Kisko and Francis [183], Li and Xu [201], and Park et al. [268]
Room	Abdelghany et al. [9], Ding [76], Pursals and Garzón [280], and Zhao and Gao [396]
Outdoor	Howard et al. [154], Mudassir et al. [252]
Other	Lim et al. [209], Ng and Waller [258], Opasanon and Miller-Hooks [264], Zarboutis and Marmaras [390], and Zheng and Liu [402]
Design of bottlenecks	Bakuli and Smith [26], Berseth et al. [34], Johansson and Helbing [167], and Tavares [341]
Crowd management	Selim and Al-Rabeh [301]

Thirdly, Selim and Al-Rabeh [301] study crowd management to improve the safety and comfort of pedestrians at mass crowd events. In each of these problem types, different objective function measures can be chosen to evaluate the quality of a solution (see Table 2.6). In the case of evacuation problems, the evacuation time is an important measure of the quality of the proposed plan. Both the average and the maximum evacuation time for all evacuees are used, but the latter is a more popular indicator as it indicates the time that the last person is brought to safety and thus optimises the safety of the least fortunate person. Opasanon and Miller- Hooks [264] also include the number of people evacuated before a certain time. Other researchers minimise the number of people left in the building at each discrete time step (Hoppe and Tardos, [151]), minimise the maximum probability of congestion that might occur in the evacuation network (Lim et al., [208]), or provide the reader with a set of alternatives to choose from (Zarboutis and Marmaras, [390]). For a further discussion of the many possible performance measures that can be employed for evacuation systems, see Løvås [229]. For design purposes, the maximisation of flow is often used to increase the efficiency of pedestrian facilities, which is important both for normal situations where large pedestrian traffic takes place and for evacuations to reduce congestion and egress times. In the crowd management model (Selim and Al-Rabeh, [301]), the author minimises a penalty function based on the number of people that are denied access at each time interval. In addition to the objective function measures employed, models can also be classified according to the decisions that are included, as is shown in Table 2.7.

The choice of evacuation routes for people to use is the most obvious type of decision included in evacuation models. Some models, however, also incorporate phased evacuation, where different groups of people start evacuation at different times. Phased evacuation is used to reduce congestion on the evacuation routes and consequently improve overall egress times. Zarboutis and Marmaras [390] instead develop generic guidelines for evacuations under different disaster scenarios, instead of proposing a fixed plan for a specific scenario. A different type of decision is modelled by Selim and Al-Rabeh [301], who develop an admission control policy for pedestrians on the Jamarat Bridge to ensure crowd density does not reach hazardous levels. For the category of design problems, Bakuli and Smith [26] determine the optimal widths of exits in a building that maximise throughput, whilst Berseth et al. [34] derive the optimal placement of obstacles in corridors and at exits to reduce the amount of clogging.

Table 2.6: Objective function measure and problem type.

	Evacuation	**Design**	**Crowd management**
Average evacuation time	Abdelghany et al. [9], Chalmet et al. [49], and Ng and Waller [258]		
Maximum evacuation time	Borrmann et al. [37], Cepolina [47, 48], Chalmet et al. [49] , Chen and Feng [53], Choi et al. [61], Deng et al. [74], Ding [76], Fahy [86], Georgoudas et al. [110], Hoppe and Tardos [151], Kang et al. [174], Kisko and Francis [183], Li and Xu [201], and Park et al. [268], Pursals and Garzón [280], Zhao and Gao [396] and Zheng and Liu [402]		Bakuli and Smith [26], Tavares [341]
Number of people evacuated to safety	Arbib et al. [22–24], Howard et al. [154], Mudassir et al. [252],Choi et al. [61], Hoppe and Tardos [151], and Opasanon and Miller-Hooks [264]		
Flow	Arbib et al. [22–24], Howard et al. [154], Mudassir et al. [252]	Bakuli and Smith [26], Berseth et al. [34], Johansson and Helbing [167]	
Other	Hoppe and Tardos [151], Lim et al. [209], Zarboutis and Marmaras [390]		Selim and Al-Rabeh [301]

2.6 Model realism

It is important that optimisation models represent crowd dynamics in a realistic way and are calibrated with empirical data to provide useful results for evacuation and design purposes. In Section 2.6.1, we first present a summary of the main findings of the empirical research on pedestrian and

Table 2.7: Decisions considered and problem type.

	Evacuation	**Design**	**Crowd management**
Evacuation Route Choice	Borrmann et al. [37], Cepolina [47, 48], Chalmet et al. [49] , Chen and Feng [53], Choi et al. [61], Deng et al. [74], Ding [76], Fahy [86], Georgoudas et al. [110], Hoppe and Tardos [151], Kang et al. [174], Kisko and Francis [183], Li and Xu [201], and Park et al. [268], Pursals and Garzón [280], Zhao and Gao [396] and Zheng and Liu [402]		
Phased Evacuation	Abdelghany et al. [9], Cepolina [47, 48], and Ng and Waller [258]		
Generic Evacuation guidelines	Zarboutis and Marmaras [390]		
Facility layout and location obstacles		Bakuli and Smith [26], Berseth et al. [34], Johansson and Helbing [167], and Tavares [341]	
Admission control policy			Selim and Al-Rabeh [301]

crowd dynamics. In Section 2.6.2 , we discuss the implications of these findings for the development of optimisation models and the problem of parameter calibration.

2.6.1 Empirical research on pedestrian and crowd dynamics

A lot of early empirical research focused on the relationship between free-flow walking velocity, $v(\frac{m}{s})$, and density, $\rho(\frac{people}{m^2})$, of pedestrian flows. In the same way, the relationship between flow, $q(\frac{people}{ms})$, and density can be derived, where $q(\rho) = \rho v(\rho)$. These relationships are called the 'fundamental diagram', because of their importance in determining the optimal dimensions of pedestrian facilities [298]. An early study in 1958 by Hankin and Wright [133] carried out experiments with schoolboys, in which they measured speeds at various concentrations and various passage widths, to obtain the shape of the speed-density and flow-density curves. Then observations were done at a London underground station in order to obtain absolute values for the established relationships. The four parameters that describe this relationship are q_{max} , i.e. the maximum density at which walking speed reaches zero, v_0, i.e. the maximum free walking speed at zero density, and ρ_c and q_{max}, which denote the critical density at which the maximum flow is reached. There are, however, significant differences between the results of various studies (Fruin [100]; Johansson et al. [168]; Mōri and Tsukaguchi [250]; Polus et al. [276]; Seyfried et al. [302, 303]). Table 2.8 summarizes the

Table 2.8: Parameters for speed-density and flow-density relationship from literature.

Experiment	$v_0\left(\frac{m}{s}\right)$	$\rho_{max}\left(\frac{\textbf{people}}{m^2}\right)$
Fruin [100]	1.30	6.60
Hankin and Wright [133]	1.61	6.46
Johansson et al. [168]	0.60	10.79
Mōri and Tsukaguchi [250]	1.40	9.00
Polus et al. [276]	1.25	7.18
Seyfried et al. [302, 303]	1.34	5.55

values obtained by different authors. Several explanations have been suggested for the differences in the obtained results (Schadschneider and Seyfried [298]): Helbing et al. [141] argue that the incentive of the movement matters; and Oeding [261] suggests the type of traffic plays a role (e.g., commuters compared to shoppers).

Aside from studies that derive quantitative results for pedestrian flows under normal circumstances, other studies have focused on evacuations, since the correct estimation [263] study the evacuation times of three university buildings. They specifically include pre-movement times, i.e. the time people need to realise that they need to evacuate and to decide on a course of action. They argue that the SIMULEX software can be used in evacuation scenario analysis to obtain reliable results. Kady [170] studies the relationship between the density and crawling movement of pedestrians in the event of a fire. The author finds that exit width has a significant impact on crawling speed, whilst population size is less important. Spearpoint and MacLennan [329] use a Monte Carlo simulation model to investigate the impact of gender, age, and obesity on the evacuation time from a high-rise building. Furthermore, an important factor of safety concerns the pressures which are experienced by pedestrians in extremely high- density crowds (Helbing and Johansson, [140]; Helbing et al., [141]). Smith and Lim [325] investigate the pressure which people can 'comfortably' endure when pushed against barriers. Finally, various self-organising crowd phenomena have been observed [82, 140, 251]. These phenomena are self-organising because they are the result of local interactions between many pedestrians, without any conscious actions of pedestrians to arrive at these phenomena [140]. The most important phenomena are:

- Lane formation: In bidirectional flows, pedestrians automatically start forming a number of lanes of varying width, with people in each lane moving in the same direction [297].

- Stripe formation for two intersecting flows: When two pedestrian flows intersect, stripes are formed in which pedestrians move forward with the stripes and side-wards within the stripes. This is a result of pedestrians trying to minimise friction with pedestrians moving in opposite directions. For three or more intersecting flows, no stable patterns emerge [138].

- Stop-and-go waves: At high densities pedestrians cannot move continuously. Instead, the crowd moves in waves [141].

- Turbulence: At extremely high densities pedestrians cannot control their own movements anymore, but are pushed around by the forces acting upon them [141].

- Herding: When individuals do not have knowledge of the optimal route, they start following others. This happens especially during evacuations [138].
- Zipper effect: In a bottleneck individuals move diagonally in front of others such that narrower lanes are formed and the capacity of the bottleneck increases [148].
- Faster-is-slower effect: When people keep moving forward when a bottleneck is congested, crowd motion is slowed down by the resulting friction [140].

2.6.2 Implications for modelling

In order to provide realistic results, optimisation models for evacuation or design problems should explicitly incorporate the different empirical results described in the previous section. To asses the realism of the models reviewed, we first focus on three model attributes which capture the different elements of pedestrian and crowd dynamics:

- *Congestion:* Does the model include the relationship between walking speed and density? This means that travel times or flow capacities cannot be assumed to be constants, but should be modelled as endogenous variables dependent on the number of pedestrians present at a certain location.
- *Bottlenecks:* Are bottlenecks such as exits explicitly included in the model? Bottleneck capacities should be based on the width of the bottleneck and the number of people queuing upstream of the bottleneck.
- *Direction of flow:* Does the model distinguish between uni- and bidirectional flows?

The first part of Table 2.9 lists the models which explicitly include these modelling aspects. We see that the majority of articles include congestion in their models, whilst only a smaller number explicitly include bottlenecks. Finally, most articles do not distinguish between uni- and bidirectional flows. Overall, these results might be considered as being positive, because the most important aspect (congestion) is included in most of the recent articles. Furthermore, incorporation of the direction of flow is less important, because there is still debate as to whether there even is a significant difference between the parameter values for uni- and bidirectional flows [299]. A second way to judge the realism of optimisation models is by looking at their ability to reproduce (some of) the self-organising crowd phenomena that have been observed empirically. We base our assessment on the information the authors provide in their articles (we have not tested the models ourselves. The second part of Table 2.9 shows the results). In only three articles do the authors validate their model by testing its ability to reproduce these phenomena. Of course, only microscopic simulation models, in which each pedestrian is modelled individually, are able to show these dynamics explicitly. However, this does not imply that other modelling techniques cannot reproduce realistic results for evacuation or design purposes.

Table 2.9: Model Realism

Incorporation of crowd dynamics	
Congestion	Abdelghany et al. [9], [22–24], Bakuli and Smith [26], Berseth et al. [34], Borrmann et al. [37], Cepolina [47, 48], Choi et al. [61], Deng et al. [74], Fahy [86], Georgoudas et al. [110], Johansson and Helbing [167], Kang et al. [174], Lim et al. [209], Mudassir et al. [252], Park et al. [268], Pursals and Garzón [280], Tavares [341], Vermuyten et al. [357], Zarboutis and Marmaras [390], Zhao and Gao [396], and Zheng and Liu [402]
Bottlenecks	Berseth et al. [34], Borrmann et al. [37], Cepolina [47, 48], Chen and Feng [53], Johansson and Helbing [167], Kang et al. [175], Li and Xu [200], Park et al. [268], Pursals and Garzón [280], Tavares [341], and Zhao and Gao [396]
Direction of flows	Berseth et al. [34], Deng et al. [74], Georgoudas et al. [110], Tavares [341], Zarboutis and Marmaras [390], and Zhao and Gao [396]
Reproducing crowd phenomena	Borrmann et al. [37], Johansson and Helbing [167], and Zhao and Gao [396]
Calibration	
Model tweaking	Borrmann et al. [37], Zhao and Gao [396] , and Zheng and Liu (2010)
Real-world data	Arbib et al. [22–24], Howard et al. [154], Mudassir et al. [252] Cepolina [47, 48], Fahy [86], Georgoudas et al. [110], and Pursals and Garzón [280]

2.7 Modelling and solution techniques

In this section, we discuss the different modelling and solution techniques that are proposed in the literature for evacuation problems and design of pedestrian facilities. To provide some background information and ideas for the development of more realistic optimisation models, we explore the main techniques used in descriptive models in subsections 2.7.1 and 2.7.2 to realistically represent pedestrian walking behaviour. Afterwards, we compare this with the modelling and solution techniques that are currently used in optimisation models in Table 2.10. Figure 2.10 gives a general overview of the different modelling techniques used in descriptive models. A more detailed assessments of these existing modelling techniques can be found in Duives et al. [82], Papadimitriou et al. [266], and Zheng et al. [403]. Approaches which are used to model evacuation problems may come from different problem fields, such as, network flow problems, traffic assignment problems, and simulation. Table 2.10 lists classes of models which can be used in the evacuation problem modeling although some of them may have been originally developed for different purposes. In general, there are two approaches used to model evacuation problems which emphasize on the estimation of the egress time, namely macro- and microscopic models.

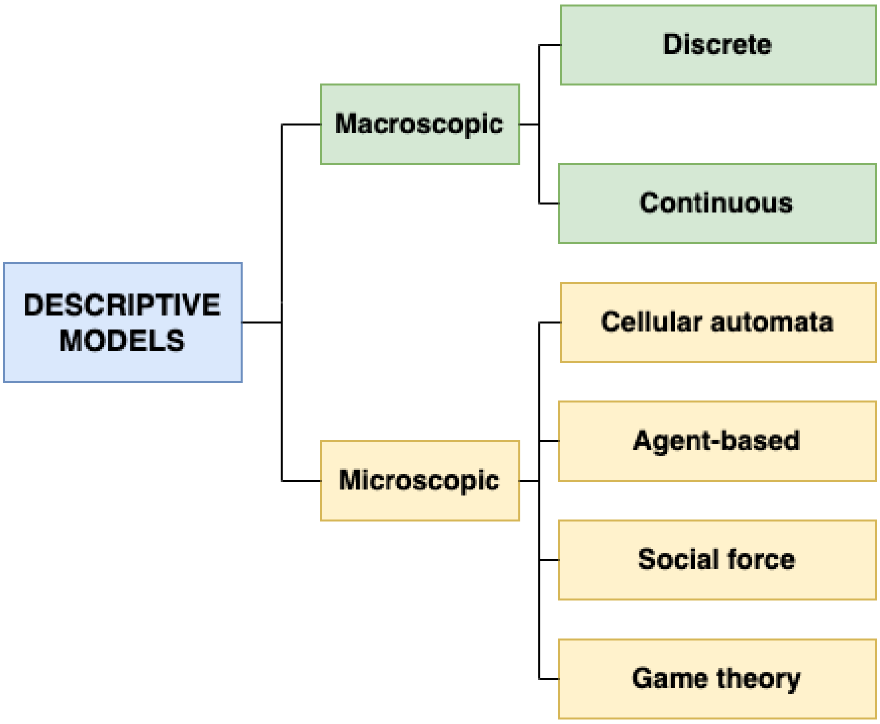


Figure 2.10: Overview of descriptive modelling techniques.

2.7.1 Macroscopic models

Macroscopic models are mainly based on optimization approaches and do not consider individual differences and decisions for selecting egress routes, i.e. occupants are treated as a homogeneous group where only common characteristics are taken into account. Since the time is a decisive parameter in the evacuation process, most macroscopic approaches are based on dynamic network flow models (see e.g. [41, 49, 60, 61, 86, 183, 186]). The common idea of these models is to represent a building and the attributes of the building's components in a static network $G = (V, A)$. The modeling of evacuation over time is then done in a dynamic network $G_T = (V_T, A_T)$ which is the time expanded version of G and the network flows correspond to evacuation processes (see, for instance, [13] for an overview on network flow theory). The static network G is used to model supply and demand points, and routes which are used to transfer supplies to demands. These routes may have some intermediate transshipment points. In the static network ow models, supply, demand and transshipment points are modeled by nodes while routes are modeled by paths of the graph. A path of the graph is composed by nodes and arcs, where an arc connects two adjacent nodes. The interrelation between nodes and arcs can, for instance, be described by the node-arc incidence matrix. In the representation of a building using a static network, nodes may represent rooms, lobbies or intersection points, while arcs can be used to model corridors, hall- ways, stairways or a connection between two intersection nodes. Some locations in the building that house a significant number of evacuees are considered to be source nodes in the network. The supply of a source node is given by an estimate of the number of evacuees in the location that the node represents. The building exits or safety locations that might be considered as the final destination of evacuees' movement, are considered as sink nodes. In the evacuation problem we have only one sink node by connecting all the exit nodes to one artificial node and assign the total number of evacuees as the demand value of this node. Hence, evacuation problems can be modeled as multi-source/single sink network ow problem. Each node has a capacity which is the upper bound of the number of evacuees simultaneously allowed to stay in the node. Macroscopic models are mainly used to produce good lower bounds for the evacuation time and do not consider any individual behavior during the emergency situation. These bounds can be used to analyze existing buildings or help in the design phase of planning a building. Macroscopic approaches which are based on dynamic network ow models (minimum cost dynamic flow, maximum dynamic flow, universal maximum flow, quickest path and quickest flow) are considered in Table 2.10. A special feature of the presented approach is the fact, that travel times of evacuees are not restricted to be constant, but may be density dependent. Using multi- criteria optimization priority regions and blockage due to re or smoke may be considered. It is shown how the modelling can be done using time parameter either as discrete or continuous parameter.

A discrete time dynamic network flow problem is a discrete time expansion of a static network flow problem. In this case the flow is distributed over a set of predetermined time periods $t = 1, 2, \cdots, T$. The discretization plays a vital role in the modeling of evacuation using dynamic network flows. To increase the accuracy of the model one can set the basic time unit θ very small, but this will enlarge the size of the network and thus the computational complexity of the solutions algorithm. Obviously, a trade off is necessary between good accuracy and computational tractability. Independent of this, the fact that the choice of discretization by choosing a specific basic time unit θ predetermines the possible set of evacuation plans is some what unsatisfying. There researchers tackle this problem by using a continuous-time approach to evacuation modelling. Continuous time dynamic network flow problems have been considered by various authors including Anderson et al. [18], Grinold [114], Tyndall [352, 353], Perold [273], Philpott [274], Philpott and Craddock [275] and Pullan [278, 279]. Most of existing works emphasize on the analysis of primal-dual relationships and the existence of the optimal solution.

2.7.2 Microscopic models

Microscopic models, in which the individual evacuees' movement is emphasized, are based on simulation. These models consider individual parameters (e.g. walking speed, reaction time, physical ability) and interaction of each evacuee with other evacuees during the movement. In recent years there is a growing interest to use CA as the base of microscopic simulation in the field of pedestrians and traffic movement (see for example [33, 184, 256]) which have close interrelations with evacuation problems. Microscopic models are able to model the individual evacuee's characteristics and the interaction among evacuees which influence their movement. Due to the corresponding huge amount of data one uses simulation approaches. Some probabilistic laws for individual evacuee's movement are presented. Moreover ideas to model the evacuee's movement using CA are discussed. In microscopic models each evacuee is considered as a separate flow object. An evacuee will be exposed to accident effects depending on the route he/she follows and the length of time spent in different locations. An evacuee selects the route 'step by step', which means that the choice of the next piece of the route is decided at every node along this route. The initially selected route might be changed due to some reasons, for instance, blockage by re or high congestion. Microscopic models emphasize the modeling of human behavior during an emergency situation. The human model can be provided with some personal attributes, for example, walking speed, personal memory and psychological condition. These attribute will be used to determine the movement decisions to select the nearest walkway, move on the walkway only when there is no blockage at the end, or change the destination target before reaching it. Løv as [231] proposed some different probability laws for personal movement relative to the route components (nodes and arcs).

Cellular automata models are microscopic simulation models where pedestrians are considered individually. They represent the evacuation area lay-out by a grid divided into cells. Usually, each cell can be occupied by a single pedestrian [36]. However, some models allow several pedestrians into one cell for scaling purposes, whilst others use smaller cells where each pedestrian occupies multiple cells, to allow for a greater degree of detail. Time is discretised and at each time step, pedestrians either move to a neighbouring cell or remain at their current location. The decision taken by a pedestrian depends on the status of the adjacent cells and is based on a predefined set of rules. Updating of cells can be executed either sequentially [118] or in parallel [36], in which case movements can only be executed when all conflicts between pedestrians are resolved. One of the first cellular automata models for the simulation of pedestrian movements was developed by Blue and Adler [36]. The authors focus on the various phenomena observed in bidirectional flows. Guo et al. [118] develop two route choice models, for the case of good and bad visibility respectively. Pereira et al. [272] explicitly include the relationship between average speed of a pedestrian and the density in the model. An advantage of the approach is its computational efficiency.

Agent-based models take a bottom-up approach as well, where only the behaviour of individual pedestrians is modelled and the resulting interactions between them determine the macroscopic behaviour. Agent-based models can use both discrete and continuous time and space representations. Each agent can have a unique set of behavioural rules, which allows for modelling heterogeneity in the population. A disadvantage of this flexibility is the high computational cost of running the model. Antonini et al. [21] use a discrete choice framework in which pedestrians choose a direction and speed based on the utility of each of the alternatives. This utility is influenced by the presence of other pedestrians. Chooramun et al. [62] combine three space representations (continuous space, fine network, and coarse network) into a single model to achieve an optimal trade-off between computational efficiency and model realism. Behaviour of agents is based on a different set of rules at each representation level. The MOBEDIC tool developed by Doheny and Fraser [78] models the actions of people in specific emergency situations, specifically focusing on the evacuation of an offshore environment. EXODUS is a similar software tool, developed by Galea and Galparsoro, intended for the evacuation of mass-transport vehicles such as aircraft [104]. It is also able to simulate crawling movement during evacuations [253]. A third software tool, developed for simulating the evacuation of geometrically complex buildings, is the SIMULEX model of Thompson and Marchant [344–346]. Wagner and Agrawal [360] developed an agent-based model for the evacuation of concert venues. The propagation of fire and smoke is included in the model and influences the route choice behaviour of individuals. However, there are still many challenges involved in the development of agent-based models [69].

A third set of microscopic models consists of the so-called social-force models. In this type of model, pedestrians have a desired velocity in the direction of their destination and their acceleration (deceleration) is the result of different forces. An individual experiences an attractive force in the direction of his target destination, and repulsive forces from obstacles (e.g. walls) and other pedestrians. Time and space are modelled in a continuous way. The social-force model was developed by Helbing [137] and Helbing and Molnar [142]. The model reproduces well-known self-organising crowd phenomena such as lane formation in bidirectional flows and oscillatory effects at bottlenecks. Langston et al. [193] represent pedestrians by three intersecting circles instead of a single circle, to incorporate the rotation of the pedestrians into the model. The model is realistic for dense crowd flow scenarios, but more complex scenarios are not yet fully realistically represented. Yuen and Lee [389] extend the social-force model to include overtaking behaviour, where pedestrians with a higher desired velocity catch up with and move past pedestrians heading in the same direction with a lower desired velocity. Qu et al. [282] also use a three-circle representation to model rotation and extend the social-force model to describe pedestrian movement on stairs.Huang et al. [156] instead use a reactive user equilibrium principle in which pedestrians only evaluate the immediate conditions of their environment without anticipating the behaviour of pedestrians in their surroundings. Their model is an extension of the macroscopic model of Hughes [157]. Lachapelle and Wolfram [192] present a pedestrian crowd model based on the theory of mean field games. The model is macroscopic, i.e. it describes crowd behaviour in terms of aggregates, but it is based on a realistic microscopic model in the sense that it considers smart pedestrians with rational expectations. Pedestrians are represented as agents having preferences (i.e. they want to maximise their utility) and perform strategic interactions within the crowd. They also anticipate the future.

2.8 Discussion and conclusion

In this chapter, we have reviewed optimisation models from the field of pedestrian walking behaviour and crowd dynamics. These models are used for a wide range of evacuation and design problems. We have also discussed the relevant empirical research and descriptive modelling techniques to provide a background for the reader and to substantiate the criteria that are used in the assessment of the different models. Studies with relevance to the prescriptive aspects of pedestrian evacuation, i.e. evacuation optimisation studies, were systematically reviewed and analysed. It appeared that the prescriptive domain of pedestrian evacuation studies has some catching up to do compared to the descriptive domain. Within the prescriptive domain also, the same was the case about the behavioural modification/training method compared to the architectural and path/schedule optimisation approaches. Currently, most of the attention is directed to the development of optimal evacuation plans, followed by the effective design of pedestrian facilities. However, there are other interesting problems related to pedestrian flows which have not yet received much attention in the literature, such as crowd management under normal conditions. An example is the minimisation of flows resulting from the timing and location of certain events, such as the assignment of lectures to rooms and time-slots in a university timetable, the scheduling of acts at music festivals, or the planning of different disciplines at large sports events, to ensure the safety (i.e., crowd densities do not reach hazardous levels) and comfort (i.e., people do not have to walk large distances or through high-density crowds and can reach their destinations in time) of the people present.

We also concluded that the behavioural modification approach, as a relatively overlooked method, has shown great potential in terms of the effectiveness based on the limited studies that have explored this area. Building on the idea that, in cases of disasters, people may not necessarily be the problem to control and they could rather be part of the solution, this approach could offer new possibilities in evacuation management. The method also appears to be offering better promise in terms of its practicality and the possibility of implementation compared to the architectural and path/schedule planning solutions. However, very little is still known about optimum individual strategies and much further work may still be needed before the knowledge becomes translatable to comprehensive guidelines and case specific training programs. Also, similar to the architectural method, the knowledge in the behavioural domain is predominantly coming from numerical studies whose findings are still awaiting rigorous empirical testing. This could potentially be a worthwhile area to consider for future research, along with identifying effective ways of delivering evacuation training programs. Whilst many of the earlier models concerning evacuation problems did not include the fundamental relationship between walking speed and crowd density, and instead assumed constant travel times, most of the recent articles represent these dynamics in their models. By way of contrast, the calibration of models should receive more attention in future work. However, calibration is still difficult because of the lack of consensus between data of different empirical studies. More research is needed in this area to reconcile or explain the contradictory results obtained in experiments. Closely related to this is the validation and application of optimisation models. Currently, most authors only test their models on theoretical data. To implement the models in practice, it is important that their results and predictions closely resemble real-world values. Furthermore, practitioners could benefit if authors describe the different challenges and pitfalls in implementing their models. Finally, there currently is a discrepancy between the techniques used in descriptive models and those used in optimisation models. The former are mostly variants of microscopic simulation models, because they seek to represent pedestrian dynamics as realistically as possible. By way of contrast, the latter gravitate towards net- work models in combination with flow transshipment algorithms or queuing processes, because of their mathematical tractability. Some of the recent models use an iterative process where a heuristic searches for good solutions, which are consequently tested by a simulation model that represents the resulting crowd dynamics in a realistic way. Future research should focus on integrating techniques of descriptive models within an optimisation framework to find the optimal trade-off between model realism and tractability.

Table 2.10: Modelling and solution techniques

Model Class	Evacuation Model	References
Static Network		
	Shortest Path	Chen and Feng [53], Fahy [86], Park et al [268], Yamada [378]
	Minimum cost flow	Yamada [378]
	Transshipment	Borrmann et al. [37], Chalmet et al. [49], Choi et al. [61] and Kisko and Francis [183]
	Integer Programming	Kang et al. [175], Lim et al. [209], and Vermuyten et al. [358]
	Chance constraint	Ng and Waller [258]
	Quickest Path	Chen and Chin[55], Chen et al. [55], Kagaris et. al. [171], Rosen et al. [291]
Discrete Time Dynamic network		
	Min turnstile cost	Chalmet et al. [49], Choi et al. [61], Kisko & Francis [183]
	Quickest Flow	Burkard [41], Fleischer et al. [93]
	Universally max flow	Hoppe and Tardos [150], Minieka [249], Wilkinson [370]
	Min weight path	Kostreva and Wiecek [186]
	Lexicographically minimal cost	Kagaris et. al. [171]
	Flow dependent exit capacity	Choi et al. [61], Chen and Chin[55]
Continuous time dynamic network		
	Constant capacity and travel time	Fleischer [94]
	Time dependent capacity	Anderson et al. [19], Philpott [274]
	universally maxi flow with zero travel time	Fleischer [95], Ogier [262]
Traffic assignment		
	Transportation network	Sheffi et al. [310], Zawack [391]
	Density dependent travel time	Carey & Subrahmanian [43], Chen & Hsueh [51], Janson [162], Jayakrishnan et al. [163], Ran & Boyce [283]
Heuristics		
	Simulated annealing	Cepolina [47, 48]
	Genetic algorithm	Abdelghany et al. [9] and Johansson and Helbing [167]
Simulation		
	Cellular automata	Abdelghany et al. [9], Georgoudas et al. [110], Blue, VJ & Adler [36], [33], Doheny and Frase [78], Klüpfel et al. [184], Nagel [256], and Zhao and Gao [396]
	Agent-based modelling	Tavares [341] and Zarboutis and Marmaras [390]
	Queuing	Bakuli and Smith [26], Deng et al. [74]
	Dedicated Algorithm	Choi et al. [61], Ding [76], Georgoudas et al. [110], Hoppe and Tardos [150, 151], Kang et al. [174], Li and Xu [201], Opasanon and Miller-Hooks [264], Pursals and Garzón [280], and Selim and Al-Rabeh [301]
	Probabilistic models	Ebihara et al. [84], Løvås [228, 229]
	Other	Berseth et al. [34], Deng et al. [74], Johansson and Helbing [167], and Zheng and Liu [401]

Chapter 3

Network Generation and Conversion

3.1 Introduction

Network flow optimization models, particularly the so-called system optimal traffic assignment models, have recently been applied to generate initial evacuation plans for emergency response. These optimization-based models are generally believed to be more capable of finding a good scheme among numerous alternatives than are the earlier "evaluate-then-pick" tools (e.g., Oak Ridge Evacuation Modeling System (OREMS) [285], IMDAS [132], NETSIM [284]), in which a limited number of evacuation plans are evaluated and compared. Hobeika and Jamei [145] proposed an evacuation planning model based on the static system optimal traffic assignment. To capture the dynamic features of network flows, Sattayhatewa and Ran [294] formulated a System Optimum Dynamic Traffic Assignment (SO-DTA) model by using the optimal-control theory. Liu et al. [219] encapsulated a similar SO-DTA model into an adaptive control framework for emergency evacuation In work by Chiu et al. [59], the best possible evacuation scheme was generated by the SO-DTA module of Dynasmart-P. Sbayti and Mahmassani [295] adopted a bilevel evacuation planning framework in which the combination of desired departure times, routes, and destination choices are produced by the SO-DTA module of Dynasmart-P. Recently, the cell-based model of Ziliaskopoulos [406] has been applied by a number of authors to solve the emergency evacuation problem. This model is built on the well-embraced cell transmission model (CTM) [71, 72] to represent traffic dynamics and has an appealing simple linear programming (LP) structure. Tuydes and Ziliaskopoulos [351] extended the earlier work of Ziliaskopoulos [406] by introducing a reversibility ratio to yield the optimal evacuation contraflow. A heuristic solution algorithm using the tabu-search was proposed in a subsequent paper [350]. Liu et al. [224] conducted a case study by using a simplified cell-based SO-DTA model. In their next paper [225], binary variables were introduced to the model to optimize staging orders. Chiu et al. [359] proposed to reduce the multiple-destination SO-DTA into a single-destination one by using a "superzone." More researches has been carried out on the properties of CTM, examinations on the congested and non congested freeway traffic to validate the model (Lin and Ahanotu [216]; Lo and Szeto [227]; Isak et al. [160]). Further researches were then carried out on the freeway flow behavior; expanding the CTM to represent the integrated freeway/surface street systems by proposing the adjustable cell length and signalized intersection

(Lee [195]; Isak et al. [160]). Not just for freeway, CTM usage was expanded for its application in roundabouts and signalized intersections (Chang and Lo [50]; Feldman and Maher [89]). Despite the substantial efforts in applying the cell-based SO-DTA model in the emergency evacuation context, little attention has been paid to the development of numerical solution procedures. This chapter addresses the following:

- Generation of an underlying network for the dynamic evacuation models using following closely the CTM developed by Carlos F. Daganzo.
- The proposal of the advanced cell transmission network optimization model and node-arc to cell-connector network transformation technique to encompass its application for large scale networks.

3.2 Cell Transmission Model - Daganzo's traffic simulation model

Carlos F. Daganzo [71, 72] proposed the alternative traffic simulation model called CTM using a simple representation of traffic on a highway with a single entrance and exit. He proposed that the difference equations used to predict traffic's evolution are the discrete analog of the differential equations arising from a special case of the hydrodynamic model of traffic flow. His equations for the traffic flow tried to mimic the real-life development of stop-and-go traffic within moving queues [71]. Following the research, again in the year 1995, Daganzo presented how the evolution of multi-commodity traffic flows over complex networks can be predicted over time, based on a simple macroscopic computer representation of traffic flow that is consistent with the kinematic wave theory under all traffic conditions. However his model lagged for it could not explain the freeway flow behavior under normal condition [72].

The CTM proposed by Daganzo in 1994-1995 is an innovative transformation of the differential equations based on Lighthill-Whitham-Richards (LWR) [207, 287] hydrodynamic traffic flow model to simple difference equations by assuming a piecewise linear relationship between flow and density at the cell level. One can view the CTM as a macroscopic traffic simulation model. The model accurately describes traffic propagation on street networks and captures traffic phenomena, such as disturbance propagation and creation of a shock-wave on freeways and can be easily adapted to account for traffic signal control and ramp metering devices. More specifically, Daganzo [71, 72] showed that if the relationship between traffic flow *(q)* and density *(k)* follows the function form (Equation 3.1) as depicted in Figure 3.1 where v, q_{max}, w, k and k_j denote the free flow speed, maximum flow (capacity), the speed with which disturbances propagate backwards when traffic is congested (the backward wave speed), density, and the maximum (or jam) density respectively. The fundamental diagram as shown in Figure 3.1 is assumed to be trapezoidal, where the slope v denotes the forward wave speed, or the free-flow velocity, and slope $-w$ denotes the backward wave speed. The ratio δ is denoted by $\delta = \frac{-w}{v}$ is the traffic flow parameter. Empirical experiments show that $v > -w$, and hence $\delta < 1$. The (LWR) equations for a single highway link can be approximated by a set of difference equations with current conditions (the state of the system) being updated at every time interval.

$$q = \min\{vk, q_{max}, w(k_j - k)\} \quad \text{for} \quad 0 \leq k \leq k_j \tag{3.1}$$

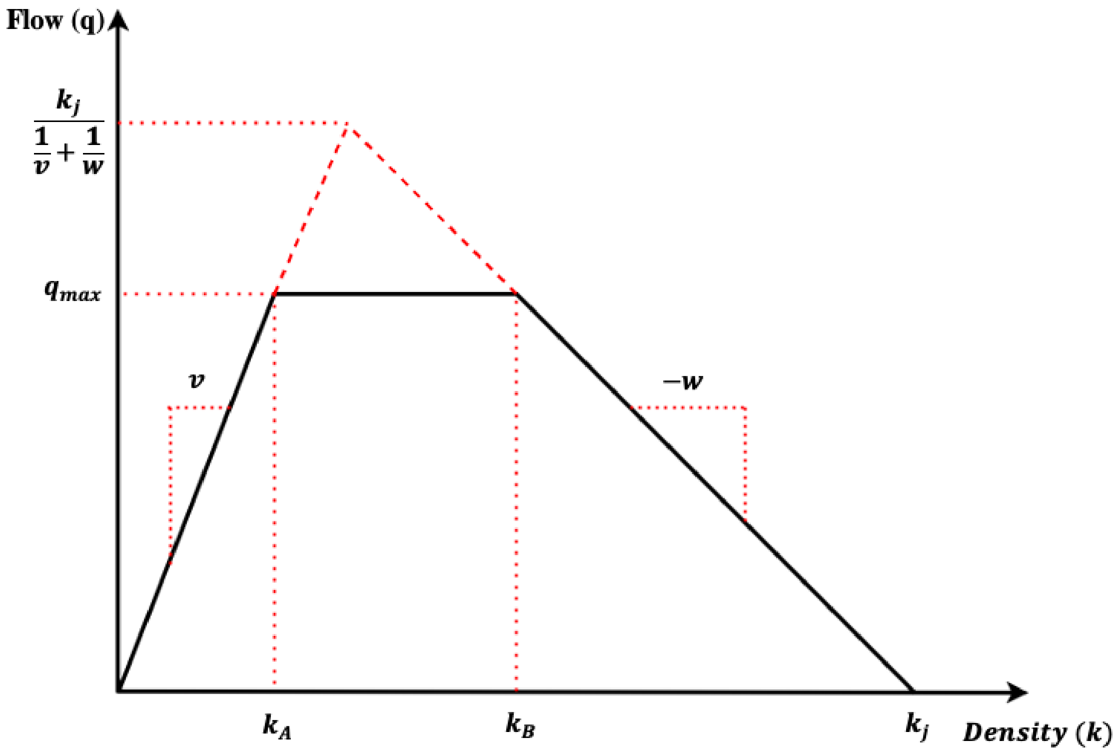


Figure 3.1: Fundamental Diagram in the CTM Model

Compared to conventional macroscopic node-arc network, cell transmission model stands a step ahead towards mesoscopic level of traffic flow analysis. It divides street-links into elementary homogeneous smaller sections called cells which can be traverse in any direction at the same time, such that the length of each cell is the distance traveled by a pedestrian with a free-flow walking velocity under normal conditions in a unit time step. Cells may in general have different shapes or sizes: for the purpose of this work, it is important that every cell can approximately be traversed in a single time unit. Depending on size, the i-th cell has a capacity n_i equal to the maximum number of people it can host and, at any given time t, the state of the network is given by the number of persons that occupy cell i time t, y_i^t. Moreover, depending on street size, a limited amount $x_{ij}^t \leq c_{ij}$ of people can move in the unit interval $[t, t+1]$ from cell i to an adjacent cell j, where c_{ij} is the capacity of the passage between cell i and cell j, that is the maximum number of people that can traverse the passage in the time unit. Also Q_i^t, is the maximum number of pedestrians that can flow into or out of cell i at time t. The cells are generally classified into ordinary, diverging, merging, source and super-sink cells as depicted in Figure 3.2. Different types of cells have different associated difference equations to ensure that the traffic dynamics are reasonably represented.

Hence the maximum outflow (inflow) from (into) a cell can be constrained respectively as:

$$S_j^t = \min\left\{y_j^t, Q_j^t\right\} \tag{3.2}$$

$$R_i^t = \min\left\{Q_i^t, n_i - y_i^t\right\} \tag{3.3}$$

Equation 3.2 is the maximum number of pedestrians that flows from cell j to any cell i while Equation 3.3 is the maximum number of pedestrians allowed into cell i at time t. Therefore the possible number of pedestrians that can flow from cell j to cell j to cell i in the time interval $(t, t+1]$ is given as $x_{ji}^t := \min\left\{S_j^t, R_i^t\right\}$. Thus the state of the system is updated at every time-slot for every cell by the following flow balance equation

$$y_i^{t+1} = y_i^t + x_{ki}^t - x_{ij}^t \tag{3.4}$$

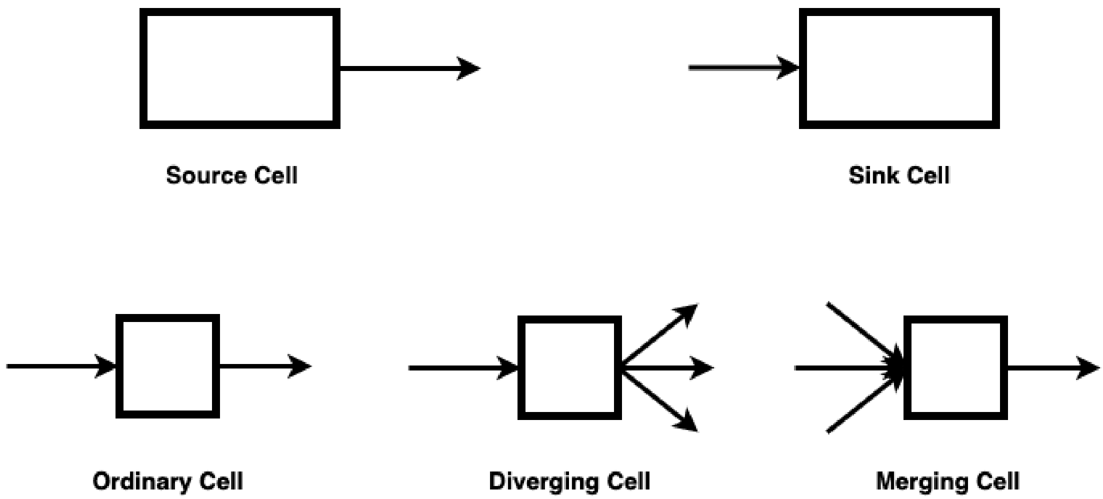
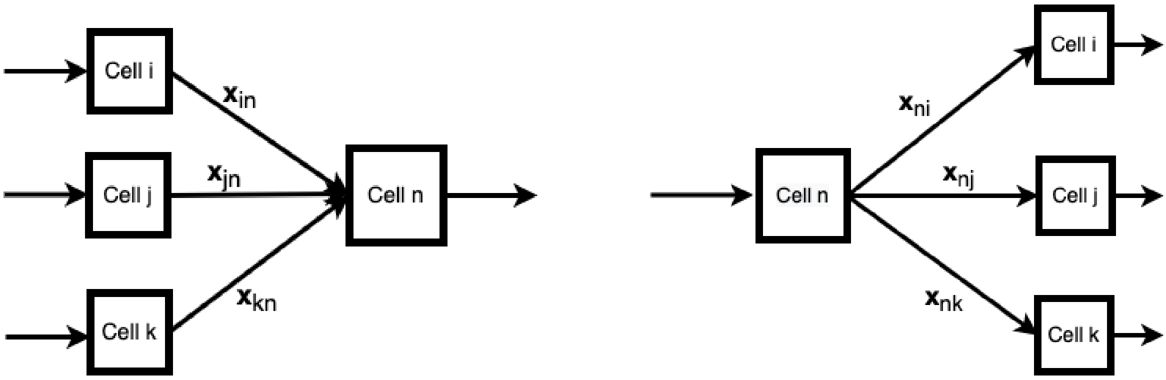


Figure 3.2: Illustration of the various types of cells used in the cell transmission model

In a system of network modeling, merging and diverging of cells occur at intersections. The merging junction consists of a cell which has multiple inbound flows and a single outbound flow from it as illustrated in Figure 3.3a, the flows from multiple upstream cells i, j and k enter the merging cell n. The possible inbound flows from cell i to cell n, cell j to cell n and cell k to cell n are given by x_{in}, x_{jn} and x_{kn} respectively. These inbound flows are constrained by R_n, the maximum flow that downstream cell n can receive and $S_i, S_j,$ and $, S_k$, the maximum flow that upstream cells $i, j$and $, k$ can send satisfying the following relationship.

$$x_{in}^t \leq S_i^t; \quad x_{jn}^t \leq S_j^t; \quad x_{kn}^t \leq S_k^t; \quad x_{in}^t + x_{jn}^t + x_{kn}^t \leq R_n^t \tag{3.5}$$

The diverging junction consists of a cell which has single inbound flow and multiple outbound flows in it. As illustrated in Figure 3.3b, the flow from diverging cell n divides and enters the multiple



(a) Merging Junction Cell. **(b)** Diverging Junction Cells.

Figure 3.3: Depiction of Merging and Diverging Cells in the CTM

outbound cells i, j and k. The possible outbound flows from cell n to cell i, cell n to cell j and from cell n to cell k, are respectively defined by the x_{ni}, x_{nj} and x_{nk}. Similarly, the outbound flows are constrained by S_n, the maximum flow that upstream cell n can send and $R_i, R_j,$ and $, R_k$, the maximum flow that downstream cells $i, j$and $, k$ can receive satisfying the following relationship.

$$x^t_{ni} \leq R^t_i; \quad x^t_{nj} \leq R^t_j; \quad x^t_{nk} \leq R^t_k; \quad x^t_{ni} + x^t_{nj} + x^t_{nk} \leq S^t_n \tag{3.6}$$

The CTM put forward by Daganzo, yet very primitive certainly provides a simple approach for modeling traffic propagation in streets and highways but one cannot ignore the drawbacks the proposed model has. The model requires that all cells in the simulation network should be homogenous. Also, for a large network, there would be many cells and computation memory becomes a big constraint. Also, it was tested only on small networks where there was no proper uniformity in node-link to cell-connector conversion. In the following sections, the enhancement of the model is proposed to address the above drawbacks and is extensively used for the large scale network to propose the SO-DTA Evacuation Model.

3.3 Network Transformation and Conversion (NTC) Model

The Network Transformation and Conversion (NTC) Model converts the static node-arc network for the given evacuation scenario and eventually generates the cell-connector network for solving the dynamic optimisation model using the proposed dynamic formulation models. The NTC model has two parts.

1. Firstly, the model restructures the evacuation network defining the demand, hot-zones, and safe-zones, adds a sink and virtual connectors connecting destinations and sink. (See Section 3.3.1 for details)

2. Secondly, the model replaces the node-arc network into cell-connector network as detailed in Section 3.3.2.

3.3.1 Network Transformation

The transformation of the conventional node-arc network to generate the cell-connector network is explained in detailed in the section. To illustrate the procedure of the CTM network transformation, two simple networks will be considered. Figure 3.4 is a bi-directional sample network with 17 nodes and 29 two-way arcs (total 58 arcs; two lanes in each link) while Figure 3.5 is a uni-directional version of the same network with 17 nodes and 29 arcs.

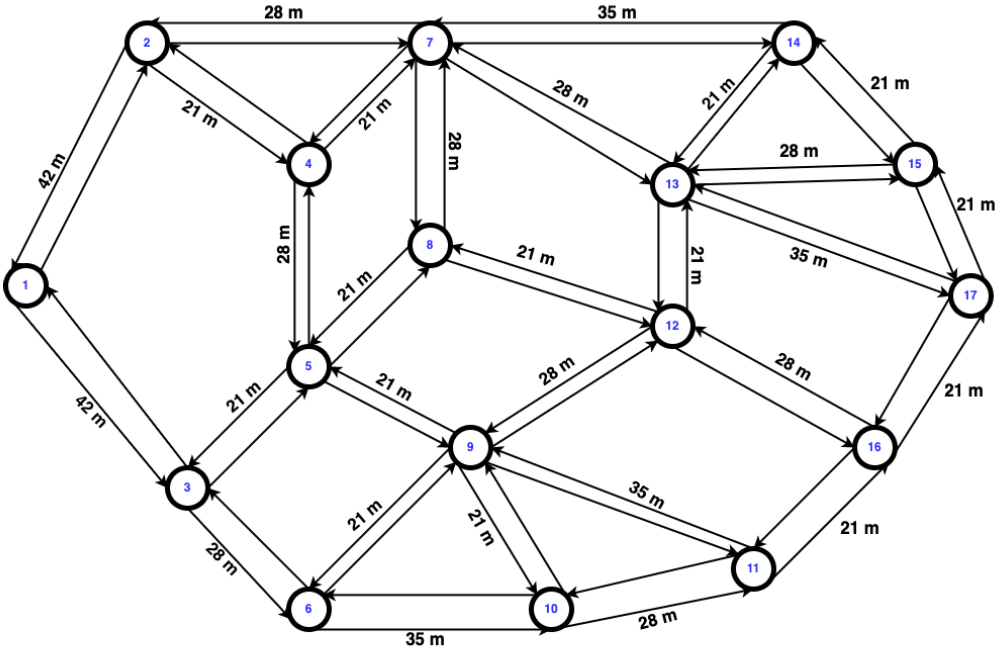


Figure 3.4: A bi-directional sample network to illustrate the CTM

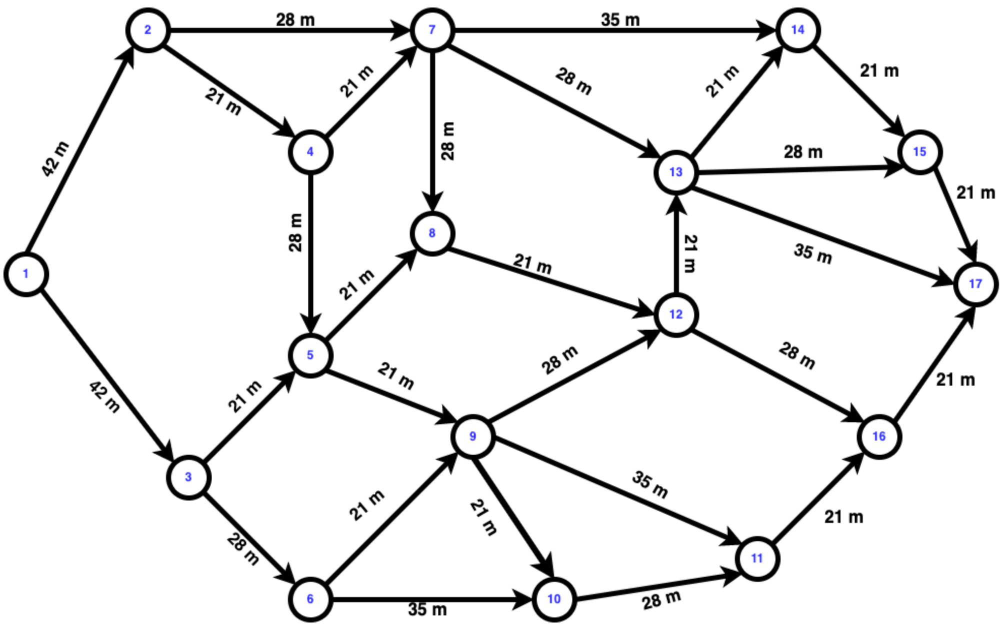
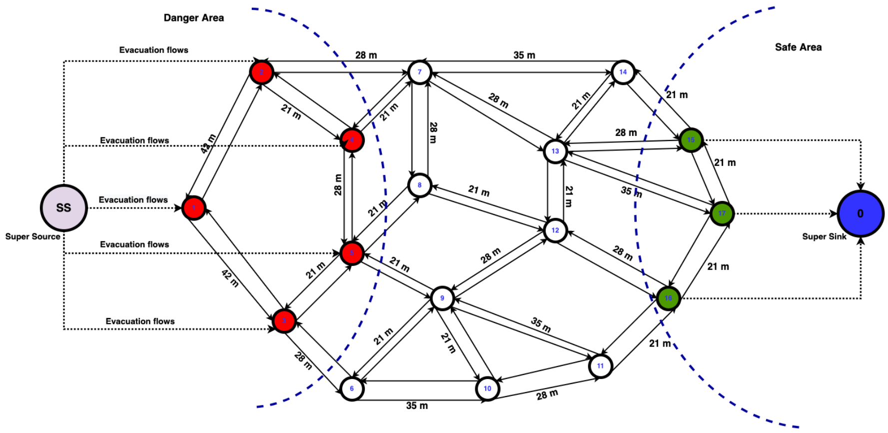


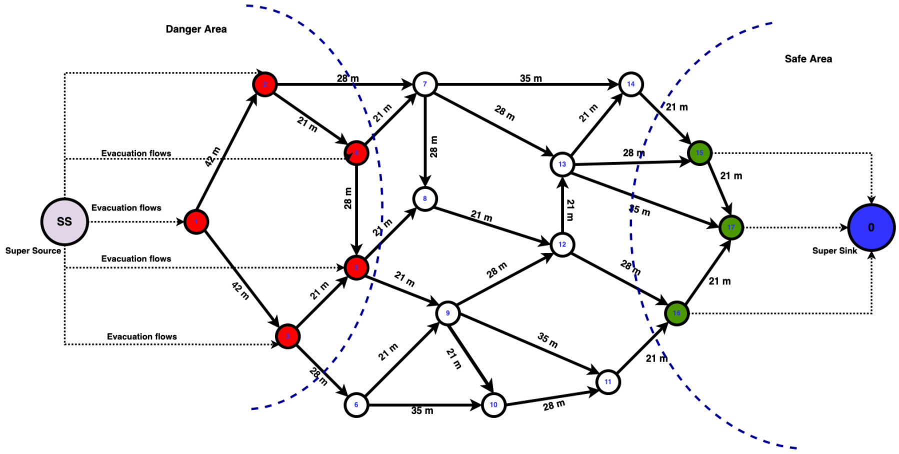
Figure 3.5: A uni-directional sample network to illustrate the CTM

Given a spatial network $G = (V, A)$ consisting of a system of nodes,V and arcs A with their directions. For an emergency evacuation scenario, we define the "Hazard or Danger Area", "Safe

Locations", "source nodes" and "sink (destination) nodes". The danger area is the area where the disaster be it natural such as earthquake, hurricane, flood, etc or artificial such as terrorist attack occurs. For this example, the west side of the sample network is considered as the Danger Zone (Evacuation Area) and thus, has all the source nodes (nodes 1 to 5). Safe Zone is the area where possible sink/destination nodes are defined to receive the evacuation flow loaded from the source nodes. The east side of the sample network is considered as the Safe Zone with all the possible destination nodes (nodes 15, 16 and 17). A virtual *super-source* node, from where all the evacuation flows are loaded into the network, is added and connected to all the source nodes. Similarly a virtual *super-sink* node 0 is added connecting all the sinks nodes o receive all the evacuation flows that reach the destinations.. All the virtual arcs from the super-source and super-sink to their respect source and sink nodes have 0 distance/length and "one-way". Figure 3.6 depicts the evacuation scenario together with the complete transformed spatial network. After the definition if the evacuation scenario, we are now ready to transform the node-arc network into cell-connector network using the CTM methodology.



(a) Transformed Evacuation Network for bi-directional network.



(b) Transformed Evacuation Network for uni-directional network.

Figure 3.6: Transformed Evacuation Scenario Network for both bi-and uni-directional networks in Figures 3.4 and 3.5

3.3.2 Cell-Connector conversion from Node-Arc Network

The Node-Arc to Cell-Connector conversion gives the cell-connector representation of the transformed evacuation network. This divides the links (arcs in the original network) into homogeneous smaller segments called *cells* which are equidistant. The grid geometry and size of the cells may lead to different levels of accuracy. It can be observed that, in general, cells may have different shapes or sizes: but for the purpose of this work it is paramount that each cell can approximately be traversed, in any direction, in a single time slot. *Cell 0* conventionally represents the super-sink or the collection of all the safe destinations. Safe places can be disconnected areas, but as their capacity is assumed large enough to accommodate all the evacuees. The length of each cell is dependent on the time value of the unit time step and the *free flow walking velocity* to be discussed later in section The length of each cell and the number of cells in every arc of the conventional node-arc network are computed respectively as:

$$\text{Cell length (m)} = \text{free flow walking velocity (m/s)} \times \text{unit time step (s)}$$

$$\text{Number of cells} = \frac{\text{arc length (m)}}{\text{cell length (m)}}$$

For the sample example network (considering Figure 3.4), assuming the unit time value of 7 seconds and a free flow walking velocity of 1.0 m/s, the number of cells in each arc is computed and reported in Table 3.1 such that 6 cells can be embedded into arcs: $\{(1, 2), (2, 1), (1, 3), (3, 1)\}$ each. Also 5 cells each can be embedded into arcs $\{(6, 10), (10, 6), (7, 14), (14, 7), (9, 11), (11, 9), (13, 17), (17, 13)\}$. A super-source cell is added for every source node and a super-sink cell 0 is added for every sink node. After the cells are generated from the arcs, they are named with unique ID numbers following the order in which they nodes, and arcs from which they were generated appears in the original node-arc network.

After the cells and their IDs are generated, they are linked with 'connectors'. Connectors define the direction of flow coming to and going out of a cell. Generation of connectors is a very critical step of the CTM as the arcs direction should be preserved same as they appear in the original network. From the section 3.2, it is clear that a link is represented by a group of ordinary cells having a single inflow and single outflow connectors and the end cells as merging and diverging. A node or intersection is represented by a group of connectors depicting the intersection flow as shown in Figure 3.7a. The proposed conversion algorithm also generates the connectors for U-turns in an intersection (see Figure 3.7b).

Figure 3.8 shows a complete transformed and converted cell-connector network using Network Transformation and Conversion (NTC) model with source cell, ordinary cells, merging cells, diverging cells, destination cell and super sink cell inter-linked with ordinary and intersection connectors. From Figure 3.8, node *SD* represent the virtual super-sink from which all the initial occupancies are loaded into the network at their respective source nodes. The nodes in red are the source nodes in the original spatial network. Also the destination cells are in green color into which all the evacuees are collected. Finally the super-sink node 0 in blue collective receive all the people

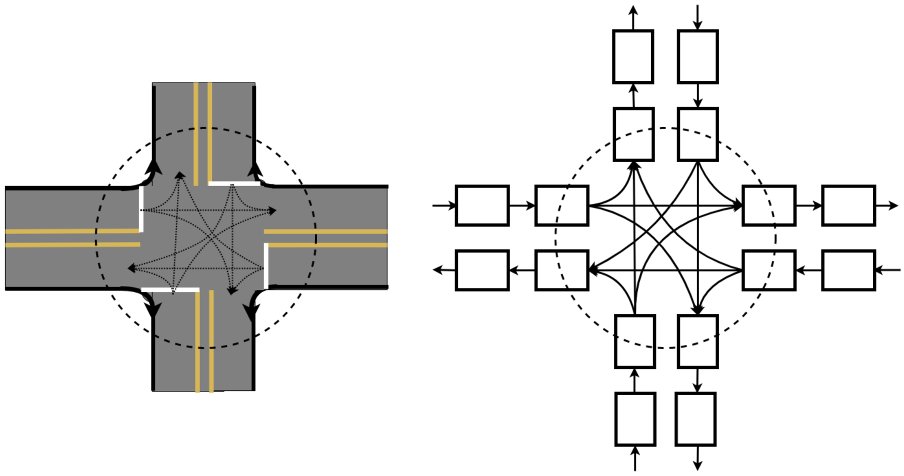
Table 3.1: Embedding static network into grids with time-step = 7 secs

Arcs	Length (m)	No. of Cells
(1, 2) ; (2, 1)	42	6
(1, 3) ; (3, 1)	42	6
(2, 4) ; (4, 2)	21	3
(2, 7) ; (7, 2)	28	4
(3, 5) ; (5, 3)	21	3
(3, 6) ; (6,3)	28	4
(4, 5) ; (5,4)	28	4
(4, 7) ; (7,4)	21	3
(5, 8) ; (8, 5)	21	3
(5, 9) ; (9, 5)	21	3
(6, 9) ; (9, 6)	21	3
(6, 10) ; (10, 6)	35	5
(7, 8) ; (8, 7)	28	4
(7, 13) ; (13, 7)	28	4
(7, 14) ; (14, 7)	35	5
(8, 12) ; (12, 8)	21	3
(9, 10) ; (10, 9)	28	4
(9, 11) ; (11, 9)	35	5
(9, 12) ; (12, 9)	28	4
(10, 11) ; (11, 10)	28	4
(11, 16); (16, 11)	21	3
(12, 13) ; (13, 12)	21	3
(12, 16) ; (16, 12)	28	4
(13, 14) ; (14, 13)	21	3
(13, 17) ; (17, 13)	35	5
(13, 15) ; (15, 13)	28	4
(14, 15) ; (15, 14)	21	3
(15, 17) ; (17, 15)	21	3
(16, 17) ; (17, 16)	21	3

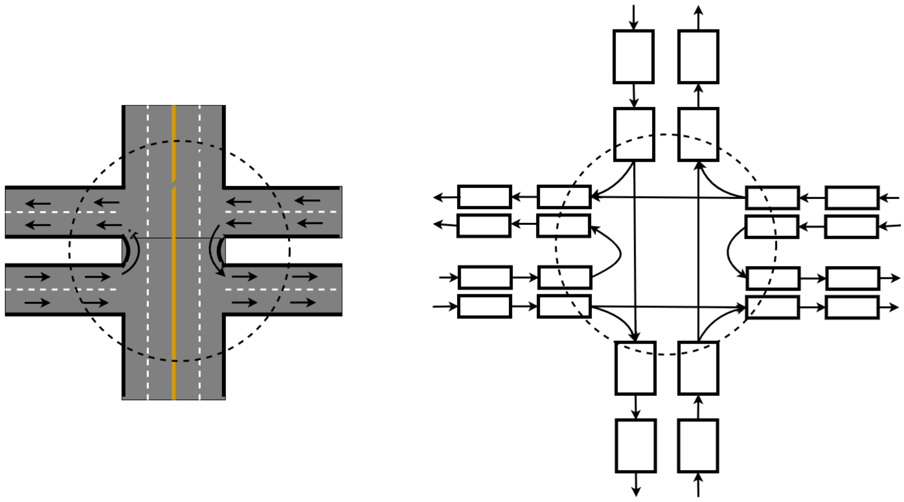
reaching the destination nodes. In addition to the above steps, the algorithm also uses the GIS data to incorporate transformation and conversion for the real, large-scale city level networks. The conversion of the uni-direction graph (see Figure 3.5) follows the same procedures outlined above. Figure 3.9 is the transformed uni-directional network.

3.4 Concluding Remark

CTM-based DTA model is a discretization of the differential equations of hydrodynamic model of Lighthill and Whitham [207] and Richards [287] (LWR) to simple difference equations by assuming a piece-wise linear relationship between flow and density at the cell level. In LWR theory, the traffic (pedestrian) flow is treated as a fluid and formulations are based on two basic assumptions: there is a one-to-one relationship between speed and density, and traffic is conserved [254] .Using the LWR theory, Daganzo [71, 72] introduce the CTM concept to simulate the trafficon a single highway link, for which Ziliaskopoulos [407] later on develops a linear programming formulation.



(a) Intersection Node with group of connectors.



(b) U-turn Node with group of connectors.

Figure 3.7: Representation of intersection and u-turn nodes with their various connectors.

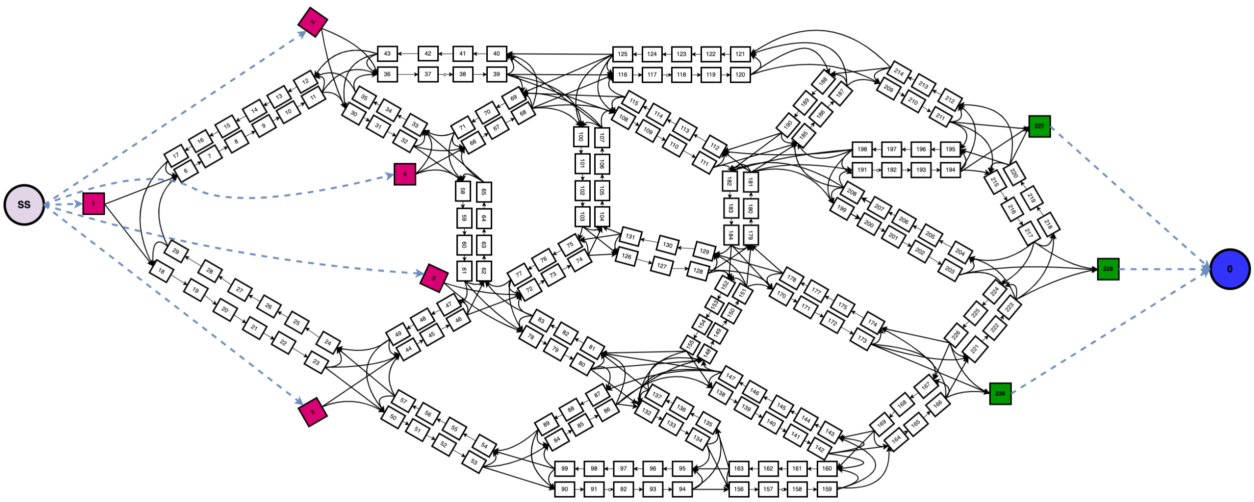


Figure 3.8: Complete transformed bi-directional cell-connector network using CTM

The transformed network in CTM is made up of cells, each of which has a length that is equal to the distance that can be traveled during the specified unit time interval at the free-flow speed. The state of the system at anytime instant t is represented by the flow volume, i.e., the number of vehicles

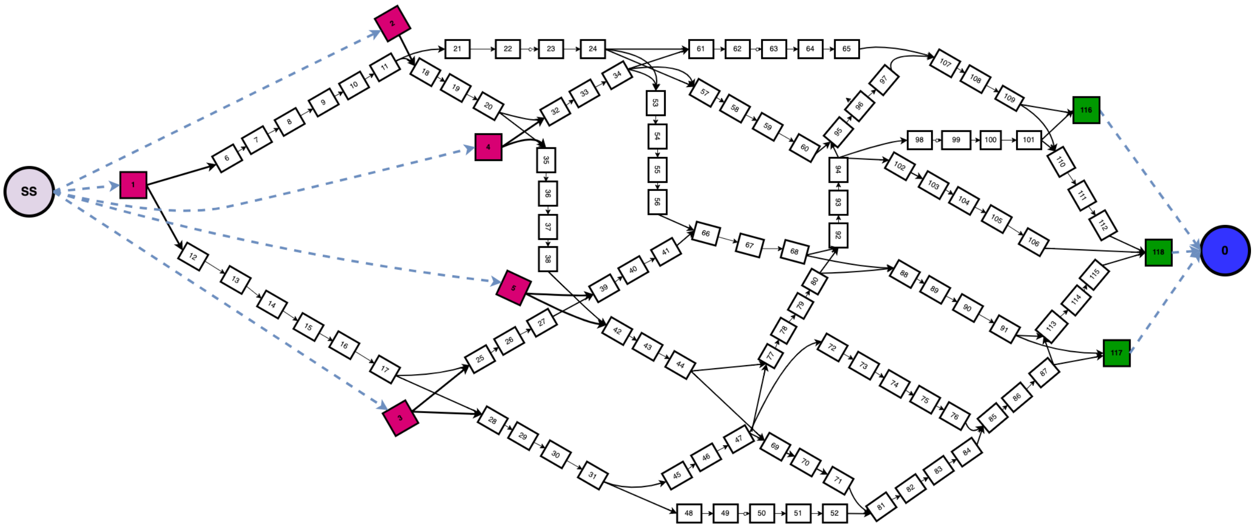


Figure 3.9: Complete transformed uni-directional cell-connector network using CTM

y_i^t contained in each cell $i \in C$, and $t \in T$. The cells are connected by connectors which carry the information of limiting values for the flow capacities. It should also be noted that, although the model assumes a piece-wise linear relationship at the cell level, it captures reasonably well the non-linearities between speed–density and travel time–density at the link level [406]. The main advantage of this formulation is that it does not need any assumption of link performance function and that it can be solved and further developed by the existing linear programming techniques. Also the CTM-based modeling is link based rather than path based.

Finally for a detailed description on the transformation of an enriched Geographical Information System (GIS),the reader is referred to [154, 252] where the authors adopted a 2-stage hierarchical approach define the underlining spatial network using several attributes such as the risk of buildings and streets, the number of occupants in buildings, streets length and widths and the waiting areas.

Chapter 4

Automatic Generation of no-notice large-scale Evacuation plans

4.1 Introduction

When a natural or technological (artificial) calamity strikes or threatens a populous area, exposing it to immediate or imminent life-threatening conditions (e.g., hurricanes, flooding, earthquakes, chemical explosions, terrorist attacks, etc.), mass evacuation is required. The efficient coordination and exploitation of roadway capacity, traffic control equipment, and available emergency response resources are critical to completing this tough task. The evacuation plan may differ depending on the sort of crisis that caused the evacuation, such as short-notice or no-notice disasters. Short-notice disasters are those that have a desirable lead time of between 24 - 72 hours [59, 354, 371, 372] allowing Emergency Management Agencies (EMA) to determine alternate evacuation strategies based on *a priori* upon the expected spatial-temporal impacts of the disaster. Examples of short-notice disasters are events such as hurricanes, flooding and wildfires. Conversely, a no-notice evacuation takes place when any large and unexpected incident occurs. The evacuation that takes place immediately after the occurrence of a disaster is defined as a "no-notice evacuation" [59]. When a no-notice disaster occurs requiring a mass evacuation, a pre-conceived evacuation plan can be immediately put in action. Traffic control and routing strategies need to be rapidly and frequently updated according to unfolding traffic conditions. An EMA is often faced with control and routing strategies that typically involve four critical operational decisions, including:

- choose a location for individuals to be evacuated (destinations);
- choose the best route (route), which is usually the safest but not necessarily the shortest.
- determine how to regulate flow rates on these routes (traffic assignment); and
- determine the rate at which evacuees from various parts of the region should be allowed to join the network (phased departure schedule).

Because typical urban transportation networks are made up of a variety of high-ways of distinct functional classes that are interconnected with diverse topology and connectivity, methodological issues arise. Methodological challenges arise since typical urban transportation networks are made up of a variety of high-ways of distinct functional classes that are interconnected with diverse topology and connectivity. Choosing an optimal evacuation destination-route-flow plan and departure time necessitates a methodical strategy that makes full use of optimization tools. Multiple evacuation destinations may exist for each evacuation zone. Evacuation destinations are specified as the final sites where evacuees are considered safe, and hence they define the perimeter of the relevant evacuation network. Multiple evacuation routes may exist for each evacuation destination. Each route may have its own geometric configuration and capability for pedestrian movement. This issue can be addressed using dynamic network flow models. For this evacuation application, it is particularly important to incorporate the explicit modeling of traffic flow dynamics with the optimal multidimensional destination-route-pedestrian assignment-departure schedule decisions into a unified model so that the optimal solutions are consistent with traffic flow dynamics. This model should also have a simple structure that can be solved efficiently so that the optimal solution can be obtained soon after the occurrence of the disaster.

4.2 Related Work

Network flow optimization models, particularly the so-called SO-DTA system optimal traffic assignment models, have recently been applied to generate initial evacuation plans for emergency response. These optimization-based models are generally believed to be more capable of finding a good scheme among numerous alternatives than are the earlier "evaluate-then-pick" tools (e.g., OREMS, IMDAS, NETSIM),in which a limited number of evacuation plans are evaluated and compared. Hobeika and Jamei [145] proposed an evacuation planning model based on the static system optimal traffic assignment. To capture the dynamic features of network flows, Sattayhatewa and Ran [294] formulated a SO-DTA model by using the optimal-control theory. Liu et al. [219] encapsulated a similar SO-DTA model into an adaptive control framework for emergency evacuation. In work by Chiu et al. [58], the best possible evacuation scheme was generated by the SO-DTA module of Dynasmart-P. Sbayti and Mahmassani [295] adopted a bilevel evacuation planning framework in which the combination of desired departure times, routes, and destination choices are produced by the SO-DTA module of Dynasmart-P. In literature Evacuation Route Planning (ERP) is addressed by either static or dynamic algorithms. Static and time-varying (dynamic) flow terms relate to the temporal characteristics of the traffic flows in evacuation models. In the static flow case, traffic flows are fixed, whereas in the time-varying case, flow rates can change with time [245]. Generally classified as Dynamic System Optimal (DSO), Dynamic User Equilibrium (DUE), Dynamic Traffic Assignment (DTA) models represent the changing patterns of the traffic flow, that is the time varying characteristics of the traffic conditions. Evacuation models are generally based on traffic assignment models, static models mostly originating from the formulation introduced by Beckmann et al. [29]. The dynamic evacuation models are mostly modified versions of the model proposed by Merchant and Nemhauser [248] and the cell transmission model (CTM) based DTA model introduced by Daganzo [71, 72] and developed into an LP by Ziliaskopoulos [406] . Also dynamic network flows based evacuation models are used as shown in [38, 131]. DTA models are mainly categorized as analytical (optimization based) and simulation-based models. A very detailed overview of DTA models can be found in Peeta and Ziliaskopoulos [270]. Analytical models have evolved since the introduction of the pioneering work by Merchant and Nemhauser [248] and efforts in this category include mathematical programming formulations, optimal control theory based formulations and variational inequality approaches. Most analytical models are modified from static formulations. The main drawbacks of these models are that they may not represent time dependent dynamic traffic characteristics and user behaviors as realistically as simulation-based models and they may be intractable for realistic size networks. Simulation-based, macroscopic, mesoscopic or microscopic DTA models overcome these difficulties. These include but are not limited to NETVAC [310], MASSVAC [145, 146], REMS [348], RouteSim [407], OREMS [99], DYNASMART [242]. Although these models are informative, they require relatively much more time, extensive data and effort to set up and computer resources to run properly. Further, the heuristic approaches used in them always brings the possibility of converging at a suboptimal solution. These models are generally better fit for real-time evacuation management purposes. Static traffic assignment has been used by traffic planners to estimate current and future use of transportation networks [172]. Static models can give relatively good estimations for planning purposes and instances with large evacuation networks can be solved to optimality using exact solution methodologies. They adequately represent no-notice evacuations as evacuees are loaded into evacuation network at once [265]. Despite their advantages, static models are not adequate to represent the traffic dynamics, information provision and user behavior that can change over time based on different conditions. In planning, offline DTA models can replace the existing static models. However, while dynamic models represent the traffic flow over time more realistically, they suffer from the drawback of solving large instances exactly and lose tractability as the evacuation road network size grows. Most of the DTA models in the literature such as Liu et al. [226], Chiu et al. [59], Ng and Waller [258], Yazıcı and Özbay [386] and Bish et al. [35] deal with relatively small networks and cannot address the challenges associated with real world networks and applications. Ziliaskopoulos et al. [408] deal with these implementation challenges related to using DTA on large scale realistic networks. However, their methodology is simulation-based and the large scale realistic implementations of evacuations using optimization based DTA models is continuing to be a challenge.

Recently, the cell-based model of Ziliaskopoulos [406] has been applied by a number of authors to solve the emergency evacuation problem. This model is built on the well-embraced cell transmission model (CTM) [71, 72] to represent traffic dynamics and has an appealing simple linear programming (LP) structure. Tuydes and Ziliaskopoulos [349] extended the earlier work of Ziliaskopoulos [406] by introducing a reversibility ratio to yield the optimal evacuation contraflow. Chiu et al. [359] proposed to reduce the multiple-destination SO-DTA into a single-destination one by using a "superzone." Arbib et al. [24] used the CTM to model the quick and safe evacuation of people from an exhibition centre in the city of L'Aquila (Italy), they later embedded the system into an Internet of Things (IoT) framework which aimed at crowd monitoring and optimum evacuation [22, 23]. In order to investigate the effect of total number of safe locations on the egress time, Howard et al. [154] run experiments on a city-wise real data, concluding that indeed the number of safe locations affect the total egress time. Also Mudassir et al. [252] developed a data science framework incorporating the CTM for both emergency evacuation and reconstruction planning. They also investigated the effect of the granularity of the cell size on the total time taken for the entire evacuation process to be completed.

4.3 Mathematical Model

The model formulation in this section is based on both proposed network transformation and demand specification techniques. The network transformation includes the categorization of all the source nodes (danger zone), destination nodes (safe zone), creating sink node (single destination concept) and virtual links that connect destination nodes to sink node. The demand specification includes assigning all the evacuation flows into respective source nodes at the beginning of evacuation. Once the network and demand are both ready, the node-arc network is converted to a CTM cell-based network using the NTC model proposed in section 3.2. Cells are connected via cell connectors. All the cells can be physically regarded as ordinary cells, merging cells, or diverging cells but in this work all the cells are assumed ordinary. From a demand specification standpoint, all the cells in the danger zone can be source cells with multiple destination cells in the safe zone receiving the evacuation flow but only one super-sink cell representing the sink node should exist. The resulting cell network is a single-sink network. All the evacuation flow-units emanating from source cells will be assigned and routed through the network to reach destination cells and to the super-sink cell by solving the proposed linear programming evacuation model. The model formulation is presented below is the DyCTEP.

4.3.1 Dynamic Cell-Transmission-based Evacuation Planning Model (DyCTEP) [1]

Based on earlier work of Choi et al. [61] and Arbib et. al [22–24] where authors devised a discrete-time network stock-and-flow model where one finds, at increasing time stamps τ, the maximum amount of people that can be evacuated within τ to a given set of safe areas. An optimal solution is found for each time stamp, up to when everyone has been evacuated. The starting point of the model is a static oriented network $G = (N, A)$, obtained from the graph of the underlining network of the area to be evacuated, by a suitable embedding of the city streets into a set N of elementary cells as discussed in section 3.2; the arcs in A connect geometrically adjacent cells in both directions. Cells may in general have different shapes or sizes: for the purpose of this work, it is important that every cell can approximately be traversed in a single time unit. Depending on size, the i-th cell has a capacity n_i equal to the maximum number of people it can host and, at any given time t, contains some number $y_i^t \leq n_i$ of people. Moreover, depending on street size, a limited amount $x_{ij}^t \leq c_{ij}$ of people can move in the unit interval $[t, t+1]$ from cell i to an adjacent cell j. The parameters n_i and c_{ij}^t are the queuing parameters. Finally, depending on scenarios,

[1] An article based on this chapter has been published as: see [154]

the network G may consists of a number of maximal connected components: in each component, safe places collectively correspond to a single super-sink 0 with a capacity large enough to host all evacuees.

Table 4.1: Notations and Parameters

Symbol	Description
Parameters:	
$\mathfrak{T}$	Set of discrete time intervals $T = \{0, 1, \cdots, \tau\}$
V	Set of nodes or cells of graph G
D	Set of sink/destination nodes in graph G
S	Set of source nodes of graph G
0	A collection of all the sink nodes of graph G or the super-sink node
A	Set of arcs or connectors in G
c_{ij}	The capacity of the connector between cell i and cell j: this is the maximum nominal amount of people that can traverse the passage in the unit time.
n_i	The maximum nominal capacity of cell i
v	Free-flow walking velocity
w	backward propagation of speed
δ_i^t	The ratio $\frac{w}{v}$:= The traffic flow parameter for cell i at time t
$\hat{y}_i$	Initial occupancy of cell i
q_i	Total number of evacuees to be evacuated from cell i
Decision Variables:	
y_i^t	The state of cell i at time t i.e the number of persons contained in cell i at time t In particular, $\sum_i q_i \leq n_0$.
x_{ij}^t	The flow of people from cell i to adjacent cell j in the time $(t, t+1]$. This gives the average speed at which pedestrian move from cell i to cell j.

In the DyCTEP we make T copies of the network generated by NTC which results in an acyclic digraph $D = (N_T, A_T)$ with node set $N_T := N \times T$ and arc set $A_T := \{(i,t) \to (j, t+1) : ij \in A, t \in T\}$. The dynamic time-expanded graph D models all the feasible transitions that could occur in the area to be evacuated in the entire time horizon. Using x_{ij}^t and y_i^t as non-negative decision variables (see Table 4.1), we obtain the following dynamic maximum flow cell-transmission-based model as follows:
The objective can either be to maximize the number of evacuees reaching the safe location 0 within the time horizon τ given as:

$$\max \quad \{y_0^\tau\} \tag{4.1}$$

or aims to minimize the total system travel time for all cells (excluding the super-sink cell) over the entire planning horizon $\mathfrak{T} = 0, 1, \cdots, T$, that is:

$$\min \quad \sum_{t \in \mathfrak{T}} \sum_{i \in V \setminus 0} \tau y_i^t \tag{4.2}$$

Since the time increment of τ is assumed to be one time unit, it can be removed from the formulation to give:

$$\text{Problem: SO-DTA (CTM)} : \min \sum_{t\in\mathfrak{T}} \sum_{i\in V\setminus 0} y_i^t \tag{4.3}$$

That is, One then seeks the least τ^* within which the totality of people can be evacuated from the endangered area: to reduce CPU time, τ^* is computed by logarithmic search. In this way, the method provides the decision maker with the Pareto-frontier of the conflicting objectives $\min\{\tau\}$, $\max\{y_0^\tau\}$.
Subject to the following constraints:

$$y_i^t - y_i^{t-1} - \sum_{j:ji\in A} x_{ji}^{t-1} + \sum_{j:ij\in A} x_{ij}^{t-1} = 0, \quad \forall i \in V \setminus \{S \cup 0\}, t \in T, t > 0 \tag{4.4a}$$

$$y_0^t - y_0^{t-1} - \sum_{j:j0\in A} x_{j0}^{t-1} = 0, \quad t \in T, t > 0 \tag{4.4b}$$

$$y_i^t - y_i^{t-1} + \sum_{j:ij\in A} x_{ij}^{t-1} = \begin{cases} q_i, & \text{for } t = 1 \\ 0, & \text{for } \forall t > 1 \end{cases}, \quad \forall i \in S \tag{4.4c}$$

$$\sum_{j:ji\in A} x_{ji}^t \leq Q_i, \quad \forall i \in V \setminus \{S\}, t \in T \tag{4.4d}$$

$$\sum_{j:ji\in A} x_{ji}^t \leq \delta_i(n_i - y_i^t), \quad \forall i \in V \setminus \{S\}, t \in T \tag{4.4e}$$

$$\sum_{j:ij\in A} x_{ij}^t \leq Q_i, \quad \forall i \in V \setminus \{0\}, t \in T \tag{4.4f}$$

$$\sum_{j:ij\in A} x_{ij}^t - y_i^t \leq 0, \quad \forall i \in V \setminus \{0\}, t \in T \tag{4.4g}$$

$$0 \leq x_{ij}^t + x_{ji}^t \leq c_{ij}, \quad \forall (ij) \in A, t \in T \tag{4.4h}$$

$$y_i^0 = \hat{y}_i, \quad \forall i \in V \tag{4.4i}$$

$$x_{ij}^0 = 0, \quad \forall (i,j) \in A \tag{4.4j}$$

Constraints 4.4a - 4.4c stands for the flow conservation at each intermediary cell, super-sink cell and source cells respectively. The total inflow into a cell is bounded by not only the inflow capacity (Constraint 4.4d) but the remaining capacity of the cell (Constraint 4.4e). Similarly, total outflow from a cell is limited by the outflow capacity (Constraint 4.4f) and the current occupancy of the cell (Constraint 4.4g). The box constraint 4.4h reflects the limit on the hosting capability of the arcs on G. Constraint 4.4i loads the initial occupancy into the dynamic network at time $t = 0$. The remaining initial conditions and the negativity conditions are implied in the remaining constraints.

The optimal solution of the DyCTEP model formulation, equations 4.1 or 4.2 and constraints - 4.4a - 4.4j characterizes the joint destination-route flow-departure schedule decision. At optimality, the time-dependent flow rate x_{ij}^t of the inbound cell-connectors of each destination cell $i \in D$ determine the time-dependent arrival of evacuees at each destination cell. A destination cell is not considered active if it does not receive any evacuation flow over the entire evacuation period. The optimal traffic assignment is represented by y_i^t and the flow rates of the cell $i's$ inbound x_{ij}^t.

The optimal time-dependent flow rates for the connectors from the source cells to the cells near the origin $x^t_{ij}, \forall i \in S$, represent the optimal discharge of evacuation flow from the source cells into the network. This characterizes the optimal evacuation departure schedule at each evacuation origin. The proposed model is a linear programming (LP) SO-DTA evacuation model based on cell transmission model, the objective of which is to minimize the total system travel time.

4.3.2 Incorporating Arc-Congestion into Model

[2] Due to the linear structure of the model, large number of variables can be allowed in solution. Adding these variables can help improve model granularity by reducing space and time units. More importantly, it can also help approximate the non-linearities along the arc capacities. When c_{ij} is constant, we fail to model arc-congestion, which is a situation where the speed at which the system empties is a decreasing function of room occupancy y^t_i. A more accurate model of congestion requires arc capacity to be a concave decreasing function of room occupancy, see Figure 4.1. We in fact assume that the capacity c_{ij} of link ij is not constant, but decreases with the flow in the link. From Figure 4.1, in order to linearize the congestion on the arcs or passages between adjacent cells, we introduce constant parameters c, c', c'' and n, n', n''. The meaning of these parameters is shown in Figure 4.1: in particular, c_{ij} is the link capacity when no flow traverses the link. As the flow of people increases in the interval $[0, n'_j]$, the capacity linearly goes down to a value c'_{ij}, with gradient $\frac{c_{ij}-c'_{ij}}{n'_j}$, corresponding to the green-dotted lines. A similar linearization is defined for flows in $[n'_j, n''_j]$ shown with the blue-dotted lines with capacity c''_{ij} with slope $\frac{c'_{ij}-c''_{ij}}{n''_j-n'_j}$, and $[n''_j, n_j]$: in the latter case, the capacity is reduced to 0 (in fact, the link is blocked when n people try to cross it). The DyCTEP model can be formulated by removing the arc capacity constraints 4.4h in 4.4 and adding the following constraints (equations 4.5a - 4.5f) to the model formulation 4.4a - 4.4g and 4.4i - 4.4j.

$$y^{t-1}_i = u^{t-1}_i + v^{t-1}_i + w^{t-1}_i, \quad x^t_{ij} = \phi^t_{ij} + \chi^t_{ij} + \psi^t_{ij}, \quad \forall (ij) \in A, t \in T, t > 0 \tag{4.5a}$$

$$u^{t-1}_i \leq n'_i, \quad v^{t-1}_i \leq n''_i - n'_i, \quad w^{t-1}_i \leq n_i - n''_i, \quad \forall i \in V, t = \{1, 2, \cdots T\} \tag{4.5b}$$

$$0 \leq \phi^t_{ij} \leq c_{ij} - \frac{c_{ij} - c'_{ij}}{n'_j} u^{t-1}_j, \quad \forall (ij) \in A, t \in T, t > 0 \tag{4.5c}$$

$$0 \leq \chi^t_{ij} \leq c'_{ij} - \frac{c'_{ij} - c''_{ij}}{n''_j - n'_j} v^{t-1}_j, \quad \forall (ij) \in A, t \in T, t > 0 \tag{4.5d}$$

$$0 \leq \psi^t_{ij} \leq c''_{ij} - \frac{c''_{ij}}{n_j - n''_j} w^{t-1}_j, \quad \forall (ij) \in A, t \in T, t > 0 \tag{4.5e}$$

$$u^t_i, v^t_i, w^t_i \geq 0, \quad \forall i \in V, t \in T \tag{4.5f}$$

Constraints 4.5b gives the upper bounds for the non-negative parameters u^{t-1}_i, v^{t-1}_i, and w^{t-1}_i which linearizes the concavity. The consistency of the ϕ, χ and ψ variables, in constraint 4.5a with the x flow variables requires $\chi = 0 (\phi = 0)$ if ϕ (if χ) does not saturate its capacity. This is ensured,

[2]An article based on this chapter has been published as: see [252]

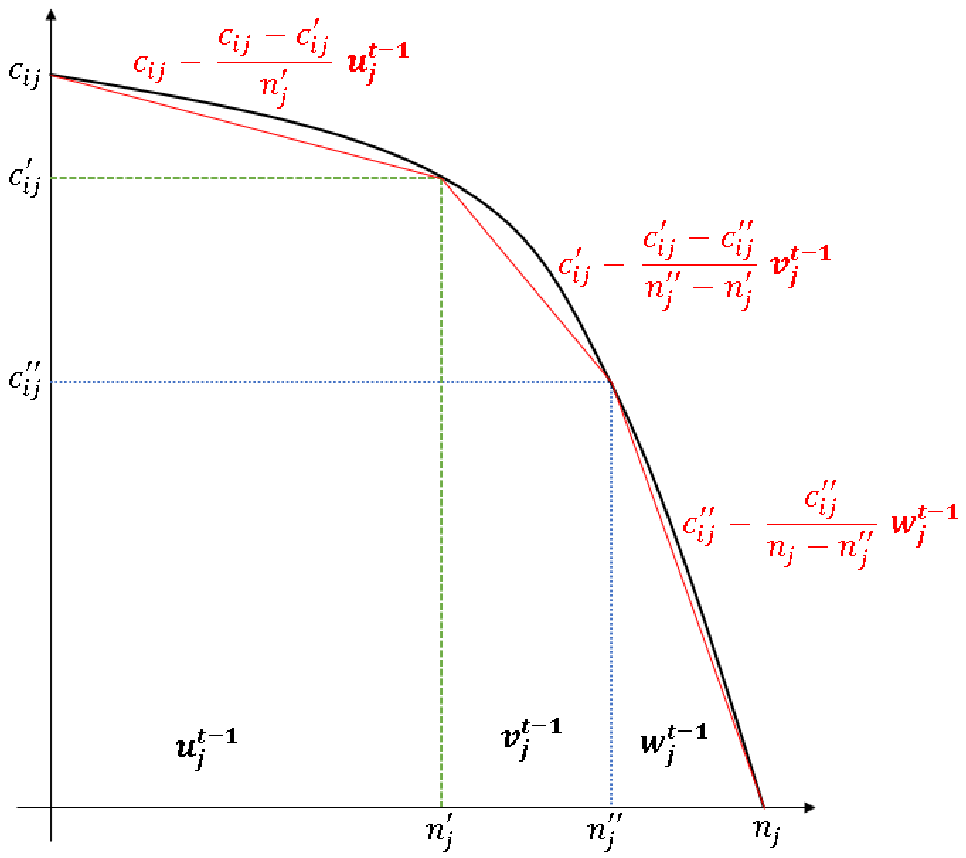


Figure 4.1: Linearization of a congestion curve.

at optimality, by the properties of basic solutions. After rephrasing inequalities 4.5c - 4.5e can be written as:

$$
\begin{aligned}
0 \leq \phi_{ij}^t, \qquad & \phi_{ij}^t + a_{ij} u_j^{t-1} \leq c_{ij} \\
0 \leq \chi_{ij}^t, \qquad & \chi_{ij}^t + a'_{ij} v_j^{t-1} \leq c'_{ij} \\
0 \leq \psi_{ij}^t, \qquad & \psi_{ij}^t + a''_{ij} w_j^{t-1} \leq c''_{ij}
\end{aligned}
\tag{4.6}
$$

where

$$
a_{ij} = \frac{c_{ij} - c'_{ij}}{n'_j}, \qquad a'_{ij} = \frac{c'_{ij} - c''_{ij}}{n''_j - n'_j}, \qquad a''_{ij} = \frac{c''_{ij}}{n_j - n''_j}
\tag{4.7}
$$

and $a_{ij} < a'_{ij} < a''_{ij}$, we observe the following fact (that can be generalized to any piece-wise linear approximation of the congestion curve Figure 4.1) Variables ϕ, χ and ψ are introduced to linearize a non-linear capacity constraint that simulates link congestion.

Proposition 4.3.1. *Assume that the following holds in a feasible solution, $n'_i > \bar{u}_i^t$ and $\bar{v}_i^t > 0$. Let $\eta = min\{n'_i - \bar{u}_i^t, \bar{v}_i^t\}$. Then a solution with $u_i^t = \bar{u}_i^t + \eta, v_i^t = \bar{v}_i^t - \eta$ and the other components unchanged is also feasible and no worse than the given one.*

Proof. By the definition of η, $u_i^t \leq n_i$, and $v_i^t \geq 0$. Moreover, since $y_i^{t-1} = u_i^{t-1} + v_i^{t-1} + w_i^{t-1}$ the occupancy of cell i at time t remains unchanged. Considering the implication of ϕ, and χ, the sum of the relevant arc capacities is increased by $\eta(a'_{ij} - a_{ij}) > 0$. Thus it is possible to compensate a decrease of $\bar{\phi}^t_{ij}$ with an identical increase of $\bar{\chi}^t_{ij}$, resulting in $x^t_{ij} = \phi^t_{ij} + \chi^t_{ij} + \psi^t_{ij}$ as an equivalent flow x^t_{ij}. ■

4.3.3 Pedestrian-Holding Cell Property

From the formulations discussed in the previous sections, it is evident that flows moving from cell i to cell j follow the following rules:

$$\begin{aligned} y_i^{t+1} &= y_i^t + x_{ki}^t - x_{ij}^t \\ x_{ij}^t &= \min\Big\{y_i^t, c_{ij}, \delta(n_j - y_j^t)\Big\} \end{aligned} \tag{4.8}$$

Overall flows moving from cell i to its adjacent cell j are controlled by three factors: the sending flow or current occupancy y_i^t, the available space for receiving flow $\delta(n_j - y_j^t)$ and the capacities the cell-connector c_{ij} that allow flow to pass through. Equation 4.8 is a disjunctive function, and its feasible region involves a nonconvex set. Ziliaskopoulos [406] relaxed it to give the following inequalities:

$$\begin{aligned} x_{ij}^t &\le y_i^t \\ x_{ij}^t &\le c_{ij} \\ x_{ij}^t &\le \delta(n_j - y_j^t) \end{aligned} \tag{4.9}$$

Equation 4.9 yields a multi-value solution set for $x^t_{ij} :\rightarrow \mathbf{R}^+$, where $0 \le x^t_{ij} \le \min\Big\{y_i^t, c_{ij}, \delta(n_j - y_j^t)\Big\}$. That is, if the solution falls into the inequality region, pedestrians are likely to be held in a cell without moving forward, even if there is enough capacity in its downstream adjacent cells. Such a solution property is known as *"pedestrian-holding"*.

Definition 4.3.1 (Pedestrian-Holding and Pedestrian Non-Holding Flow/Solution)**.** Let $f = (y_i^t, x_{ij}^t) \ge 0$ be the feasible flow/solution in a cell network. If inequality 4.10 holds for the flows on connectors/passages, f is referred to as a pedestrian-holding flow/solution; if flow on connectors satisfies equality 4.11, f is referred to as a pesdetrian non-holding flow/solution.

$$x_{ij}^t < \min\Big\{y_i^t - \sum_{k:ik\in A, k\neq j} x_{ik}^t,\, c_{ik} - \sum_{k:ik\in A, k\neq j} x_{ik}^t,\, c_{kj} - \sum_{k:kj\in A, k\neq i} x_{kj}^t,\, \delta(n_j - y_j^t) - \sum_{k:kj\in A, k\neq i} x_{kj}^t\Big\}, \quad \forall x_{ij}^t \in f \tag{4.10}$$

$$x_{ij}^t = \min\Big\{y_i^t - \sum_{k:ik\in A, k\neq j} x_{ik}^t,\, c_{ik} - \sum_{k:ik\in A, k\neq j} x_{ik}^t,\, c_{kj} - \sum_{k:kj\in A, k\neq i} x_{kj}^t,\, \delta(n_j - y_j^t) - \sum_{k:kj\in A, k\neq i} x_{kj}^t\Big\}, \quad \forall x_{ij}^t \in f \tag{4.11}$$

Shen et al. [313] demonstrated that there is always an optimal solution that retains the pedestrian non-holding property on connectors/passages. We contend, however, that imposing pedestrian non-holding on all connectors may result in suboptimal solutions. For example, instead of forcing pedestrians to take a non-queue branch that leads to a longer journey, it may be preferable to queue at a branch for the purpose of going onto a shorter path (i.e., eliminate pedestrian-holding on connectors connecting to the non-queue branch). Holding pedestrians on connectors implies that they will come to a halt along their route (assuming no restrictions are in place), even if there is sufficient room to move forward. In this scenario, pedestrian-holding is an unrealistic traffic flow phenomenon that should be avoided wherever possible in solutions.

4.3.4 Static Evacuation Route Plans: Paths generation on maps

The goal of this section, is to provide a service for city planners involved in disaster management after the implementation of the dynamic optimisation procedures described in sections 4.3.1 and 4.3.2. Since the solution of the optimisation model in sections 4.3.1 and 4.3.2 usually gives an estimate of the lower bound on the time necessary to evacuate maximum number of people from given danger zones to safe locations, we would like to provide evacuation routes for different sets of evacuees based on some characteristics. For instance, considering a simple scenario where there are two buildings, A and B to be evacuated and two coloured paths red and blue along which the evacuees need to follow. We want to optimally compute how to assign these evacuees from the buildings along the different paths to the safe locations in order to reduce lost lives, say all evacuees in building A must follow the blue route while those coming from building B must follow the red route to get to the safe locations.

Algorithm 1 is a greedy heuristic to plan an emergency evacuation routes for the evacuees to follow in case of a disaster. The algorithm generates a set of routes/paths based on the simulation dynamics of the optimisation model defined in sections 4.3.1 and 4.3.2 implemented on the network generated in section 3.2. Given the network $G_T = (N_T, A_T)$, with the list of all sources and destinations cells, together with a book-keeping time series dictionary DT, which captures all the information about the flows x_{ij}^t on the arcs A_T in G_T following the dynamics of the network evolution through time on the entire evacuation procedure for the various time steps $\tau \in T$. Note that, G_T is the dynamic time-expaned version of the static network $G = (N, A)$. From DT we obtain information on how frequent each arc $(i, j) \in A_T$ was used in the optimal solution of the evacuation procedure simulation process using the dynamic optimization model in 4.3.1 and 4.3.2. For $t = 1, ..., T$ and each $(i, j) \in A$ stored in DT, estimate w_{ij} the number of times arc (i, j) was traversed by the evacuees in the optimal solution. Next generate a weighted static graph $G' = (N', A', w)$, where the nodes, N' and arcs A' of G' are the same as that of graph G, that is, $N' = N$ and $A' = A$ and arc capacity w, are the estimated frequencies of the arc usage in the optimal evacuation dynamics. Next, all arcs $(i, j) \in A'$ in G' are then sorted from the highest weight to the lowest frequency. To generate the routes, define an empty tree T_r. Loop through the sorted weight-arcs (i, j), take the arc with the highest weight and add it to the tree T_r, and if by adding this arc to T_r a cycle is created, reject this this and do not add to T_r. Finally keep adding edges to the tree until all nodes in G' can be reached without forming any cycles. The resulting tree (or forest depending on whether the algorithm returns a single connected component or several disjointed connected components) is a maximum spanning tree (forest) which is then used as the evacuation routes (paths) along which evacuees will be assigned from the source in danger to the safe locations and collected at super-sink 0.

Algorithm 1: Greedy Heuristic for Evacuation Route Planning

Input: Dynamic network $G_T = (N_T, A_T)$, with the set of source and sink nodes, $S \subset V$ and $0 \subset V$ respectively and DT = book-keeping (using time-series dictionary) of all the network dynamics obtained after the implementation of the dynamic optimization model in sections 4.3.1 and 4.3.2.

Output: Evacuation route plans for all evacuees.

Count the number w_{ij} of occurrences of (i, j) in DT.
Generate a weighted static graph $G' = (N', A', w)$ where w gives the arc frequencies calculated above.
Sort the arcs in G' from the highest to the lowest frequency.
Initialize $T_r := (N', E')$ with $E' = \emptyset$ (empty forest)
while *(T_r is not yet connected)* **do**
    Take an arc (i, j) with the largest frequency w_{ij} and check whether it forms or not a cycle with some arcs in E
    If not, $E := E \cup \{(i, j)\}$.
Return a spanning tree T_r of maximum weight.
Re-run the dynamic optimisation model of Sections 4.3.1 and 4.3.2 on T_r.

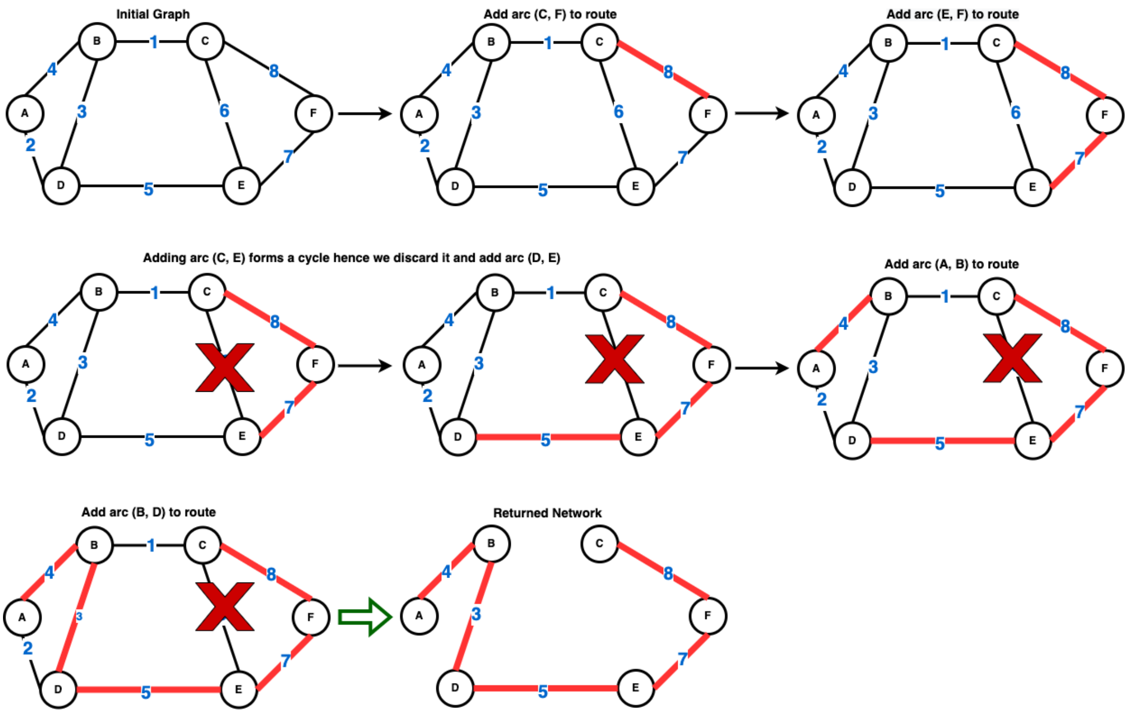


Figure 4.2: Illustrative example of how Algorithm 1 works

To illustrate how Algorithm 1 works, consider the simple network in Figure 4.2. We first sort the edges of graph in increasing order. Add arc (C, F) of weight 8 to the tree, next we add arc (E, F) with weight 7 to the tree. Adding arc (C, E) to the tree results in a cycle hence we discard it and add the next arc (D, E) in the list with weight 5 to the tree. The process continues until the maximum spanning tree is generated and the process halts.

4.3.4.1 Analysis of Algorithm 1

In this section we analyzed the time and space complexity of the proposed Algorithm 1 as well as the worst and best cases in time complexity. Given a graph $G = (N, E)$, such that $|N| = n$ and $|E| = m$, then the time and space complexities can be computed as follows (as shown in Figure 4.3):

- To tally the frequency of each arc in G_T we need: $\mathcal{O}(|T||E| \log |E|)$
- Graph generation: $\mathcal{O}(|E| \log |V|)$ because checking if a vertex has been inserted is $\mathcal{O}(1)$ and there are $|E|$ arcs in the static graph G.
- Sorting arcs based on weight: $\mathcal{O}(|E| \log |E|)$
- Creating an empty tree: $\mathcal{O}(1)$
- Constructing a spanning tree: We check if the arc needs to be in the route or not is of order $\mathcal{O}(|E|)$and then applying the union-find to check if cycles are formed with the inclusion of the arc is also of order $\mathcal{O}(\log |E|)$, hence we get: $\mathcal{O}(|E| \log |E|)$
- Overall time complexity:
  $\mathcal{O}(|T||E| \log |E|) + \mathcal{O}(|E| \log |V|) + \mathcal{O}(|E| \log |E|) + \mathcal{O}(1) + \mathcal{O}(|E| \log |E|)$
  $= \mathcal{O}(|T||E| \log |E| + |E| \log |V| + |E| \log |E| + (1) + |E| \log |E|)$.
  Since the maximum arcs in G (complete graph) can be $\frac{n(n-1)}{2}$ that is $\mathcal{O}(|V|^2)$ and in a connected graph, n vertices needs $n - 1$ arcs that is of order $\mathcal{O}(|V|)$, it always hold that $|E|log|E| \geq |V|log|E|$. Hence the total time worse case complexity is $\mathcal{O}(|T||E|log|E|)$.
- The best case scenario, we have no cycles and we have to run the *while-loop* $N - 1$ times to determine the optimal route. Time complexity will be $\mathcal{O}(|T||N-1|log|E|) \approx \mathcal{O}(|T||N|log|E|)$ in this case.

Space Complexity of Algorithm 1 can be estimated as: while sorting, we need an extra array to store sorted array of edges (Space complexity of $\mathcal{O}(|E|)$. Another array for Union-Find of size $\mathcal{O}(|E|)$. So, total space complexity would be $\mathcal{O}(log|E|)$.

4.3.5 Model Parameter Settings

The model complexity increases with both τ and the size of G. The more people to evacuate, the larger the τ^*, so the former parameter, in turn, increases with the number of evacuees. As the area considered has a scale much larger than a single building in terms of both network and people

O(TAlogA) Count the number w_{ij} of occurrences of (i, j) in DT.

O(AlogN) Generate a weighted static graph $G = (N, A, w)$ where w gives the arc frequencies calculated above.

O(AlogA) Sort the arcs in G' from the highest to the lowest frequency.

O(1) Initialize $T_r := (N, E)$ with $E = \emptyset$ (empty forest)

O(AlogA) **while** *(T_r is not yet connected)* **do**

  Take an arc (i, j) with the largest frequency w_{ij} and check whether it forms or not a cycle with some arcs in E

  If not, $E := E \cup \{(i, j)\}$.

Return a spanning tree T_r of maximum weight.

Re-run the dynamic optimisation model of Sections 4.3.1 and 4.3.2 on T_r.

Figure 4.3: Time and Space complexity analysis of Algorithm 1

involved, model size increases accordingly. Particular care must be taken in parameter setting and other implementation choices to reflect the real numbers. We next survey the main model parameters: model granularity, walking velocity, cell capacity, and street capacity.

Model Granularity : Both geographical and temporal units are affected by model granularity. It has an impact on the shape and size of the unit cells used to decompose the network, as well as the slots that make up the evacuation time horizon. We embed the road network into a grid whose cells are supposed to be isometric, meaning that they may be crossed in any direction in the same amount of time, as we discussed earlier in Chapter 3. This value helps to the set time slot duration used as the basic unit. Cells are regarded as virtual unit open spaces that communicate with one another via virtual doors. The width of the streets is supposed to be the virtual door capacities. The grid's geometry might change, although we picked a rectangular grid due to the structure of the streets - where each street is split into an integer number of cells.

Walking Velocity : The basis on which the length of each unit time slot was established is the *free flow walking velocity*, that is, the speed at which humans prefer to walk in non-congested and non-hampered conditions. This parameter is important to perceive the distance an individual can walk during a specific period of time. Through its evaluation, one can define the cells in which an area is to be divided for the best approximation of traveling time. In literature there are different evaluations of pedestrian free flow velocity, including those depending on their age ([347] [185]). Not having this information we assumed a free flow walking speed for a flat surface of 1.00 m/s ([10], [8], [9]). Table 4.2 reports different evaluations of pedestrian free flow velocity found in literature.

Table 4.2: Pedestrian free flow velocity.

Flat surface (m/s)		Reference
under 65	over 65	
1.36		Fruin [101] , Weidmann [367]
1.25	0.97	Knoblauch et al. [185]
1.042 - 1.508	0.889 - 1.083	TranSafety Inc.[347]
1.00		Abdelghany et al. [8–10]
1.20		[387]

Cell Capacity The pedestrian density, which is the number of persons per square meter monitored at any time, is vital information for crowd safety and evacuation performance, as movements are dramatically reduced in highly dense areas. According to UK fire safety regulations, the maximum allowed density corresponds to 0.3 m^2 per standing person, which increases to 0.5 m^2 for public houses, to 1.0 m^2 for dining places, to 2.0 m^2 for sports areas, and to 6.0 m^2 for office areas. In our case study, the maximum capacity of each cell is calculated by assuming 0.5 m^2 per evacuee.

Street Capacity We considered "virtual doors" as the width of the streets. Different government agencies set different standards for door capacities: the Dutch Ministry of Housing, Regional Development, and the Environment, for example, allows for a maximum of 90 people per meter width during a one-minute safe escape time; the Japanese building code suggests the same flow rate. Daamen and Hoogendoorn [70] investigated the relationship between door capacity, user composition, and stress level, concluding that a 1-meter wide door can handle 2.8 individuals per second (p/m/s). Experiments by Kretz et al. [189] show a linear decline in capacity as bottleneck width increases (varying from 2.2 p/m/s for 40 cm to 1.78 p/m/s for 70 cm width) as long as just one person may pass at a time. We assume a constant door capacity of 1.2 persons per second per 1-meter door width (p/m/s), meaning that a maximum number of 6 persons can pass through a 1-meter street width per time slot (5 seconds). Also, capacities are assumed to be proportional to street width (i.e., streets are categorized based on their width being either 3 m or 5 m or 7 m).

4.4 Numerical Experiments

This section provides illustrative examples to highlight the modelling techniques discussed in the preceding sections. The models' algorithms are written in Python and tested computationally using version 3.9.7. The formulations were implemented using the Gurobi [119] Python API and solved via Gurobi Optimizer version 9.5.0. All the experiments were run on a Core i7-3rd generation 2.9GHz computer with 16Gb of RAM memory under Windows 10 Pro 64-bits. First, we use the test network inspired by Ziliaskopoulos [407] to verify the correctness of the proposed algorithm. Secondly, an actual and real-life network, L'Aquila (in the Abruzzo region of Italy) city-wise network, is the solved using the evacuation model. The solutions are analyzed to draw convincing results and conclusions. The numerical analysis of example networks yields solutions that essentially solve evacuation-related decision-making challenges. The proposed evacuation model may handle the following main decision-making problems: system optimal time, entry queue time, network clearing time, optimal flow-staging at origins, optimal flow distribution at intersections, optimal routes taken by evacuees, and optimal destinations.

Note 4.4.1. The dynamic optimisation procedures described above in section 4.3.1 has been applied to the city-level network evacuation of the entire area of Sulmona in the Abruzzo region of Italy, in the paper [154], where we performed several analysis such as the effects of varying number of safe location on total egress times. The underlining network consisted of more than 2,000,000 cells.

4.4.1 Base Case Example

We use the numerical example shown in Ziliaskopoulos [407] as an illustrative Example for the numerical analysis. The test network in Figure 4.4, has 17 nodes and 29 arcs. However, a real network (L'Aquila network) is solved as a complex network analysis.

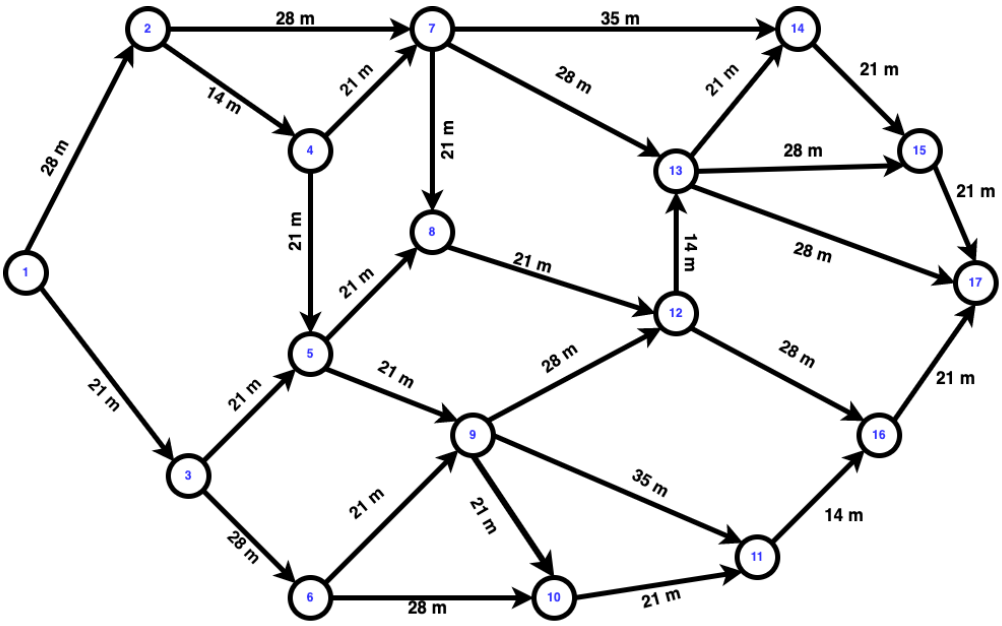


Figure 4.4: Transformed Test Network

The test network (Figure 4.4) is transformed defining the evacuation zone and safe zone. The Evacuation Zone (west side of the network) has all the possible source nodes (nodes 1 to 5) from where the evacuation flows are loaded into the network while the Safe Zone (east side of the network) has all the possible destination nodes (nodes 15, 16 and 17). It is assumed that the evacuation flow-units are considered safe after they reach the destination nodes. A super-sink Node (node 0) is added connecting all the possible destination nodes with virtual links (links 15-0, 16-0 and 17-0).

Figure 4.5 illustrates the evacuation scenario and the complete transformed network. Table 4.3, Table 4.2 and Table 4.3 give the geometric characteristics of all the links of the network. Since links 15-0, 16-0 and 17-0 are the virtual links connecting destination nodes to the sink node, they do not have any specific link length, width and speed limit. However the capacity of these virtual links is infinite and the cells generated from these links is one for each link to penalize the cost of time for evacuation flow-units to reach sink node from destination nodes.

Table 4.3: Arc widths of the street networks

Width (m)	Arcs
7m	(1,2); (1,3); (2,4); (2,7); (3,5); (3,6); (4,5); (4,7); (5,8); (5,9); (11,16); (13,15); (13,17); (12,16); (14,15); (15,16); (16,17)
5m	(6,9); (6,10); (7,13); (7,14); (8,12); (9,10); (9,11); (9,12); (10,11); (12,13); (13,14)

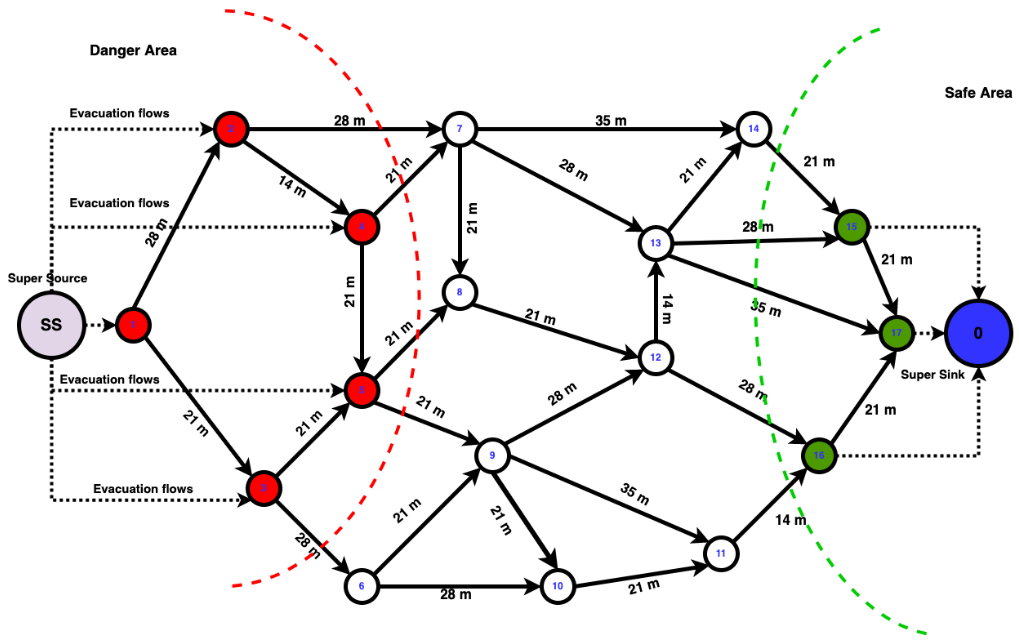


Figure 4.5: Transformed Test Network

For this test evacuation scenario, we assumed a free flow walking velocity of 1.0 m/s which then results in choosing a basic time slot (time required for crossing one cell:) of $\theta = 7$ seconds. The converted network in Figure 4.6 has 106 nodes corresponding to the cells cells. Adjacent cells are linked by 134 connectors/arcs which allow people to move within the network. Since the pedestrian speed is equal to 1 m/s for all the links, each cell has a length of 7m. Also, the capacity of each cell is calculated by assuming $0.5m^2$. For instance for a cell embedded into a street of width 5m, the capacity n_i is calculated as:

$$n_i = \frac{\theta \times width}{0.5} = \frac{5 \times 7}{0.5} = 70$$

We assume a constant door capacity of 1.2 persons per second per 1-meter door width (p/m/s), meaning that a maximum number of $8.4 \approx 9$ persons can pass through a 1-meter street width per time slot (7 seconds). Also the time-invariant property Q_i is proportional to the street width, as a rule of thumb, no more than 9 persons can pass through a 1-meter width street per every 7 seconds. Cells 1 to 5 are the source cells in which the evacuation flows (*100, 100, 100, 100 and 100 flow-units respectively*) are loaded at time 0. Cells 100, 104 and 105 are the destination cells and cell 106 is the super-sink cell where all the flows are received.

We solved problems 4.4a - 4.4j for $\tau = 1, 2, \cdots$ until a solution of value $N = 500$ is found. The main results obtained are explained as below.

- **Network clearance time:** All the evacuation flow-units, loaded in source cells at time-step 0, reached the super-sink cell within $T = 35$ time-steps.
- **System Optimal Time (Total Egress Time):** The system optimal total egress time = 11422 time-units corresponding to *3 hours 10 minutes 22 seconds.*

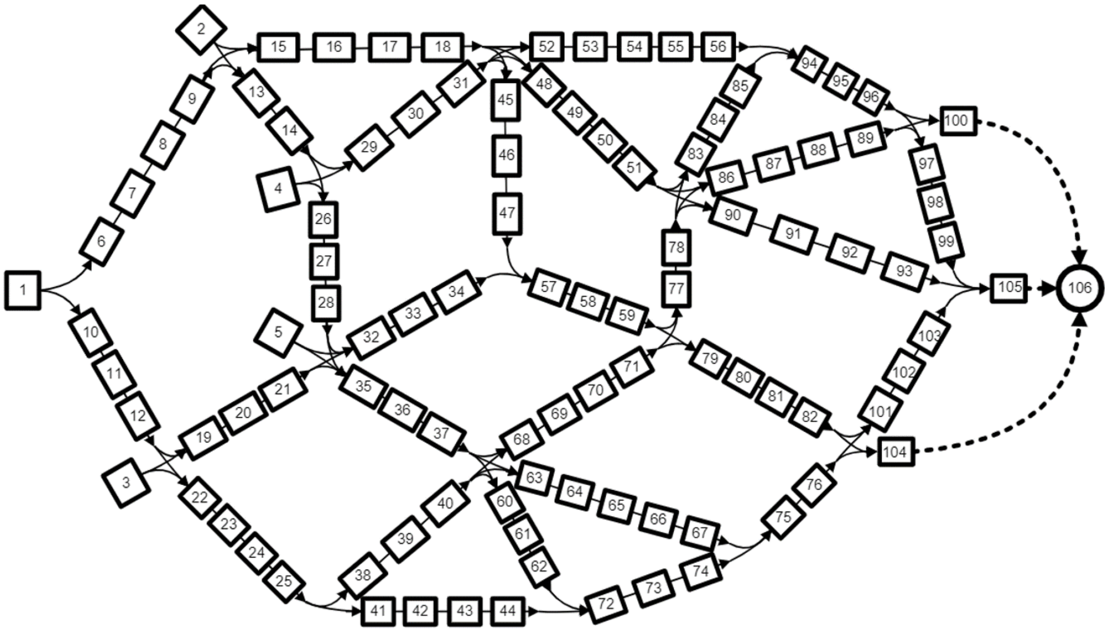


Figure 4.6: Network associated with Figure 4.5

- **Optimal flow-staging at origins:** From the optimal solutions of x_{ij}^t and y_i^t, for the source cells, we can observe evacuation flow-units are optimally distributed in different directions. For example, from source *cell 1*, 12 units of flow (6 flow units each) are discharged to cells 6 and 10 time-step 1, another 12 flow-units are sent in time-step 2 and so on. Similar kind of distribution can be observed for other source cells (Table 4.4, Table 4.5 and Figure 4.7).

Table 4.4: Optimal staging of flow units at source cells – base case

Time (T)		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Node	1	100	88	76	64	57	45	38	26	20	15	15	10	5	5	5	0	0	0	0	0	0
	2	100	90	80	70	60	60	55	50	50	45	40	35	30	25	25	20	10	5	5	5	0
	3	100	90	80	70	60	60	55	50	40	30	25	25	20	15	15	15	10	10	5	0	0
	4	100	90	80	75	70	60	55	50	50	40	30	25	25	20	20	15	10	5	0	0	0
	5	100	90	80	70	70	65	60	55	55	55	50	50	45	40	35	35	30	30	20	15	5

- **Optimal routes followed by the evacuees:** In order to provide an evacuation service for the stakeholders involved in the evacuation process, we generate the evacuation routes (paths) so as to enable evacuees follow these prescribed paths from the endangered areas to the safety areas. A new network was generated for the underlying network following the heuristic procedure described in Algorithm 1. The dynamic optimization model was then implemented and run on this newly generated maximum spanning tree network, to evacuate people to safely following the prescribed routes. This resulted in a total network clearance time of $\tau = 54$ time slots with total egress time of 14402 flow-unit times which is 4 hours and 2 seconds. An increment of an additional 20 time-steps compare to the evacuation process on the original network. Finally, the DyCTEP optimization model was applied to the shortest path network, which is obtained by generating all the shortest paths from sources

Table 4.5: Optimal distribution of flow units for source cell connectors – base case

Time-step	**Connectors / Arc**									
	(1, 6)	(1, 10)	(2, 15)	(2, 13)	(3, 19)	(3, 22)	(4, 26)	(4, 29)	(5, 32)	(5, 35)
0	0	0	0	0	0	0	0	0	0	0
1	7	5	5	5	5	5	5	5	5	5
2	7	5	5	5	5	5	5	5	5	5
3	7	5	5	5	5	5	5	0	5	5
4	7	0	5	5	5	5	5	0	0	0
5	7	5	0	0	0	0	5	5	5	0
6	7	0	0	5	0	5	5	0	0	5
7	7	5	0	5	5	0	5	0	0	5
8	1	5	0	0	5	5	0	0	0	0
9	0	5	5	0	5	5	5	5	0	0
10	0	0	0	5	5	0	5	5	0	5
11	0	5	5	0	0	0	5	0	0	0
12	0	5	5	0	0	5	0	0	0	5
13	0	0	5	0	0	5	0	5	0	5
14	0	0	0	0	0	0	0	0	0	5
15	5	0	5	0	0	0	0	5	0	0
16	0	0	5	5	0	5	5	0	0	5
17	0	0	5	0	0	0	0	5	0	0
18	0	0	0	0	0	5	0	5	5	5
19	0	0	0	0	0	5	0	0	0	5
20	0	0	5	0	0	0	0	0	5	5
21	0	0	0	0	0	0	0	0	0	0

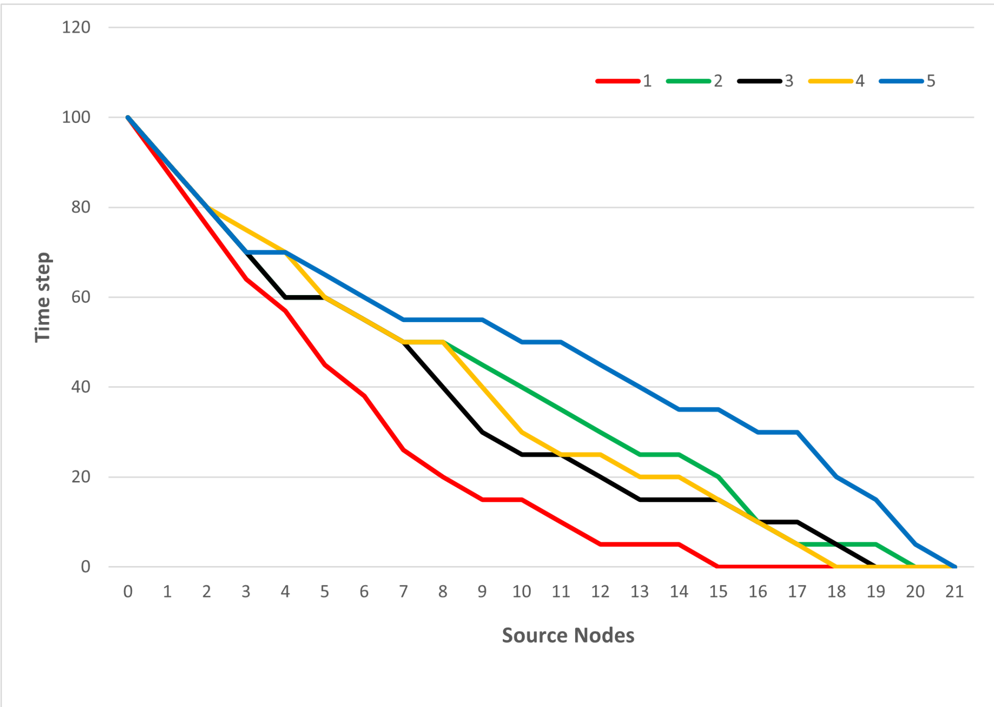


Figure 4.7: Optimal stagging and flow distributions at the source cells for each time slot τ for base model.

to sink nodes using the Dijkstra's algorithm on the original network. From Figure 4.8, it is observed that best results are obtained when the optimisation model was implemented on the original network 4.6, where all the evacuees were moved to safety after 34 times-steps, followed

by heuristics model 1 with a total egress time of 54 time-steps and the worst performance achieved by the shortest path network with an overall clearance time of 72 time-steps (and a total egress time of 19859 time-units (equivalent to 5 hours 30 minutes and 59 seconds)).
The optimal assignment of flow-units basically followed the following paths: *1-2-7-14-15, 1-2-7-13-15, 1-2-7-13-17, 1-3-5-9-11-16, 1-3-5-8-12-16* and *1-3-6-10-11-16* routes to reach the destinations. There were no flow-units observed at all on the links *7-8 (cells 45, 46 and 47), 12-13 (cells 77 and 78), 13-14 (cells 83, 84 and 85), 15-17 (cells 97, 98 and 99)* and *16-17 (cells 101, 102 and 103)*. However very few flow-units were observed on links *2-4 (cells 13 and 14), 4-5 (cells 26, 27 and 28), 6-9 (cells 38, 39 and 40), 9-10 (cells 60, 61 and 62) and 9-12 (cells 68, 69, 70 and 71)*. Figure 4.9 depicts the optimal routes generated by 1 to be used by the evacuation flow-units (evacuees) to reach respective safe destinations.

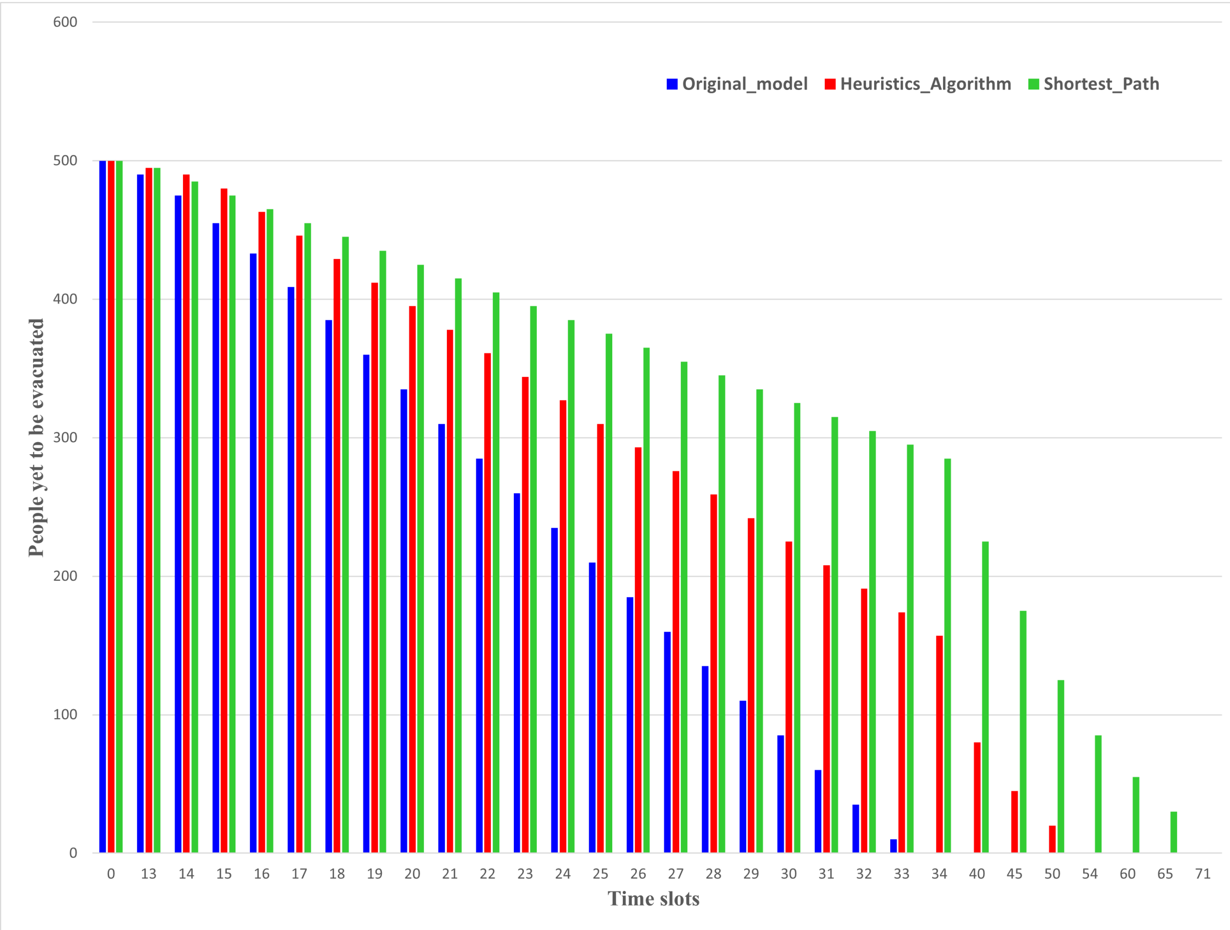


Figure 4.8: Comparison of the model performance on the various networks (the original network, the network generated by the heuristics and the shortest path network).

- **Optimal destinations:** The optimal distribution of flows at the destinations are as follows:
  - Destination 15 (cell 100) received 135 flow-units (25% of the total demand).
  - Destination 16 (cell 104) received 285 flow-units (57% of the total demand).
  - Destination 17 (cell 105) received 80 flow-units (16% of the total demand).

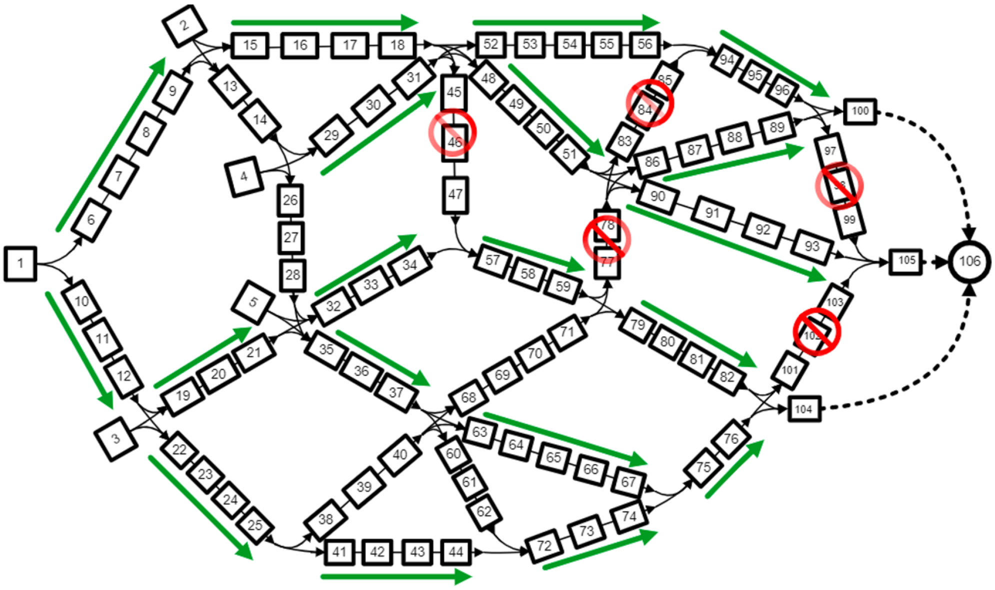


Figure 4.9: Illustration of optimal route assignment using the Heuristic Algorithm 1).

Observing the above data, we can conclude that destination node 16 (cell 104) received the most number of evacuation flow-units, thus making it the crucial destination while destination 17 (cell 105) received least number of flow-units, thus making it least used destination by the evacuees.

- **Incorporation of arc congestions:** Implementing the dynamic optimisation model taking into account possible congestions on the arcs as described in section 4.5 resulted in a network clearance time of 48 time-steps with a total egress time of 13905 base time-units flows which is equivalent to *3 hours 51 minutes 45 seconds.*

  The optimal stagging at the source nodes is depicted in Figure 4.10 where it is evident that it takes *26, 28, 31, 32 and 33* time steps for the evacuees in source nodes 1, 2, 3, 4 and 5 respectively to completely leave these nodes and enter the intermediary nodes.

  When comparing this simulation to the previous one, we can see that individuals flow freely for a short period of time. After that point, the arcs become congested, and evacuation slows down. The phenomena is depicted in Figure 4.11's graph: as one might assume, the amount of people still in the network increases with initial occupancy. From Figure 4.11 we notice that all the 500 evacuees are safely evacuated in 34 time slots using the CTM model while considering the same time slot, only 313 evacuees were moved to safety whereas, everyone was evacuated in 48 time slots.

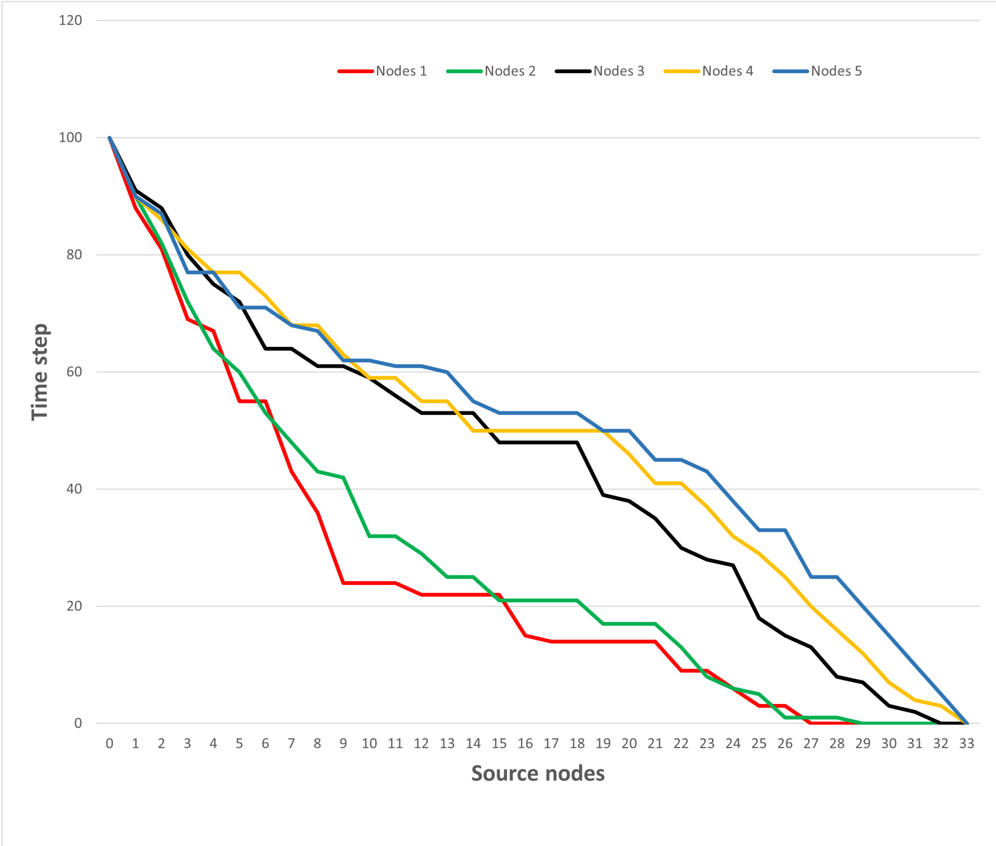


Figure 4.10: Optimal stagging and flow distributions at the source cells for each time slot τ for model with arc-congestion.

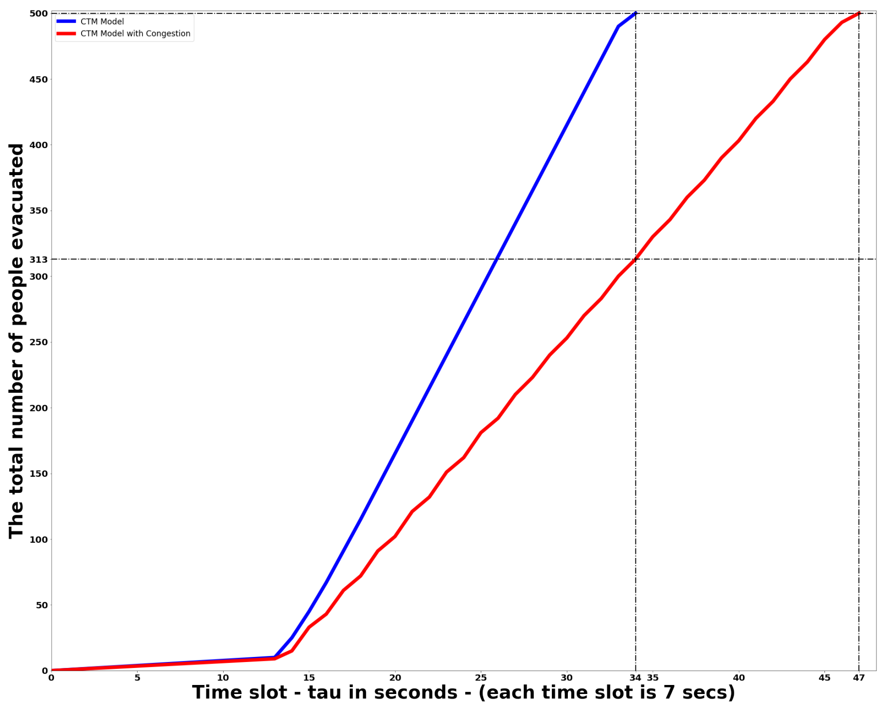


Figure 4.11: Number of people safely evacuated in CTM Model 4.4 vs CTM Model with non-linear arc congestions 4.5 at every time slot τ.

4.4.2 Real-Size Network Case Implementation

In this section, we discuss a real case study to explain the feasibility and applicability of the models discussed in the previous sections. The methodology is applied to a portion of the historic city centre of L'Aquila, in the Abruzzo region (Italy) (see Fig. 4.12a), which was severely affected by the 2009 earthquake. For our case study, we considered Piazza del Duomo (L'Aquila) and took a 750 meters radii network along the streets. This resulted in a network (see Fig. 4.12b) with total edge length of 79138.149 meters and a total street length of 47353.602 meters. In the chosen network the proportion of self-loop nodes is 0.00106.

(a) Portions of L'Aquila Network used for the real-life case study.

(b) Network representation for L'Aquila case study.

Figure 4.12: L'Aquila Network used for Real-Life case study

In the considered area, the network consist of 690 nodes and 1604 arcs depicted in Fig. 4.12b. Using a basic time unit of $\theta = 7$ seconds, the CTM model discussed in Chapter 3 is applied to network 4.12. The converted/transformed cell network is composed of 6492 cells and 7772 connectors. Given the chosen network, $G = (V, A)$, and $\forall i \in V$ the source nodes are chosen such that $deg(i) \geq 3$, that is, for a node to be considered as a source node it must have degree greater than or equal to three. This resulted in a total of *77 source nodes* for the implementations. Also the destination nodes consist of 18 nodes (namely: *nodes 2, 4, 14, 19, 23, 34, 57, 58, 71, 84, 101, 116, 135, 144, 278, 279, 381, and 642*) connected to the virtual super-sink node 0. Each of the 77 source nodes has an initial total population of 50 evacuees, making a total of N =*3850 people* to be safely evacuated from the danger zone to the safe locations. Implementing the CTM model 4.4 on the generated cell-connector network of Figure 4.12, the following results were obtained and summarized below:

- **Network clearance time:** All the evacuation flow-units, loaded in source cells at time-step 0, reached the super-sink cell within $T = 173$ time-steps.

- **System Optimal Time (Total Egress Time):** The system optimal total egress time = 127203 time-units. Which is equivalent to 35 hours 20 minutes and 3 seconds.

- **Optimal Flow distribution at Destination:** From the optimal solution, the distribution of flows at the destination is shown in Figure 4.13. Nodes 2, 19, 23, 34, 57, 144, 279, and 381 received no flows throughout the entire evacuation process. Observing the results, it evident that node 14 is the most used destination since it received 35.909% of the total flow. Nodes 4, 278 and 135 are the other frequently used destinations since the received 16.051%, 9.87% and 9.455% flows respectively.

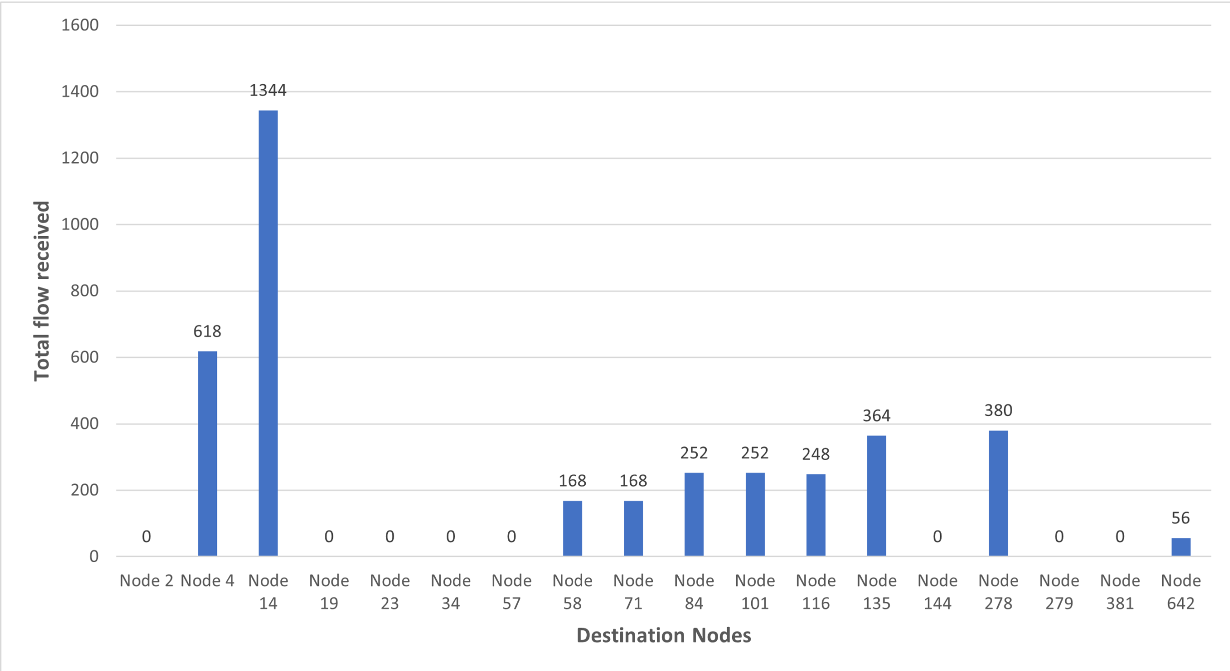


Figure 4.13: Optimal distribution of flow at the destinations.

Finally, the Heuristic Algorithm 1 was applied to the network in Fig. 4.12b to optimally assign routes to the evacuees to flow from the sources to the safe locations. Figure 4.14 is a visual representation of only 3 of these optimal routes chosen assigned with different colours.For the sake of simplicity only three routes are shown. The red route starts at node S and terminates at node D_1. Route yellow has a source node S and destination node D_2, similarly route blue starts from node S_3 and ends in sink node D_3.

4.5 Summary

In this chapter we discussed the modelling procedure for the dynamic cell transmission evacuation planning model DyCTEP based on the NTC proposed in chapter 3. We then incorporated arc-congestion (which is a situation where the speed at which the system empties is a decreasing function of room occupancy y_i^t) into the model formulation. Finally, we proposed a heuristics algorithm to generate and assign routes to evacuees based on the solution dynamics through time. Two numerical examples to examine the algorithmic characteristic of the solution was provided. The base example 4.4.1 which is a small network is used to verify the validity of the formulations and investigate the properties of the solution. Example 4.4.1 verifies that the proposed network

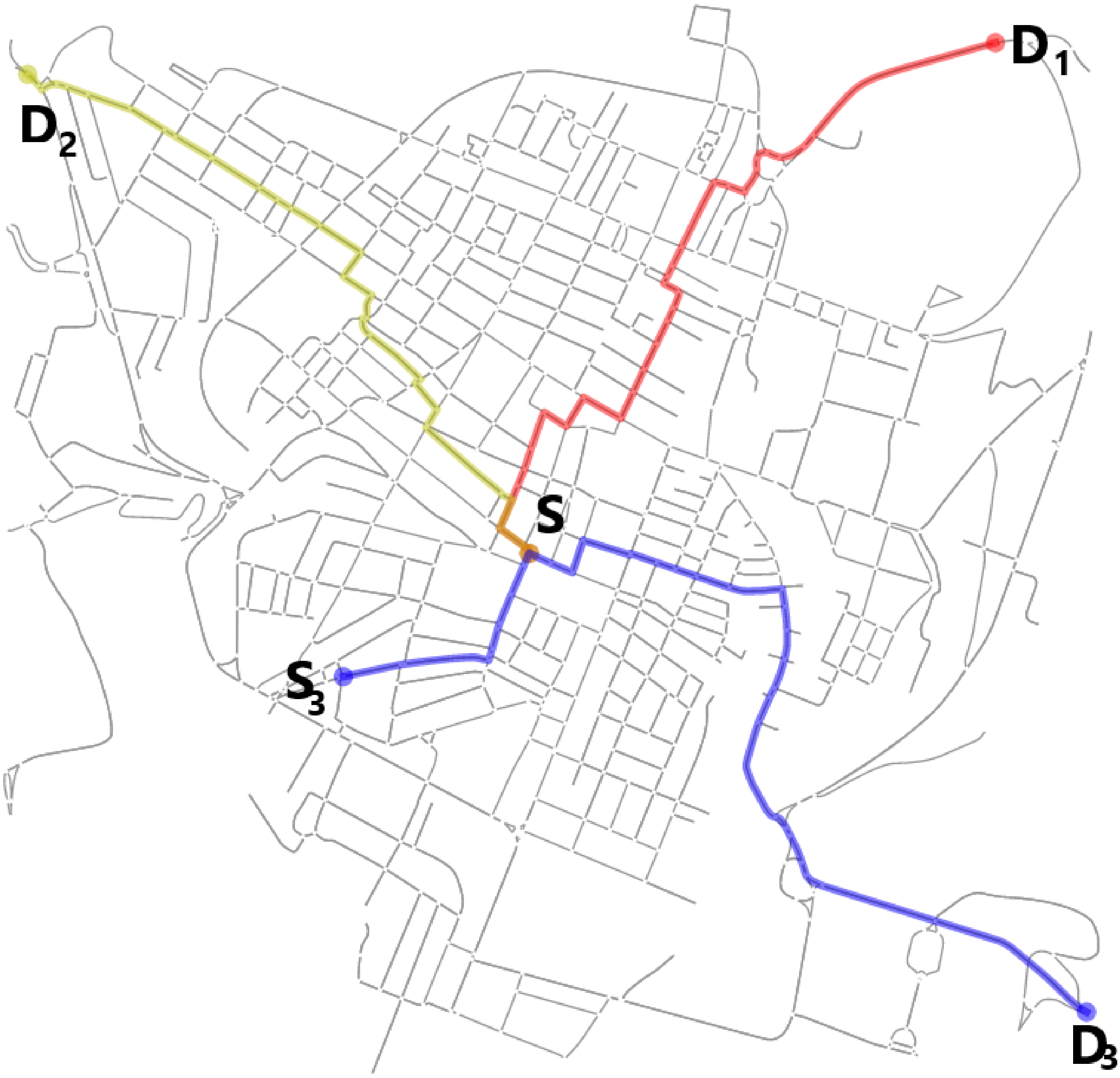


Figure 4.14: Optimal route assignment using Heuristic Algorithm 1.

heuristics algorithm 1 provides a desirable solution which is compatible with the dynamic nature of the evacuation process. The proposed heuristics algorithm 1 performs better than shortest path algorithm in terms of people evacuated and the total egress time. Finally the DyCTEP model is applied to example sec:real-size-aquila, a real-life network for the historic city of L'Aquila. It turns out that Algorithm 1 runs efficiently on this network and it generated the optimal routes for the evacuees.

Chapter 5

Modified Dynamic Pedestrian Evacuation Planning

5.1 Introduction

Evacuation, as one component of emergency processes, can be simply defined as the rapid and reliable removal of residents from a given region that has been designated as a danger zone to a safe location. There are two main evacuation situations to consider.

- Precautionary: In this type of evacuation, the evacuation time can be calculated based on the danger propagation time and the risk can be calculated apriori. As a result, the important components of this type of evacuation are time and potential threats.
- Life-saving operations: This kind of evacuation occurs when the organizer was unable to execute a pre-emergency evacuation strategy due to insufficient warning. Problems such as the rescue of injured evacuees in and around damaged areas, route clearance, and so on are more likely to arise here.

Different sorts of systems, such as buildings, cities or regions, or transportation companies, may experience evacuation issues (e.g. Train, ship and airplane). The System Structures (such as the population and behavior of persons at risk, the speed and characteristics of hazard propagation) have a significant impact on the optimal planning in the relevant system. The evacuation time, or the amount of time it takes to complete an evacuation, is made up of three main components [113, 231], namely:

- The amount of time it takes for evacuees to identify a risky scenario. This time is controlled primarily by the alarm system's reliability and evacuees' familiarity with emergency signals.
- The amount of time that evacuees have to make a decision. The evacuees' experience in dealing with the emergency scenario has an impact on this time. This can be achieved, for example, through emergency drills and training.

- The time evacuees need to move towards the safety area, which is known as egress time. The latter is influenced by emergency exit signs, well-planned evacuation protocols, constructional variables (effective path width, stair slope), and human behavior in panic circumstances.

The biggest contributors to the length of these durations are behavioral and organizational factors. The subsequent decisions are made during the evacuation, particularly when evacuees come across a "hazard" route, such as one that is affected by fire, smoke, an earthquake, or other natural disaster. The duration of the first two time components is difficult to forecast analytically because behavioural and organizational factors are the key contributors. As a result, most evacuation models put an emphasis on calculating egress time and treating the result as a lower bound on the actual evacuation time.

5.2 Related Work

In the evacuation planning literature one can identify three main, distinct yet interrelated, research streams. The first one focuses on the empirical study of pedestrian behavior and crowd dynamics. In contrast, a second stream is concerned with the development of mathematical models to describe movement and interactions of pedestrians as realistically as possible [342]. Finally, a third stream of research uses optimization-based methodologies to develop models that determine optimal evacuation plans or design solutions [9]. Most of the research falls under the first two categories. Several review articles discuss the empirical research and modeling of pedestrian and evacuation dynamics. Schadschneider et al. [297] provide a summary of the empirical studies and theoretical models developed that far, and give two examples of possible application of such a research. Helbing and Johansson [140] give a similar overview and, additionally, discuss research issues on panic and critical crowd conditions. Schadschneider and Seyfried [299] investigate the quantitative data on pedestrian dynamics for the calibration of evacuation models. They considered the implications for cellular automata models. Papadimitriou et al. [266] assess two different topics of research, namely: route choice models and crossing behavior models, the latter studying how pedestrians cross the street under different traffic conditions. Gwynne et al. [120] classify evacuation models based on the nature of the model application, the enclosure representation, the population perspective, and the behavioral perspective. Zheng et al. [403] distinguish seven methodological approaches: cellular automata, lattice-gas, social-force, fluid dynamics, agent-based, game-theoretic models, and experiments with animals. They also look at the possibility of modeling heterogeneous individuals, the scale of representation, whether time and space are discrete or continuous, whether a normal situation or an emergency is assumed, and the typical phenomena that the model can represent. In addition, Duives et al.[82] identify eight motion base cases and six self-organizing crowd phenomena that a simulation model should be able to reproduce. Furthermore, they look at ten other model characteristics, such as the ability to simulate pressure in crowds and the computational requirements of the model to assess model applicability. Their classification distinguishes between cellular automata, social-force, activity-choice, velocity-based, continuum, hybrid, behavioral, and network models. Kalakou and Moura [173] present a general overview of models from different research areas to analyze the design of pedestrian facilities, while Lee et al. [194] focus on models for the evacuation of ships. Finally, Bellomo et al. [31] focus on the mathematical properties of models for pedestrian behavior. The third category of research has received less attention in the literature. Gale [103] first showed the existence of an s-t Earliest Arrival Flow (EAF) in discrete time on a network with time-varying parameters. Philpott [274] first observed it in continuous time. The EAF may not exist in multisource, multisink networks, in which supply/demand vectors associated with sources/sinks are satisfied independently (the supply vector is satisfied regardless of which sink-entity flows are sent, and the demand vector is satisfied regardless of which source entity flows are sent from). Fleischer [94] demonstrated the absence of the EAF in a network with two sources and two sinks. Baumann and Kohler [27] further demonstrated that the earliest arrival s-t flow does not exist for load-dependent transit time. However, in the case of a single-sink network with many sources and predefined parameters, the however, the EAF does always exist (Fleischer and Skutella [92]; Richardson and Tardos [92]).

5.3 Updated Mathematical Models

The cell transmission model (CTM) discussed in Chapter 4 has a major weakness. The use of cells with fixed single size may lead to several disadvantages in terms of an unnecessary high number of cells to meet some pre-determined level of accuracy in the network presentation and too many excessive number of constraints and variables in the optimisation model caused by very high number of required cells, respectively. For this reason three (3) different approaches are considered to rectify the above mentioned problem. The proposed approaches have been outlined in the subsequent sections that follows.

5.3.1 Dynamic Earliest Arrival Flow (DEAF)

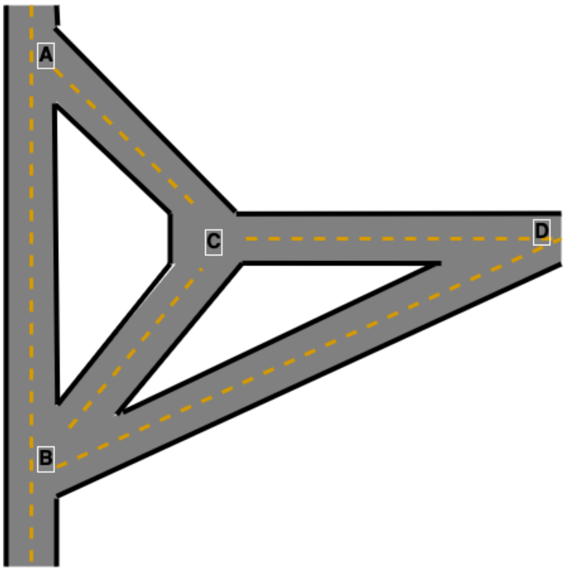
5.3.1.1 The setting

A discrete time dynamic network flow problem is a discrete time expansion of a static network flow problem. In this case we distribute the flow over a set of predetermined time periods $\{\tau = 1, 2, ..., T\}$.

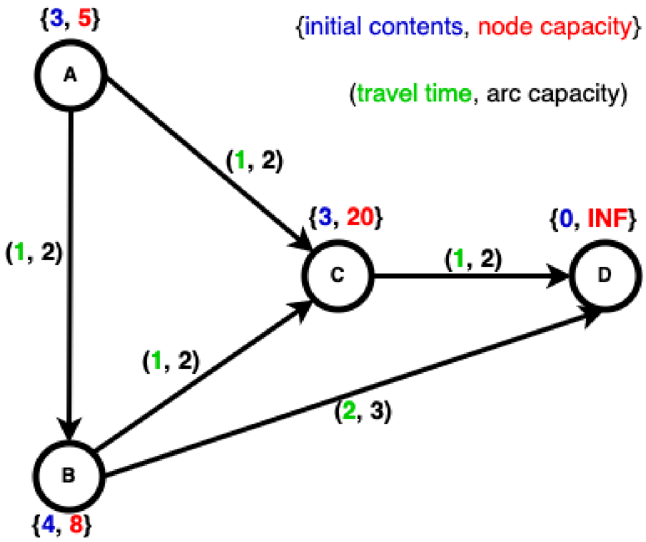
Definition 5.3.1 (Time-Expanded Network)**.** Let $G = (V, A)$ be a (bi-)directed network with V the set of nodes of G and A the set of arcs (the static network). Each node $i \in V$ has a capacity n_i which is the upper bound on the number of evacuees simultaneously allowed to stay in the node.This node capacity can be determined, for instance, by

$$\text{node capacity} := \frac{\text{floor space area}}{\text{minimum required area per person}}$$

Arcs have other attributes, such as flow capacity c_{ij} and travel time (λ_{ij}). The arc flow capacity (c_{ij}) is the upper bound of the number of evacuees per unit time that can traverse the arc. The travel time (λ_{ij}) is the time needed to travel from one node to another. This travel time is one of



(a) A section of a simple street layout.



(b) Associated network (node - arc) representation.

Figure 5.1: Representation of a Static Network G of a simple street layout

the important components that must be considered in the modeling of evacuation problems. We will assume constant attributes, i.e, constant travel time from one node to another and constant arc flow capacity. The constant travel time might be determined according to some predetermined queuing levels such that the model can be solved efficiently but still able to give quite realistic results. On each arc $(i, j) \in A$ travel times (λ_{ij}) are given which are assumed to be constant. The time expansion of G over a time horizon T defines the dynamic network $G_T = (V_T, A_T)$ associated with G where

$$N_T := \{i^t \mid i \in V; t \in T\}$$

and A_T consists of movement arcs A_M

$$A_M := \{(i^t, j^{t'}) \mid (i, j) \in A; t' = t + \lambda_{ij}, t \in T\}$$

and the set of holdover arcs A_H

$$A_H := \{(i^t, i^{t+1}) \mid i \in V; t = 0, 1, 2, 3, \cdots, T - 1\}$$

That is $A_T := A_M \cup A_H$

Figure 5.2 shows a T-time expansion of the static network of Figure 5.1, with $T = 4$.

The time period t is dependent on the basic unit θ in which travel times are measured. If we chose 7 seconds as the length of the basic unit (i.e. $\theta = 7$), then defining four time periods $(i.e.T = 4)$ for traversing an arc will take us 28 seconds. The number of time periods T is calculated by dividing the evacuation planning horizon of interest by the length of the basic unit (which is determined by the grid's size and form). The smaller θ the more accurately the model represents the actual flow's evolution. Choosing too small, on the other hand, will result in an unfavorable

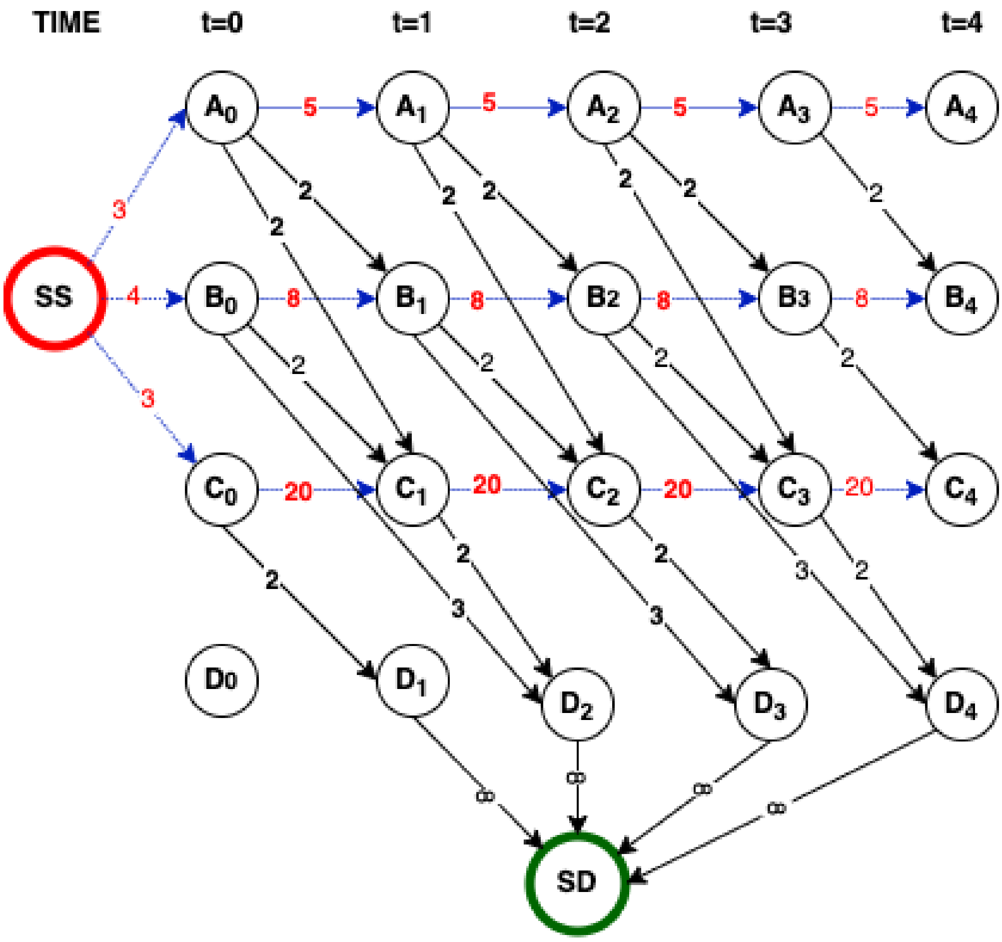


Figure 5.2: Constructed Time-Expanded-Dynamic Network G_T of the static network G of figure 5.1 with $T = 4$

network size as well as fractional arc capacities, making the problem more difficult to solve. Hence, the choice of θ is a compromise between model realism and model complexity. Since the dynamic network has $(T + 1)$ copies of each source node and each sink node, the dynamic network will have multiple sources and multiple sinks. Therefore in order to handle many sources and sinks, one introduces a super-source SS and a super-sink SD to create a single source/single sink network (see Figures 5.2 and 5.3). How the super-source *(SD)* is connected to the source is actually problem-dependent. In the network clearing problem (clearing the network from initial occupancies), the super-source only to the time zero copy of the source nodes (see Figure 5.2), which in this case, we may have holdover arcs for source nodes ("blue dotted arcs" in Figure 5.2). Arcs from the super source have zero travel time and capacities are equal to initial occupancies. We can also consider the case, where the super-source is connected to all time-copies of the source nodes. In this case, we do not have holdover arcs for source nodes which do not have predecessors. Arcs from the super-source to other nodes have zero travel time and infinite capacities. On the other hand, all copies of every sink node are connected to the super-sink and there is no holdover arc for sink nodes. All connections to the super-sink have zero travel time and infinite flow capacities. By constructing the dynamic network as defined above, dynamic network flow problems can always be solved as static flow problems in the expanded network. Proposition 5.3.1 gives an upper bound

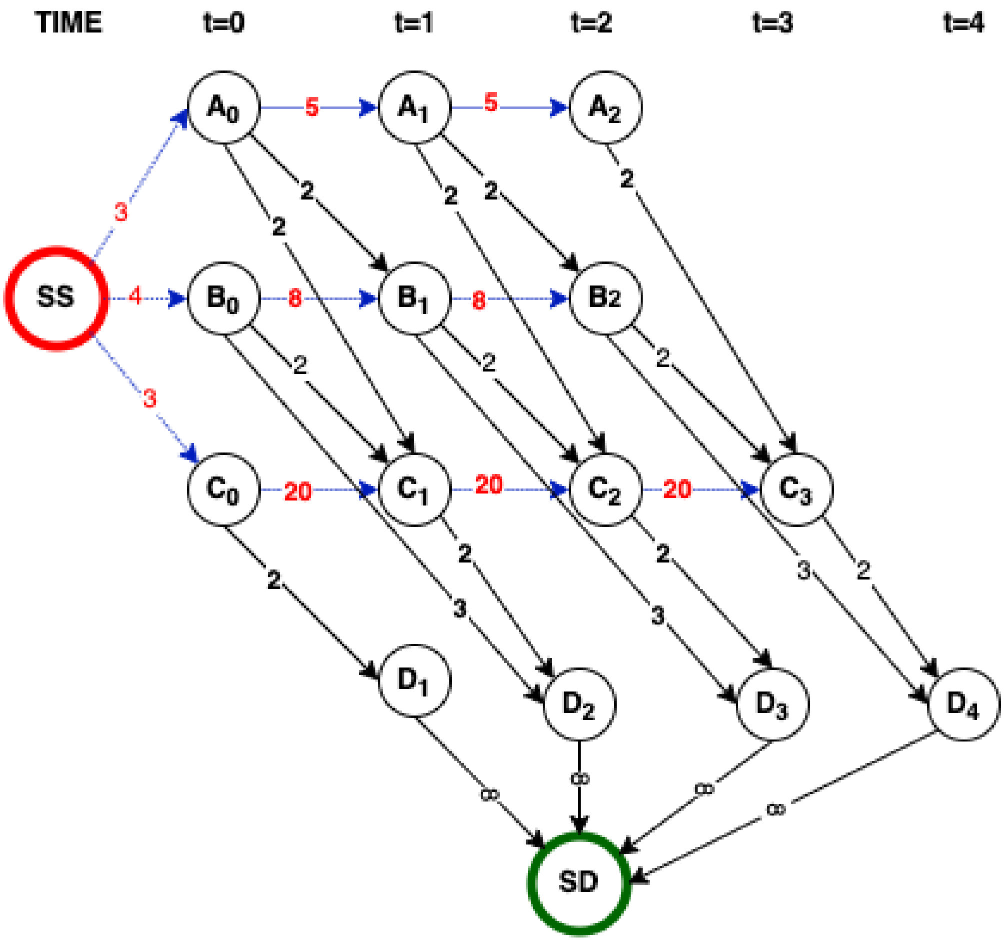


Figure 5.3: Dynamic Network G_T of the static network G of figure 5.1 with $T = 4$ by Deleting Inessential Arcs and Nodes

for the number of nodes and arcs in the discrete time dynamic network.

Proposition 5.3.1. *If* $n := |N|$ *and* $m := |A|$ *then* $n(T+1)$ *and* $(n+m)T + m - \sum_{(i,j)\in A} \lambda_{ij}$ *are the upper bound for the number of nodes and arcs in* G_T *without considering super-source and super-sink, respectively.*

We can reduce the size of the time-expanded network by deleting inessential arcs and their related nodes since we don't use any arc in the path from the super-source to any sink node at times greater than T (see Figure 5.3).

For convenience, we denote by x_{ij}^t the flow (e.g. the number of evacuees moving at time t) that leave node i at time t and reach node j at time $t + \lambda_{ij}$. We introduce a new variable z_i^{t+1} as the flows in node i at time t to the same node with travel time $\lambda_{ii} = 1$ to represent the number of evacuees who prefer to stay in the node component represented by node i at time t for at least one unit time, i.e.

$$z_i^{t+1} := x_{ii}^t$$

The capacity of movement arcs $(i(t), j(t + \lambda_{ij})) \in A_M$ is denoted by c_{ij}^t (but in this research we considered time-invariant arc capacities) where we assume without loss of generality that

$$c_{ij}^t := min\{c_{ij}^{t'} \mid t' = t, t+1, \cdots, t+\lambda_{ij}\}$$

For instance, in the simple network considered in Figure 5.1, the capacity of movement arcs are the values shown in black in Figure 5.2). The capacity of a holdover arc $(i(t); i(t+1)) \in A_H$ is determined by the node capacity n_i^t, and represents how many evacuees can stay in the node at a given time. Under assumptions of constant capacities, we have $(c_{ij}^t = c_{ij}, \forall (i,j) \in A$ and $n_i^t = n_i; \forall i \in V; \forall t)$. Also, we let q_i be the initial occupancy of node $i \in V$.

Generally, for a given time horizon T, a Time Expanded Graph (TEG) $G_T = (V_T, A_T)$ is constructed by creating a copy of each node in V for each time unit τ (i.e. $V_T = \{i(t) | i \in V, t \in \{0, 1, ..., T\}\}$). An arc $(i(t), j(t+\lambda_{ij}))$ with transit capacity c_{ij} is added to A_T if there is an arc $(i,j) \in A$ with transit time λ_{ij} and capacity c_{ij}. A_T also contains holdover arcs $((i(t); i(t+1))$ with capacity n_i to designate flow that waits at node i from time t to $t+1$. This time-expanded network allows all variations of dynamic flow problems to be solved by polynomial static flow algorithms over the expanded graph.

5.3.2 Modified Optimization Model

Let denote by $S \subset V$ the set of source nodes of the static network G and $D \subset V$ the set of all sink/destination nodes and 0 the super-sink node SD and s be the super-source node. Then the problem can be modelled as:

$$\text{Problem (EAF): min } \sum_{t=1}^{T} \sum_{i \in D} x_{i0}^t \tag{5.1a}$$

$$z_i^{t+1} - z_i^t - \sum_{j:ji \in A} x_{ji}^{t-\lambda_{ji}} + \sum_{j:ij \in A} x_{ij}^t = 0, \quad \forall i \in V \setminus \{S \cup 0\}; t = 0, 1, \cdots, T \tag{5.1b}$$

$$z_0^{t+1} - z_0^t - \sum_{j:j0 \in D} x_{j0}^t = 0, \quad \forall t = 0, \cdots, T \tag{5.1c}$$

$$\sum_{t=0}^{T} \sum_{i \in D} x_{i0}^t = \sum_{j \in S} q_j \tag{5.1d}$$

$$\sum_{j:ji \in A} x_{ji}^t + z_i^t \le n_i, \quad \forall i \in V \setminus \{0\}, t \in T \tag{5.1e}$$

$$0 \le x_{ij}^t \le c_{ij}, \quad \forall (ij) \in A, t = \{0, 1, \cdots, T - \lambda_{ij}\} \tag{5.1f}$$

$$x_{si}^0 = q_i, \quad \forall i \in S \tag{5.1g}$$

$$z_i^0 = 0, \quad \forall i \in V \tag{5.1h}$$

$$z_i^t = 0, \quad \forall i \in D, \forall t \in T \tag{5.1i}$$

Equations 5.1b and 5.1c are the flow balance constraints at the transshipment nodes and the super-sink respectively. Constraints 5.1e and 5.1f deals the hosting capacities of the nodes and arcs. Also, the initial occupancies are modeled by using flow from the super-source s to each source node (Equation 5.1g). Equation 5.1d ensures that at the end of the evacuation process all the evacuees reach the safe locations.

Definition 5.3.2 (Earliest Arrival Flow)**.** Given a time-expanded dynamic network $G_T = (V_T, A_T)$, where each arch $(i,j) \in A_T$ has an associated capacity c_{ij} and transit time λ_{ij}, a flow in G_T that simultaneously optimises the amount reaching the sink for every time interval $[0,\tau], \forall\tau = 0,1,\cdots,T$ is called the *earliest arrival flow (EAF).*

Let $f_{max}(\tau)$ be a maximum dynamic flow at time τ, then EAF holds $f_{max}(\tau)$ simultaneously for $\tau = 1,\cdots,T$ [96].

Theorem 5.3.2. *(Equivalence of SO-DTA (CTM) and EAF). If it is feasible to send the demand $\sum_{i\in S} q_i$ from the sources to the (super-) sink during the time horizon, then a flow of* SO-DTA *4.4 is optimal if and only if it is an earliest arrival flow.*

Proof. Combining the flow-mass-balance constraint in 4.4 for source cells

$$y_i^t - y_i^{t-1} - \sum_{j:ji\in A} x_{ji}^{t-1} + \sum_{j:ij\in A} x_{ij}^{t-1} = 0, \quad \forall i \in V \setminus \{S \cup 0\}, t \in T, t > 0$$

and transshipment cells

$$y_i^t - y_i^{t-1} + \sum_{j:ij\in A} x_{ij}^{t-1} = \begin{cases} q_i, & \text{for } t = 1 \\ 0, & \text{for } \forall t > 1 \end{cases}, \quad \forall i \in S$$

and taking the sum over the cells, we obtain

$$\sum_{i\in V\setminus 0} y_i^t = \sum_{i\in V\setminus 0} y_i^{t-1} + \sum_{i\in S} q_i^{t-1} + \sum_{i\in V\setminus S}\sum_{j:ji\in A} x_{ji}^{t-1} - \sum_{i\in V\setminus 0}\sum_{j:ij\in A} x_{ij}^{t-1} \tag{5.2}$$

Since each transshipment cell i acts as a predecessor to outbound arc (i,j) and serves as a successor to inbound arc (j,i), for $i \in V$, $\sum_{i\in V\setminus\{S\cup 0\}}\sum_{j:ji\in A} x_{ji}^t = \sum_{i\in V\setminus\{S\cup 0\}}\sum_{j:ij\in A} x_{ij}^t$, equation 5.2 cab be written as

$$\sum_{i\in V\setminus 0} y_i^t = \sum_{i\in V\setminus 0} y_i^{t-1} + \sum_{i\in S} q_i^{t-1} - \sum_{k:kl\in A} x_{kl}^{t-1} \tag{5.3}$$

Equation 5.3 can be solved as a recursion and hence can be written as (by eliminating $\sum_{i\in V\setminus 0} y_i^{t-1}$)

$$\begin{aligned} &\sum_{i\in V\setminus 0} y_i^t = \sum_{t=1}^{\theta}\sum_{i\in S} q_i^{t-1} - \sum_{t=1}^{\theta}\sum_{k:kl\in A} x_{kl}^{t-1} \\ &\sum_{i\in V\setminus 0} y_i^0 = 0 \end{aligned} \tag{5.4}$$

Let $\theta = \{0, 1, \cdots, T\}$, summing equation 5.4 gives

$$\sum_{t\le T}\sum_{i\in V\setminus 0} y_i^t = \sum_{t\le T}\sum_{i\in S} tq_i^{T-t} - \sum_{t\le T}\sum_{k:kl\in A} tx_{kl}^{T-t}$$
$$\sum_{t\le T}\sum_{i\in V\setminus 0} y_i^t = -\sum_{t\le T}\sum_{i\in S}(T-t)q_i^{T-t} + \sum_{t\le T}\sum_{k:kl\in A}(T-t)x_{kl}^{T-t} + T\left(\sum_{t\le T}\sum_{i\in S} q_i^{T-t} - \sum_{t\le T}\sum_{k:kl\in A} x_{kl}^{T-t}\right) \tag{5.5}$$

Evidently we have

$$\sum_{t\le T}(T-t)q_i^{T-t} = \sum_{t\le T} tq_i^t \quad \text{and} \quad \sum_{t\le T}(T-t)x_{kl}^{T-t} = \sum_{t\le T} tx_{kl}^t$$

Hence

$$\sum_{t\le T}\sum_{i\in V\setminus 0} y_i^t = -\sum_{t\le T}\sum_{i\in S} tq_i^t + \sum_{t\le T}\sum_{k:kl\in A} tx_{kl}^t + T\left(\sum_{t\le T}\sum_{i\in S} q_i^t - \sum_{t\le T}\sum_{k:kl\in A} x_{kl}^t\right) \tag{5.6}$$

Since the flow is feasible, we obtain

$$\begin{aligned}\sum_{t\le T}\sum_{k:kl\in A} x_{kl}^t &= \sum_{t\le T}\sum_{i\in S} q_i^t\\ \sum_{t\le T}\sum_{i\in V\setminus 0} y_i^t &= -\sum_{t\le T}\sum_{i\in S} tq_i^t + \sum_{t\le T}\sum_{k:kl\in A} tx_{kl}^t\end{aligned} \tag{5.7}$$

Since q_i is predefined, the objective function of SO-DTA $\mathcal{P}$ 4.3 is equal to minimizing 5.8

$$\sum_{t\le T}\sum_{k:kl\in A} tx_{kl}^t \tag{5.8}$$

The remainder of the proof is to show that a flow with an objective of equation 5.8 is equivalent to the SO-DTA $\mathcal{P}$ 4.3.
Assume that such flow is not the earliest arrival at time, which implies that, there is at least $\epsilon > 0$ unit flow at $t' > t$ is able to arrive at t. This strictly decreases the objective of $\sum_{t\le T}\sum_{k:kl\in A} tx_{kl}^t$ violating the condition that $\sum_{t\le T}\sum_{k:kl\in A} tx_{kl}^t$ is minimal. Next, we show that if a flow $f = (\sum_{k:kl\in A} x_{kl}^t)^*$ is an SO-DTA, then it must be with the minimum of $\sum_{t\le T}\left(\sum_{k:kl\in A} tx_{kl}^t\right)^*$. As this flow is the earliest arrival, it strictly holds 5.9,

$$\sum_{t=0}^{\theta}\sum_{k:kl\in A}(x_{kl}^t)^* \ge \sum_{t=0}^{\theta}\sum_{k:kl\in A} x_{kl}^t; \quad \forall\theta = 0, 1, \cdots, T \tag{5.9}$$

where $\sum_{k:kl\in A} x_{kl}^t$ is any feasible arrival flow such that 5.10 holds ,

$$\sum_{t=0}^{T}\sum_{k:kl\in A} x_{kl}^t = \sum_{t=0}^{T}\left(\sum_{k:kl\in A} x_{kl}^t\right)^* = \sum_{i\in S} q_i \tag{5.10}$$

Taking a sum of 5.9 over all $\theta = 0, 1, \cdots, T$; we obtain

$$\sum_{t=0}^{T} \sum_{k:kl \in A} (T - \tau + 1)(x^{\tau})^* \geq \sum_{t=0}^{T} \sum_{k:kl \in A} (T - \tau + 1)x_{kl}^t \tag{5.11}$$

Because $\sum_{t=0}^{T} \sum_{k:kl \in A} (x_{kl}^t)^* = \sum_{\tau=0}^{T} \sum_{k:kl \in A} x_{kl}^t$ and $\sum_{t=0}^{T} \sum_{k:kl \in A} T(x_{kl}^t)^* = \sum_{\tau=0}^{T} \sum_{k:kl \in A} T x_{kl}^t$, we have:

$$\sum_{\tau=0}^{T} \sum_{k:kl \in A} t(x_{kl}^t)^* \leq \sum_{\tau=0}^{T} \sum_{k:kl \in A} t x_{kl}^t \tag{5.12}$$

■

Theorem 5.3.2 shows that if the objective function of SO-DTA in $\mathcal{P}$ 4.3 is uniform, and the flow conservation conditions 4.4a - 4.4c are satisfied, the DEAF problem equals the SO-DTA. The proof indicates that this equivalence proposition holds on a single destination network, regardless of whether the network parameters are time-varying or not.

5.4 Extension of the DyCTEP Model

In the following section, we'll show you how to incorporate multiple cell sizes into the DyCTEP model discussed in Chapter 4 and discuss the advantages of doing so.
In order to represent a specific network using the CTM, a cell size that appropriately fits the length of the network arcs must be chosen. As one might expect, this will result in a trade-off between the number of cells (which has a significant impact on the number of side constraints and variables) and the network representation accuracy. Due to the discrete nature of the Cell-Transmission method (CTM), we will extend the DyCTEP model by using multiple cell sizes in this section. Larger cell sizes will be integer multiples of the reference (standard) cell size. To demonstrate this concept, consider a very small network. Figures 5.5a and 5.5b illustrate how this concept works in the context of a relatively small network. At 40 meters, 30 meters, and 20 meters, we model four street portions. As can easily be seen, the needed number of cells can be reduced from eleven (11) in Figure 5.5a to six (6) cells in Figure 5.5b. Obviously, pedestrians need two time periods to pass larger cells in this scenario.

We assume |K| distinct cell sizes in the mathematical formulation, with a given cell size k being k-times larger than the basic cell size 1. If we assume the same free-flow pedestrian walking velocity, $|K| = 3$ results in three different cell sizes (and three sets of cells, namely C_1, C_2, C_3), where all cells $i \in C_2(C_3)$ are two-times (three times) larger than cells $i \in C_1$. Figures 5.5a and 5.5b show how several smaller cells can be joined into a larger cell without compromising network representation accuracy. The following are some of the benefits of this strategy: First, the accuracy of the network representation using the same number of cells can be improved since a smaller standard (basic) cell size (and integer multiples of this cell size) tends to match the underlying arc lengths more accurately. Furthermore, because standard sized cells can be merged into one larger cell, the same precision and accuracy in network representation can be accomplished

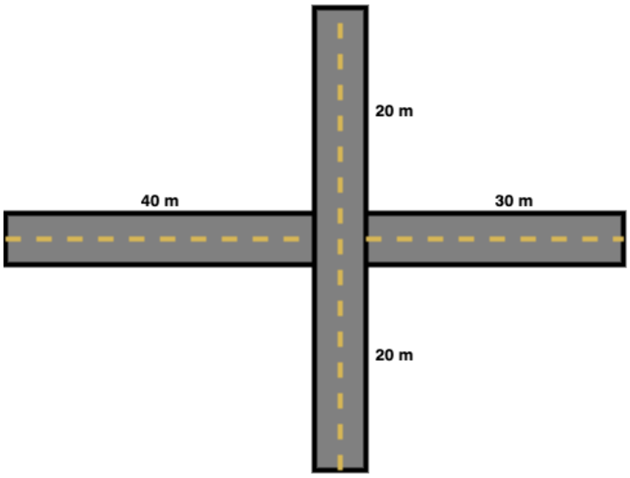
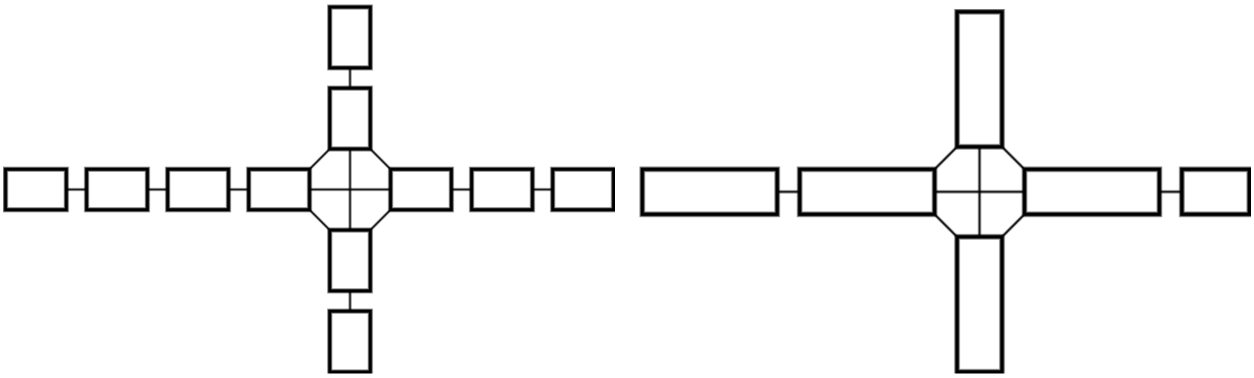


Figure 5.4: A section of a road network.



(a) Network representation using one cell size. **(b)** Network representation using two cell sizes.

Figure 5.5: Network representation using multiple cell sizes.

with fewer cells. Second, because the number of needed cells is usually fewer, the computing effort can be minimized. Although the mathematical formulation of the (extended) CTM will become more sophisticated, the benefits of a smaller number of cells should still prevail. Table 5.1 gives the additional parameters needed in this section together with the parameters defined in 4.1

5.4.1 Approach 1: Extended CTM Approach

The basic idea of this approach is to divide a cell into subcells, where the number of subcells corresponds to the cell size of the cell $(1, \cdots, n)$. A pedestrian needs at least one period to pass a subcell so that n subcells lead to a minimum travel time of n periods. In order to capture vehicle movement from subcell to subcell, a new decision variable $x^t_{i(k,k+1)}$ must be introduced. This variable is an auxiliary flow variable which displays the number of people moving from subcell k to subcell $k+1$ in cell i in time period t. Thus, there must be $n-1$ additional flow variables for a cell of cell size n. Now, the CTM with multiple cell sizes using this approach can be formulated by replacing equation 4.4a by 5.13a, 4.4c by 5.13b and adding four more constraints 5.13c - 5.13f:

Approach 1: Extended CTM Approach:

Table 5.1: Additional Parameters

Symbol	Description
Parameters:	
$\mathfrak{T}$	Set of discrete time intervals $T = \{1, \cdots, \tau\}$
$K = \{1, \cdots, \lvert K\rvert\}$	The index of different cell size multipliers (where $\lvert K\rvert$) denotes the max cell size
$C = \{1, \cdots, \lvert C\rvert\}$	The index set of cells
C_n	Index of cells of size n ($\cup_{n\in K} C_n = C$)
Decision Variables:	
y_i^t	The state of cell i at time t i.e the number of persons contained in cell i at time t
x_{ij}^t	The flow of people from cell i to adjacent cell j in the time $(t, t+1]$. This gives the average speed at which pedestrian move from cell i to cell j. number of evacuees who prefer to stay in node i at time t for at least one unit time.
$x_{i(k,k+1)}^t$	An auxiliary flow which displays the number of people moving from subcell k to subcell $k+1$ in cell i at time step t.

$$y_i^t - y_i^{t-1} - \sum_{j:ji\in A} x_{ji}^{t-1} + \sum_{j:ij\in A} x_{ij}^{t-1} = 0, \quad \forall i \in C_1, t = \{1, \cdots, T\} \tag{5.13a}$$

$$y_i^t - y_i^{t-1} + \sum_{j:ij\in A} x_{ij}^{t-1} + \sum_{k\in K} x_{i(k,k+1)}^{t-1} = \begin{cases} q_i, & \text{for } t = 1 \\ 0, & \text{for } \forall t > 1 \end{cases}, \quad \forall i \in S \tag{5.13b}$$

$$y_i^t - y_i^{t-1} - \sum_{j:ji\in A} x_{ji}^{t-1} + \sum_{j:ij\in A} x_{ij}^{t-1} - \sum_{k=1}^{n-1} x_{i(k,k+1)}^{t} + \sum_{k=1}^{n-1} x_{i(k,k+1)}^{t-1} = 0$$
$$; \quad n \in K : n \geq 2; i \in C_n; t = \{2, \cdots, T\} \tag{5.13c}$$

$$x_{i(k+1,k+2)}^t = x_{i(k,k+1)}^{t-1}, \quad n \in K : n \geq 3; k = 1, \cdots, n-2; i \in C_n; t = \{2, \cdots, T\} \tag{5.13d}$$

$$\sum_{j:ij\in A} x_{ij}^t = x_{i(k-1,k)}^{t-1}, \quad k \in K : k \geq 2; i \in C_n; t = \{2, \cdots, T\} \tag{5.13e}$$

$$x_{i(k,k+1)}^t \geq 0, \quad k \in K; i \in V; t \in T \tag{5.13f}$$

Equation 4.4c must be replaced by 5.13b in order to cover the pedestrian movements from subcell to subcell in the objective value. The standard pedestrian flow equation 4.4a now only holds for cells of size 1, see 5.13a. For larger cells, an extended pedestrian flow equation 5.13c must be introduced. Pedestrian flows from subcell to subcell are captured by 5.13d and 5.13e. However, this approach has some disadvantages in terms of traffic flow representation. First, traffic holding is only possible in the first subcell, because of 5.13d and 5.13e forcing traffic to flow from one subcell to the next subcell in successive periods. Secondly, all evacuees starting their evacuation in a cell of cell size $|K| \geq 2$ also have to pass all subcells before they can leave the cell.

5.4.2 Approach 2: Multiple Cell Sizes

The concept of the second approach to capture multiple cell sizes is to limit traffic outflow with respect to traffic inflow of a cell so that a minimum travel time of n periods for a cell of size n can be ensured. Because of constraint 4.4a, this assumption automatically holds for cells with size 1. For cells of size $k \geq 2$, we introduce constraint 5.14k to ensure a minimum travel time of k_i periods for a cell i of size k_i . The CTEPM with multiple cell sizes using the seconds approach can be formulated by adding constraint 5.14k to the model formulation 4.4.

Problem: Multiple - Approach 2:

$$\min \sum_{t\in\mathfrak{T}} \sum_{i\in V\setminus 0} y_i^t \tag{5.14a}$$

$$y_i^t - y_i^{t-1} - \sum_{j:ji\in A} x_{ji}^{t-1} + \sum_{j:ij\in A} x_{ij}^{t-1} = 0, \quad \forall i \in V\setminus\{S\cup 0\}, t\in T, t>0 \tag{5.14b}$$

$$y_0^t - y_0^{t-1} - \sum_{j:j0\in A} x_{j0}^{t-1} = 0, \quad t\in T, t>0 \tag{5.14c}$$

$$y_i^t - y_i^{t-1} + \sum_{j:ij\in A} x_{ij}^{t-1} = \begin{cases} q_i, & \text{for } t=1 \\ 0, & \text{for } \forall t>1 \end{cases}, \quad \forall i\in S \tag{5.14d}$$

$$\sum_{j:ji\in A} x_{ji}^t \leq Q_i, \quad \forall i\in V\setminus\{S\}, t\in T \tag{5.14e}$$

$$\sum_{j:ji\in A} x_{ji}^t \leq \delta_i(n_i - y_i^t), \quad \forall i\in V\setminus\{S\}, t\in T \tag{5.14f}$$

$$\sum_{j:ij\in A} x_{ij}^t \leq Q_i, \quad \forall i\in V\setminus\{0\}, t\in T \tag{5.14g}$$

$$\sum_{j:ij\in A} x_{ij}^t - y_i^t \leq 0, \quad \forall i\in V\setminus\{0\}, t\in T \tag{5.14h}$$

$$0 \leq x_{ij}^t + x_{ji}^t \leq c_{ij}, \quad \forall (ij)\in A, t\in T \tag{5.14i}$$

$$y_i^0 = 0, \quad \forall i\in V \tag{5.14j}$$

$$\sum_{j:ij\in A}\sum_{\tau=1}^{t} x_{ij}^\tau \leq \sum_{j:ji\in A}\sum_{\tau=1}^{max(t-k_i,1)} x_{ji}^\tau + \sum_{\tau=1}^{max(t-\lceil k_i/2\rceil+1,1)} y_i^\tau, \quad i\in V: k_i\geq 2; t=2,\cdots,T \tag{5.14k}$$

This constraint limits the total number of pedestrians leaving a cell i between periods 1 and t to the total number of pedestrians entering the cell between periods 1 and $t-k_i$ plus the pedestrians who begin their evacuation between periods 1 and $t-\lceil k_i/2\rceil+1$. Where k_i is the size of cell i. When compared to the first technique, this approach has a number of advantages. Firstly, when cells of size $|K|\geq 3$ are used, no new variables must be introduced, and fewer constraints are required. Secondly, after the minimum travel time has elapsed, waiting pedestrians can escape from a cell. Finally, if the term $t-\lceil k_i/2\rceil+1$ is used, evacuees begin their evacuation in the "center" of a cell. However, this approach allows to modify the "starting point" as desired by the decision maker.

5.5 Numerical Experiments

In this section, we use the base example Figure 4.4 in section 4.4.1 to illustrate how to apply the algorithms proposed in sections 5.3.2, 5.4.1 and 5.4.2 to solve the multi-source multi-sink emergency evacuation problem. We then compare the results for the different algorithms on the dynamic network. As in Chapter 4, the models' algorithms are written in Python and tested computationally using version 3.9.7. The formulations were implemented using the Gurobi [119] Python API and solved via Gurobi Optimizer version 9.5.0. All the experiments were run on a Core i7-3rd generation 2.9GHz computer with 16Gb of RAM memory under Windows 10 Pro 64-bits.

5.5.1 Base Case Example

We construct the Time-Expanded Graph (TEG) of network 4.4 using all the model parameters discussed in section 4.3.5 as follows. Consider arc (1,2) as an example. Since arc (1, 2) is composed of 4 cells, the transit time on arc (1,2) is 4. The same operation is performed on the rest of the arcs; the cell network is converted to the dynamic network G_T, as shown in Figure 5.6. Note that since cell properties are defined following the trapezoidal/triangular fundamental diagram, the basic unit of arc transit time in G_T is one time step, i.e, $\theta = 7$ seconds. To make the results comparable, we create dummy sources. Consider source 2 as an example; create a dummy source s_2 and load the initial occupancy into s_2 instead of node 2, so that node 2 serves an intermediate node in the node-arc instance. Create dummy arcs, with infinite capacity and zero transit time, connecting between source node s_i and intermediate nodes, to model the procedure wherein pedestrians move into the sources. For the same reason, we also connect sink nodes to super-sink (0) by uncapacitated arcs with transit time 0.

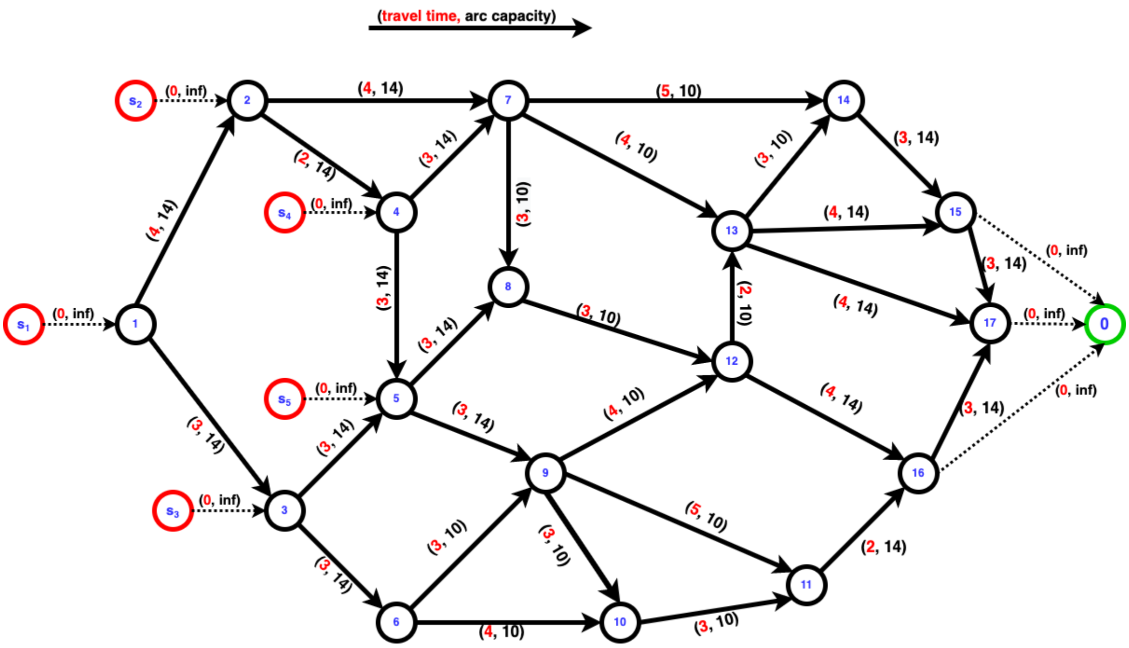


Figure 5.6: Constructed Dynamic Time Expanded Network for Figure 4.4

5.5.1.1 Impact of Modification on Problem Size

To illustrate the effectiveness of the three approaches, we compute the number of constraints and variables that would emerge in models discussed in sections 5.3.2, 5.4.1 and 5.4.2 and together with their extensions incorporating the congestions respectively. In Table 5.2, the number of constraints as well as the number of variables are calculated assuming an evacuation process of time period $\tau = 60$ time steps after presolve. The results in the upper part of the table represents the four models considered whilst the bottom half of the table represents the models with congestion. Bracketed percentages display the relative change in comparison to the CTM model (Section 4.3.1) . Negative percentages depicts a reduction while a positive value represents an increment. Two major findings can be derived from Table 5.2: firstly, massive improvements in terms of problem size reduction can be achieved in terms of the number of variables and constraints. Secondly, the incorporation of arc congestions in the models results in an astronomical increase in the problem sizes. That is the relative increment in the problem size in models with arc congestions is larger than the relative reduction in problem size in models without arc congestions.

Table 5.2: Model size comparison

Model	**# Variables**	**# Constraints**
DyCTEP	14760	39474
DEAF	3416 (-76.9%)	8667 (-78.0%)
APPROACH 1 (Extended CTM)	6776 (-54.1%)	12206 (-69.1%)
APPROACH 2 (Multiple Cell Sizes)	5700 (-61.4%)	10954 (-72.3%)
Model with Congestion		
DyCTEP	59040 (+300%)	70175 (+77.8%)
DEAF	13440 (-8.9%)	22913 (-42.0%)
APPROACH 1 (Extended CTM)	18278 (+23.8%)	24758 (-37.3%)
APPROACH 2 (Multiple Cell Sizes)	22800 (+54.5%)	26820 (-32.1%)

5.5.1.2 Comparison of Model Performance

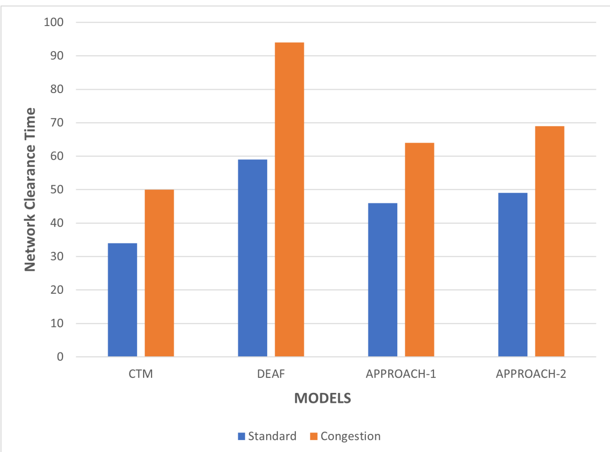
In order compare the performance of the various models discussed: Dynamic Cell-Transmission-based Evacuation Planning (DyCTEM) Model, Dynamic Earliest Arrival Flow (DEAF), Extended CTM Approach (Approach 1) and Multiple Cell Sizes (Approach 2) in sections 4.3.1, 5.3.1, 5.4.1 and 5.4.2 respectively, we run these models on the base-case example in Figure 4.4 and the corresponding TEG, Figure 5.6. The main results obtained are explained as below:

- **Network clearance time:** All the 500 evacuees were safely evacuated in time steps: $T = 59$ for the DEAF model, $T = 46$ in the case of Approach 1 and $T = 49$ for the Approach 2 procedure. In comparison to the CTM model, an additional 25 time-steps is needed to evacuate everyone in the DEAF model, whereas extra 12 and 15 time-steps are required to safely evacuate everyone in Approaches 1 and 2 respectively. Similar analysis can be made for the models with arc congestion as can be inferred from Table 5.3. Figure 5.7a shows the side-by-side comparison of the standard models versus the models with arc congestion for the four models discussed above.

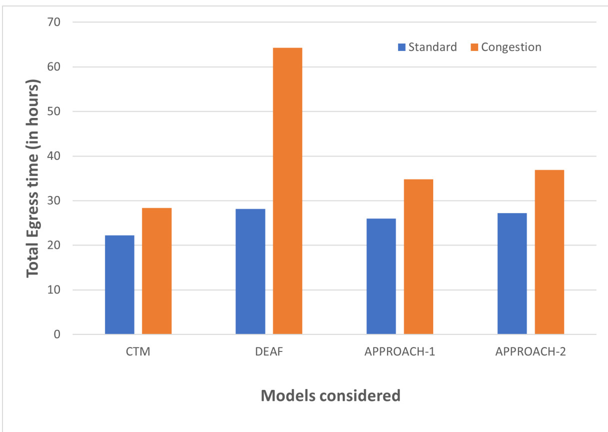
- **System Optimal Time (Total Egress Time):** The system optimal total egress time for the various models are as follows: the total egress times for models DEAF, Approaches 1 and 2 are respectively estimated as 14605 (4 hours 3 minutes and 25 seconds), 13354 (3 hours 42 minutes and 34 seconds) and 14006 (3 hours 53 minutes 26 seconds). The third column of Table 5.3 gives the results of the models performance for the various models based on the total egress times. Also, model analysis fore the arc congestion can also be obtained from Table 5.3. Finally, Figure 5.7b shows the side-by-side comparison of the standard models versus the models with arc congestion for the four models discussed above based on the total system optimal egress times.

Table 5.3: Comparison of model performance

Models	**Network Clearance Time** (Time steps)	**Total Egress Time** (Time units)
DyCTEP	34	11422 (3 hr 10 min 22 secs)
DEAF	59	14605 (4 hr 3 min 25 secs)
APPROACH-1	46	13354 (3 hr 42 min 34 secs)
APPROACH-2	49	14006 (3 hr 53 min 26 secs)
Model with Congestion		
DyCTEP	48	13905 (3 hr 51 min 45 secs)
DEAF	94	33060 (9 hr 11 min 1 secs)
APPROACH-1	64	17896 (4 hr 58 min 16 secs)
APPROACH-2	69	18971 (5 hr 13 min 11 secs)



(a) Model performance comparison based on Network clearance time.



(b) Model performance comparison based on System total egress time.

Figure 5.7: Comparison of model performance.

- **Optimal flow-staging at destinations:** From the optimal solutions of x_{ij}^t, for the destination cells, we can observe different amount evacuation flow-units arrive at the super-sink node 0 at different times in the various models. are optimally distributed in different directions. For example, as can be seen from Figure 5.7, at time-step $\tau = 34$ all 500 evacuees were safely evacuated in the CTM model but only 302 evacuees were evacuated in Approach 2 and 389 people were safely evacuated in Approach 1. Also, at time-step $\tau = 46$ all 500 evacuees were safely evacuated in Approach 1 model while in the same time-step 468 people were evacuated in DEAF model and 482 evacuees brought to safety in Approach2. Finally, it takes $\tau = 49$ to safely evacuate all evacuees in Approach 2 and $\tau = 59$ to evacuate everyone in the DEAF model. Similar analysis waas performed for the models with the arc congestion.

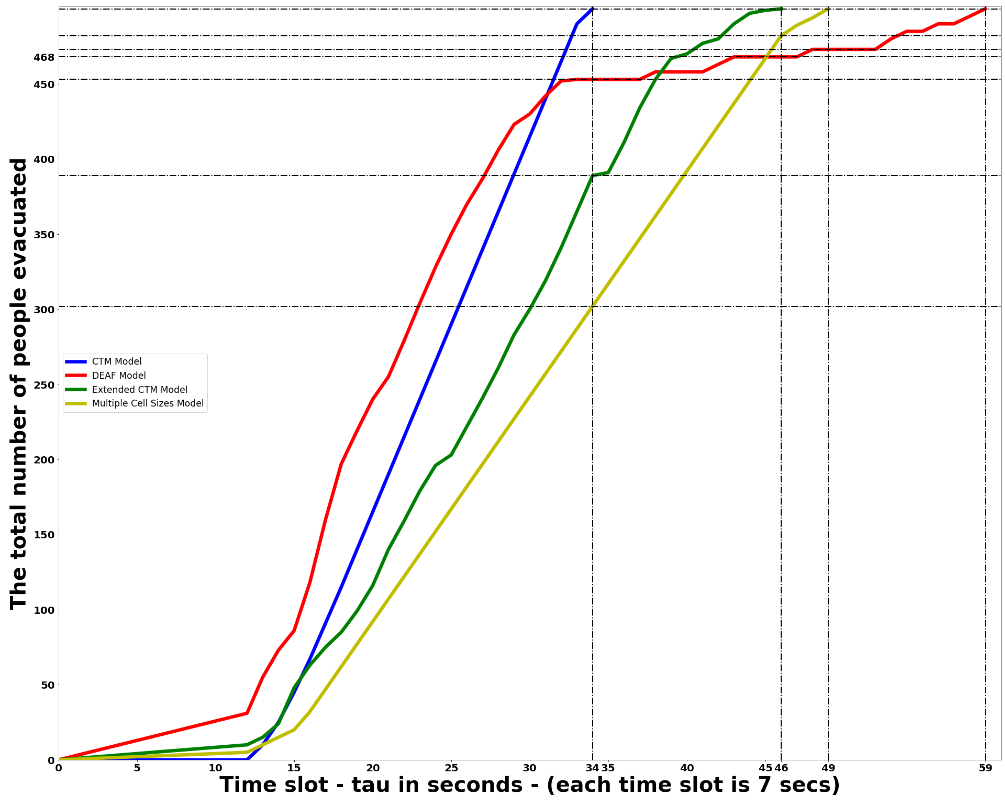


Figure 5.8: Number of people safely evacuated in each Model at every time slot τ.

5.5.2 Real-Size Network Case Implementation

In this section, we discuss some results for the L'Aquila network Figure 4.12, same as the network used in section 4.4.2, by applying the dynamic earliest arrival flow (DEAF) model on the transformed time-expanded graph of Figure 4.12, same as the network used in section 4.12 without diving it into cells. Recall that, the L'Aquila network Figure 4.12 analysed in Chapter 4, it used $\tau = 173$ time steps to clear the network and with a total egress time of 127203 time-units. Also, destination nodes 2, 19, 23, 34, 57, 144, 279, and 381 received no flows. Below is the summary of the results obtained compared to those of section 4.4.2 in Chapter 4.

- **Network clearance time:** All the evacuation flow-units, loaded in source cells at time-step 0, reached the super-sink cell within $T = 205$ time-steps.

- **System Optimal Time (Total Egress Time):** The system optimal total egress time = 144885 time-units. Which is equivalent to 40 hours 14 minutes and 30 seconds. An extra 5 hours needed to evacuate all the evacuees in DEAF as compared to CTM.

- **Optimal Flow distribution at Destination:** Figure 5.9 shows the comparison between the amount of flow each sink node received in the two models considered. The first observation is that in the case of the DEAF model only node 279 received no flow throughout the entire evacuation process whereas in the CTM eight (8) sink nodes received no flows.Furthermore in contrast to the CTM model, the most used sink node is 19 which received 23% of the evacees by the DEAF model. The next three frequently used destination nodes are 14, 135 and 278 with flow proportions 10.181%, 10% and 9.272% Finally, the optimal distribution of flows is much more even in the DEAF as compared to CTM.

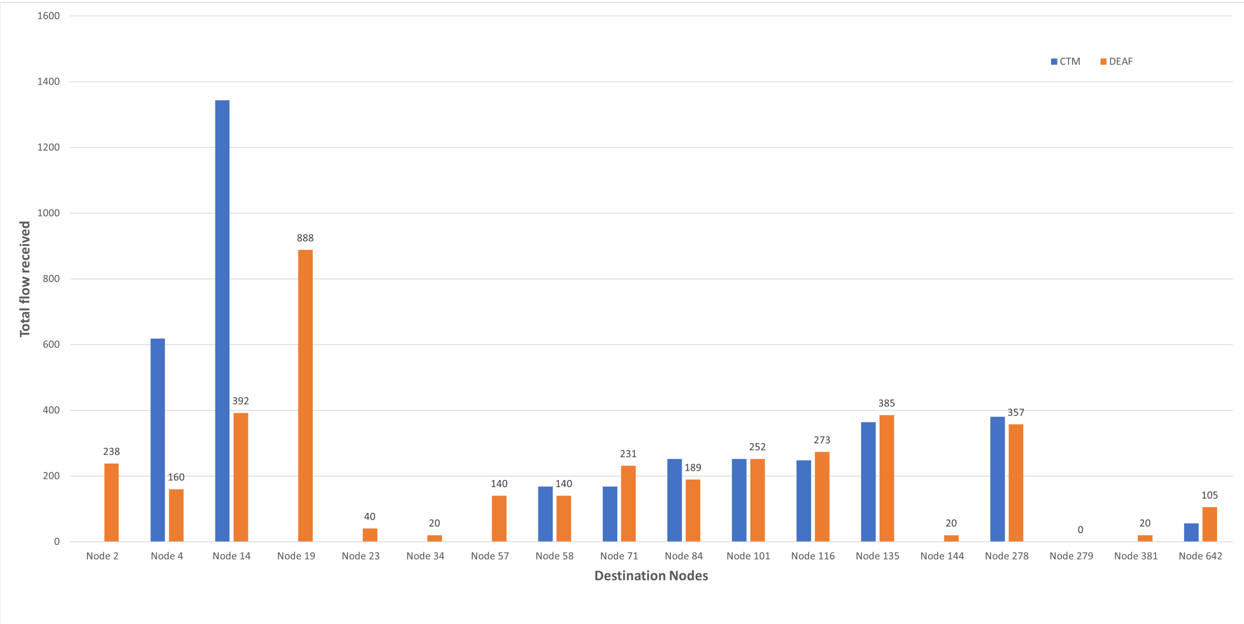


Figure 5.9: Comparsion of Optimal destination flow distribution for models DyCTEP and DEAF.

Finally, same as was done in section 4.4.2, the Heuristic Algorithm 1 was applied to the network in Fig. 4.12b to optimally assign routes to the evacuees to flow from the sources to the safe locations. Figure 5.10 is a visual representation of of the alternate routes (in green) assigned to the evacuees. For the initial paths generated by the DyCTEP model, route red (S to D_1) has a length of 1216 meters, route yellow (S to D_2) has a length of 1118 meters and route blue (S_3 to D_3) is 1627 meters long. But the alternate routes generated bt the DEAF model has lengths 1330m, 1202m and 1745m respectively for routes S to D_1, S to D_2 and S_3 to D_3. These alternate routes are very important when a particular route becomes inaccessible due to the uncertainties characterising the effects of disasters, the stakeholders can then prompt the evacuees to use these alternate routes.

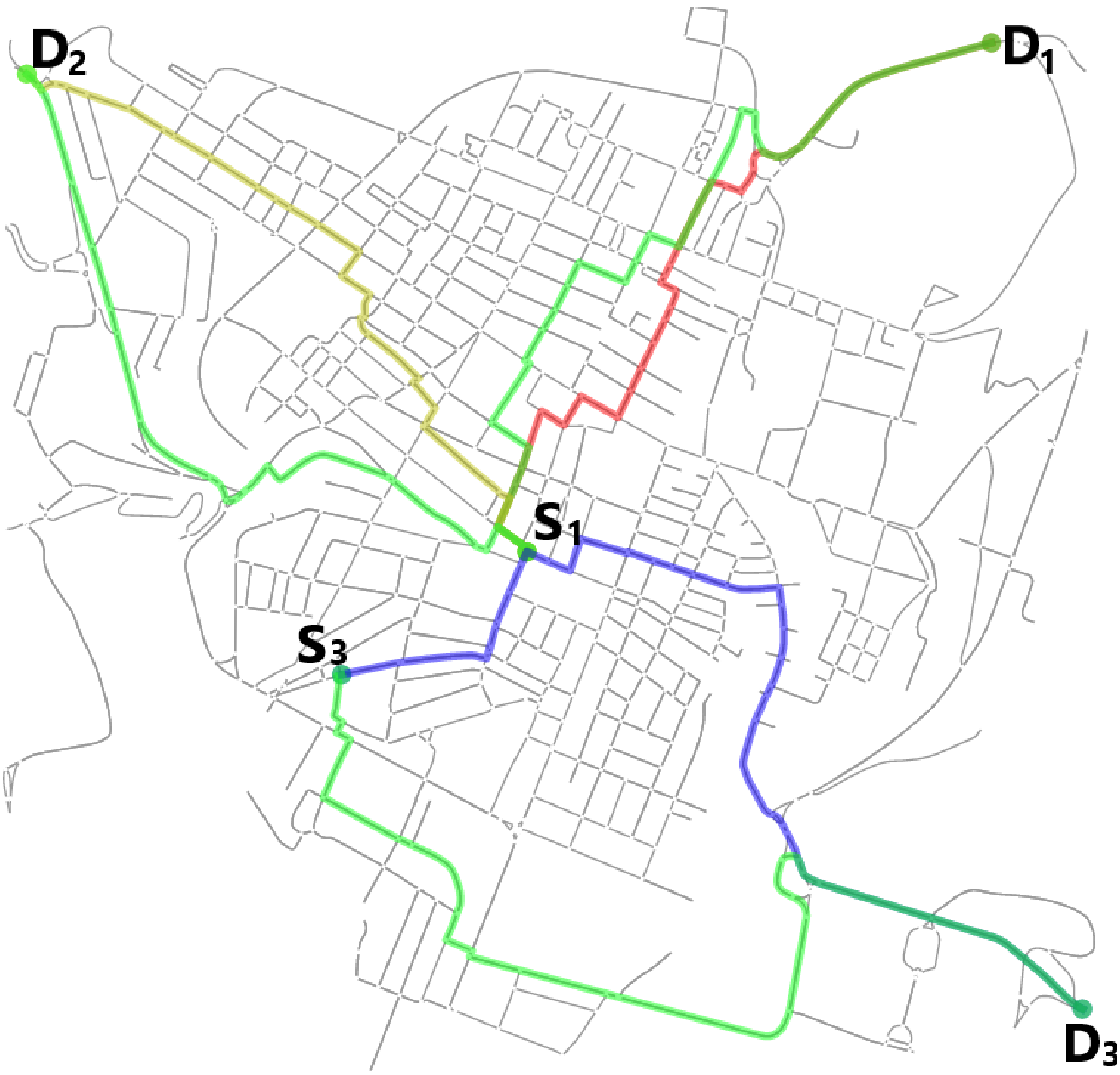


Figure 5.10: Optimal route assignment applying Heuristic Algorithm 1 on the model dynamics obtained by DyCTEP (in red, yellow and blue) and DEAF (in green).

Remark. Using different cell sizes, we investigated the model granularity and realised that it affects both the shape and size of the unit cells in which the network is decomposed, as well as the slots that form the evacuation time horizon. We concluded that, in order to obtain feasible solutions, $|T|$ must be chosen sufficiently large so that all evacuees have the ability to escape within the planning horizon. A lower bound for $|T|$ can be computed by $|T|_{LB} = \frac{\sum_{i \in S} q_i}{\sum_{i \in D} Q_i}$. However, larger values of $|T|$ will not lead to any severe computational issues.

5.6 Summary

Due to the fact that the DyCTEP model discussed in Chapter 4 has a major weakness that, the use of cells with fixed single size may lead to a too large number of cells, unnecessary to meet the required level of network and operation accuracy, in this chapter we proposed three different approaches (Dynamic Earliest Arrival Flow (DEAF), Extended CTM and the Multiple Cells Approaches) to cope with this inconvenience. So many cells imply an excessive number of constraints and variables in the optimization model, which may turn out to be unpractical for real use. Two numerical examples to were used to examine the algorithmic characteristics of the proposed models in terms of solution properties and computational performance.

Example 5.5.1, a small network 4.4 was used to investigate the model performance in terms of the number of variables and constraints in the three models compared to the DyCTEP model and the computational performance. Also example 5.5.2 was used to verify the equivalence between the DyCTEP and DEAF. The solution properties of the three model formulations were also investigated. The DEAF algorithm was efficiently implemented on a real-life-size network without basically dividing the arcs into elementary cells. This implementation provided alternate route assignment using Algorithm 1 which is very useful when any of the streets becomes inaccessible during an evacuation process.

Chapter 6

Towards an Emergency Evacuation Planning Service

6.1 Introduction

Evacuation Route Planning (ERP) is an important part of emergency management that aims to reduce the number of people killed or injured during natural or artificial disasters. The need for emergency preparedness in densely populated areas is demonstrated by events like the 2009 earthquake in L'Aquila, Italy and the 2019/2020 Australia wildfires. While local authorities had prepared for such situations, most of the evacuation process was chaotic and confusing in each case. Few would deny, however, that much more can be done to increase emergency preparedness. During the occurrence of a disaster, rescue teams must know not only which routes minimize the time to evacuate the helpless populace, but also how to respond to secondary occurrences that were not foreseen in the initial preparation, such as bridge failures and traffic accidents. Emergency preparedness as discussed in Chapter 1 has multiple complicated layers. Way before a disaster strikes, policymakers and local authorities must decide which means of transportation to employ during an evacuation (e.g., walking, private vehicles, and public transit), which locations will take too long to evacuate, and which techniques will be implemented (e.g., traffic contraflow or phased evacuation). During a real emergency, first responders must know not just which routes would take the least amount of time to evacuate the most vulnerable people, but also how to deal with unexpected events like bridge failures and traffic accidents.

In this chapter, we propose an algorithmic methodology developed for ERP that we envision to be the basis of an online service that guides evacuees to safe places via the better route calculated considering the actual situation. This service needs smart city infrastructure that collects updated information about the city possibly asking also real-time data to users. Given a transportation network $G = (N, E)$, the number of evacuees and rescue teams, their initial locations, and the safe locations, our goal is to determine an evacuation plan consisting of a set of source–sink routes and evacuee scheduling on each route with the aim of minimizing the total evacuation egress time (i.e the time between the start of the evacuation and the arrival of the last evacuee at their destination) satisfying the following constraints:

- Route scheduling should take into account the capacity constraints of the transportation network and
- Reasonable computational time despite the limited computer resources.

Minimizing the evacuation egress time is crucial since it reduces exposure to potential risks. Also minimizing computational time is vital for both planning and during evacuation since we envision to embed the algorithm in an online smart city infrastructure. During the planning phase, methods that reduces computational time allow for the study of a wide number of scenarios based on mode of transportation, event location, and time. Unexpected occurrences may occur during the evacuation (e.g., the bridge failure as a result of Hurricane Katrina or the 170-km traffic jams due to Hurricane Rita in 2005). In addition, new evacuation routes may be required in response to occurrences of disasters.

6.2 Related Work

The categorization of the ERP approach falls under three distinct and interrelated categories: (1) Network flow methods [13, 49, 130, 152, 183, 252, 348] consist of minimizing total evacuation time under constraints through time expanded graphs (TEG) or using iterative algorithms optimizing cost functions, (2) Simulation methods [32, 242, 243] focus on individual movements to such a labor-intensive extent that the effort attenuates into the game of "herding cats." and (3) Heuristic methods [109, 150, 311, 382, 399] which have proved recently to be very promising, including CCRP, which uses quick and dirty time-aggregated graphs with the capacity constraints to rapidly and repetitively identify workable routes. Heuristic approaches, in contrast to prior approaches, use approximation methods to obtain near-optimal solutions while minimizing computational cost. The CCRP is a well-known technique that comes under this category [232–234]. To discover the evacuation route at each time step, these algorithms leverage time-aggregated graphs [109] and evaluate a shortest route with capacity limitations. It's good for medium-sized networks (like a 1-mile evacuation zone), but it's not good for huge networks (e.g., 50-mile evacuation zone). Kim et al. [179] propose a new scalable heuristic based on bottleneck saturation checks that reuses shortest paths. It demonstrated a 95% reduction in computing time with only minor degradation in solution quality. These methods have proved the dynamism of a crowd in network utilization, including variations in crowd movement and changes in route selection. As a result, metaheuristic techniques are limited in their ability to provide optimal evacuation performance(s). Meta-heuristic techniques can minimize computational complexity despite their stochastic nature. As a result, the meta-heuristic method is deemed excellent and appropriate for addressing the dynamic character of the ERP problem.

6.3 Proposed Approach

In a standard evacuation planning scenario, the geographical structure is represented and analyzed as a network model with non-negative integer capacity constraints on the nodes and edges. With additional information pertaining to initial locations of all evacuees, rescuers and their final destinations, the ERP problem produces a set of origin and destination routes for evacuees. Consider a simple ERP problem in Figure 6.1, where each node, N of G typically has two parameters: current population, y_i and maximum capacity, n_i [131]. The current population can vary over time but maximum capacity is constant and remains a limiting factor of any given node. Each edge has two parameters: travel time, λ_{ij} and maximum edge capacity, c_{ij}. Travel time describes the duration of time steps to traverse the entire edge connected between two nodes. Edge capacity however, unlike a nodes maximum capacity, does not describe the maximum population limit of a given edge, but rather the maximum rate at which people may enter the edge [293]. This distinction is quite subtle, but is however more akin to limitations of flow rates and evacuation times within reality. Also, this distinction will also simplify our implementation of CCRP, and it may be considered one of the reasons why this method is less computationally expensive and scalable than other alternatives [293, 311].

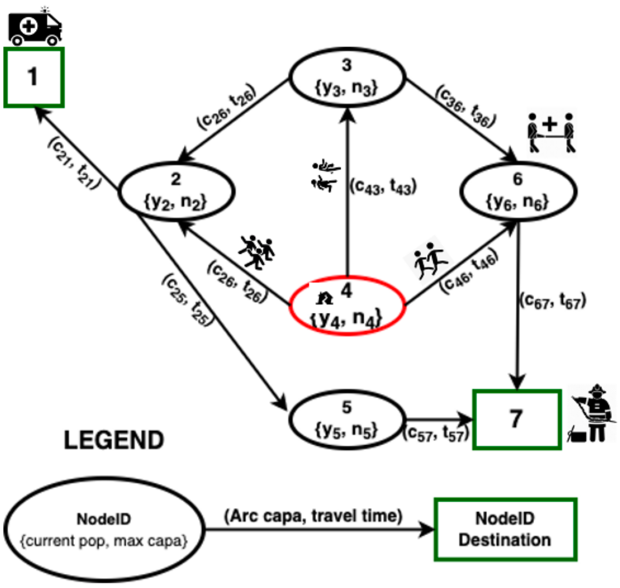


Figure 6.1: Network Model for a multi-party evacuation route planning.

The proposed method aims to estimate the total evacuation egress time for multiple parties involved in an emergency evacuation process, where each of these parties has separate objectives, such as evacuees starting from a dangerous source and migrating to a safe location, and rescuers starting from anywhere with the goal of migrating to a dangerous destination. Areas describing both risks and safety are established for any form of emergency evacuation planning, providing an evacuee route planner with a list of endangered sources and safe sites. As a result, we would like to create evacuation plans for all evacuees while keeping the total evacuation time to a minimum. The Priority Multi-Party Capacity Constraint Route Planning (PMP-CCRP) in Algorithm 2 is an extension of CCRP [293, 311]. The CCRP takes an iterative approach to developing a comprehensive evacuation plan. The method searches for a route R with the earliest arrival time to any destination node from any source node in each iteration, taking into account previous reservations and possible wait delays. The actual number of evacuees who will pass through R is then calculated by CCRP. The remaining number of evacuees and R's available capacity have an impact on this amount. The lowest of the available capacities on the component edges in R determines the maximum number of evacuees to be sent on R; CCRP reserves the node and edge capacity on R for these evacuees. When all of the evacuees have been given an evacuation path to one of the destinations, the algorithm ends. The determination of the route R with the earliest arrival time is a crucial stage in CCRP. Executing Dijkstra's method [65, 75] for each source and destination node, then selecting the minimum, is a basic technique to get the route R. The proposed PMP-CCRP is a modification of CCRP by simply taking the idea of super-sources and super-sink just a step further by introducing sub sources and sub destinations that are linked to each party's locations or nodes. These sub sources serve as an intermediary between the capacity constrained network and the fictitious super nodes.

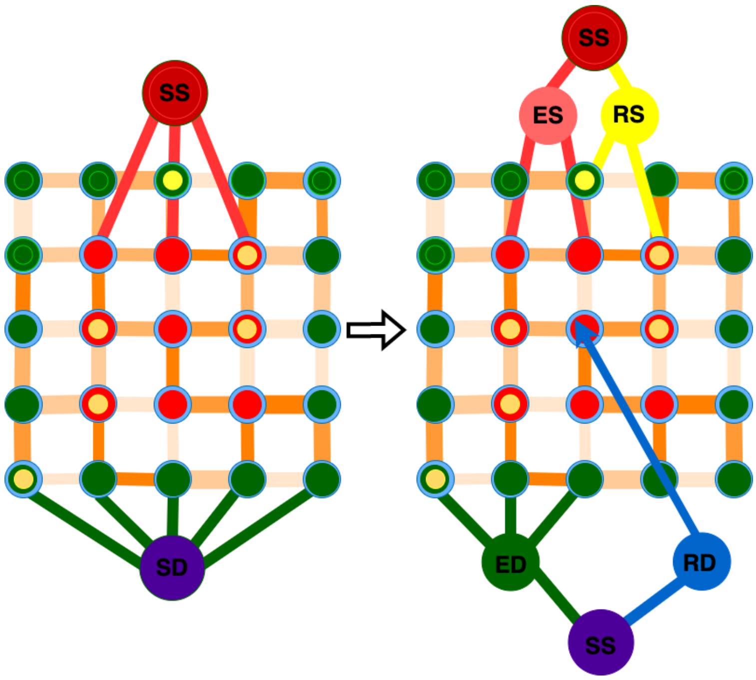


Figure 6.2: Network Model representation of CCRP vs PMP-CCRP.

Given a list of sources and destinations, PMP-CCRP calculates the fastest possible route at the earliest available time. This is accomplished by creating a single pair of fictitious super-source and super-destination vertices that connect to the list of sources and destinations using zero-travel-time and infinite-capacity edges respectively. In order to cater for the multi-party nature of the algorithm, a party-specific sub-sources (E_S, R_S) and sub-sinks (E_D, R_D) are generated and connected to their respective sources and sink nodes, while also sharing a common super-source or super-destination parent see Fig 6.2. Nodes are the categorized based on priorities such that areas/nodes that are assumed to be high risk need to be evacuated first before low risk nodes.

This allows for a modified Dijkstra's algorithm to solve for the shortest path between the two super nodes using edge travel time and node priorities as the weight criteria. This ensures that the current shortest path comprises a source and sink for a single party. Once this path R has been identified, the maximum flow along it is computed by determining the minimum of the three parameters along the path: current source population, minimum available edge, and node capacity. A time-series dictionary is used to keep track of available capacities in the graph, allowing the algorithm to check and update reservations along the route. If the quickest path has no more available capacity at the current start time, it repeatedly searches into the future by a time step and checks for available capacity along the same path. This flow computation assures that any given path's capacity is not exceeded while simultaneously optimizing evacuation times. The pseudo-code for PMP-CCRP is shown in Algorithm 2.

Algorithm 2: Priority Multi-Party Capacity Constraint Route Planning (PMP-CCRP)

Input: spatial network $G = (N, E)$, with the set of source and sink nodes, $S \subset N$ and $D \subset N$ respectively and book-keeping of available capacities of G using time-series dictionary

Output: Evacuation plan: Routes with schedules of evacuees on each path

```
Generate party specific pseudo sub-sources (E_s and R_s) and pseudo sub-sinks (E_D and R_D)
  connected to the respective source and sink nodes with 0 travel times and ∞ capacities.
Add super-source (S_S) and super-sink (D_S) connected by edges of 0 travel times and ∞
  capacities to the respective sub-sources and sub-sinks.
Categorize each source node based on priority
while (any source has evacuees) do
    Find the shortest path P between the two super nodes (S_S and D_S) using the
      generalized Dijkstra's algorithm with edge travel times and node priorities as the
      weight criteria
    Calculate the maximum flow x_max along this path P
    Reserve the node and arc capacities
    Update the book keeping dictionary
Output evacuation plan
```

The proposed PMP-CCRP seeks to achieve the ability to plan for multiple parties with different objectives. That is, evacuees may begin their journey from an endangered source and travel to a safe destination, while inversely emergency responders may begin their journey from anywhere and travel to a dangerous location. This list of distinct sources and destinations for distinct parties adds to the complexities in optimizing the counterflows. A simple solution would be to apply CCRP consecutively for emergency responders after completion of the algorithm for evacuees. While this might not greatly affect the evacuation egress time, this remains non-optimal in terms of response time, essentially under-utilizing the capacities that become available throughout the progressive evacuation. As stated previously, we proposed to implement an algorithm that would provide improved response time by allowing a slight trade off in evacuation time, thus benefiting the survival rates of victims who are trapped or left behind and are the most in danger. This is accomplished by modifying the Dijkstra's algorithm to properly solve for the fastest paths between matching sources and destinations, as well as expanding the time-series dictionary to reflect multiple party populations with separate time series while maintaining the shared reservation list for the entire network. Because practically any combination of evacuee and responder source and destination overlaps is possible, such as rescuers and evacuees sharing the same source, or evacuees having the same destination as a responder's source and vice versa. By creating party-specific sub-sources and sub-destinations, a parallelized technique was devised. Simply put, our improved search algorithm ensures that the current quickest path found has a common source and destination. Additional precautions are necessary to ensure that fictitious paths that backtrack down one party sub-source and up another that provide a teleportation-like behavior across the real transportation network are not utilized.

6.4 Implementation

To make the algorithm usage more efficient and reusable a hierarchical Object Oriented Programming (OOP) approach was adopted to define the evacuation scenario. The code for the implementation was written in Python 3.10 using the NetworkX library for the graph generation. We first define the MPCCRP object which basically initiates the Capacity Constrained Route Planning calling the following classes:

- *DrawGraph* class (makes the specified Capacity Constrained Graph (CCG)) using the following methods: makeCCGraph, makeCCGraph_grid2d (makes 2D grid CCG), makeCCNodes (makes CCG nodes), makeCCEdges(creates CCG edges), and genSD (generates sources and destinations)

- *Population* class (gets Total Population) which also calls the following methods: getNodePop (gets node population of party at time t), setNodePop (sets node population of party at time t)

- *Route* class (generates the best and quickest routes for each party in G) which makes use of the following methods: party_dijkstra (computes shortest paths and lengths in a weighted graph G of multiple parties), getRoute (gets the best path R) and

- *Party* class (gets information about the location of each party in G) which similarly calls the methods: getPartyN (gets node locations for a party and time t), addPartySuper (add fictitious super-nodes to G), removePartySuper (removes fictitious super-nodes from G)

Finally, running the functions *applyCCRP* and *getStage* respectively applies the PMP-CCRP algorithm to the graph and get the stage of the evacuation plan given route R and time t.

6.5 Experimentation

For initial illustrative purpose, we generate a small 7×7 two-dimensional capacity constrained Manhattan grid by constructing a MPCCRP object using the parameters we defined below in Table 6.1. Next we define the 6×6 interior grid as the evacuation zone and the very center of the

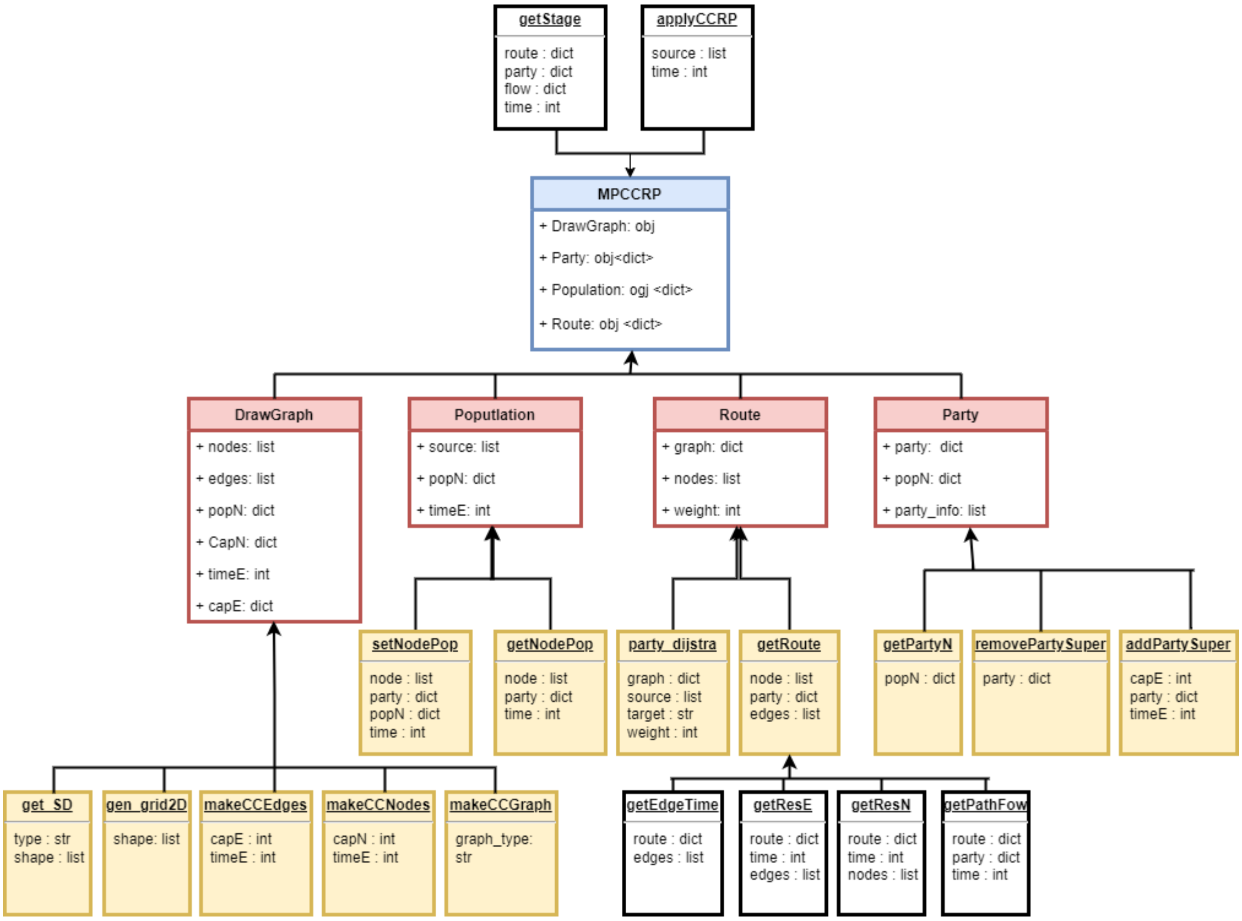


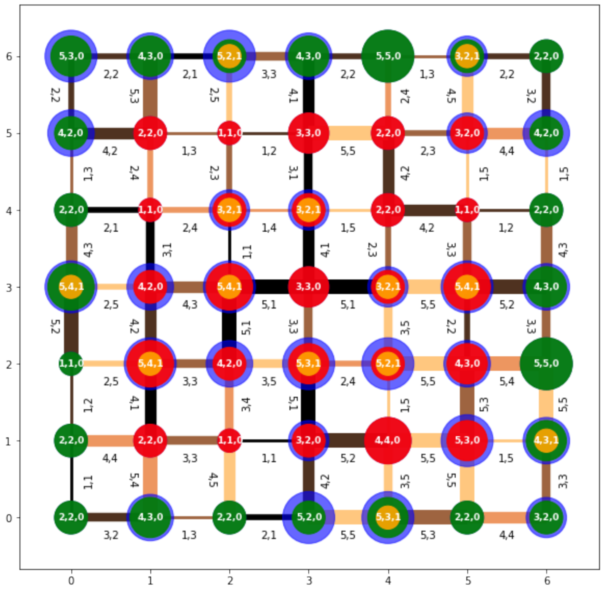
Figure 6.3: Object Oriented Programming procedure for the proposed Algorithm 2

grid as the disaster node, thus the destination for all responders. From this we will get the sources and destinations for all that affected evacuees. We also make sure that no responders are already on-site on the disaster node at the beginning time of the simulation. This results in a network with total number of nodes 49 and 84 arcs. Also there are 134 total population to be evacuated.

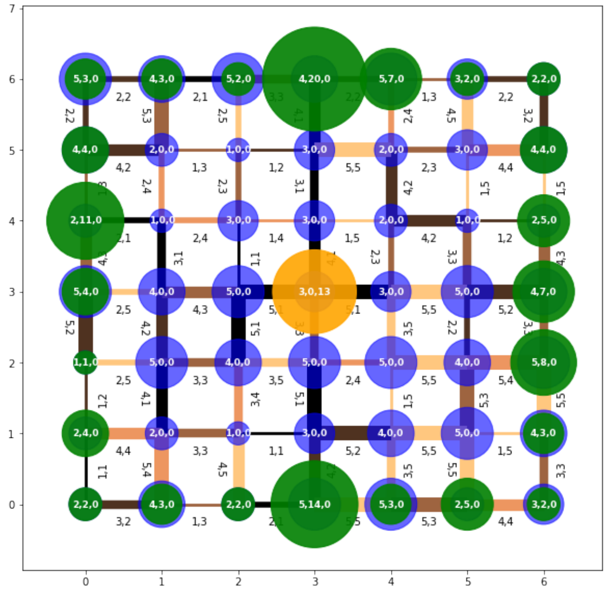
Table 6.1: Possible parameters for all nodes for each party

Parameter	Min	Max
Evacuees	2	5
Responders	0	1
Node Capacity	1	5
Arc Capacity	1	5
Arc Travel time	1	5

Figure 6.4 are visual representations of the capacity constrained networks used for the algorithm testing. On each node are three numbers, the first of which is the maximum capacity, denoted by the size of the blue shaded outline, the second number is the current population denoted by the green color (the capacity of the destination nodes is large enough to accept all the evacuees but for purpose this illustration, they seem quite small in the figures.) and the third number denotes the presence of responders in the node depicted by the yellow color. The edge numbers represent arc



(a) Endangered Capacity Constrained Graph.



(b) Evacuated Capacity Constrained Graph.

Figure 6.4: The graph on the left shows the population before evacuation while the graph on the right shows the population after evacuation and response.

capacity denoted by edge width and travel time denoted by orange to black for fast to slow. It is obvious from Figure 6.4b that all evacuees have exited the evacuation zone through the quickest routes available, and thus coagulate around the major exits consisting of wider and faster edges. The emergency responders have also accumulated onto the center disaster node. The entire evacuation process was completed in $T = 17$ time steps.

A simple comparison of the new and original CCRP algorithms in terms of evacuation time may not be the appropriate performance descriptor for the proposed PMP-CCRP method. Because the start and end times for evacuees will be arbitrary within the new evacuation plan's time sequence, As a result, a more interesting question could be whether it is better to evacuate sooner after a disaster or over a shorter period of time. This is comparable to the question of whether the risk is incurred in time spent exposed while moving versus time spent immobile, as in hurricanes or forest fires. By analyzing both systems in multiparty emergency scenarios, we propose a more general comparison. Because the original CCRP algorithm does not intrinsically support multiple parties, we will simply run the original algorithm twice; once for each party, sequentially one after the other. The overall completion time of both methods can then be compared to one another. For the test trials, the two CCRP algorithms are simulated 1000 times on a 9×9 Manhattan grid network, with the very center node serving as the disaster location and all but the edge vertices falling into the risk zone. For both approaches, a random capacity constrained graph was constructed for each trial, with random maximum node capacity between 5 and 10, arc capacity between 3 and 5, and arc travel time between 3 and 7. The initial population is also random, ranging from 3 to the maximum node capacity, with each node having a 50% chance of including a responder if the maximum node capacity allows it.

6.6 Discussion

The proposed PMP-CCRP algorithm, as seen in the findings, provides a more responsive and realistic route planner for multiple parties. Rather than waiting for one party's migration to be completed before proceeding, both parties travel as soon as they are able while sharing the same capacity-constrained transportation network. This is more akin to how genuine emergency situations are handled, as all personnel must be dispatched quickly. We've demonstrated how to organize all parties involved in order to reduce total completion time. Table 6.2 gives the comparative analysis of the 1000 trials performed on the chosen graph. This gives a brief statistics on the entire experiments. It can been seen that of all the 1000 simulations, the minimum population to evacuated is 395 with maximum population size being 505. It can also infer similar statistics for the other procedures carried out. Finally, Figure 6.5 is the plot of the differences between the CCRP used sequentially for the parties involved versus the PMP-CCRP used for the multi-party evacuation process. Of particular interest is Figure 6.5 give depicts the amount of time saved using the new proposed algorithm over CCRP proposed by Shekhar et al. [311].

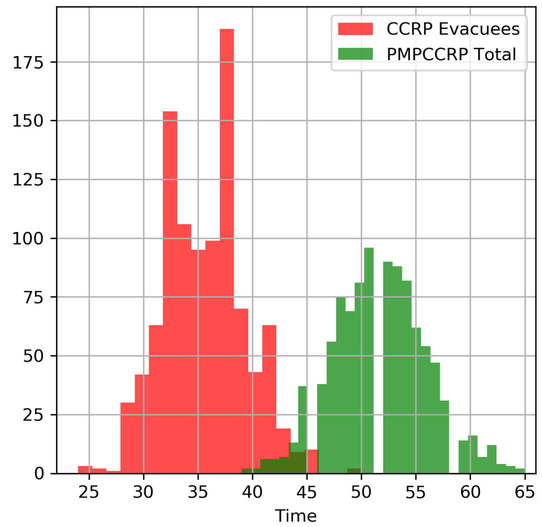
Table 6.2: Results of the comparative analysis performed of Figure 6.5

			Total Egress Time		
	Population	**CCRP Evacuees**	**CCRP Responders**	**CCRP Both**	**PMP-CCRP**
count	1000	1000	1000	1000	1000
mean	451.4	35.654	33.643	69.297	51.715
std	16.999617	3.751848	2.375119	4.681956	4.355542
min	395	24	27	56	39
0.25%	441	33	32	66	49
0.50%	452	36	34	69	52
0.75%	462	38	35	72	55
max	505	50	42	85	65

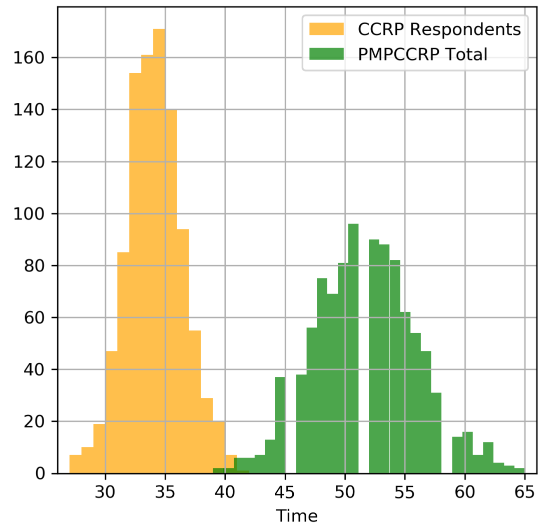
6.7 Conclusion

We proposed an approach which provides a better total egress time for multiple parties emergency evacuation taking into consideration node priorities in the underlying network. Moreover, because almost all arrangements of evacuee and rescuer source and destination overlaps are possible, such as rescuers and evacuees sharing the same source location, or evacuees having the same destination as a rescuers' source and vice versa, additional precautions are necessary to ensure that fictitious paths that backtrack down one party sub-source and up another that provide a teleportation-like behavior across the real transportation network are not utilized.

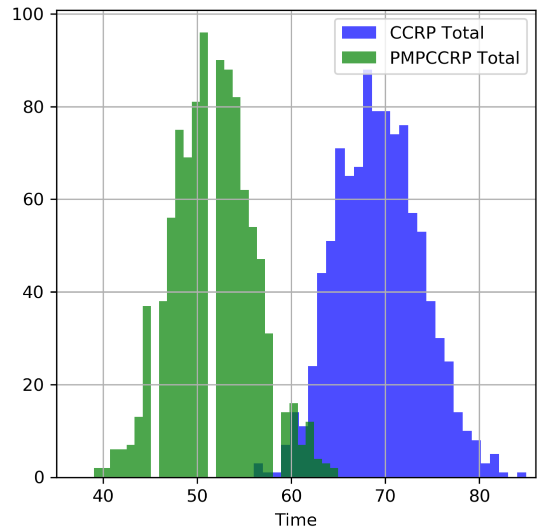
Such an approach will be the core engine of a novel smart city service that is able to guide evacuees and rescuers after a disaster to bring to safety as many people as possible out the risky places. The service must be fed by real-time information (which roads are safe enough, which are damaged by the disaster, how many people are in a specific area, and so on). Starting from



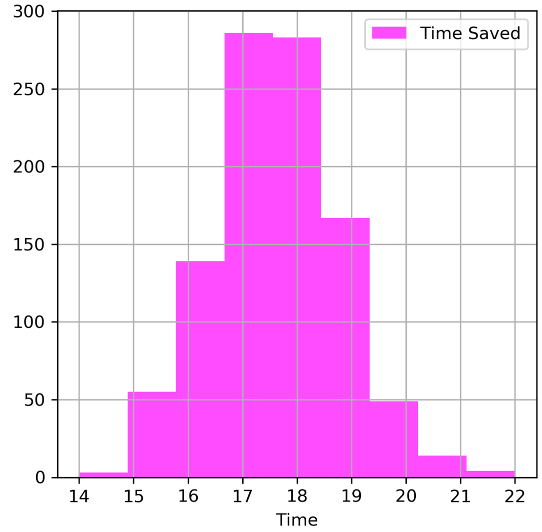
(a) CCRP evacuation egress time vs PMPCCRP total egress time.



(b) CCRP respondents egress time vs PMPCCRP total egress time.



(c) CCRP total egress time vs PMPCCRP total egress time.



(d) Total time saved.

Figure 6.5: Comparison of the total egress time for CCRP and PMP-CCRP. **Top Left:** Histogram comparing CCRP Evacuation vs PMP-CCRP Total Time. **Top Right:** CCRP Response vs PMP-CCRP Total Time. **Bottom Left:** CCRP Total Egress Time vs PMP-CCRP Total Time. **Bottom Right:** Total Time Saved using PMP-CCRP on a trial by trial basis.

our proposed algorithm, we will able to specify, design and implement a smart city infrastructure and connected mobile app able to collect all the needed data. These together with the proposed algorithm will realize the rescue and evacuation service for smart cities of the future.

Chapter 7

Summary, Conclusions and Future Research

7.1 Summary and Conclusions

Due to the complexity of traffic dynamics, traffic management in evacuation scenarios is a difficult challenge. If major urban regions are being studied, this process becomes even more difficult. So far, most literature only covers the evacuation of pedestrians escaping from buildings, stadiums or ships. If urban evacuation is the goal, either limited areas are evacuated, or low-detail network flow optimization models or simulation models (without optimization) are utilized.

In chapter 3 we developed the network transformation and conversion NTC model to convert any sized node-arc network into the cell network no matter how small or large the underlining network is. The NTC model has enabled the application of all the different model formulations to large-scale real-world networks for SO-DTA analysis employing cell transmission models. The NTC inherently helps us to generate the evacuation network by defining the danger zones, set of safe locations or the haven and the transshipment and intermediary nodes.

In chapter 4 we proposed and integrated the DyCTEP model into the CTM. We considered ways on modeling possible congestions that might occur on the streets/arcs during an evacuation process. Adding arc-congestions to the model formulations, resulted in the increment in the total evacuation time due to the fact that the free flowing pedestrian velocity reduces in the arcs when too many people try to traverse these arcs during the evacuation process. Also, we developed the optimal route assignment heuristic model to assign routes to evacuees during the evacuation process. Two papers (Definition of an enriched GIS network for evacuation planning [154] and Toward Effective Response to Natural Disasters: a Data Science Approach [20]) have been publish based on this chapter. In [154] the authors contributed to literature in threefold: *i)* the definition of a new algorithm able to generate an enriched network from GIS data, specifically tailored to include useful information for emergency management, *ii)* the adaptation of the optimization model developed by [23] to outdoor scenarios, that is the evacuation plan of a city in case of natural disaster; *iii)* the validation of the previous step to a real case study, i.e., the historical centre of

Sulmona city in Italy. The CTM model had to be customized with respect to several parameters, and re-scaled to the network of several orders of magnitude. In the case study of Sulmona, we solved the problem with over 2,000,000 nodes. The results obtained were encouraging in terms of the approach viability. The effects of the number of safe locations on the total egress time was also investigated to arrive at the conclusion that the number of safe locations has a significant effect on the total egress time. In [20], we proposed a comprehensive data science framework called DiReCT for evacuation and reconstruction planning in case of natural disasters. The contributions of this paper are: i) an integrated framework that, based on data science, can help decision makers to face natural disasters. As first realization, we embed automatic support to evacuation and reconstruction planning. ii) the definition of the *GisToGraph* algorithm to generate an enriched underlining network of any location, specifically tailored to include useful information for disaster management, especially in the *preparedness, response and reconstruction* phases. iii) the adaptation and validation of the dynamic optimization model incorporated with arc congestions designed to timely formulate an evacuation plan of an area struck by an earthquake, and *ii)* a decision support system, based on double deep Q Network, able to guide efficiently the reconstruction the affected areas. The feasibility and applicability of our framework was investigated on a real case study, the historical center of L'Aquila city for emergency evacuation and reconstruction purposes.

In chapter 5, we proposed three different model formulations to handle the weakness of the CTM. For the first model proposed DEAF, there is no need to explicitly partition and embed the underlining evacuation network into elementary cells instead we converted the network using travel times to generate the TEG. We verified the equivalence between DyCTEP and DEAF. The other two model formulations are extensions of the DyCTEP. We analysed the effects of these new approaches on the model size in terms of the number of variables and constraints as well as the computational and egress times. Using different cell sizes, we examined the model granularity and realised that it affects both the shape and size of the unit cells in which the network is decomposed, as well as the slots that form the evacuation time horizon. We concluded that, in order to obtain feasible solutions, $|T|$ must be chosen sufficiently large so that all evacuees have the ability to escape withing the planning horizon. A lower bound for $|T|$ can be computed by $|T|_{LB} = \frac{\sum_{i \in S} q_i}{\sum_{i \in D} Q_i}$ Finally, using Algorithm 1 we generated alternative optimal route assignment for the emergence evacuation planners.

Finally, the proposed PMP-CCRP algorithm in Chapter 6, as seen in the findings, provides a more responsive and realistic route planner for multiple parties. Rather than waiting for one party's migration to be completed before proceeding, both parties travel as soon as they are able while sharing the same capacity-constrained transportation network. This is more akin to how genuine emergency situations are handled, as all personnel must be dispatched quickly. We demonstrated how to organize all parties involved in order to reduce total completion time. Due to the party constraints caused by adding additional party sources and destinations, debugging and verifying our modified version of Dijkstra searching algorithm was one of the most challenging aspects of building our multiparty CCRP method. Some of the CCRP's disadvantages were among the things we found. The CCRP will simply look for the quickest path in terms of edge transit times, but it will change the flow rate to compensate for the available capacity. This entails first establishing a path under optimal conditions with no capacity constraints, and then retrofitting the route"s actual constraints. A similar comparison would be a theme park visitor who prefers to wait in a long line for the closest food seller rather than walking to other vendors with shorter queues where food may be purchased sooner. More optimal routes can be identified using methods like time expansion, which finds the fastest way given the current time and future capacity limitations. However, the higher memory utilization and processing expense make large-scale citywide evacuations extremely expensive. This makes CCRP a viable option because the increased complexity of multiparty computing is mitigated by the general simplicity of the CCRP.

7.2 Research Contribution

In this thesis, we focused on large-scale no-notice and short-notice emergency pedestrian evacuation. We proposed models which solved large scale pedestrian evacuation efficiently. Specifically, the contribution of this doctoral research is summarized as follows:

1. We proposed and applied the dynamic cell-transmission-based evacuation planning model to large scale networks to give better global solutions. For networks with intermediate destinations with limited capacity of holding evacuation flow-units, the single sink concept proposed by Ziliaskopoulos was improved and extended to a multiple sink SO-DTA model. The cell transmission model which was limited to only small networks (refer to Arbib [22–24]) was improved by developing network conversion model (NTC) in Chapter 3, to convert any size node-arc network into cell network.

2. We then incorporated arc-congestion, which is a situation where the speed at which the system empties is a decreasing function of cell/node occupancy y_i^t into the model formulation, to mimic the bottlenecks on the streets in the real-life evacuation processes.

3. We proposed a Heuristic Algorithm for optimal route assignment taking into consideration all network optimal flow dynamics captured in time. Its performance with the Dijkstra's shortest path algorithm was investigated.

4. We proposed and implemented three new approaches, namely Dynamic Earliest Arrival Flow (DEAF), Extended CTM and the Multiple Cells Approaches to cope with the inconveniences associated with the DyCTEP in the sense that, usage of cells with fixed single size may lead to a too many number of cells (imply an excessive number of constraints and variables in the optimization model), unnecessary to meet the required level of network and operation accuracy which may turn out to be unpractical for real use. Model performnce comparison was then carried out.

5. Finally, we proposed the priority multi-party capacity constrained route planning PMP-CCRP, a heuristic algorithm and an extension of the CCRP by Shekhar et al. [311]. The proposed PMP-CCRP is equipped with the ability to plan for the evacuation of multiple

parties with different objectives. That is, evacuees may begin their journey from an endangered source and travel to a safe destination, while inversely emergency responders may begin their journey from anywhere and travel to a dangerous location. PMP-CCRP ensures that during the evacuation process, priority is given to high risk areas, that is, evacuees in highly endangered zone are evacuated first before those in less risky areas.

7.3 Research Publications

The research presented in this thesis is mostly based on the following peer-reviewed publications:

- Evans Etrue Howard, Pasquini Lorenza, Arbib Claudio, Di Marco Antinisca and Clementini Eliseo "Definition of an Enriched GIS Network for Evacuation Planning". *In Proceedings of the 7th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM 2021), pages 241-252* (Thesis authour's contribution: Model formulation and implementation of all the optimisation models.)

- Ghulam Mudassir, Evans Etrue Howard, Lorenza Pasquini, Claudio Arbib, Antinisca Di Marco, and Giovanni Stilo "Toward Effective Response to Natural Disasters: a Data Science Approach" *In IEEE Access 2021, volume 9, pp.167827-167844* (Thesis author's contribution: Mathematical formulation, implementation and experimentation of the evacuation section. Evaluation and writing under the guidance of the supervisor and other team members).

- Evans Etrue Howard, Antinisca Di Marco and Claudio Arbib "Towards an Emergency Evacuation Planning Service". *7th Italian Conference on ICT for Smart Cities And Communities, 2021* (Thesis author's contribution: The entire manuscripts.)

In progress:

- Evans Etrue Howard, Pasquini Lorenza, Arbib Claudio, Di Marco Antinisca and Clementini Eliseo "Automatic generation of evacuation plans from real GIS data"

- Evans Etrue Howard, Antinisca Di Marco and Claudio Arbib. "Mapping knowledge structure and research trends of Pedestrian Emergency Evacuation Models: A State of the Art." *The entire Chapter 2 is based on this article.*

7.4 Future Research

The future work will be the incorporation of the methods, algorithms and procedures described in this thesis in a novel smart city service that is able to guide evacuees and rescuers after a disaster to bring to safety as many people as possible out the risky and endangered places. The service must be fed by real-time information (which roads are safe enough, which are damaged by the disaster, how many people are in a specific area, and so on). Starting from our proposed algorithms, we plan to be able to specify, design and implement a smart city infrastructure and connected mobile app able to collect all the needed data. These together with the proposed algorithms will realize the rescue and evacuation service for smart cities of the future.

We are studying to incorporate additional risk factors into the model, like those associated with each node/building and/or each arc/street. Other aspects we are willing to explore in the future are further optimization models, exact or approximate, to be employed in order to reduce the computational effort presently required by simulations. We also want to research on the development of a hybrid approach for evacuation planning by performing a mesoscopic study, where the solutions of the CTM-based approaches will serve as lower bounds to calibrate the microscopic models by using agent-based modeling to capture human behaviours much more realistically in order to better understand the individual microscopic interactions between pedestrians during evacuation. Finally, we aim to make a better trade-off analysis between the number of safe places and the total evacuation time. This will be very useful for pre-disaster evacuation plan definition.

In the case of the multi-party capacity constrained route planning discussed in Chapter 6 we are researching to include an examination on N number of party's interaction and route planning times. Specifically how the growth in the number of agents in unique parties can affect an individuals and all parties' completion time. Another feature valuable for real-life emergency coordinators would be an ability to apply weighted priorities to better address the non-uniform urgency and importance each party brings in regard to the larger scheme of things.

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