Regional evacuation planning is complex and timely. These planning studies can be assisted by a transportation model. In this thesis, we investigate the requirements for such a model, and develop, implement, and test a new model, called EVAQ, which meets these requirements. Two case studies show how EVAQ can be used to assess the success and robustness of an existing evacuation plan, as well as design an optimal plan anticipating uncertainty in traveller compliance behaviour. The analyses yield a number of practical recommendations to improve evacuation planning.

About the Author
Adam Pel received his MSc. degree in Civil Engineering in 2007, after which he continued at the Delft University of Technology for his PhD research. His research focus is dynamic traffic assignment and its applications to evacuation modelling and planning.
Transportation Modelling for Regional Evacuations

Adam J Pel
Cover illustration: Adam J. Pel
Transportation Modelling for Regional Evacuations

Proefschrift

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Adam John PEL

civiel ingenieur
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This dissertation is the result of a PhD research carried out from 2007 to 2011 at Delft University of Technology, Faculty of Civil Engineering and Geosciences, Transport and Planning Department. The research was sponsored by the Emergency Evacuation and System Resilience project under the Next Generation Infrastructures (NGI) program, and by the VICI project Travel Behaviour and Traffic Operations in case of Exceptional Events financed by the Netherlands Organization for Scientific Research (NWO). For more information, please visit www.nextgenerationinfrastructures.eu and www.nwo.nl.
Das Talent arbeitet, das Genie schafft

(Talent works, genius creates)

Robert Schumann
Preface

Research is fun. It is the discovering, explaining, and exploiting of one’s environment, in my case the field of travel behaviour and traffic flow. Doing a PhD research is even more fun, as it provides both the freedom to now and again step away from one’s main research and look into other areas of research, as well as an inspiring environment to do so. For this, my thanks goes to Michiel Bliemer and Serge Hoogendoorn. Both of you have supported my work, in different and mostly complementary ways. I very much appreciate the plentiful opportunities that were given and the liberty that I had throughout the past years to give direction to my research. Also, many thanks for your mixture of criticism, suggestions, ideas, and other remarks which have helped and motivated me in my research, publications, and dissertation. Next to your professional contributions to my work, I am also grateful for the joy that I had in working together with you.

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Doing a PhD research requires more than just doing research. I needed a laptop, trips to conferences, meetings with supervisors and others, and everything from prints and forms to hotel reservations and new computer hardware. Many thanks Priscilla, Dehlaila, Kees, and Nicole, for all your help with these practicalities.

Writing a thesis and having a public defence is a time-consuming and bureaucratic process (where I think this is unnecessarily so, but I will leave that to my propositions). A fairly large number of people are involved, however, as a preface is commonly used for giving thanks, I will mention only few of these people here. I am grateful to Mike Taylor, Satish Ukkusuri, Henk van Zuylen, John Stoop, and Karel Brookhuis. Your comments on an
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Adam J. Pel

July 2011, Delft
## Contents

Preface vii

### Contents ix

1. **Introduction** 1
   1.1 Emergency evacuation and transportation models 2
   1.2 Research scope 4
   1.3 Research relevance and contributions 5
     1.3.1 Theoretical contributions 6
     1.3.2 Practical contributions 7
   1.4 Thesis outline 7

2. **Evacuation Behaviour, Modelling Paradigms, and Current Practices and their Suitability** 11
   2.1 Introduction 12
   2.2 Historic perspective on evacuation transportation models 13
   2.3 Traveller behaviour under evacuation conditions 16
     2.3.1 Psycho-behavioural research and empirical observations 17
     2.3.2 Discussion 19
   2.4 Travel demand modelling 20
     2.4.1 Sequential travel demand model 20
     2.4.2 Simultaneous travel demand model 24
     2.4.3 Discussion 27
   2.5 Trip distribution modelling 28
     2.5.1 Factors determining type of evacuation destination 29
     2.5.2 Destination choice modelling 29
     2.5.3 Discussion 30
   2.6 Traffic assignment modelling 31
     2.6.1 Pre-trip route choice models 31
     2.6.2 En-route route choice models 33
### 2.6.3 Hybrid route choice models .............................................................. 33
### 2.6.4 Discussion ......................................................................................... 34
### 2.7 Concluding remarks ............................................................................. 36

#### 3. A Mathematical Traffic Model for Regional Evacuations 39

<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1</td>
<td>Introduction ..........................................................</td>
<td>40</td>
</tr>
<tr>
<td>3.1.1</td>
<td>Shortcomings reviewed ....................................................</td>
<td>40</td>
</tr>
<tr>
<td>3.1.2</td>
<td>Level of analysis .........................................................</td>
<td>41</td>
</tr>
<tr>
<td>3.2</td>
<td>Conceptual framework ......................................................</td>
<td>41</td>
</tr>
<tr>
<td>3.3</td>
<td>Model formulation ..........................................................</td>
<td>43</td>
</tr>
<tr>
<td>3.3.1</td>
<td>Departure time choice model ............................................</td>
<td>44</td>
</tr>
<tr>
<td>3.3.2</td>
<td>Destination and route choice model ...................................</td>
<td>45</td>
</tr>
<tr>
<td>3.3.3</td>
<td>Special cases ...............................................................</td>
<td>51</td>
</tr>
<tr>
<td>3.3.4</td>
<td>Dynamic network loading model and road dynamics ...............</td>
<td>52</td>
</tr>
<tr>
<td>3.3.5</td>
<td>Heterogeneous travel behaviour .........................................</td>
<td>53</td>
</tr>
<tr>
<td>3.4</td>
<td>Test example ...............................................................</td>
<td>54</td>
</tr>
<tr>
<td>3.4.1</td>
<td>Network and evacuation description ...................................</td>
<td>54</td>
</tr>
<tr>
<td>3.4.2</td>
<td>Experimental setup .........................................................</td>
<td>55</td>
</tr>
<tr>
<td>3.4.3</td>
<td>Numerical results ..........................................................</td>
<td>56</td>
</tr>
<tr>
<td>3.5</td>
<td>Concluding remarks ..........................................................</td>
<td>61</td>
</tr>
</tbody>
</table>

#### 4. Impact of Variations in Travel Demand and Network Supply Factors 63

<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.1</td>
<td>Introduction ..........................................................</td>
<td>64</td>
</tr>
<tr>
<td>4.2</td>
<td>Case study .............................................................</td>
<td>65</td>
</tr>
<tr>
<td>4.2.1</td>
<td>Case study description ..................................................</td>
<td>65</td>
</tr>
<tr>
<td>4.2.2</td>
<td>Base scenario ............................................................</td>
<td>65</td>
</tr>
<tr>
<td>4.2.3</td>
<td>Experimental setup .......................................................</td>
<td>67</td>
</tr>
<tr>
<td>4.2.4</td>
<td>Means of analysis ........................................................</td>
<td>68</td>
</tr>
<tr>
<td>4.3</td>
<td>Trip generation ...........................................................</td>
<td>69</td>
</tr>
<tr>
<td>4.3.1</td>
<td>Sensitivity range ..........................................................</td>
<td>69</td>
</tr>
<tr>
<td>4.3.2</td>
<td>Numerical results ..........................................................</td>
<td>70</td>
</tr>
<tr>
<td>4.4</td>
<td>Departure times ...........................................................</td>
<td>74</td>
</tr>
<tr>
<td>4.4.1</td>
<td>Sensitivity range ..........................................................</td>
<td>74</td>
</tr>
<tr>
<td>4.4.2</td>
<td>Numerical results ..........................................................</td>
<td>74</td>
</tr>
<tr>
<td>4.5</td>
<td>Traffic information ......................................................</td>
<td>78</td>
</tr>
<tr>
<td>4.5.1</td>
<td>Sensitivity range ..........................................................</td>
<td>78</td>
</tr>
<tr>
<td>4.5.2</td>
<td>Numerical results ..........................................................</td>
<td>78</td>
</tr>
<tr>
<td>4.6</td>
<td>Traveller compliance ....................................................</td>
<td>82</td>
</tr>
<tr>
<td>4.6.1</td>
<td>Sensitivity range ..........................................................</td>
<td>82</td>
</tr>
<tr>
<td>4.6.2</td>
<td>Numerical results ..........................................................</td>
<td>83</td>
</tr>
<tr>
<td>4.7</td>
<td>Road capacities ............................................................</td>
<td>87</td>
</tr>
<tr>
<td>4.7.1</td>
<td>Sensitivity range ..........................................................</td>
<td>87</td>
</tr>
</tbody>
</table>
4.7.2 Numerical results ............................................................................... 87
4.8 Free speeds .......................................................................................... 91
4.8.1 Sensitivity range ............................................................................. 91
4.8.2 Numerical results ............................................................................. 94
4.9 Discussion and practical implications .................................................. 95
4.10 Concluding remarks ........................................................................... 97

5. Optimal Evacuation Instructions and the Role of Traveller Compliance 99
5.1 Introduction ....................................................................................... 100
5.2 Studies on traveller compliance behaviour ....................................... 101
5.3 Optimization approach ..................................................................... 102
5.3.1 Optimization objective ................................................................. 102
5.3.2 Optimization framework ............................................................... 103
5.4 Case study .......................................................................................... 104
5.4.1 Case study description ................................................................. 104
5.4.2 Experimental setup ....................................................................... 106
5.5 Impact of full compliance assumption .............................................. 107
5.5.1 Analysis setup ............................................................................... 107
5.5.2 Numerical results ......................................................................... 108
5.6 Impact of anticipating partial compliance ........................................ 112
5.6.1 Analysis setup ............................................................................... 112
5.6.2 Numerical results ......................................................................... 112
5.7 Discussion and practical implications ............................................... 116
5.8 Concluding remarks .......................................................................... 118

6. Synthesis, Implications, and Future Research Directions 121
6.1 Synthesis and main findings ............................................................... 122
6.2 Research implications ....................................................................... 126
6.3 Future research directions ................................................................. 127

Bibliography 133

Appendix A. Traffic Assignment Model Implementation 147

Appendix B. Evacuation Plan Optimization Heuristic 151

Summary 155

Samenvatting (Dutch summary) 159
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Author's Biography</td>
<td>163</td>
</tr>
<tr>
<td>Author's Publications</td>
<td>165</td>
</tr>
<tr>
<td>TRAIL Thesis Series</td>
<td>169</td>
</tr>
</tbody>
</table>
Chapter 1

Introduction

The first chapter of this thesis introduces the scope of the work. After briefly discussing evacuation planning and transportation modelling in general, it points at potential benefits of applying traffic models within evacuation planning studies. Naturally following, the scope of this research is discussed, after which we look ahead at the relevance and contributions of the research written down in the thesis. Finally, the framework for setting up the research is presented, and is matched to the outline of the thesis.

Chapter 1 is introductory to the subsequent chapters. Chapter 2 continues the discussion on traffic models within evacuation studies by reviewing the body of literature hereon. In Chapter 3, an evacuation model is developed, implemented and tested, while furthering the understanding of the model characteristics that are required for this type of application. This allows in Chapters 4 and 5 to apply the newly developed model to gain insight into the determining factors for the success of an evacuation plan – from a transportation modelling perspective – and to anticipate on these while designing an evacuation plan. A synthesizing perspective is then given in Chapter 6, highlighting the main research implications and finalizing by making a number of recommendations for future research.
1.1 Emergency evacuation and transportation models

Large-scale disasters caused by natural and man-made hazards, such as wildfires, floods, hurricanes, large storms, mudflows, terrorist attacks, chemical spills, industrial accidents, and the like, are the source of massive economic and social damage as well as loss of lives every year (Newkirk 2001). Ways in which societies can deal with these disasters depends largely on the nature of the hazard, where explicit cost-benefit analyses can help to determine the most appropriate approach (e.g., Lave et al. 1990). These disaster control policies and strategies for hazard-prone regions may focus on avoidance – where precautionary measures reduce the probability of the hazard to occur – or mitigation – where responsive measures reduce the consequences of such a hazard. Examples of measures to avoid the disaster are reinforcing dams, raising dikes, and clearing fire control lines, while the consequences of the disaster can be mitigated by, for instance, an effective and well organised evacuation. The latter is looked at in this thesis.

Clearly not all hazards can be dealt with by means of pre-emptive evacuation. For instance, let us consider the predictability of the occurrence and consequences of a number of different hazards. We can set out various typical hazards along the spectrum ranging from very short warning time of say less than an hour (e.g., terrorist attacks, earthquakes) to intermediate warning time (e.g., mud slides, volcano eruptions, nuclear threats), to very long warning time up till almost a week (e.g., river flooding, hurricanes). Similarly, we can order hazards according to how well the scenario can be predicted (once they occur) as to the way in which such a hazard will affect a certain region and evolve in a specific way over time and space. Here, the spectrum ranges from difficult-to-predict hazards (e.g., earthquakes, terrorist attacks) to reasonably-well-predictable hazards (e.g., wildfires, nuclear threats), to well-predictable hazards (e.g., flooding, volcano eruptions, hurricanes). Now, a pre-emptive evacuation is most effective with sufficient time to transport those who are in danger to safe refuge locations, along safe evacuation routes. The “sufficient time” requires a minimum warning time, and hence that the occurrence of the hazard is well predictable. The “those who are in danger to safe refuge locations, along safe evacuation routes” requires knowing how the hazard will evolve over time and space, and hence that the scenario following the hazard is well predictable.

Hazards that tend to be sufficiently well predictable regarding their occurrence as well as their consequences are, for instance, hurricanes, flooding, and (up to a certain level) wildfires. These hazards allow pre-emptive evacuation as a viable approach in dealing with the disaster following from such a hazard. The specific evacuation strategies for these different hazards however differs by the characteristics of these hazards. As an example, wildfires are certainly lethal, yet most of the danger is gone once the fire front has passed. This has led to the Australian ‘stay, or go early’ policy, where people are advised to evacuate well in time or otherwise remain at home, under the principle that “the house will protect you as the fire front approaches, and once the fire front has passed you can protect your house by moving outside and extinguishing spot blazes and smouldering embers” (Taylor and Freeman 2010). Another example of shelter-in-place strategies could be in
response to large-scale flooding or tsunamis (then sometimes referred to as ‘vertical evacuation’). A fraction of the public is first relocated to safe locations within the threatened region. In this case, these people are still evacuated afterwards, once the danger of adverse weather conditions or strong currents has reduced. The post-hazard evacuation is needed because of the remaining danger caused by, for instance, contamination of the flood water and public water supply, lack of consumables, need for medical treatment, and possible structural, electrical, or gas-leak hazards.

Nevertheless the individual differences in evacuation strategy, when a hurricane, flood, or wildfire is predicted, in many cases (mass) evacuation is warranted. However, these mass evacuations are becoming increasingly more difficult and resource-consum ing as the population and urban development of hazard-prone regions grow faster than the road infrastructure capacity (Plowman 2001; Barrett et al. 2000). Furthermore, the success of an evacuation strongly depends on many factors, such as amount of warning time, public preparedness and response time, information and instructions dissemination procedure, evacuation shelters and routes, traffic conditions, dynamic traffic management measures, etc. (Dash and Gladwin 2007; Lindell and Prater 2007). This complexity in the underlying processes and the multitude of factors influencing these processes can be dealt with via a model-based approach. An evacuation simulation model is then used for the analysis and planning of a large-scale emergency evacuation (Barrett et al. 2000; Hardy et al. 2010).

Such an evacuation transportation model can be applied to obtain a better understanding of the network conditions and the effect of traffic regulations and control measures hereon, by predicting departure and arrival patterns, travel times, average speeds, queue lengths, traffic flow rates, etc. This insight into this dynamic process is necessary to make well-supported decisions on, for instance, the latest possible time to order the start of the evacuation, the best evacuation routes, the most suitable traffic management measures, and the determining factors for a successful evacuation.

Current practice uses transportation models in this manner. As an example, the evacuation plan for the Dutch city of Almere was recently constructed with the assistance of a transportation model (De Jong et al. 2009; Tu et al. 2010). The municipality designed an evacuation plan, which was then evaluated by means of a transportation model, and adjusted accordingly and re-evaluated. This was repeated a few times until satisfaction. Thus, the transportation model used in this case allowed testing and improving the evacuation plan. However, in order for such a transportation model to be applicable in evacuation studies, certain requirements must be met as to the adequate representation of travellers’ evacuation behaviour and the impacts hereof and of the hazard on the road network. This is the first main topic of this thesis. Furthermore, the way in which these models can assist in evacuation planning studies far exceeds the application for the city of Almere. This is the second main topic of this thesis. More details on the focus of this thesis and the manner in which this thesis research is structured are given in the remainder of this introductory chapter.
1.2 Research scope

The main topic of this thesis is mentioned shortly at the end of the previous section. That is, the formulation and application of a transportation model which adequately describes travellers’ evacuation behaviour and can assist in evacuation planning studies. The scope of the thesis is further elaborated in this section by means of a number of delimitations.

**Delimitation 1: The scale of the evacuation is regional.**

The type of evacuation that is considered in this thesis is regional. That is, the area that needs to be evacuated is large-scale, for instance, spanning a metropolitan area or a region with multiple cities. This as opposed to, say, the evacuation of a large building, airplane, or ship.

**Delimitation 2: The warning time is measured in days.**

Given the regional scale of the evacuation and the focus on evacuation planning, we focus on the type of evacuation where the amount of warning time is measured in days. Examples are evacuations due to river flooding, and hurricanes, and to a lesser extent tsunamis, and wildfires. This as opposed to short-notice or no-notice evacuations due to, for example, flash flooding, earthquakes, and terrorist attacks.

**Delimitation 3: The mode of evacuation is car.**

Throughout this thesis the evacuation behaviour that is looked at and modelled relates to travellers evacuating by car. Hence, mode choice is not incorporated. Instead, we focus on the share of travellers who has decided to evacuate by car. Nevertheless, parts of the thesis that relate to car traveller behaviour may also relate to travel behaviour by public and organized transport, or multimodal evacuation.

**Delimitation 4: This thesis is on travellers’ evacuation choice, departure time choice, destination choice, and route choice.**

This thesis is on travellers’ choice behaviour during an evacuation regarding their decision to evacuate, their departure time, safe destination, and evacuation route. Also, we consider the factors determining these decisions, such as travellers’ knowledge on the traffic and hazard conditions (or lack thereof), traffic information, instructions, and their willingness to comply. Hence, this thesis does not focus on other behavioural adaptations due to the evacuation conditions, such as changes in driving behaviour. Nor will this thesis look at the travel decisions made by others than the evacuating travellers, such as authorities deciding to deploy emergency services. Finally, the ‘traveller’ considered throughout this thesis is one who can make the decision to evacuate, when to depart, which destination to
go to, and which route to take. Thus, this thesis is not on the non-self-reliant evacuees – e.g., the sick, infirm, handicapped, institutionalized, and incarcerated – who typically require assistance or escort, and hence do not make these travel decisions themselves.

**Delimitation 5:** This thesis is on the mathematical formulation of a transportation model, and its face-validity (i.e., qualitative verification) with observed evacuation travel behaviour as reported in literature.

This thesis is on the development (and testing and application) of a transportation model of which the model framework and corresponding mathematical formulation produce face-valid model outcomes. The face-validity of the model formulation and characteristics is checked against empirical observations on evacuation travel choice behaviour (as within the scope of Delimitation 4) as reported in literature. Hence, this thesis research does not undertake experimental and real-life observations on evacuation behaviour. Nor does this thesis consider model calibration based on data describing evacuation behaviour.

**Delimitation 6:** This thesis is on the applicability and potential of a transportation model in evacuation planning.

This thesis is on how the transportation model (as within the scope of Delimitation 5) can assist in evacuation planning studies. The focus lies on predicting and influencing traveller behaviour (in line with Delimitation 4). This thesis considers the potential of such a model in testing the effectiveness of an (existing) evacuation plan and identifying the robustness of the plan, and determining the optimal evacuation plan. Within these analyses, focus lies on travel behaviour and the emerging traffic conditions. This thesis does not consider the implementation of the evacuation plan in practice in the sense of, for example, identifying the best way to communicate the evacuation plan to the public. Nor does this thesis consider the applicability of a transportation model in, for example, educating authorities on evacuation management by means of serious gaming, and real-time evacuation traffic control and the deployment of dynamic traffic management measures.

### 1.3 Research relevance and contributions

This thesis deals with evacuation transportation modelling. In particular, the model formulation which adequately describes observed evacuation travel behaviour on the one hand, and the potential of applying such a transportation model in evacuation planning studies on the other hand. Along this line, the work written down in this thesis makes contributions to these fields of evacuation modelling and planning. We highlight the main contributions, here grouped as theoretical contributions and practical contributions.
1.3.1 Theoretical contributions

Four main theoretical and methodological contributions are listed below. These are on synthesizing the state of the art in evacuation modelling and making recommendations on future research, identifying model requirements and current shortcomings, formulating a hybrid route choice model, and showing the relevance and role of travel choice behaviour in evacuation modelling.

i. **Synthesis of current knowledge and practices, and identification of potential future research.** This thesis (Chapter 2 and Section 6.3) provides a comprehensive discussion on the state of the art in evacuation modelling practices. A large number of studies is reviewed related to observed evacuation behaviour, different model formulations that aim to describe this evacuation behaviour, and the setup of transportation models that are used in evacuation studies. Potential future research is suggested on topics, such as, modelling interactions between household members using a hybrid route choice model, and predicting dynamic departure time decisions using time series.

ii. **Construing of model requirements, and identification of shortcomings in current modelling practices.** This thesis (Chapter 2 and Section 3.1) compares different model formulations by the underlying assumptions that are made on evacuation travel choice behaviour, and how these assumptions relate to observed evacuation behaviour. Model shortcomings (i.e., requirements that are not sufficiently met in current models) are identified, relating to the modelling of travellers’ response to the time-varying hazard conditions and (traffic) information, and travellers’ compliance towards warnings, discretionary advice and evacuation orders.

iii. **Formulation of a hybrid route choice model thereby incorporating travellers’ rerouting due to traffic information, network dynamics, and traveller compliance.** This thesis (Chapter 3) develops, implements and tests a new dynamic traffic assignment model which enables describing travellers’ pre-trip destination and route choice decisions (here based on the evacuation plan) as well as their en-route switching to an alternative route, possibly with an alternative destination, thereby responding to changing network conditions once they receive information hereon. The new model formulation endogenously models travellers’ compliance towards an evacuation plan, distinguishing whether the instructions are given as advice or orders.

iv. **Showing the relevance and role of travel choice behaviour in evacuation modelling and planning, including traveller compliance behaviour.** This thesis (Section 2.3) argues from literature on observed evacuation behaviour that accounting for travel choice behaviour in evacuation modelling is essential. Also, it (Section 3.4 and Chapter 4) tests and explains the role of travellers’ choice behaviour. Furthermore, it (Chapter 5) explains the role of traveller compliance in optimal evacuation planning. This by showing how the efficiency of an evacuation plan depends on the level of travellers’ partial compliance, and how this evacuation efficiency can
be maximized when this partial compliance is anticipated, and the evacuation plan is adjusted accordingly.

### 1.3.2 Practical contributions

Three main practical contributions are listed below which relate to the evacuation model EVAQ, the model-based optimization framework, and general recommendations that are made for evacuation planning studies.

1. **Providing a practical tool by means of the evacuation transportation model EVAQ to assess evacuations and evacuation plans.** This thesis (Chapter 3) constructs, implements, tests, and applies the transportation model EVAQ which enables predicting the traffic operations and evacuation process for a regional evacuation. EVAQ enables evaluating the impact of traveller choice behaviour and how this is impacted by traffic information, evacuation instructions, and traveller compliance.

2. **Providing a framework for model-based evacuation plan optimization accounting for traveller compliance.** This thesis (Chapter 5) constructs and applies a framework based on EVAQ which enables the design of optimized instructions on individual departure times, destinations, and routes while assessing and accounting for the effect that travellers’ partial or non-compliance may have on the efficiency of these evacuation instructions.

3. **Making general recommendations for evacuation planning.** This thesis (Chapters 4 and 5) shows and explains the role of a number of travel behaviour and traffic control factors on the evacuation traffic conditions using two model applications. These research findings yield practical implications for evacuation planning studies (Sections 4.9 and 5.7, and summarized in Section 6.2). Recommendations are made relating to, for instance, the use of traffic information and instructions, how network-wide traffic conditions can be improved, how the evacuation can be accelerated, and the best level of traveller compliance for different types of evacuation plans.

### 1.4 Thesis outline

The outline of this thesis is graphically represented in Figure 1.1 and discussed in more detail in this section. This first chapter is introductory to the thesis, in the sense that it sets out the topic of emergency evacuation and the role of transportation models herein, as well as the scope of the research on this topic. Furthermore, it contains a brief outlook on the relevance of the work presented in this thesis, as discussed in the previous section. A main notion put forward in Chapter 1 is that transportation models have a strong potential to well support evacuation planning studies, and that this model application sets certain requirements to the formulation of the model. These requirements, how these are best met,
and the way in which the emerging transportation model can then be used within evacuation planning studies is elaborated in the ensuing chapters.

Chapter 2 continues in more detail on the requirements for transportation models in evacuation studies by reviewing the body of literature on evacuation travel behaviour and how this travel behaviour is represented in those traffic models that are used in evacuation studies. Here, the focus lies on how travellers’ decisions are predicted through modelling the choice to evacuate, departure time choice, destination choice, and route choice. A main purpose of this chapter is to identify current modelling limitations, and at the same time make corresponding suggestions on promising future research directions. A number of these limitations is then further studied and relaxed in Chapter 3.
In Chapter 3, a new evacuation transportation model is developed, implemented and tested. The model formulation builds on the previous review as it specifically deals with relaxing those earlier limitations that relate to travellers’ full compliance and perfect knowledge, and travellers’ behavioural response to the possible impact of the hazard on the road network conditions. The mathematical model formulation is explained in terms of the underlying behavioural assumptions that are made and how these coincide with the earlier reviewed observations on evacuation travel behaviour. An illustrative hypothetical example shows the face-validity of the model characteristics.

Chapters 2 and 3 primarily elaborate on modelling issues regarding an adequate description of evacuation travel behaviour. The work in these chapters yields: insight into evacuation travel behaviour, a mathematical model formulation consistent with these insights, and the corresponding simulation model programmed such that it can be used in evacuation planning studies. Naturally following, Chapters 4 and 5 exploit this model to address application issues regarding the possible benefits of a transportation model within the context of evacuation planning. Within these chapters the model is used to evaluate a possible real-life evacuation plan and to design optimal evacuation plans, respectively.

In Chapter 4, the newly developed model is used to investigate the influence of various travel demand and network supply factors on the traffic conditions and the overall evacuation time. This is done by performing a sensitivity analysis, systematically varying factors related to trip generation, departure time rates, route flow rates, road capacities, and maximum speeds. Specifically the influence of the variations in traffic information and traveller compliance is also tested, made possible by the model formulation derived in the preceding chapter. The analysis is conducted on the Rotterdam metropolitan area network in the Netherlands. The findings are interpreted and generalized where possible, yielding a number of practical implications.

Chapter 5 uses the flexibility of the transportation model developed in Chapter 3 to address the observation made in Chapter 2 that in practice a share of travellers decides not to comply. To this end, the newly developed model which describes travellers’ compliance behaviour is here embedded within an optimization framework. This enables studying the following two questions: ‘What is the impact of partial compliance towards an evacuation plan that is optimized assuming full compliance?’ and ‘What are the benefits of deploying an evacuation plan that anticipates partial compliance?’. The questions are answered in applying the model-based optimization framework to the evacuation of the Walcheren peninsula in the Netherlands. Similarly as in Chapter 4, the findings are interpreted and generalized where possible, and lead to a number of practical implications.

In conclusion, in Chapter 6, a synthesis is given of the preceding chapters, reviewing the thesis from the perspective of its main contributions to the modelling of rerouting behaviour and network dynamics, the incorporation of traveller compliance and its role in optimal evacuation planning, and the findings on factor sensitivity in evacuation models and plans. The research implications for evacuation planning studies are highlighted.
Furthermore, the overall research approach and findings are reflected upon, ending with a number of recommendations for future research directions.
Chapter 2

Evacuation Behaviour, Modelling Paradigms, and Current Practices and their Suitability

As discussed in the introduction section, dynamic traffic simulation models are frequently used to support decision-making when planning an evacuation. This chapter reviews the different (mathematical) model formulations underlying these traffic simulation models used in evacuation studies and the behavioural assumptions that are made. The appropriateness of these behavioural assumptions is elaborated on in light of the current consensus on evacuation travel behaviour, based on the view from empirical observations on evacuation behaviour as well as the social sciences. The focus lies on how travellers’ decisions are predicted through modelling the choice to evacuate, departure time choice, destination choice, and route choice. While discussing these travel choice models, we point at current limitations and make corresponding suggestions on promising future research directions.

The literature review in this chapter structures the state-of-the-art and provides a set of model requirements, following from observed evacuation behaviour. Chapter 2 therewith allows positioning and underlining the proposed formulation for the evacuation model presented and implemented in Chapter 3 and applied in Chapters 4 and 5.

2.1 Introduction

In the previous chapter, we discussed how traffic simulation models are helpful or even indispensable for the analysis and planning of emergency evacuations. On the one hand, this is due to the complexity of the underlying traffic and travel behavioural processes and the multitude of factors influencing these processes. Evacuation simulation models allow studying and incorporating research findings on driver and traveller behaviour under these kind of emergency conditions. On the other hand, these simulation models provide a better understanding of the evacuation conditions and the effect of traffic regulations and control measures thereon. Applying these models in real-life case studies allows qualitative and quantitative analysis of predicted evacuation conditions, and hence supports, for instance, the evaluation or optimization of an evacuation strategy.

In the current chapter, we elaborate on the different model formulations underlying the many simulation models used in evacuation studies and the behavioural assumptions that are made. We look at both (commercial) traffic simulation models used in evacuation studies as well as evacuation research and proposed model formulations. The focus lies on how travellers’ decisions regarding their choice to evacuate, departure time choice, destination choice and route choice are modelled. Hence, the literature review presented here is complementary to other reviews on aspects such as how these traffic simulation models are used to evaluate and design optimal evacuation instructions and management strategies (e.g., Yusoff et al. 2008; Abdelgawad and Abdulhai 2009a), the issues that must be dealt with once implementing these evacuation plans in practice (e.g., Wolshon et al. 2005a, 2005b), the data requirements to manage and model emergency situations (e.g., Wilmot et al. 2009; Henson et al. 2009), and driving behaviour under adverse conditions (e.g., Hoogendoorn 2010; Wolshon 2008). Finally, as mentioned in the introduction chapter, throughout this thesis, and hence also in the ensuing discussion, we consider the car as the main mode of transport for evacuation. Many of the evacuation modelling and simulation issues relating to car travel behaviour also relate to evacuation by public and organized transport, as well as multimodal evacuation. However, these modes of transport will not be reviewed here explicitly.

Figure 2.1 shows the framework of a typical dynamic traffic simulation model that can be used in evacuation studies. Here, the dark boxes on the left-hand side represent the model components: dynamic travel demand model, dynamic trip distribution model, and dynamic traffic assignment model. The light boxes on the right-hand side indicate the behaviour that is described by each of these model components: evacuation participation and departure time choice, destination choice, and route choice. The outline of this chapter follows this model framework as follows. We start with giving an overview of the history of evacuation simulation models and the current state-of-the-practice in Section 2.2. After that, we discuss in Section 2.3 the current view on travellers’ choice behaviour in case of evacuation, making reference to both a number of empirical studies on evacuation behaviour as well as insights from the behavioural sciences related to decision making under emergency conditions. Then Sections 2.4 up till 2.6 form the main body of this
chapter, elaborating on the (implicit) assumptions regarding traveller behaviour that are generally made in evacuation traffic simulation models or proposed model formulations – including those models discussed in Section 2.2 – in light of the view on evacuation behaviour presented in Section 2.3. More precisely, we discuss travel demand modelling (i.e., travellers’ evacuation and departure time choice decisions) in Section 2.4. We discuss trip distribution modelling (i.e., travellers’ destination choice decisions) in Section 2.5. And we discuss traffic assignment modelling (i.e., travellers’ route choice decisions) in Section 2.6. Each of these sections ends with a critical discussion on current practices and promising future research directions. The final section of this chapter then gives a concluding discussion on the main findings from this literature review and makes some final remarks.

Figure 2.1: Evacuation traffic simulation model framework and chapter outline

2.2 Historic perspective on evacuation transportation models

In the late 1970’s, a number of simulation studies were started to analyse and evaluate emergency evacuation plans. Early studies in the 1980’s focused mainly on evacuation in case of nuclear power plant emergency due to the Three Mile Island reactor incident in 1979. Then, after a number of extremely devastating hurricanes hitting the coast line of the
U.S. in the 1990’s, much evacuation modelling research shifted focus to hurricane evacuation. Since the September 11, 2001 incident in the U.S., also mass evacuation due to terrorist attacks is getting more attention. Due to tsunamis and otherwise-caused floods in China and wildfires in Australia over the past decades, evacuation research in these countries focus on these types of evacuation. For the Dutch situation, rising sea levels and a perceived increasing threat of flooding has led to the start of a national program initiating flood evacuation research and applications within the Netherlands.

In many of these early studies, evacuation is recognized as an exceptional event regarding different travel demand patterns, driver behaviour, traffic management, etc., resulting in new traffic models being developed specifically for evacuation studies. A few examples are NETVAC (Sheffi et al. 1980), DYNEV (KLD 1984), MASSVAC (Hobeika and Jamei 1985; Hobeika and Kim 1998), TEDSS (Sherali et al. 1991), IMDAS (Franzese and Han 2001), OREMS (Rathi and Solanki 1993), and CEMPS (Pidd et al. 1993). Some basic model characteristics and applications of these models are listed in Table 2.1. A note can be made here that TEDSS is set up as a decision support system based on the simulation model MASSVAC, which in turn can be seen as a successor of NETVAC. And OREMS is based on the microscopic traffic simulation model CORSIM, which was developed for simulating regular daily traffic conditions. These earlier simulation models are typically developed and customized for the evacuation of specific regions in response to a specific type of hazard. For instance, NETVAC is designed to plan evacuation in response to a nuclear power plant accident and therefore models the evacuation of all inhabitants from a predetermined area (10 miles radius from plant site) in radial outward direction, while MASSVAC is developed for hurricane evacuation of a rural area and requires evacuation routes as model input from all origin locations to all safe destinations, where the origins and safe destinations depend on the projected path of the hurricane. A distinguishing feature of DYNEV which is worth mentioning is that it is the only model listed in Table 2.1 where multimodal evacuation can be simulated, although in a limited form. Car and bus transport are incorporated, where bus services are modelled explicitly by route, schedule, and stop locations. Earlier models that have also been applied more recently and on reasonably large scale are DYNEV (e.g., Goldblatt 2004; Wolshon et al. 2005a) and OREMS (e.g., Han and Yuan 2005; Li et al. 2006; ORNL 2002).

More recently, a large number of evacuation studies are conducted using well-established dynamic traffic simulation models initially developed for regular daily traffic applications, including both microscopic models, such as PARAMICS (Cova and Johnson 2003), CORSIM (Williams et al. 2007), VISSIM (Han and Yuan 2005), and INTEGRATION (Mitchell and Radwan 2006), and mesoscopic or macroscopic models, such as DYNASMART (Murray-Tuite 2007), DynaMIT (Balakrishna et al. 2008), DynusT (Noh et al. 2009), TransCAD (Wang et al. 2010), and INDY (Klunder et al. 2009). In a number of studies using microscopic models, model parameters describing driving behaviour (such as headway, acceleration, reaction time) have been adjusted for the case of emergency evacuation (e.g., Tu et al. 2010a, 2010b). Other than that, the model structure and parameter settings are typically not changed.
Table 2.1: (Early) evacuation traffic simulation models and their characteristics and applications

<table>
<thead>
<tr>
<th>Model</th>
<th>Traffic representation</th>
<th>Time dimension</th>
<th>Application</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>micro</td>
<td>macro</td>
<td>static</td>
</tr>
<tr>
<td>NETVAC</td>
<td>x</td>
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<tr>
<td>DYNEV</td>
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<td>x</td>
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<td>MASSVAC</td>
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<td>TEDSS</td>
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<td>OREMS</td>
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<td>CEMPS</td>
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In all these models, the origin-destination travel demand matrix describing travellers’ evacuation participation and destination decisions is either model input or is computed using a gravity-model based trip distribution model, or a combination of the two. The departure times are generally computed by applying an exogenous response curve stating the percentage of departures in each time interval. Such a response curve has been assumed to follow a number of different distributions (e.g., Uniform distribution, Poisson distribution, Weibull distribution). A user-defined dynamic origin-destination matrix allows evaluating (mandatory) evacuation instructions, since the matrix can be chosen following dedicated departure time (windows) and destinations.

These trips are then in most models assigned to the road network according to the (dynamic or static) user-equilibrium assignment assumption, although one may wonder whether an equilibrium assumption will hold in an emergency evacuation. In addition, most models allow user-defined routes as model input, thus enabling evaluating (mandatory) instructions regarding prescribed evacuation routes. Exceptions are the route choice models incorporated in INTEGRATION and DYNASMART modelling en-route route switching based on prevailing traffic conditions.

In most models, traffic flow is simulated in which road network characteristics are mostly static. In some models, road network characteristics such as capacity and maximum speed vary to incorporate the damaging effect of the hazard on the road infrastructure (e.g., links becoming less accessible due to flooding) and dynamic traffic management and control measures (e.g., contraflow operations to increase outbound capacity). For example, MASSVAC allows modelling several consecutive time intervals (time-sliced static traffic assignment) in which road network characteristics change, and INDY incorporates so-called ‘events’ in which network characteristics and model parameters can vary in time.
A final addition to this overview of prior and current evacuation traffic models is the development of decision support systems and traffic information systems which are integrated with a dynamic traffic simulation model. For instance, the Evacuation Traffic Information System ETIS (PBS&J 2000a) is set up as a web-based monitoring tool for collection and distribution of traffic information during the process of evacuation. ETIS uses real-time information from different sources on, for example, evacuation participation rates, traffic management and control measures, prevailing traffic conditions, and weather conditions. The tool then predicts traffic conditions for a short time ahead based on historic evacuation data, and evaluates the effect of applying traffic control measures such as contraflow and lane closures. ETIS has been applied in practice in the south eastern states of the United States, including North Carolina, South Carolina, Georgia, and Florida, and later also Alabama, Mississippi, Louisiana, and Texas (Wolshon et al. 2005a).

This overview of past and current evacuation traffic simulation models does not aim to be complete, but to provide a framework of the current practices in traffic simulation models used in many evacuation studies. Here we only discussed the more ‘full-fledged’ traffic simulation models. A number of interesting proposed model formulations in evacuation research will be introduced and discussed in Sections 2.4 to 2.6 when we elaborate on the individual model components of a typical evacuation traffic simulation model.

### 2.3 Traveller behaviour under evacuation conditions

The models introduced in the previous section aim to simulate traffic conditions on a road network in case of evacuation. They thereby unavoidably make assumptions on how travellers may behave in these types of conditions. To allow us to investigate the suitability of these behavioural assumptions in the following sections of this chapter, we will here discuss the viewpoint of the behavioural sciences on evacuation travel choice behaviour and show how empirical observations on evacuation behaviour underline or question this view.

Before discussing the psycho-behavioural research and empirics on evacuation behaviour, two notes can be made here. First of all, there exists quite an extensive amount of literature in the field of behavioural sciences relating to humans’ psychological response to, for example, (imminent) emergency conditions, and decision making under time-pressure and safety concerns (for an overview see Court et al. 2004; Dombroski et al. 2006; Mawson 2005). This research has found almost no reference in evacuation traffic modelling and simulation studies. This might be partly due to its often non-quantitative or experimental set up. Second of all, remarkably enough, in contrast to network evacuation modelling, in crowd evacuation modelling surprisingly many simulation models attempt to incorporate more realistic human behaviour. This is done by extending these pedestrian simulation models to more sophisticated agent frameworks. For instance, applying cognitive-behavioural frameworks to model individuals’ behaviour under specific conditions (e.g., the so-called belief-desire-intension framework is often applied), or
different structures are built-in to model leadership and herding behaviour, or travellers’ information acquisition and exchange is modelled to include possible unfamiliarity and learning characteristics (see e.g., Murakami et al. 2002; Pelechano et al. 2005; Pelechano and Badler 2006; Shendarkar et al. 2006).

2.3.1 Psycho-behavioural research and empirical observations

A large number of observations on real life emergency situations collected and discussed by Quarantelli (1957) and Leach and Campling (1982) indicate that the psycho-behavioural response of people is remarkably consistent across different types of disastrous conditions. This structural pattern is divided into a number of temporal phases showing how behavioural responses change over time as the emergency conditions develop, summarized in Figure 2.2. These phases range from pre-impact when an emergency is becoming probable to post-impact when the emergency has passed. Equivalent models have been proposed by, for example, Glass (1959) and Tyhurst (1951). The main value of this framework is that each phase is accompanied by a specific behavioural response which is found to be then predominantly prevailing.

![Figure 2.2: Phases in emergency conditions and their most prevalent behavioural responses (from Hoogendoorn et al. 2009, based on Leach and Campling 1982)](image)

An equivalent dynamic approach focusing on the individual decision-making task states, that individuals experience a number of quasi-consecutive psycho-behavioural phases. The decision-making task starts with information acquisition, followed by situation assessment, and finally action execution (first posed by Woodworth 1958). Since individuals cannot assess all available information, the first two phases are undertaken simultaneously (Baddeley 1972; Wickens 1987). Information is filtered based on relevance and trustworthiness according to how the current situation is perceived. This filtering process makes the task easier, however may delay accepting and appropriately responding to changing conditions. This can be explained through the phenomenon of cognitive dissonance. For example, when people perceive themselves as safe yet receive information on a possible threat, then the logical inconsistency in these beliefs is (initially) resolved by rejecting or ignoring this warning information. A large number of real life
examples are discussed by Leach and Campling (1982) where people in danger choose to ignore the possibility of the disaster despite the warnings prior to the disaster. In all cases, the conflicting information is discarded as being not relevant or untrustworthy.

This pattern of behaviour is resembled by the findings in a number of empirical studies specific to evacuation. For instance, Miletī et al. (1975) reports that the more information the initial warning contains, the more likely it is that people respond. And, when warnings are heard and believed, then evacuation is the end result. This is also underlined by the findings of Baker (1991). Twenty-six post-hurricane surveys in the period 1961 till 1989 in the U.S. indicated that next to factors such as risk level, public instructions, housing type, and storm threat, the personal risk perception was most prominent in the decision whether to evacuate. Similarly for the case of cyclones in Australia, Raggatt et al. (1993) found that people with less warning time were more likely to deny their personal risk and reside in a general feeling of complacency. De Jong and Helsloot (2010) report on the results from surveys held during a Dutch national exercise on flood evacuation. In this study, a large share of people (48% to 66%) remains unaware of the actual risk although warning is given and voluntary evacuation is advised. At the same time, the credibility of the information that is given is deemed low by the majority (52% to 88%). An informative discussion is given by Dash and Gladwin (2007). One of their statements is that it is the perception of risk that motivates people to evacuate, not the hearing of warnings and evacuation orders. This is also in line with the psycho-behavioural frameworks from the behavioural sciences, as well as a strikingly common finding in many empirical studies.

Once the danger is recognized and people start responding, their information processing and decision making capabilities might be limited due to mentally demanding circumstances, associated with anxiety and (the perception of) time-pressure. Wills (1998) argues that in these situations people rely more on instincts and experience, thereby avoiding the time needed for making rationally thought-over decisions. Leach and Campling (1982) and Schmidt and Warner (2002) found evidence for this by showing that people typically tend to remain calm, and only once they perceive inescapability do they express behaviour which can be seen as irrational and habitual (note that to express habitual behaviour under disaster conditions, for instance, for the case of exit choice, can be seen as irrational or illogical). Leach and Campling (1982) further argue that during the impact phase there is evidence of a clear distinction between the psycho-behavioural responses of three types of individuals (also supported by Quarantelli and Russell 1977). Once people undertake action in the impact phase, people may remain calm and rational, may be stunned by the situation and react in a semi-automatic manner, or may mentally breakdown and react (in a manner which seems to be) uncontrolled and inappropriate. Leach and Campling found that overall approximately 75% of the individuals express the second type of behaviour, while the behaviour of the remaining share corresponds evenly with the first and third type. It should be noted that although the appearance of egocentric behaviour is widely agreed on, especially panicking behaviour has been shown to be quite an uncommon reaction to an emergency situation (Aguirre 2005; Blake et al. 2004; Bohannon 2005; Cornwell 2003; Mawson 2005).
A number of empirical studies on evacuation behaviour show a slightly different pattern. This might have to do with the fact that the circumstances (during the impact phase) which these psycho-behavioural constructs are based on are more imminent than typically seen (or perceived) in these empirical evacuation studies. The surveys by De Jong and Helsloot (2010) in the Dutch flood exercise show that once the actual dike breach and flood occur, the need for information on aspects as the expected flooding area, water height, and possible government aid in the evacuation increased. With a number of people, this lack of information impaired them on making a decision whether to evacuate. Those people that do decide to evacuate show a similar prominent need for information. This need for traffic information on appropriate evacuation routes is reported, for example, by Dow and Cutter (2000) and Lindell et al. (2005) after conducting post-hurricane surveys and by Robinson and Khattak (2010) based on stated preference surveys. In cases where this traffic information is not available, travellers might be impaired in their route decisions. Dow and Cutter (2002) held a survey among South Carolina residents after hurricane Floyd. One of their findings was that, despite the congestion on the main egress routes, travellers did not switch to alternative routes using rural roads. The authors suggest that this might have been due to travellers’ uncertainty that alternative (rural) routes would not provide breakdown services and cell phone coverage. Likewise, Lindell and Prater (2006) report that for the case of hurricane Katrina, travellers relied slightly more on past familiarity with the evacuation route than on prevailing traffic conditions, likely due to the lack of traffic information.

The last phase of recoil and rescue (see Figure 2.2) will not be discussed here since the evacuation is most likely to have ended by then.

2.3.2 Discussion

The above perspective on evacuation travel behaviour shows that a number of factors play an important role in determining the travel decisions of individuals. In sum, individuals react according to how they perceive the changing situation. They thereby respond to their perception on both the hazard’s evolution in space and time, as well as the dynamic traffic (management) conditions, possibly with some delay. This explains the evacuees’ need for information. That people do not automatically follow the advice and orders from public officials, but tend to seek information, assess their personal risk, and make independent evacuation decisions, is supported by a substantial number of empirical studies (e.g., Baker 1991, 1995; Dash and Morrow 2001; De Jong and Helsloot 2010; Dow and Cutter 1998, 2000; Knowles 2003; Rasid et al. 2000). It is therefore essential that dynamic traffic simulation models that aim to simulate an evacuation include this reactive traveller behaviour, therewith incorporating the important role of time-varying disaster conditions, (traffic) information, and travellers’ compliance towards warnings, discretionary advice and evacuation orders.

We should remark here that, as in Section 2.2, this overview of socio-psychological research and empirics on evacuation behaviour attempts in no way to give a complete
discussion on all (multi-disciplinary) research related to evacuation behaviour. Instead, this discussion adequately provides a general background of the current consensus on evacuation behaviour. This background is needed in the following sections when discussing the suitability of the (mathematical) model formulations that are proposed and used to simulate travellers’ choice behaviour under evacuation conditions.

2.4 Travel demand modelling

Travel demand models predict the number of people who will evacuate and when these people will depart. In other words, these models describe the decisions of travellers regarding evacuation participation and departure time. These decisions are generally made at the household level (Dash and Gladwin 2007; Dow and Cutter 2000; Heath et al. 2001; Whitehead et al. 2000). We will in the following discussion however not focus on which level the decision is made at, but how the resulting evacuation participation rates and departure time patterns are simulated.

A commonly used approach to dynamic travel demand modelling is to do so in two or three consecutive steps. Logically, the first step is to identify the region that needs to be evacuated. The first step of establishing the region that will evacuate or needs to be evacuated is often done by expert judgement going by the hazard scenario characteristics. For hurricane evacuations, this procedure is formalized by Wilmot and Meduri (2005) using hurricane attributes such as the track, speed, and size to identify evacuation zones. Easily identifiable zones (by, e.g., ZIP code and landmarks) are then assigned a specific risk and are expected to evacuate in case of specific scenarios. Here, regions above the maximum surge flood limit are not considered. However, evidently, also areas which are in fact not at risk may start evacuating (shadow evacuation). Especially considering the findings in the previous section that evacuation is primarily motivated by people’s perception of being at risk. Durham (2007) points out that this may particularly happen during mass evacuations and it would lead to larger travel demand thus hindering those in real need to evacuate.

After the first step is undertaken and the evacuation region is identified, the share of people that will evacuate is predicted, and their departure time. Herein, two approaches are distinguished as to whether these choices of travellers are modelled as sequential decisions (Section 2.4.1) or conducted simultaneously (Section 2.4.2).

2.4.1 Sequential travel demand model

In the sequential approach, once the evacuation region is identified, the second step in predicting travel demand is to predict the share of people who will evacuate (at some time). For the case of hurricanes, Baker (1991) listed five attributes determining the decision to evacuate: the risk level within the area, actions by public authorities, type of housing, prior perception of personal risk, and a storm specific threat factor. In the past, these attributes have served for an empirically based approach to predict evacuation
demand by Tweedie et al. (1986). Later, PBS&J (2000b) developed a cross-classification type of trip generation model based on survey data collected in the south-eastern states of the U.S. where the evacuation participation specified by county depended on the hurricane category and speed, tourist occupancy, and type of housing in that area. The performance of this behaviour-based model was tested against a number of data-driven models, namely logistical regression and various forms of neural network models, by Wilmot and Mei (2003) on a data set collected in south-west Louisiana following hurricane Andrew. The findings showed that the data-driven models (particularly a feed forward neural network structure) were better able to predict the observed participation rate. The drawbacks of these types of models (especially neural networks) are, however, that they require specific data for calibration and the results are typically not transferable to other settings. This while behaviour-based models do not have these drawbacks and provide more insight into the evacuation participation behaviour of people. Recently, Hasan and Ukkusuri (2011) developed a threshold model of social contagion to describe how the decision to evacuate may propagate through a community (represented as a social network), investigating the role of the community structure, the initial seeds, and the evacuation willingness, on the cascade propagation of the evacuation decisions.

The third step to predict the dynamic travel demand is to model travellers’ departure time choice. This is often done by applying an exogenous response curve stating the percentage of departures in each time interval. Since some origins will be earlier under threat than others, such a response curve is typically predicted for each origin (or zone) separately. The departure response curve has been assumed to follow many different distributions. Some examples are instantaneous departure (Lewis 2001; Chen and Zhan 2004; Chiu et al. 2006), a Uniform distribution (Liu et al. 2006; Yuan et al. 2006), a Rayleigh distribution (Tweedie et al. 1986), a Poisson distribution (Cova and Johnson 2002), a Weibull distribution (Jonkman 2007; Lindell 2008) or sigmoid curve (Kalafatas and Peeta 2009; Xie et al. 2010). The Weibull distribution and sigmoid curve are most often used and claimed to be most realistic. The Weibull distribution is defined by

\[ D(t) = 1 - e^{-\beta t^\gamma} \]  

(2.1)

where \( D(t) \) is the cumulative percentage of people who have evacuated until time instant \( t \). The shape of the distribution is determined by two parameters, \( \beta \) and \( \gamma \). The effect of these parameters is shown in Figure 2.3. Higher values for \( \beta \) and \( \gamma \) lead to a faster response, while lower values represent a slower response. The sigmoid curve is defined by

\[ D(t) = \frac{1}{1 + e^{-\alpha(t-h)}} \]  

(2.2)

The shape of the curve is determined by two parameters, \( \alpha \) and \( h \). The effect hereof is more distinguishable and allows a clearer behavioural interpretation (Figure 2.4). The response rate \( \alpha \) sets the slope of the curve, such that low values produce a more uniform departure profile (slower response). The half loading time \( h \) sets the midpoint of the curve, and thus states the time at which half of the total number of travellers have departed.
Sensitivity analyses on these parameters as done by Ozbay and Yazici (2006) and Pel et al. (2010) (the latter is also more extensively discussed in the Rotterdam case study presented in Chapter 4) conclude that advancing or postponing the half loading time $h$ has no impact on the evacuation process since travellers depart at the same rate and thus queue lengths and average travel times are equal for all cases (unless road network characteristics are stochastic or the road network is not fully available throughout the duration of the evacuation). On the other hand, the response rate $\alpha$ has a substantial non-linear impact on the evacuation traffic conditions and arrival pattern, especially when the network load is relatively high (which can be expected during evacuation conditions). The reason is that a higher response rate leads to more traffic on the road network which may result in more congested traffic conditions. These worse traffic conditions lead to lower network performance (measured by, e.g., traffic flow and arrival rates), which in turn further deteriorates the network performance. This amplifying feedback loop implies that a higher response rate does not guarantee a faster evacuation; it may even be slower. This underlines the importance of estimating the appropriate parameter values when using these models that apply an exogenous response curve.

![Evacuation response curve following Weibull distribution for different parameter settings](image)

**Figure 2.3: Evacuation response curve following Weibull distribution for different parameter settings:** solid graph, base ($\beta:=0.085, \gamma:=2.55$); blue dashed graph, increase $\beta$ ($\beta:=0.135$); blue long-dashed graph, decrease $\beta$ ($\beta:=0.035$); green dash-dotted graph, increase $\gamma$ ($\gamma:=3.05$); green long-dash-dotted graph, decrease $\gamma$ ($\gamma:=2.05$)
Figure 2.4: Evacuation response curve following sigmoid curve for different parameter settings: solid graph, base ($\alpha:=2.5, h:=4$); green dashed graph, increase $h$ ($h:=5.5$); green long-dashed graph, decrease $h$ ($h:=2.5$); blue dash-dotted graph, increase $\alpha$ ($\alpha:=3.5$); blue long-dash-dotted graph, decrease $\alpha$ ($\alpha:=1.5$)

All of the response curves used in the mentioned studies are strictly monotonic, while the sigmoid curve is also symmetrical. It should be noted that monotonicity and symmetry may not be representative of many emergency conditions that provoke evacuation as a means of damage mitigation. That is, conditions provoking evacuation often generate risk that develops more rapidly as time progresses, making specifically a symmetrical response likely less appropriate. Also, some factors influencing the evacuation response, for example, opening and closing of contraflow to increase outbound capacity, yield non-smooth evacuation departure patterns over time. The latter can only be adequately dealt with by the simultaneous travel demand models discussed in the next section.

The sequential approach discussed above is applied most often. Ozbay and Yazici (2006) suggest that this is due to the mathematical simplicity of the approach and the fact that relatively little situation-specific data is required. Model attributes and parameters are usually estimated based on expert judgment and/or past evacuation data. However, the drawback of this sequential approach (and particularly the response curves) is that there is no clear behavioural basis to justify the method on as the response curves are exogenous input instead of endogenously determined by (the threat of) the hazard within the model. It is cumbersome, if not impossible, to incorporate earlier research findings on the important (socio-psychological and circumstantial) factors determining individuals’ evacuation decisions as discussed in Section 2.3. This is also underlined by Fu (2004) pointing out that response curves are typically constructed for short-lasting evacuations (up till several
hours, while many evacuations may last for several days), time-of-day variations are not included (e.g., the behavioural effect of day/night time on the departure times as observed in real-life), hazard specific dynamics known to influence the travel demand are not included (e.g., the speed, intensity and track of a hurricane or wildfire inappropriately have no effect on travel demand), and the effect of an evacuation plan cannot be realistically assessed (since the impact of the evacuation order is not addressed).

### 2.4.2 Simultaneous travel demand model

Another approach relaxing many of these limitations is to execute the steps of predicting trip generation and departure time decisions simultaneously as an endogenous process. The dynamic travel demand is modelled by applying a repeated binary logit model where we repeatedly in time predict the share of people who decide to evacuate and depart presently, or postpone the decision to evacuate, see Figure 2.5.

![Figure 2.5: Conceptual framework repeated binary logit model](image)

The decision to evacuate, modelled by this binary logit model, is based on the differential utility associated with evacuating (compared to not evacuating) based on the (subjectively perceived) prevailing conditions, such as the proximity of the hazard. This is given by
where \( D(t) \) is the cumulative share of all people who have evacuated until time instant \( t \). This depends on the relative utility to evacuate compared to the alternative of postponing the decision, denoted by \( V(t) \). This relative evacuation utility is typically estimated as a weighted combination of factors determining the attractiveness of evacuating. Examples of possible factors which may influence the decision to evacuate (or not) are socio-demographic characteristics (e.g., age, gender, household composition), spatial-temporal disaster characteristics (e.g., wind speed, intensity, distance to hazard), the opportunity to undertake property protection, whether neighbours evacuate, the presence of pets, prior evacuation experiences, and whether an evacuation order is given. For a more complete overview of the many different factors that have been reported to determine the evacuation decision we refer to Carnegie and Deka (2010). Apart from these measurable factors, subjective non-observable factors may also play a role. The effect of the variance\(^1\) within a group of evacuees as to these subjective non-observed factors is modelled by the scale parameter \( \mu \) in Equation (2.3), where a higher value suggests a smaller variance among people.

Equation (2.3) maximizes over \( t' \leq t \) since the cumulative share of evacuees is computed and it is assumed that people do not return back home once they have decided to evacuate. Therefore, the current share of evacuees equals the share of people who would decide on evacuating given any of the previously prevailing conditions. Or in other words, it equals the maximum share of people who have decided to evacuate in any of the previous time instants given the then prevailing utility to evacuate.

The performance of the repeated binary logit model depends evidently on how accurately the relative evacuation utilities \( V(t) \) are estimated. Relative utility functions have been estimated for the case of wildfires (Alsnih et al. 2005) and hurricanes (Fu and Wilmot 2004; Fu et al. 2006) using both stated preference surveys and post-hurricane revealed preference surveys. For the case of wildfire evacuation, Alsnih et al. selected a number of attributes – describing weather and wildfire conditions – from literature and a pre-study focus group. Surveys were carried out with different combinations of attribute levels. A multinomial logit model and mixed logit model were estimated based on the collected stated choice experiment data identifying a number of statistically significant factors: temperature, wind speed, wind direction, fire type, fire distance, and household specific socio-demographic characteristics. Since the levels of these attributes are time-dependent, the evacuation participation behaviour can be predicted dynamically as the wildfire evolves. Remarkably, the parameter for the attribute modelling whether the

\[ D(t) = \max_{t' \leq t} \frac{1}{1 + e^{-\mu V(t')}} \]

\(^1\) Applying a multinomial logit model as in Eq. (2.3) is justified in case the assumption is made that the utilities drawn from the non-observed factors are identically and independently extreme value type I distributed. Alsnih et al. (2005) relax this limitation by estimating a mixed logit model, thus allowing correlation in unobserved factors over time as well as random taste variation (heterogeneity in the weights).
evacuation route was under threat of being cut off by the fire (originally included in the survey) was found to be statistically not significant. This suggests that in this case the decision to evacuate was made independently from the route choice decision. This would mean that the travel demand and traffic assignment can be modelled independently (sequentially). Follow up research is needed to show whether this holds in more cases.

For the case of hurricane evacuation, Fu and Wilmot (2004) estimated a repeated binary logit model based on evacuation behaviour data for hurricane Andrew. They identified as being statistically significant: the distance to the storm, the forward speed of the hurricane, time-of-day (three periods were introduced using dummy variables: morning, afternoon, and night), the presence of an evacuation order, possibility of flooding, and housing type. Later, Fu et al. (2006) estimated the same model (now also including hurricane wind speed and time-to-landfall) for a dataset from hurricane Floyd in South Carolina and tested the calibrated model on the hurricane Andrew data collected in Louisiana. The predicted dynamic travel demand proved to be similar to the observed travel demand suggesting the transferability of weights to different sites and hurricane scenarios.

In the travel demand models discussed here, where a possible evacuation order is included, the impact of the order is typically modelled by estimating the change in evacuation behaviour (i.e., the increase in departure rate) directly after the evacuation order is given. This may be appropriate when the order to evacuate immediately is given suddenly (unexpected). However, more complex departure behaviour is likely to occur in case of a staged evacuation where (groups of) travellers receive different designated departure time windows in advance, where these instructed departure time windows follow from an evacuation plan set up to moderate evacuation flows and avoid congestion. For instance, people may consider postponing their preferred departure time in order to comply. In order to model this type of behaviour, Pel et al. (2008) proposes including a dynamic term in the evacuation utility function. This factor measures the time difference between the current departure time and the instructed departure time window. This factor decreases the relative utility of evacuating early, where earlier time instants are associated with a larger disutility, while it increases the relative utility of evacuating late. The latter is justified since the evacuation decision is modelled as a repeated decision whether to evacuate, thus in order to ‘comply’ once the departure time window has passed people would have to evacuate belatedly. The compliance to the designated time window is then determined by the corresponding weight in the utility function. This weight most likely depends on both the traveller’s willingness to comply as well as the level of enforcement conveyed by the authority executing the evacuation plan. For example, instructions distributed through the media may lead to lower compliance than instructions given directly by the police going door-to-door.
2.4.3 Discussion

The sequential and simultaneous approaches of predicting the evacuation participation rate and departure time profile are both used. Generally speaking, the simultaneous approach applying the repeated binary logit model is typically used in evacuation research focusing on predicting the dynamic travel demand under various evacuation conditions. As also mentioned earlier, this might be due to the fact that it provides insight into the actual decisions of evacuees. The sequential approach with a fixed participation rate and exogenous response curve is typically used in practice (including the traffic models used in evacuation studies discussed in Section 2.2), and evacuation research focusing on other aspects than departure time choice behaviour (e.g., with a focus on traffic management).

As mentioned earlier, this might be due to its simplicity. The sequential approach using logistical regression or a neural network to predict travel demand has the drawbacks of both approaches. These methods are both not simple in the sense that they require elaborate and specific data, as well as do not provide as much insight into travellers’ behaviour as the simultaneous approach. Using neural networks here in particular seems of little value since these models are not generalizable.

The sequential approach as modelled by PBS&J (2000a) using a cross-classification model was compared with the repeated binary logit model by Fu and Wilmot (2007). As expected, the binary logit model more closely models observed dynamic travel demand behaviour (based on a data set containing evacuation behaviour in southwest Louisiana for hurricane Andrew). The reason why this is expected is that the repeated binary logit model is a predictive method, whereas a cross-classification model (as well as a response curve or a regression model) is a descriptive method. Hence the former is better capable of modelling evacuation behaviour given that elaborate and specific data is available for calibration. In other words, the predictive repeated binary logit model better allows incorporating all insights on evacuation decision making from the behavioural sciences and empirical studies discussed in Section 2.3. We would like to emphasize a number of clear behavioural advantages to this approach also pointed out by Fu and Wilmot (2007): the model allows estimating how people dynamically respond to changing hazard conditions, road network conditions, and evacuation instructions, the model provides insight into the observed evacuation choice behaviour, and the results (weight ratios) appear to be up to a certain level transferable to other sites and situations. Whether the latter advantage can be generalized needs to be shown by future research. In sum, the repeated binary logit model provides insight into trade-offs made in the decision to evacuate, resulting in travel demands that on an aggregated level are more or less consistent with the observed decisions. Thereby, given that it is well calibrated, it yields exactly the information that we need within our evacuation traffic simulation models.

A note can be made here on future research on the repeated binary logit model. Current practice is to use the prevailing conditions to estimate the dynamic differential utility to evacuate (compared to not evacuating), as discussed earlier. There is good reason to believe that people not only consider current conditions, but base their decision on the predicted conditions. That is, they also distinguish patterns in changing hazard conditions,
such as an increase in wind speed, a rising water level, a growing levee breach and resulting increase in flooding speed, and an increasing wildfire intensity. Similarly, people may distinguish steady conditions from temporary fluctuations, for instance, a wind continuously pushing the wildfire towards the individual or household is perceived differently from a temporary change in wind direction (though having the same instantaneously prevailing conditions). Hence, it might prove worthwhile to estimate these models not on the dynamic prevailing conditions at the time instant that the decision is made, but on the dynamic predicted conditions. As a proxy for these predicted conditions, the recently-past conditions that lead up to the time instant that the decision is made could be used. Clearly, future research needs to show the possible benefit of this approach (regarding enhanced predictive power versus the (slight) increase in model complexity by incorporating time series).

To conclude this section, travel demand is typically predicted as single trips from origin (often home or work location) to destination (either network exit point or final refuge location)\(^2\). A number of empirical studies support the view that households evacuate as a unit (e.g., Heath et al. 2001; Sime 1993; Zelinsky and Kosinski 1991). Hence, it is implicitly assumed that evacuees belonging to a single household are either already all together upon evacuation or evacuate independently and meet up after arriving outside the threatened region. This is relaxed in work by Murray-Tuite and Mahmassani (2003, 2004). They propose an evacuation model formulation accounting for trip chains due to household interactions. It is simulated how the carless household members are picked up by the other household member(s) at their school, work or residential location to then continue their trip together. Incorporating this household trip chaining principally allows capturing otherwise unexplained evacuation travel patterns (such as longer trips and initially ‘evacuating’ towards the disaster area) and avoids too optimistic evacuation time predictions. Meeting locations are currently arranged before evacuation, as well as are the carless household members assigned to drivers. The authors point out that further research may consider the impact of communication and traffic information provision on drivers switching pick-ups and rerouting en-route, thus leading to a more realistic representation of household travel behaviour as well as more efficient evacuation. One way of doing so is by using a hybrid route choice model. This is discussed in Section 2.6.4 after introducing different route choice models.

\section*{2.5 Trip distribution modelling}

Trip distribution describes the result of individuals’ destination choice. Much fewer studies are conducted on this choice behaviour than on the previously discussed

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\(^2\) The focus of this thesis, and hence the literature review here, is the evacuee. A component of travel demand which is often not explicitly dealt with in evacuation models is the counter-traffic by, for example, fire trucks, ambulances, and humanitarian aid. For a discussion on how these emergency services can be quantified and included in an evacuation planning case study, we refer to Wikkerink (2010).
participation and departure time choice behaviour. Also, these studies all share a common approach. Generally speaking, this approach consists of two steps. The factors determining the type of location that people evacuate to are identified first. Second, a (often gravity model based) trip distribution model is used to relate these location type preferences to actual destination choice. Each of these steps is discussed next.

2.5.1 Factors determining type of evacuation destination

A small number of studies identify the factors which determine the type of location people evacuate to. This is done using both stated preference and revealed preference data. For instance, Whitehead et al. (2000) and Brodie et al. (2006) report that people with higher income and education tend to evacuate towards hotels and motels, while people with lower income and education tend to evacuate to shelters, based on post-hurricane evacuation data. Deka and Carnegie (2010) build on this by conducting a stated preference survey relating socio-economic and demographic characteristics to the decision whether to evacuate to a shelter location or to a non-shelter location, such as friends or relatives and a hotel or motel. The estimated binary logit model supports similar findings. The probability that a household evacuates to friends or relatives is modelled by Cuellar et al. (2009) in their model for the U.S. Gulf coast by the likelihood that the household belongs to the “region’s dominant racial group”. Whether this can be generalized to other settings can be questioned.

2.5.2 Destination choice modelling

The U.S. Army Corps of Engineers (1995), in a guideline for hurricane evacuation studies, suggests that evacuees can be allocated to destinations proportionally to the population in this possible destination, weighted by a function of the travel distance. This is essentially the gravity-based trip distribution model which is applied to predict the origin-destination matrices used as model input in all the traffic simulation models introduced in Section 2.2.

In other studies, different location types and accompanying different determining factors as identified by Whitehead et al. (2000) and Brodie et al. (2006) are recognized. For instance, Cuellar et al. (2009) compute attraction potentials per type of location. The attraction for hotels and motels is estimated based on the accommodation availability and a presumed average occupancy rate. Whereas the attraction for refuge shelters is estimated based on the presence of schools with gymasia where these shelters are often constructed. Location type specific trip potentials and trip attractions are then computed and used in the location-type specific gravity-based trip distribution models to predict travellers’ destination decisions.

Similarly, Cheng (2007) used post-hurricane survey data to estimate a ‘friend/relative trip distribution model’ and a ‘hotel/motel trip distribution model’. In this case, the observed origin-destination matrix was reconstructed based on the survey data and the trip distribution models were estimated to produce the best fitting estimated origin-destination
matrix. The gravity-based trip distribution models were calibrated assuming that trip frequencies are inversely proportional to the travel distance once outside the threatened zone. Testing the trip length distribution as predicted by the calibrated trip distribution models against observed trip length distributions gave good statistical results. However, little behavioural inferences can be made from such an approach. Therefore, in a later study (Cheng et al. 2008) the same data was used to estimate two multinomial logit models. It was found that, for the friend/relative model, as expected, the parameters for travel distance and the probability that the destination was at risk by the hurricane were negative, indicating that a destination at larger distance and higher risk is less likely to be chosen. Factors having a positive influence on the destination choice of travellers were the destination population, whether the destination is a metropolitan area, and the “percentage of white population” at the destination. For the hotel/motel multinomial logit model the factors travel distance, risk indicator, and white population percentage were also found, with the same effect. Here, also the number of hotels at the destination and the proximity to the interstate motorway had a positive effect. The static approach in this study is relaxed in a subsequent study by Cheng and Wilmot (2009) where time-dependent travel times are included in a quasi-dynamic destination choice model. However, it should be remarked that these time-dependent travel times were reconstructed using the TransCAD traffic simulation model which computes a quasi-dynamic user equilibrium assignment based on link travel times following the Bureau of Public Roads (BPR) function. The authors themselves point out that this approach likely leads to wrong estimates on the prevailing travel times, and suggest improving the destination choice model by applying a realistic dynamic traffic assignment model.

2.5.3 Discussion

The available research on evacuation destination choice behaviour shows consistent findings on distinguishing determining factors for destination choice depending on the type of location people evacuate to. Also, it suggests that gravity-based trip distribution models can be used to reconstruct evacuees’ destination decisions. However, given that the number of studies is limited and a number of these rely on the same data set, it remains unclear whether these findings can be generalized. More research is needed to show whether this is the case. Future research on evacuation trip distribution modelling should preferably be focused on a dynamic approach as this allows capturing the time-dependent destination availability, prevailing travel times, and prevailing risk threat to the destinations (Cheng et al. 2008).

Less focus is laid on travellers’ destination choice by the evacuation model formulated in Chapter 3 of this thesis, and in general by simulation models particularly used in short-notice evacuation (e.g., Peeta and Hsu 2009). In these traffic simulation models it is assumed that travellers do not choose their destination upon departure, but instead tend to choose the route which leads them out of the threatened region as soon as possible. Once safe, they continue their trip to their final destination. This and other route choice models are discussed next.
2.6 Traffic assignment modelling

Traffic assignment relates to assigning travellers to routes, thereby modelling travellers’ route choice decisions. A number of studies report on computing evacuation time estimates without the use of traffic assignment as defined here (e.g., Lindell and Prater 2007; Van Zuilekom et al. 2005). These methods sidestep route choice behaviour by simply looking at the total spatially distributed travel demand, the available network exit points, and the capacity bottlenecks in the road network. The ratio of the travel demand (in number of travellers) and network supply (in number of travellers that can pass per unit of time), together with some correction terms, then may give a quick prediction on the minimum time required for the complete evacuation. However, this approach certainly does not provide full insight into the actual evacuation times of regions and neighbourhoods, nor the dynamic evacuation traffic conditions, nor the determining factors underlying the evacuation process. Therefore, we will not discuss this type of models here, since this thesis focuses on travellers’ choice behaviour in evacuation traffic simulation models (and the fact that these models are usually applied to gain insight into the determinants of the success or failure of an evacuation and how these can be manipulated).

We structure the following discussion on route choice models by distinguishing models that assume route decisions to occur pre-trip (Section 2.6.1), en-route (Section 2.6.2), and those combining pre-trip and en-route route decisions (Section 2.6.3). The user equilibrium assignment assumption applied in most of the traffic simulation models discussed in Section 2.2 falls under the pre-trip route choice models discussed next.

2.6.1 Pre-trip route choice models

Within pre-trip route choice models, travellers are assumed to choose their route from origin to destination upon departure (thus termed pre-trip) and do not switch routes while travelling. These routes are chosen based on the currently prevailing or expected route utilities. The chosen routes may prove to be not the most attractive routes when the resulting traffic conditions (derived after simulation) deviate from the initially predicted traffic conditions on which the route choices were based. Therefore, typically an iterative procedure is used that allows travellers to choose a different route in the next iteration, based on the actually experienced route costs. Repeating this process over a sufficiently large number of iterations leads to a user equilibrium assignment in which no traveller can unilaterally switch routes and be better off (Wardrop’s equilibrium law, see Wardrop 1952).

In simulating pre-trip route choice, route flow fractions are computed at the origins and travellers are propagated from origins to destinations along these routes. The route flow fractions are determined by the probabilities that each route has the highest route utility, where these expected route utilities more closely resemble the actual (experienced) route utilities with a larger number of iterations. These pre-trip route choice models within an
equilibrium framework are generally used for many dynamic traffic assignment applications, though mainly for long-term planning purposes where it can be assumed that travellers have past experiences leading to well-informed expectations about the future traffic conditions that they will encounter during their trip. This assumption on travellers’ learning and habit formation is most likely not an appropriate assumption for the case of evacuation route choice behaviour. The reason for this is that evacuation is a low-frequent exceptional event accompanied by an unusual travel demand pattern and unusual network capacity (due to the combination of different driving behaviour, dynamic traffic control measures, and the adverse disaster conditions) resulting in different-from-normal traffic conditions, which are difficult to anticipate on.

The pre-trip route choice model in an equilibrium framework is applied in most of the dynamic traffic simulation models discussed in Section 2.2, as well as in a number of other evacuation studies (e.g., Goemans and Jansen 2009; Lin et al. 2009, Song et al. 2009).

An approach which is equivalent to an iterative user equilibrium assignment is by applying an incremental assignment method adopted by, for instance, Brown et al. (2009) while developing a hurricane evacuation model. Here, (pre-trip) route choices are modelled sequentially, instead of iteratively. Travellers are assigned to a route in a step-wise fashion. In one step, the (predicted) route costs are computed and a small number of travellers are assigned to the then most attractive routes. In the next step, the route costs are updated based on the new route flows, and again a small number of travellers are assigned to the most attractive routes. When the increments (i.e., the number of travellers assigned to a route in each step) are sufficiently small, then a user equilibrium assignment is reached once all steps are executed and all travellers have been assigned to a route. Therefore, the same (likely inappropriate) behavioural assumption is made as with the iterative procedure computing the user equilibrium assignment.

In a number of the traffic simulation models discussed in Section 2.2 (OREMS, MASSVAC, VISSIM, INDY) user-defined routes and route flow fractions can be model input. This allows evaluating (mandatory) instructions when the defined routes and route flow fractions are defined such that they follow the prescribed evacuation routes. These prescribed evacuation routes do not necessarily minimize individual travel costs, thus leading to a user equilibrium, but may instead aim at minimizing, for instance, the total travel costs, thus leading to a system optimum (simulated by, e.g., Li et al. 2006; Liu et al. 2007; Kalafatas and Peeta 2009; Zheng et al. 2010). Other optimization objectives than the system optimum have been used. An overview can be found in Yuan and Han (2009a) and Huibregtse et al. (2010) (see also discussion in Section 5.3). The important issue here is that testing evacuation route instructions while simulating pre-trip route choice disables incorporating (partial) traveller compliance behaviour. It is necessarily assumed that travellers fully comply, since the pre-trip route choice model does not allow travellers to deviate from their (prescribed) evacuation route during their trip. The discussion in Section 2.3 clearly shows that this full compliance assumption is most certainly too strict.
2.6.2 En-route route choice models

The assumption that travellers cannot deviate from their (pre-trip) chosen route is relaxed in case of en-route route choice. Here, travellers observe prevailing traffic conditions as they travel, and make route choice decisions accordingly. En-route route choice models thus simulate travellers who travel from one intersection to the next, every time deciding on the next downstream direction based on intervention (e.g., route guidance or police direction) and/or the available information on the prevailing (instantaneous or predicted) traffic conditions.

In simulating en-route route choice, link flow fractions (also called split proportions or turn fractions) are computed at all intersection nodes, and travellers are propagated from one intersection node to the next along the downstream links. The link flow fraction for a downstream link is computed by the probability that any route (starting at the intersection node) in this downstream direction has the lowest route costs. This myopic opportunistic travel behaviour is described by, for instance, a set of fuzzy rules (Peeta and Yu 2005), recurrent neural network (Yang et al. 1995), fuzzy network (Hawas 2004), or discrete probabilistic choice model (Dia et al. 2001; Adler et al. 1993). This approach has been mainly applied in dynamic traffic assignment applications on the impact of route guidance or traffic information. Evacuation studies using the en-route route choice model are scarce. In the work by Tu et al. (2010a) and Tamminga et al. (2011), PARAMICS is applied to evaluate the evacuation plan of the Dutch city of Almere. Another possible example is the study by Mitchell and Radwan (2006) using INTEGRATION (Rakha and Van Aerde 2004) to study the impact of evacuation staging on network clearance time. However, regarding the latter, it should be mentioned that INTEGRATION provides both pre-trip and en-route route choice models and it is not fully clear which route choice model alternative was used in this study.

2.6.3 Hybrid route choice models

The assumption that travellers fully rely on past experiences in their route decisions (as made in pre-trip route choice models), as well as the assumption that travellers base their route decisions solely on prevailing traffic conditions (as made in en-route route choice models), are both relaxed in hybrid route choice models. The hybrid models incorporate the impact of unfamiliarity with traffic conditions and the provision of en-route traffic information by combining pre-trip route choice with en-route route switching. Travellers are assumed to choose an initial route upon departure, after which they may adapt their route during their trip. They might do so when prevailing traffic conditions are such that travellers are better off (or have the feeling of being better off) by deviating to another route. A hybrid route choice model is used in DYNASMART (Mahmassani 2001) and EVAQ (discussed in Section 3.2.2; see also Pel et al. 2009). The main difference is that in the mesoscopic DYNASMART model the route switching is checked for each individual traveller, while in the macroscopic EVAQ model this is checked for each intersection node and each class of travellers having the same initial route.
In the macroscopic hybrid route choice model used in EVAQ (explained in more detail in the next chapter), travellers who initially follow the same (pre-trip) route are said to belong to the same class. The class-specific route flow fractions are computed at all intersection nodes, and travellers of all classes are propagated along these routes until some travellers decide to switch to an alternative route. The route flow fractions for travellers of a specific class (i.e., initially following the same route) switching to an alternative route is given by the probability that this alternative route has the lowest route costs.

Note that the pre-trip route choice model and en-route route choice model are special cases of the hybrid route choice model. In both of the hybrid route choice models mentioned above, travellers only consider switching routes when the alternative route provides some minimum improvement. In the special case when this minimum improvement is set to infinite, travellers never deviate from their pre-trip chosen route (thus modelling pre-trip route choice). Whereas in the special case when this minimum improvement is set to zero, travellers always choose the then most attractive route, independent of their initial pre-trip chosen route (thus modelling en-route route choice). Values for the minimum improvement between zero and infinite allow modelling intermediate states where travellers make a trade-off between continuing on the pre-trip chosen route and diverting to a more attractive route.

Hybrid route choice models allow modelling and evaluating evacuation route instructions, while accounting for partial traveller compliance. In this case, the initial (pre-trip chosen) routes can be set as the prescribed evacuation routes. Hence, the minimum improvement for travellers to deviate from their route represents the level of travellers’ compliance, where a higher minimum improvement leads to a higher compliance level (since this reduces the probability of a more attractive alternative route), and vice versa. This way, the hybrid route choice model formulation in EVAQ has been exploited to evaluate the impact of partial traveller compliance on existing evacuation traffic plans (Chapter 4), and to design new optimal evacuation plans while anticipating partial traveller compliance behaviour (Chapter 5).

2.6.4 Discussion

Pre-trip route choice is implemented in many traffic simulation models including most of those used in evacuation studies reported in Section 2.2. That the underlying behavioural assumption that travellers have well-informed expectations about the future traffic conditions that they will encounter during their trip (possibly from past experiences) is inappropriate, is supported by the discussion in Section 2.3 as well as a number of empirical studies. These empirical studies show the large role of rerouting behaviour, thus favouring the en-route and hybrid route choice models. For instance, Knoop et al. (2010) analyse how travellers use the provided traffic information when faced with otherwise unfamiliar traffic conditions (in this case not evacuation, but the aftermath of large-scale traffic accidents). They found that a large share of travellers (up to 50%) is inclined to
switch routes based on the prevailing traffic information. Also, rerouting is much more often observed when the origin of the adverse traffic conditions is an uncommon event (in this case the major traffic accident), as compared to equal adverse traffic conditions due to a recurring event (e.g., day-to-day fluctuations in travel demand and network capacity). Similar conclusions were drawn by Robinson and Khattak (2010) using stated preference surveys on route choice under hypothetical evacuation situations. They observed that a large share of respondents (up to 72%) anticipated that they would reroute in case of evacuation, regardless of whether or not they frequently altered routes under non-evacuation conditions to avoid congestion. This rerouting behaviour can only be simulated using en-route or hybrid route choice models.

En-route and hybrid route choice models have another related advantage over pre-trip route choice models. Namely, the ability to model travellers’ real-time responses to changes in the road network conditions due to the hazard’s evolution in space and time (e.g., road sections becoming inaccessible due to flooding) and dynamic traffic regulations and control measures (e.g., contraflow operations to increase outbound capacity). The effect of these road infrastructure dynamics can only be properly modelled by en-route and hybrid route choice models. This is due to the fact that in models with pre-trip route choice there is no way to avoid travellers from following the chosen route, even if the next link is obviously inaccessible. Therefore, the possibility of inaccessible road sections due to network fall-out prohibits pre-trip route choice and requires en-route route decisions once travellers become aware of the changes in network conditions. Consequently, travellers will take detours around prevailing inaccessible sections of the road network.

Finally, when testing and evaluating optimal evacuation routes, hybrid route choice models allow simulating partial traveller compliance behaviour, which is most likely to occur, as argued in Section 2.3. By varying the minimum improvement that travellers require before deviating from their dedicated evacuation route, insight can be gained into the impact of evacuation instructions under various traveller compliance levels. This enables both testing the robustness of existing evacuation plans towards uncertain traveller compliance levels (see Chapter 4), as well as designing optimal evacuation plans while anticipating the expected traveller compliance behaviour (see Chapter 5).

In Section 2.4.3 where we discussed travel demand modelling, we referred to Murray-Tuite and Mahmassani (2003, 2004) simulating how carless household members are picked up by other household member(s) at their school, work or residential location to then continue their trip together. As was mentioned, how carless household members are assigned to drivers is currently arranged before evacuation. Future research considering the impact of communication and traffic information provision on drivers switching pick-ups and rerouting en-route can be simulated through the use of a hybrid route choice model. A potential modelling setup would be to allow drivers to reroute at decision points (network intersections) then minimizing not their individual generalized route costs, but the household generalized costs comprised of the (weighted) sum of the individual route costs of all drivers belonging to the household. This way pick-ups (and order and switches
herein) are determined by the prevailing traffic conditions as perceived by the drivers of a household.

In sum, hybrid route choice models are the most flexible and likely also the most appropriate approach in modelling travellers’ route choice behaviour during evacuation, as these allow incorporating the impact of dynamic traffic information, changes in the road network conditions, and partial traveller compliance behaviour towards evacuation route instructions. That these factors play an important role in evacuation studies is concluded by the discussion in Section 2.3.

A final note can be made here on the fact that simulated route choice decisions are often determined by (expected) (prevailing) route travel times. The generalized route costs can arguably be appended with other attributes playing a role in travellers’ route decisions. For instance, Chiu and Mirchandani (2008) argue that there is a bias towards using familiar routes and motorways, where the latter might be ascribed to the perception of these roads being more reliable. This is supported by the studies by Dow and Cutter (2002) and Lindell and Prater (2006), also mentioned in Section 2.3, reporting high traffic volumes on the interstate motorways in the evacuations preceding respectively hurricane Floyd and hurricane Katrina despite the availability of alternative routes using rural roads. Further research is needed to show the actual role that these and similar route attributes play in evacuation route decisions.

### 2.7 Concluding remarks

Within this chapter, a perspective is given on the current consensus on evacuation travel behaviour, a background on past and present evacuation traffic simulation models, and the various modelling paradigms that are applied in evacuation studies. This chapter, first of all, provides a set of model requirements based on observed evacuation behaviour. We showed that, following empirical observations and studies, evacuees do not automatically follow the advice and orders from public officials, but tend to seek information, assess their personal risk, and make independent evacuation decisions. It is therefore essential that dynamic traffic simulation models that aim to simulate an evacuation include this reactive traveller behaviour, therewith incorporating the important role of time-varying disaster conditions, (traffic) information, and travellers’ (partial) compliance towards warnings, discretionary advice and evacuation orders. Based on these behaviour-based model requirements, various modelling paradigms were elaborated on regarding their suitability to the case of evacuation. For the evacuation participation and departure time choice we argue in favour of the simultaneous approach to dynamic evacuation demand prediction using the binary logit model. For the destination choice we show how further research is needed to generalize the current preliminary findings on the location-specific destination choice. For the evacuation route choice we argue in favour of hybrid route choice models that enable both following instructed routes and en-route switches.
Second of all, the discussion presented here gives direction to the current state-of-the-art in modelling travel choice behaviour in regional-scale traffic evacuations. This is done by reviewing and consolidating the many research efforts on different model formulations describing the evacuation choice, departure time choice, destination choice, and route choice. Within each of these discussions, we pointed at current limitations and made corresponding suggestions on promising future research directions.

Finally, the literature review in this chapter structures the current state-of-the-practice in evacuation modelling studies. This overview forms the basis for the evacuation model formulated, implemented and tested in the next chapter, and applied in a number of case studies in later chapters of this thesis.
Chapter 3

A Mathematical Traffic Model for Regional Evacuations

In Chapter 2, evacuation models and the suitability of various modelling paradigms as to simulating observed evacuation behaviour are discussed. The current chapter presents the evacuation model formulation building on the previous review. The following discussion focuses on how some of the previously identified limitations relating to travellers’ full compliance and perfect knowledge (under the user equilibrium assignment assumption) are relaxed, and how changes in the road network conditions, e.g., due to hazardous (weather) conditions and traffic control, are adequately modelled such that these lead to en-route rerouting behaviour. The proposed evacuation model is implemented and tested. The face-validity of the model characteristics is illustrated using a hypothetical example. Above all, the illustrative example shows the importance of capturing compliance and information levels in the traffic simulation model, as they have a large impact upon the evacuation efficiency.

The current chapter introduces the evacuation model developed, implemented, and tested within this thesis. Therewith, it allows in later chapters to use the model in case studies on real-life networks, for evaluating the impact of various travel demand and network supply factors (Chapter 4) and designing optimal evacuation plans (Chapter 5).

3.1 Introduction

3.1.1 Shortcomings reviewed

The literature review in the previous chapter addresses the many behavioural assumptions that are generally made while simulating travellers’ choice behaviour and infrastructure dynamics, and discusses their suitability in light of observed evacuation behaviour. Here we highlight the main limitations relating to modelling travellers’ behaviour as applied in the various evacuation models, as elaborated in Chapter 2. Two typical shortcomings are here referred to as traffic information and compliance.

Regarding traffic information, since evacuation is an unfamiliar situation, it needs to be considered that travellers cannot rely on prior experience and knowledge on future traffic conditions. This makes the user-equilibrium assignment assumption inappropriate stating that travellers are fully aware of, and anticipate on, future network conditions in their route choice decisions. Instead, travellers need to rely on the available traffic information, and hence a more myopic choice behaviour is to be expected. This is supported by empirical findings from, for example, Knoop (2009), Lindell et al. (2005), and Robinson and Khattak (2010).

The second limitation relates to travellers’ compliance. Since the evacuation instructions (on, e.g., departure time, destination, and route) may differ from the travellers’ preferred travel decisions, the travellers’ level of compliance need to be considered. Thus, it is inappropriate to simply model travellers’ behaviour equal to the instructed behaviour. Instead, partial compliance is to be expected. Empirical findings supporting this can be found in studies by, for instance, Dash and Morrow (2001), De Jong and Helsloot (2010), Dow and Cutter (2000), Knowles (2003), and Rasid et al. (2000).

These important aspects are often insufficiently incorporated in evacuation models (as also more elaborately discussed earlier), and hence in the scenario analyses that use these models, although they have occasionally been identified as a promising future research direction (e.g., Abdelgawad and Abdulhai 2009; Chiu 2004; Peeta and Hsu 2009). As to travellers’ compliance to advice under non-evacuation conditions, a number of studies have been done on identifying the factors that affect travellers’ willingness to comply, and how this traveller compliance can be modelled endogenously (for an overview, see Chorus et al. 2009). The body of research empirically studying compliance behaviour may prove helpful when generating hypotheses on the explanatory variables which determine travellers’ compliance. Although one may question whether the explanatory factors found under daily conditions (such as travel time variability, network familiarity, information quality, relative travel times under normal conditions, and a range of traveller characteristics) and their relative importance can be directly transferred to the case of an emergency evacuation, the research efforts nevertheless give direction to further study on travellers’ willingness to comply with an evacuation plan.
In the remainder of this chapter, we formulate a traffic model specifically aimed at relaxing these limitations, while building on the previous literature review, and hence tailored to the circumstances of an extreme event such as evacuation. Although these two limitations on travellers’ compliance level and their lack of prior experiences and hence reliance on traffic information are highlighted, to a lesser extent, also other limitations need to be dealt with. One of the more important ones is driving behaviour and traffic operations. The behaviour of drivers (i.e., driver-vehicle combinations) under mentally demanding and emergency conditions is suspected to differ from that expressed in normal conditions. This is supported by experimental and empirical findings (e.g., Hamdar 2008; Hoogendoorn 2010; Hoogendoorn et al. 2010, 2011; Knoop et al. 2009; Ni 2006). Before discussing the proposed model formulation, we first explain why driving behaviour is only indirectly dealt with in this thesis.

3.1.2 Level of analysis

The driving task is only considered implicitly throughout this thesis since the proposed model formulation is macroscopic and thus considers aggregated traffic flows instead of (the interactions between) individual driver-vehicle combinations. Hence, the impact of changes in driving behaviour under evacuation conditions on, for instance, average speeds and road capacity, would be incorporated through the model input. The way this should be done is certainly not trivial, nor sufficiently studied yet. Nonetheless, there are strong arguments for defining our evacuation model at a macroscopic level of analysis:

- **Scalability, computation time, memory usage;** The model applications considered in this thesis, relating to region-wide evacuation planning and model-based optimization of evacuation plans/instructions (typically done within an iterative search-and-evaluate framework), require efficient model scalability, computation time and memory usage. These requirements are, in general, better met by macroscopic traffic simulation models than microscopic models.

- **Model complexity matching data availability;** Given the lack of detailed empirical data, a more detailed (microscopic) level of traffic simulation which yields a higher model flexibility and complexity leads to problems regarding underdetermined (and hence unreliable) model calibration and validation. The principle of parsimony here strongly favours a high-end macroscopic approach.

The conceptual framework of the proposed macroscopic evacuation transportation model is introduced next.

3.2 Conceptual framework

In the remainder of this chapter, we elaborate on the proposed model formulation and show how the first three of the previously identified limitations can be relaxed. In short, this is done by modelling a one-time dynamic network loading (instead of an iterative
traffic flow convergence algorithm yielding, e.g., a user-equilibrium assignment). Within this one-time execution of the dynamic network loading procedure (i.e., the traffic simulator), the impact of the prevailing available traffic information and infrastructure dynamics are incorporated by combining pre-trip route assignment and en-route route switching. In the pre-trip assignment, travellers are assigned to the prescribed evacuation routes to the prescribed safe destinations (coming from an evacuation plan). While en-route, travellers can decide to switch routes to any of the safe destinations, thereby responding to the changing (traffic) conditions (but not anticipating these conditions, as otherwise assumed by an iterative user-equilibrium assignment). This way, the realized departure time, destination and route decisions are a result of the trade-off that travellers make between complying with the prescribed travel behaviour and following their preferred travel behaviour (i.e., the travel decisions that would have been made in absence of an active evacuation plan). For the departure time choice, the level of compliance is modelled exogenously. For the destination and route choice, compliance behaviour is modelled endogenously by introducing an additional attribute representing the possible disutility associated with non-compliance. This approach allows modelling travellers full compliance, no compliance, and any state in between. The way in which both pre-trip and en-route route choices are incorporated is derived from a hybrid route choice model developed in an earlier study (Pel et al. 2009).

The framework of the proposed model, called EVAQ, is in line with that of any traditional transportation model, and is presented in Figure 3.1. The conceptual framework shows the three model components describing how travellers’ departure time decisions, and destination and route decisions are realized, and the traffic flow propagation over the road network (implicitly modelling driving behaviour). The model input comprises of: the hazard conditions, influencing the preferred departure times of evacuees, and (the accessibility of) the road infrastructure; the evacuation instructions, having an effect on the actually realized travel decisions, as travellers’ decisions are a trade-off between their preferred decision and the instructed departure time, destination, or route; and the level of traffic information, as this influences which routes are preferred. Each of the three model components is described in more detail in the following section. Subsequently, in Section 3.4, the model characteristics and face-validity of the proposed formulation is evaluated on a small test-network and hypothetical disaster scenario. The impact of varying levels of compliance and traffic information is tested and discussed. In the closing section of this chapter, we discuss the presented simulation approach and make some final remarks concerning issues on model calibration and validation, which remains a general challenge to these models due to the lack of sufficient quantitative empirical data. The practical applicability of the proposed model is shown in following Chapters 4 and 5 making use of case studies describing the evacuation of the city of Rotterdam and Walcheren peninsula.
3.3 Model formulation

We model road infrastructure as nodes and links, where $N$ is the set of network nodes and $A$ is the set of directed network links (arcs). The set of all nodes $N$ consists of origin nodes $r \in R \subset N$ (where travellers depart and enter the road network), safe destination nodes $s \in S \subset N$ (where travellers arrive and exit the road network), and intersections $n \in N \setminus (R \cup S)$ (where travellers may decide to change the remainder of their route). All nodes are connected by directional links, representing roads or connector links. Links are indicated by subscript $a \in A$, and have characteristics, such as maximum speed, length, number of lanes, and inflow capacity. Figure 3.2 can be used as visual reference for clarification of the variables introduced throughout this chapter.
Figure 3.2: Model variables: origin $r$, intersection $n$, and safe destination $s$; dynamic travel demand rate $d'(k)$ at departure time $k$; route flow rate $f_p(t)$ at time $t$; instructed evacuation route $p$, (relevant) route choice set $Q^n(t)$, with for each alternative route $q \in Q^n(t)$ a route-specific flow fraction $\chi_{pq}(t)$.

### 3.3.1 Departure time choice model

In Section 2.4, the repeated binary logit model (Fu 2004; Fu and Wilmot 2004) was introduced as a method to predict travel demand – and hence departure time decisions. In this model, the shares of people who prefer to evacuate and depart now, or to postpone evacuation, are predicted repeatedly as time goes by (see Figure 2.5). The share of people choosing to evacuate is then determined based on the prevailing conditions, relating to factors such as the hazard force and the velocity with which it approaches. As mentioned earlier, such a departure time choice model and accompanying utility functions have been estimated for the case of wild fires (Alsnih et al. 2004) and hurricanes (Fu et al. 2006) using surveys on stated preference and post-disaster revealed preference.

In principle, this model would allow predicting the dynamic travel demand under varying conditions (including travellers’ level of compliance). Therefore, such a departure time choice model was incorporated and tested in earlier studies (Pel and Bliemer 2008; Pel et al. 2008). However, due to the lack of sufficient data to calibrate the repeated binary logit model, the dynamic travel demand in the examples and case studies in this thesis is instead approximated as
\[ D'(k) = \eta D'_{\text{instr}}(k) + (1 - \eta) D'_{\text{pref}}(k) \] (3.1)

Here, \( D'(k) \) is the cumulative realized travel demand from a specific origin \( r \) until time instant \( k \in T \), where \( T \) denotes the modelling time horizon. The realized travel demand is a weighted sum of the cumulative travel demand according to the evacuation instructions regarding the prescribed departure time (window) for origin \( r \), given by \( D'_{\text{instr}}(k) \), and the cumulative travel demand following from travellers’ preferred departure times (in case of no instructions), given by \( D'_{\text{pref}}(k) \). More precisely, we assume that fraction \( \eta \in [0,1] \) of travellers complies and heeds the instructed departure time, while the remaining travellers (equal to fraction \( 1 - \eta \)) do not comply and depart at their preferred departure time.

Evacuees’ preferred departure times likely depend on a number of socio-demographic characteristics and the hazard’s spatial temporal dynamics (as also used in the repeated binary logit model). In the examples and case studies discussed in this thesis, we assume that the preferred departure times can be represented by the sigmoid curve\(^3\),

\[ D'_{\text{pref}}(k) = \frac{1}{1 + e^{-\alpha(k-h)}} B' \] (3.2)

The total number of travellers who wish to evacuate (at some time) from origin \( r \) is denoted by \( B' \), while the term in front of it determines the share of travellers who prefer to depart at time instant \( k \) or earlier (since we are computing the cumulative demand). This way the first term is the departure time profile of which the shape is determined by parameters \( \alpha \) and \( h \) (for the effect of these parameters see Figure 2.4). As the preferred departure times will in most cases differ per origin, the parameters \( \alpha \) and \( h \) are usually estimated for each origin separately.

Given the cumulative dynamic travel demand computed by (3.1), the corresponding realized dynamic travel demand rates from origin \( r \) at departure time \( k \) is given by

\[ d'(k) = \frac{\partial D'(k)}{\partial k} \] (3.3)

### 3.3.2 Destination and route choice model

**Pre-trip route assignment**

Suppose that a traveller from origin \( r \) is assigned a prescribed evacuation route \( p \in P'(k) \) upon departure, implying also a specific destination, where \( P'(t) \) is the set of instructed routes from origin \( r \) to any (safe) destination \( s \in S \) at time \( t \). Throughout this chapter,  

\(^3\) The use of the sigmoid curve fits the purpose of testing and evaluating the impact of travellers’ compliance behaviour in the synthetic example in Section 3.3 and the case studies in Chapters 4 and 5. However, it should be noted that, in general, the sigmoid curve may not always be appropriate due to its strictly monotonic and symmetrical shape (see discussion in Section 2.4.1).
each route has its own index and thus once a route is defined, also its start and end point is known. Therefore, to keep the notation short, indices for origins, destinations, and other nodes on the network are left out since they are implicitly known through the route index. The route flow rate of travellers being prescribed to a specific route \( p \) at departure time \( k \) is given by

\[
f_p(k) = \chi_p(k)d'(k), \quad \text{for } p \in P'(k)
\]

In words, the total travel demand rate from origin \( r \), \( d'(k) \), can be distributed according to prescribed route fractions \( \chi_p(k) \in [0,1] \). Since \( P'(k) \) denotes the set of all routes that are prescribed from origin \( r \) when departing at time instant \( k \), evidently \( \sum_{p \in P'(k)} \chi_p(k) = 1 \), since all travellers are assigned a route. Travellers with the same prescribed route \( p \) can be seen as belonging to the same class of travellers. Hence, the formulation in this section can also be seen as a multiclass formulation where each class \( p \) is a distinct prescribed route.

Travellers are assigned to an initial route upon departure, after which they may adapt their route (and destination) during their trip. They might do so when prevailing traffic conditions are such that travellers are better off (or have the feeling of being better off) by deviating to another route (possibly with another destination). Evidently, travellers need to be aware of these traffic conditions in order to switch routes. This way the level of available traffic information plays a role in (en-route) destination and route switching decisions. We distinguish two phenomena: route updating decisions and route choice decisions. These are described in the following sections.

**Route updating decisions**

Travellers decide to update their route based on changes in the perceived route travel times. Presumably, slight changes in traffic conditions are ignored (or go unnoticed) and therefore do not affect the prevailing route flow rates, whereas larger changes do lead to travellers deciding on considering switching to a new route. For example, travellers are insensitive to, say, ten percent change in route travel times on alternative routes. Then route flow rates remain the same while travel times vary within this ten percent margin compared to the prevailing route travel times when the route was last updated. As soon as route travel time variations exceed this ten percent margin, new route flow rates are computed.

This behavioural route updating rule shows similarity with the bounded-rationality route switching rule in the DYNASMART model where an alternative route must provide some minimum improvement in order for drivers to switch routes (Mahmassani 2001). The main difference is that in the mesoscopic DYNASMART model the route updating is checked for each specific driver, while in our macroscopic model route updating is checked for each network node (excluding safe destinations).

We let \( Q'(t) \) denote the set of all alternative routes from intersection node \( n \) to any (safe) destination \( s \in S \) at time instant \( t \). Then the set of nodes for route updating, denoted by \( \bar{N}(t) \subseteq N \setminus S \), is given by

\[
\bar{N}(t) = \{ n \in N \mid \text{route updating possible at node } n \text{ for all } t \}
\]
\[ \tilde{N}(t) = \{ n \in N \setminus S \mid \exists q \in Q^n(t), \text{ for which } \left( \frac{\tau_q(t) - \tau_q(t^n)}{\tau_q(t^n)} \right) \geq \tau_{\text{min}} \} \] (3.5)

In words, the set \( \tilde{N}(t) \) consists of all nodes \( n \in N \setminus S \) for which the travel time on at least one of the alternative routes \( q \in Q^n(t) \) from this node \( n \) to any safe destination, denoted by \( \tau_q(t) \), differs (relatively) from the travel time on this same route \( q \) at an earlier time instant when the route flow rates where last updated, \( \tau_q(t^n) \), by more than \( \tau_{\text{min}} \). Here, \( t^n \) denotes the time instant when routes from node \( n \) where last updated, while \( \tau_{\text{min}} \) denotes the minimum relative travel time difference as a threshold for route updating\(^4\).

As an example, consider travellers from an upstream link coming onto an intersection node \( n \). Say, there are three relevant routes from this node \( n \) to any of the safe destinations. At a certain time, the prevailing travel times on these routes are (perceived as) 45, 48, and 52 minutes. When assuming travellers require a minimum relative travel time difference of 10 per cent, i.e. \( \tau_{\text{min}} = 0.1 \), then travellers coming onto this intersection are assumed to only consider rerouting when, for at least one route, its travel time drops below 41.5, 43.2, respectively 46.8 minutes, or exceeds 49.5, 52.8, respectively 57.2 minutes. Then, \( n \in \tilde{N}(t) \). As long as the (perceived) travel times of all three routes stay within these margins, travellers continue on their earlier chosen route, as \( n \not\in \tilde{N}(t) \).

Travellers arriving at any of the nodes \( n \in \tilde{N}(t) \) at time \( t \) decide to update their route (since here the threshold for route updating is exceeded). Note that \( R \subset N \), implying that travellers may ‘reroute’ upon departure and hence may deviate from their prescribed route directly from their origin \( r \in R \) (they do not need to travel along the prescribed route to the first non-origin intersection before deciding on switching routes). Once travellers have decided to update their route, they choose their route based on the perceived route costs. This is explained next.

**Route choice decisions**

At time \( t \), travellers can switch routes at any intersection node \( n \in \tilde{N}(t) \). That is, travellers may decide on switching to any route \( q \in Q^n(t) \), where \( Q^n(t) \) denotes the set of all alternative routes from intersection node \( n \) to any safe destination \( s \in S \). The fraction of travellers of class \( p \) (i.e., having route \( p \) instructed) selecting route \( q \) is determined by the probability that route \( q \) minimizes their perceived generalized route costs\(^5\),

---

\(^4\) The threshold for route updating is expected to be lower in case of emergency conditions as compared to normal conditions based on empirical observations, as discussed earlier in Section 2.6.4 (in particular Knoop et al. 2010, and Robinson and Khattak 2010).

\(^5\) Other formulations than cost minimization – equivalent to expected utility maximization – which explicitly deal with decision making under uncertainty are conceivable, such as (cumulative) prospect theory, and regret minimization. To the author’s knowledge, these have not been studied for the case of choice behaviour under evacuation conditions. (See also the discussion in Section 6.3 on future research into the understanding of evacuation decision making behaviour.)
\( \chi_{pq}(t) = \Pr\left( c_{pq}(t) \leq c_{pc}(t), \quad \forall z \in Q^a(t) \right) \) (3.6)

Here \( \chi_{pq}(t) \) is the fraction of class \( p \) travellers switching to route \( q \) at time instant \( t \), based on the prevailing perceived generalized route costs, \( c_{pq}(t) \). These costs, \( c_{pq}(t) \), are the costs of following route \( q \) (to any of the safe destinations) as perceived by travellers who are actually instructed to follow route \( p \) (to their instructed destination). These generalized route costs are computed as

\[ c_{pq}(t) = \tau_q(t) \left( 1 + \xi_{pq} \alpha \right) \] (3.7)

where \( \tau_q(t) \) is the travel time on route \( q \), and \( \left( \xi_{pq}, \alpha \right) \) is the additional disutility of non-compliance. This additional disutility depends on the perceived costs, \( \alpha \geq 0 \), and the route deviation proportion, \( \xi_{pq} \in [0,1] \). The perceived costs, \( \alpha \), state that the new route \( q \) should be \( \alpha \) times faster in order to make this route more attractive than the prescribed route \( p \). The route deviation proportion is the relative length of route \( q \) which does not coincide with the instructed route \( p \),

\[ \xi_{pq} = \frac{\sum_{a \in A} \delta_{aq} \left( 1 - \delta_{ap} \right) \ell_a}{\sum_{a \in A} \delta_{aq} \ell_a} \] (3.8)

where \( \ell_a \) is the length of link \( a \), and \( \delta_{aq} \) is the link-route incidence indicator that equals 1 if link \( a \) belongs to route \( q \), and zero otherwise. Consequently, we assume that the more route \( q \) deviates from the instructed route \( p \), the larger the additional disutility is to switch routes, which seems reasonable.

As an example, consider the situation sketched in Figure 3.3. The top part shows the road network with four links and their lengths. The bottom part shows the three alternative routes that travellers may choose from, which we will call route 1, 2, and 3, counting from top to bottom. Travellers with instructed route \( p \) being route 1, indicated with the red solid arrow, may deviate to the middle (green dashed) route, 2, or the upper (blue dash-dotted) route, 3. The route deviation proportion for these travellers to switch to route 2 is the length of route which does not overlap with route 1 (equal to 4) divided by the total route length (equal to 7), hence \( \xi_{1,2} = \frac{4}{7} \). The route deviation proportion for these same travellers to switch to route 3 is \( \xi_{1,3} = \frac{1}{2} \) (or \( \frac{12}{12} \)), as the upper route nowhere overlaps with the prescribed route 1. Similarly, for travellers being instructed to follow route 2, the values are 1 (upper route) and \( \frac{2}{3} \) (lower route), and for the travellers instructed to follow route 3, the values are 1 for both other routes.

Travellers’ route choice decisions as computed by (3.6)-(3.8) are based on travel time. The cost function given by (3.7) can be extended with other attributes, for instance, travel distance, perceived travel time reliability, network familiarity, and risk exposure, in case of empirical evidence for this. We refer to the discussions in Sections 2.3 and 2.6.4 on the few (empirical) studies suggesting a number of these attributes, in particular a tendency to use familiar routes.
Presumably, the perceived route travel times used in (3.7) to compute the generalized route costs are more accurate (i.e., closer to the actual route travel times) when travellers receive more information, and vice versa. This means that more information principally leads to a larger share of travellers selecting the present fastest route (assuming travellers wish to minimize their expected travel costs, as stated by (3.6)), while less information principally leads to a more uniform share of travellers selecting each alternative route (depending on the route compliance behaviour). The traffic information may relate to the expected future traffic conditions accounting for future traffic dynamics, or relate to the instantaneous traffic conditions where the current traffic state is expected to continue during the remainder of the trip (sometimes referred to as frozen field). Throughout this thesis, we let route updating and switching be based on instantaneous prevailing travel times, since this is available information nowadays from most information sources, such as, radio broadcasting, internet traffic information services, variable message signs (VMS), dynamic road-side information panels (DRIPs), in-car navigation systems, etc. (the impact of considering predictive information instead, is discussed in Section 3.3.3, while presenting the numerical results to the test example).

The perceived route travel times on a route $q$, denoted by $\tau_q(t)$, can be computed as

$$\tau_q(t) = \sum_{a \in A} \left[ \delta_{aq} \theta_a(t) \right] + \epsilon_q(t)$$

Here the route travel times consist of the travel times on all links belonging to the route, where $\theta_a(t)$ denotes the actual instantaneous link travel time, and $\delta_{aq}$ equals 1 if link $a$ belongs to route $q$, and zero otherwise. The route error $\epsilon_q(t)$ is the error between the
perceived (instantaneous) route travel time and the actual (instantaneous) travel time on route \( q \). Alternatively, in case the error terms are specified on link level then the perceived route travel times are computed as

\[
\tau_q(t) = \sum_{a \in A} \delta_{aq} \left( \theta_a(t) + \varepsilon_a(t) \right)
\]

(3.10)

where \( \varepsilon_a(t) \) is the error between the perceived link travel time and the actual travel time on link \( a \). Actual instantaneous link travel times are computed by the dynamic network loading model (discussed in Section 3.2.4). The route-based error formulation of (3.9) can be solved by a logit model, while the link based error formulation of (3.10) can be solved by a probit model. The choice between these model formulations is made as a trade-off between the computational costs (as logit provides a closed form expression, yet probit requires simulation) and some drawbacks (as probit automatically accounts for spatially overlapping route alternative, while logit need a correction term for this). A more detailed discussion is given in Appendix A. This trade-off leads to the choice to use the probit formulation in the test example at the end of this chapter, and to use the logit formulation in the larger case studies in Chapters 4 and 5.

We assume that the error terms follow a distribution where the variance (>0) is related to the prevailing level of available traffic information. This way, high information levels are implied in case of small variance in the error distributions. The perceived travel times then closely resemble the actual travel times as the effect of the error term becomes negligible. As a consequence, route fractions (given by the probabilities in (3.6)) are only non-zero on the fastest route(s) (depending on the route compliance behaviour). On the other hand, low information levels are implied in case of large variance in the error distributions. The perceived travel times are then dominated by the error term, and route fractions are more uniformly distributed over alternative routes in the route choice set \( Q'(t) \) (depending on the level of compliance).

Synthesis

In sum, the previous sections on the destination and route choice model describe the following. The dynamic travel demand rates, \( d'(k) \), at the origins \( r \in R \) are distributed over the set of prescribed evacuation routes, \( P'(k) \), according to route fractions, \( \chi_p(k) \), following from the evacuation plan. During their trip, travellers may switch routes in case of a more attractive route. They may do so when the perceived travel times on any of the alternative routes \( q \in Q'(t) \) varies more than a certain threshold for route updating, \( \tau_{\min} \). The share of class \( p \) travellers then switching to a new route \( q \), \( \chi_{pq}(t) \), is based on the perceived route travel times and an additional disutility of deviating from the instructed evacuation route. This additional disutility of non-compliance depends on the route deviation proportion, \( \xi_{pq} \), and the perceived costs of non-compliance, \( \omega \). Travellers then follow this new route \( q \) until variations in the perceived route travel times again exceed the route updating threshold compared to the prevailing route travel times when the route was last updated. And so forth until they have reached any of the safe destinations.
This way, the dynamic network loading (DNL) procedure is executed only once (instead of many times within an iterative traffic flow convergence framework yielding, e.g., a user-equilibrium assignment). Within this one-time execution of the DNL procedure, travellers are initially assigned to their instructed route (and destination), yet may continuously update their destination and route during their trip – while accounting for the disutility associated with non-compliance – thereby responding to the changing (traffic) conditions (but not anticipating these conditions, as otherwise assumed by an iterative user-equilibrium assignment).

The mathematical model has been implemented in Matlab, with a user-defined road network, hazard scenario, and traveller behaviour (in terms of model parameters) as model input. For readers who are interested in model implementation, we refer to Appendix A where we discuss how the proposed destination and route choice model formulation can be solved, and give a step-wise algorithm to do so.

### 3.3.3 Special cases

The parameters $\eta$ and $\omega$ describe travellers’ compliance behaviour, where $\eta$ determines the compliance level in departure time (in (3.1)), while $\omega$ determines the compliance level in destination and route decisions (in (3.7)). These parameters are influenced by the travellers’ willingness to comply and the authority’s enforcement to control. Hence, the authority can steer the evacuation by deploying instructions as well as by enforcement to which the evacuees respond in their travel behaviour. By the latter we can discriminate the effect of discretionary advice (e.g., route guidance via information panels) and mandatory orders (e.g., applying police force and road blocks to regulate the evacuating traffic).

Regarding departure time compliance, in the limiting case that $\eta = 1$, we get $D^r(k) = D^{\text{inst}}_r(k), \forall k \in T$, indicating full compliance. On the contrary, $\eta = 0$ leads to $D^r(k) = D^{\text{pref}}_r(k), \forall k \in T$, such that all travellers depart at their preferred departure time. For $0 < \eta < 1$, a share of travellers complies and departs at the instructed time, while the remainder of travellers does not comply and departs at their preferred departure time.

Similarly for route compliance, full compliance can be simulated when a high value is chosen for $\omega$. In this situation, the generalized route costs are predominately determined by the term associated with the additional disutility of deviating from the instructed route. Consequently, the costs of deviating from the instructed route $p$ (that is, when $\xi_{pq} \neq 0$) become very large (or approach infinity) such that all travellers comply. On the other hand, non-compliance can be simulated by setting $\omega$ equal to zero. The additional disutility for deviating from the prescribed evacuation route then equals zero, such that travellers always follow their perceived fastest route, independent of which route is instructed. Partial compliance, depending on the traffic conditions, is modelled as $0 < \omega \ll \infty$, where a higher value of $\omega$ allows for higher compliance rates, since travellers then require larger (travel time) gains before deviating from the instructed route.
3.3.4 Dynamic network loading model and road dynamics

The dynamic network loading (DNL) model simulates the departing traffic flows \( f_p(k) \) (given by (3.4)) through the road network, while accounting for the dynamic class-specific route flow fractions \( \chi_{pq}(t) \) (given by (3.6)) given at all intersections. The DNL model yields the traffic conditions (travel times) used to provide information to the travellers, based on which they may update their route (thus determining the route flow fractions), see Figure 3.1. Essentially any DNL model can be used, such as a queuing model, cell transmission model (Daganzo 1994) or link transmission model (Yperman 2007).

Throughout this thesis, we use the multiclass dynamic spatial queuing model proposed by Bliemer (2007), consisting of a link model and a node model. The link model describes the flow propagation through each link, accounting for different speeds for different vehicle types (for the sake of simplicity not included in the explanation of the route choice model) and a dynamic horizontal queue. The link model thus computes the maximum traffic flow that may potentially enter a link based on the space availability, and the maximum traffic flow that may potentially exit a link as it reaches the downstream end. The node model then uses the potential inflows and outflows to compute the actually realized inflows into and outflows out of each node according to the dynamic route choice rates, accounting for possibly restricted flow capacities due to, for instance, queue spillback from downstream links, conflicting flows on the node, or traffic signal control. For details we refer to Bliemer (2007).

A single adaptation to the original model by Bliemer (2007) is the incorporation of an explicit drop in the outflow capacity of a link when queuing occurs, and full capacity is restored once the queue has dissolved\(^6\).

The (actual) instantaneous prevailing link travel times, \( \theta_a(t) \), used in the route choice model are computed from the DNL model as the minimum of the link travel time under free-flow conditions, and the travel time in case of a queue determined by the current link load divided by the current link outflow rate.

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\(^6\) The outflow capacity of a link is a function of the demand (i.e., the maximum traffic flow that may potentially exit the link). In all simulations presented in this thesis, the outflow capacity always remains fully available as long as the demand does not exceed this capacity (and hence queuing does not occur), and always equals the queue discharge rate (set as 90 % of the original capacity) when the demand does exceed this capacity (and hence queuing does occur, and the capacity drop sets in). In reality, this transition from full capacity to queue discharge rate is not deterministic. Instead, due to stochastic arrival and merging processes at intersections, queuing may occur (and hence a drop in the outflow capacity can be observed) with a certain probability, particularly when the demand approaches the capacity. The effect of this stochastic arrival and merging processes – and the consequential capacity decrease – can be incorporated by computing an expected value for the capacity, as a function of the demand. The expected capacity then equals the original capacity when the demand is relatively low, while it gradually approaches the queue discharge rate when the demand approaches or exceeds the capacity.
Road Infrastructure Dynamics

We model time-dependent road infrastructure, hence characteristics such as speed limits, road capacity and flow direction can vary over time. These variations can be due to the hazard’s evolution in space and time (e.g., road sections becoming inaccessible due to flooding) and prevailing traffic regulations and control measures (e.g., contraflow operations to increase outbound capacity). Capturing these important changes in the road infrastructure over time makes the model (outcomes) more realistic. Also, this feature enables simulating an acute short-notice evacuation in which network disruption plays a major role in the evacuation process, and testing the robustness of an evacuation plan towards uncertainty in the hazard scenario. To realistically model the impact of road infrastructure characteristics which vary over time, travellers need to be able to adapt their route choice decisions during their trip in response to these unforeseen and changing conditions. The way in which this is done is similar to the simulation of en-route route switching in case travellers receive new information on traffic conditions as explained previously (the only difference being that travellers’ now receive – and respond to – new information on the accessibility of the road network).

Considering dynamic network characteristics necessitates time-dependent route choice sets \( Q^t(t) \), since the choice set includes all alternative routes from a network node \( n \) to any safe destination that are available at time \( t \). Therefore, these route sets are (when needed) generated during execution of the dynamic network loading model based on the prevailing traffic and network conditions.

3.3.5 Heterogeneous travel behaviour

For reasons of clarity, the model framework has been formulated here for homogeneous travel behaviour. That is, all travellers behave similarly when making departure time and route choice decisions, receive the same travel information, and react similarly towards this information and their instructions. In reality, there are differences between travellers with respect to, for instance, preferred departure time, destination and route, information availability, response to information, willingness to comply, etc. This differentiation in behavioural response is in line with findings from socio-psychological studies on emergency situations (see Section 2.3, in particular Leach and Campling 1982; Quarantelli and Russell 1977).

When dealing with heterogeneous travellers, we may choose to form multiple discrete classes\(^7\), where travellers belonging to the same class show (sufficiently) similar travel behaviour. In applying a multiclass assignment, each distinct class shows distinct travel behaviour and hence has its own parameter settings. The proposed model is generalized, in order to allow a (user-specified) number of classes with class-specific departure time

\(^7\) Instead of discrete classes, heterogeneity in traveller behaviour and information level can also be represented by a continuous probability distribution for each of the parameters \( a, h, \sigma_a, \eta, \) and \( \omega \) (similar to the mixed logit construct). Solving for travel demand and route flow rates then requires simulation (as a closed form expression cannot be given).
choice parameters $\alpha$ and $h$, class-specific error variance in the perceived link costs $\varepsilon_a \sim N(0, \sigma_a^2)$, and class-specific traveller compliance behaviour represented by $\eta$ and $\omega$. The variables in the formulas above are then appended with the subscript $m$ to indicate the class of travellers. The total number of travellers from an origin, $B^r$, is then given per class, and subsequently dynamic travel demand, generalized route costs, and route flow rates are computed for each traveller class, while the route fractions aggregated over all traveller classes sums to 1.

### 3.4 Test example

Where the previous section explains the mathematical formulation of the model which generalizes the previously identified limitations in evacuation modelling, in this section we verify the model characteristics by applying it to an example of a test network and disaster scenario. The test network and disaster scenario are introduced first, after which we present the experimental setup and discuss the numerical results.

#### 3.4.1 Network and evacuation description

The proposed model is applied to the hypothetical test network shown in Figure 3.4, containing two origins $r$, two destinations $s$, and nine bi-directional links. Each of the two origins inhabits 5,000 travellers, here for simplicity leading to a travel demand of 5,000 vehicles. The lengths of the road links are indicated in the figure. Other characteristics of all network links are set to be equal, where capacity = 2,000 veh/h, speed limit = 80 km/h, number of lanes = 1 lane, and maximum queue density (jam density) = 150 veh/km. The two connector links, starting from the origins on the left-hand side, are assumed to have sufficient storage capacity (i.e., no spillback occurs upstream of these connectors).

![Network diagram](image)

Figure 3.4: Test network and disaster scenario
Figure 3.5: Preferred departure profile for α = 12 and h = 0.6; green solid graph shows cumulative departures [travellers], and blue dash-dotted graph shows departure rate [travellers/hour]

The considered disaster is a hypothetical flood approaching from the South (see Figure 3.4). The linear flood front reaches the lower network links and origin r_2 1.5 hours after the start of the evacuation and propagates in upward direction with a speed of 2 km/h. Furthermore, we assume the preferred departure times can be represented by the sigmoid curve shown in Figure 3.5, where the actually realized departure times depend on the compliance behaviour as explained in the previous section.

### 3.4.2 Experimental setup

A number of assignments are computed, while varying travellers’ willingness to comply and the level of available traffic information. The setup of these assignments is discussed here, while the numerical results are presented in Section 3.4.3.

To illustrate the impact of accounting for traveller compliance behaviour, we design straightforward evacuation instructions. Travellers at origin r_1 are prescribed to follow evacuation routes p_1 and p_2 (see Figure 3.6), while travellers at origin r_2 are prescribed to follow evacuation routes p_3 and p_4. Each route is prescribed to 2,500 travellers in total. Departure times are instructed leading to constant departure rates of 2,000 vehicles per hour (avoiding congestion to occur). Travellers’ compliance level to these instructions is systematically varied to show the effect hereof. The tested parameter values for departure time compliance, η, and destination and route compliance, ω, are listed in Table 3.1.
The effect of accounting for traffic information is shown by varying the corresponding parameters. The parameter values for route updating (minimum travel time difference $\tau_{\text{min}}$) and route selection (link error variances $\sigma^2$) that we test for are listed in Table 3.2.

### Table 3.1: Parameter settings relating to traveller compliance behaviour corresponding to compliance levels that are tested for

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<td>.6</td>
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### Table 3.2: Parameter settings relating to traffic information corresponding to information levels that are tested for

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</thead>
<tbody>
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<td>.3</td>
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<tr>
<td>route selection $\sigma^2$</td>
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<td>.03</td>
<td>.02</td>
<td>.01</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

### 3.4.3 Numerical results

In our hypothetical example, all travellers, when they fully comply to the prescribed evacuation instructions, are capable of reaching their prescribed safe destination. With partial traveller compliance behaviour, a number of travellers might not be able to evacuate in time before the flood causes the network links to become inaccessible and the
evacuation to come to a halt. As expected, generally speaking, a lower compliance level has a larger negative impact on the number of arrivals. This is shown in Figure 3.7 where the number of arrivals is evaluated for different traveller compliance levels (red solid line).

In this example, with higher traveller compliance levels, the reduction in the number of arrivals (as compared to that in the full compliance case) is caused by the non-compliance with departure time instructions. This can be seen by the fact that an equivalent reduction is observed when only lowering compliance towards the prescribed departure times, while simulating full compliance towards the destination and route instructions (see blue dash-dotted graph). Relatively high arrival rates are maintained as (most) travellers still follow the dedicated evacuation routes, thereby avoiding (severe) congestion. Below a certain compliance level, the number of arrivals drops further, where the additional reduction is due to the lower compliance level towards destination and route instructions (as seen from comparison with the green dashed graph showing the impact of lowering the compliance level towards the prescribed destinations and routes while simulating full compliance with departure time instructions). This is explained as follows. The low traveller compliance level leads to a more peaked dynamic travel demand, as it more closely replicates the preferred departure profile (see Figure 3.5). In turn, this results in a high network load. In such conditions, the impact of route guidance (i.e., compliance towards the prescribed evacuation routes) is larger, as compared to when the network load is low. Or, in reverse, lower compliance (towards the prescribed destinations and routes) results in additionally lower network outflow rates (see Figure 3.9) and longer evacuation times (see Figure 3.8).

![Figure 3.7: Number of arrivals for different traveller compliance levels: red solid line, varying departure time (DP) and destination and route (D&R) compliance level; green dashed line, varying D&R compliance level (with full compliance to DP); blue dash-dotted line, varying DP compliance level (with full compliance to D&R) (see Table 3.1)
Figure 3.8: Cumulative departures (upper lines) and arrivals (lower lines) over time: red solid lines, compliance level 2; green dashed lines, compliance level 7; blue dash-dotted lines, compliance level 10 (see Table 3.1)

Figure 3.9: Network outflow rates over time: red solid line, compliance level 2; green dashed line, compliance level 7; blue dash-dotted line, compliance level 10 (see Table 3.1)
Figure 3.10: Number of arrivals for different traffic information levels (see Table 3.2)

Figure 3.11: Cumulative departures (upper black line) and arrivals (lower coloured lines) over time: red solid line, information level 3; green dashed line, information level 8; blue dash-dotted line, information level 10 (see Table 3.2)
Figure 3.12: Network outflow rates over time: red solid line, information level 3; green dashed line, information level 8; blue dash-dotted line, information level 10 (see Table 3.2)

In contrast to traveller compliance, the impact of traffic information is non-monotonic. That is, a higher information level need not necessarily lead to a larger number of arrivals, and vice versa. This can be seen in Figure 3.10. When travellers receive complete traffic information (information level 10), then all travellers will select the (perceived and actual) instantaneous fastest route. The fastest route from each of the origins is the direct route using the horizontal network links. The network outflow rates in this case thus equal the capacity of these routes (see Figure 3.12). Note that queues build up on the connector links when departure rates exceed these route capacities, yet this does not lead to rerouting, since these routes remain fastest. In case of lowering the traffic information level, a share of travellers may perceive the alternative route using the diagonal network links as fastest and decide to reroute. The usage of the alternative parallel routes then increases the network outflow rate. Further lowering the traffic information level subsequently leads to larger shares of travellers diverting to alternative routes. Initially, this reduces network outflow (rates) due to longer travel times and more (and larger) conflicting flows on the network nodes. However, lowering the traffic information below a certain level may spread the traffic more evenly over alternative routes, thus removing traffic from the (actual) fastest routes and consequently increasing throughput on these evacuation routes which slightly restores the overall network outflow (see Figures 3.11-3.12).

The cause of the very low arrival rates observed in case of full information (i.e., all travellers choosing the direct route and other routes not being used) is specific to the topology of the example network. However, the principal that fully informed travellers...
yield lower arrival rates than highly informed travellers is more general, as it may occur in many cases including the larger case study on the real-life road network of Rotterdam, presented in the next chapter (see the discussion in Section 4.4.3). Similarly, when predicted travel times are to be used (recall that the traffic information provided here are the instantaneous travel times), in some cases all travellers are better off, while in other cases the results are worse due to the well-informed individualistic route choice behaviour.

3.5 Concluding remarks

In Chapters 1 and 2, we discussed how traffic simulation models aid in the analysis and planning of the traffic flow operations during a possible evacuation, respectively how the modelling paradigms applied in these models are consistent (or not) with the observed choice behaviour of travellers under evacuation conditions. In the current chapter, we formulated a simulation model aiming to relax some of the identified limitations in many models regarding traveller choice behaviour and road infrastructure dynamics. The face-validity of the model characteristics was illustrated on a test network, clearly showing the importance of capturing compliance and information levels, as they have a large impact upon the evacuation efficiency.

Elaborating on the conceptual framework and mathematical model formulation as done in this chapter may be beneficial to those who develop evacuation models, as it provides a discussion on the role of incorporating travellers’ response behaviour towards traffic information and road infrastructure dynamics, and their compliance with evacuation instructions. Also, it (particularly the illustrative example in Section 3.4) may benefit those who apply these models to forecast, plan, or optimise an evacuation as it helps in distinguishing and evaluating the various evacuation model formulations, and in understanding the role of the discussed behavioural aspects in the evacuation process and the design and evaluation of evacuation plans, including testing for robustness towards uncertainties in travellers’ behavioural response. The latter receives stronger support by a more elaborate model application, as is discussed in Chapters 4 and 5.

Special attention needs to be paid to parameter settings, as traffic simulation models that are used in evacuation studies tend to suffer from the lack of adequate real-life data, and our proposed model is no exception. The unfortunate consequence of this is that the traveller choice behaviour described within these simulation models is often limitedly validated or inappropriately calibrated on traffic data representing regular daily traffic conditions. This need for appropriate data could possibly be addressed, first of all, by combining (i) the limited amount of available post-disaster evacuation data with (ii) data describing traveller behaviour in (sufficiently) equivalent conditions, for example, route guidance and rerouting behaviour due to large-scale incidents on the road. Second of all, the lack of appropriate empirical data can be anticipated and evacuation traffic simulation

8 Another anticipative manner of addressing the lack of (detailed) empirical data is by selecting an appropriate level of analysis, as reasoned in Section 3.1.2.
models can be formulated such that model parameters have a clear behavioural interpretation. The latter is attempted in the model formulation in this chapter and allows (with appropriate caution) simulations based on expert judgment or non-quantitative literature from the behavioural sciences. The uncertainty due to the lack of data can then be relaxed by (elaborate) scenario analyses and sensitivity analyses on variations in both model parameters and factors determining travel demand and network supply. This will be done in the next chapter.
Chapter 4

Impact of Variations in Travel Demand and Network Supply Factors

Evacuation analyses tend to focus on traffic dynamics and the effect of traffic control measures in order to locate possible bottlenecks and predict evacuation times. To provide a clearer view on the crucial factors that determine the emergent traffic states and the overall evacuation time, in this chapter we identify and quantify the impact of variations in travel demand and network supply for the case of evacuation. This is done by performing a structured and comprehensive sensitivity analysis. The analysis is conducted applying the evacuation model presented and implemented in the previous chapter, while systematically varying aspects such as trip generation, departure time rates and route flow rates (also testing the effect of traveller compliance), road capacities, and free speeds. The case study describes the evacuation of the Rotterdam metropolitan area in the Netherlands.

This and the next chapter continue on the discussion in Chapter 1, arguing the benefit of using transportation models in evacuation planning studies. In the current chapter, we use the model, developed in Chapter 3 and building on the literature review in Chapter 2, to perform a sensitivity analysis on a real-life evacuation plan and road network. In Chapter 5, the model is used to design optimal evacuation plans.

4.1 Introduction

Chapter 3 introduced the evacuation traffic simulation model EVAQ dealing with traveller behavioural issues, such as compliance to evacuation instructions and response to traffic information and road dynamics. With that, we relaxed a number of limitations typically found in evacuation models, as reviewed in Chapter 2. The face-validity of these relaxations is shown towards the end of the previous chapter on a test example network. A larger-scale real-life application of the evacuation model gives a more in-depth insight into the essential factors that determine the evacuation time and traffic flow operations. Also, it may remove some of the uncertainty on model parameter calibration and validation – related to the lack of empirical data – discussed in the concluding remarks of the previous chapter. Such a model application will be done here in Chapter 4.

More precisely, in this chapter, we identify and quantify the impact of variations in both travel demand and network supply for the case of an evacuation by performing a structured and comprehensive sensitivity analysis using EVAQ. Regarding travel demand, we look at the effect of trip generation and departure time rates, and route flow rates – including the impact of different levels of traffic information and travellers’ compliance. With respect to network supply, we study the effect of road capacities and free speeds\(^9\). All of this is done on the road network of Rotterdam, a large municipality located in the Netherlands, for which evacuation planning can be important due to the hazardous materials in the large harbour.

In the ensuing, we first present the setting of the case study, the base scenario, and the experimental setup describing the variables and their ranges for which sensitivity is tested (Section 4.2). Then, the subsequent sections (Sections 4.3 through 4.8) each relate to one of the considered factors. The factor is briefly described and the numerical results are presented and elaborated. We conclude this chapter with a summarizing discussion on the generalizability of the findings of this case study to other evacuation studies (Section 4.9), and some concluding remarks relating to model calibration and validation (Section 4.10).

\(^9\) Road capacities and maximum speeds are clearly a derivative of the collective of drivers’ driving behaviour. In Section 3.1, we argue that empirical findings support the view that driving behaviour most likely changes under evacuation conditions. This may relate to both changes in mean driving behaviour as well as changes in heterogeneity of driving behaviour (i.e., the behavioural differences between individual drivers). Although it is currently not sufficiently studied how these changes in driving behaviour influence the aggregated traffic flow (and hence how the effects hereof should be incorporated in macroscopic simulation models through the model input – as also pointed out in Section 3.1.1), we wish to here nevertheless analyse the effects of these changes by looking at the effects of varying road capacities and maximum speeds. We acknowledge that this may be appropriate for investigating the impact of changes in mean driving behaviour, but arguably disregards changes in driver heterogeneity. For a study on the latter, we refer to Tu et al. (2010b) were it is found through sensitivity analysis using a microscopic traffic simulator that changes in mean driving behaviour (particularly mean time headway and minimum gap acceptance – both strongly related to road capacity) have a substantial effect on the network conditions during an evacuation, while changes in heterogeneity among drivers plays a smaller role.
4.2 Case study

4.2.1 Case study description

The metropolitan area of Rotterdam is situated in the western part of the Netherlands. With a population exceeding 600,000 inhabitants, the municipality forms the second largest in the country. Given the setting of the city as a large harbour area, evacuation due to river flooding, coastal flooding, industrial accidents, or terrorist threats, is conceivable. In fact, several programs on national, regional, and municipal level have been initiated over the past years dealing with the preparation for a possible hazard of these types. The road network used in the following analysis consists of the Rotterdam ring road, motorways connected to this ring road, main provincial and urban arterials, and residential neighbourhood collector roads, leading to approximately 500 links, and 220 nodes, including 80 origins (see Figure 4.1).

For the Rotterdam case study network, simulating the individual scenarios in EVAQ (implemented in Matlab) and applying a simulation time step of 20 seconds and time horizon of approximately 36 to 48 hours results in a CPU running time on a Windows XP notebook with 2.2 GHz processor of 10 to 20 minutes.

4.2.2 Base scenario

The (type of) hazard clearly affects the evacuation process characteristics in terms of warning time, scale of evacuation, safe destinations, possible network degradation, etc. For the base scenario in the analysis here we choose a setting in line with the evacuation plans currently developed by the municipality of Rotterdam in preparation for possible evacuation due to a flooding from the river Rhine. We assume sufficient warning time to evacuate before the hazard occurs (and thus not consider the occurrence of network degradation). The designated exit points are the freeways A15, A16, and A29 in southeast direction as indicated in Figure 4.1.

In the following analyses, some of the imposed variations to test the sensitivity of a number of factors are pivoted around a base scenario. This base scenario is explained here.

The base travel demand corresponds with the evacuation demand that is predicted for the current evacuation plans of the municipality of Rotterdam, which equals the number of registered cars in the area for the year of 2004 (371,137 vehicles in total). Hence, it is assumed that everyone departs from home and other sources of (background) traffic are negligible. This is a rather reasonable assumption for a hazard – such as a river flooding – that provides sufficient forewarning (Lindell and Prater 2007).

In the analyses on the impact of trip generation, road capacities, and free speeds, a travel demand profile is used corresponding to travellers departing within a 32 hour time window (sigmoid curve with \( h = 16 \), and \( \alpha = 0.5 \), see green dashed graph in Figure 4.2). Testing of the impact of traffic information and traveller compliance is done using a 48
hour travel demand profile (sigmoid curve with $h = 24$, and $\alpha = 0.3$, see black graph in Figure 4.8) since this results in slightly less congested traffic conditions and as a consequence better demonstrates the impact of these factors. Findings reported here on the effect of traffic information are in line with the original analysis in Pel et al. (2010) where the same 32 hour travel demand profile is used.

Figure 4.1: Rotterdam metropolitan area (source: Google Maps). Top: area and evacuation exit points: (from left to right) motorways A29, A16, and A15. Bottom: road network (black graph) and zones (blue polygons)
Base values for road capacities are set as 2,200 vehicles per hour per lane on the ring road and surrounding motorways, 2,000 vehicles per hour per lane for the main arterials, and 1,800 vehicles per hour per lane for the urban roads. These values are more or less similar to the road capacities in the calibrated network\textsuperscript{10} used by the municipality of Rotterdam for traffic management studies.

Base values for the free speeds are set equal to the current local speed limits. These are 100 and 120 km per hour on the motorways, 80 km per hour on most of the main arterials, and 50 and 60 km per hour on most urban roads.

The level of traffic information is represented by the threshold (minimum relative difference in route travel times) with which travellers update their route, $\tau_{\text{min}}$, and the logit scale parameter by which travellers select their (new) route, $\mu$. For the analyses on trip generation, departure time rates, road capacities, and free speeds, these parameters are set as $\tau_{\text{min}} = 0.2$, and $\mu = 1$. For the analysis on traveller compliance, the base values of $\tau_{\text{min}} = 0.5$, and $\mu = 1$, are used.

Evacuation instructions are only deployed in those scenarios where the impact of traveller compliance is tested. In all other analyses, no instructions are given (and thus travel behaviour is fully based on the assumed preferred departure times, and route flow rates following from the current traffic information). In the analyses on travel compliance, the straightforward evacuation instructions that are deployed appoint travellers to their nearest exit point via the fastest route (under free flow conditions), and set departure times to obtain a uniform departure rate in order to limit congestion. Note that these instructions tested here are likely not the best instructions. In Chapter 5, we discuss optimal evacuation instructions, and the role of traveller compliance therein.

### 4.2.3 Experimental setup

The sensitivity analysis will focus on various input factors affecting demand and supply. Regarding demand, we elaborate on the total number of people who evacuate (trip generation), how this overall demand evolves over time (departure times, and departure time compliance), and how this demand is distributed over alternative routes (based on traffic information, and route costs of non-compliance). Road network supply is, apart from network topology, characterized by road capacities (link capacities) and free speeds (free-flow link speeds). Variation in these latter factors may be due to, for instance, prevailing dynamic traffic management measures and evacuation instructions, different driving behaviour and travel behaviour, and network degradation due to hazard effects. Table 4.1 shows an overview of the considered input variables and their ranges for which sensitivity is discussed in the following sections. Each factor is elaborated on in the corresponding section below.

\textsuperscript{10} Calibrated in 2004 on aggregated traffic counts collected under ‘normal’ traffic conditions.
Table 4.1: Overview of demand and supply variation factors considered in sensitivity analysis

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<table>
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4.2.4 Means of analysis

In the following sections, we subsequently describe the numerical results of varying each of the travel demand and network supply factors. To evaluate the effect of each of these factors, a number of key figures will be presented, as well as a number of graphs. The following key figures will be reported:

- *Travel time*; sum of all individual travel times, and average individual travel time.
- *Delay time*; the travel times minus the free travel time, summed over all travellers, and average for an individual traveller.
- *Queue time-length*; duration and length of all queues on network. For instance, if a queue of 1 km of length lasts 1 hour, then the total queue = 1 km-hours.
- *Distance travelled*; sum of all individual travel distances, and average individual travel distance.
- *Percentage arrivals over time*; number of arrivals as a percentage of the total population. For analyses on trip generation, departure times, road capacities, and free speeds, measured at 16, 24, and 32 hours. For analyses on traffic information and traveller compliance measured at 24, 36, 48 hours.
• **Evacuation time for 60%, 80%, 95%;** time until percentage of travellers have reached their safe destination (exit point).

The following graphs will be looked at:

• **Cumulative departures and arrivals over time;** here, we plot the evolution of the total cumulative number of travellers that have departed from any one of the origins and that have arrived at any one of the safe destinations. First of all, this shows how the overall evacuation time scales with the variation in the considered factor. Also, it gives a first general impression of network-wide traffic loads and delays. The latter two are derived from the vertical distance, respectively horizontal distance, between the two graphs representing the cumulative departures and cumulative arrivals.

• **Arrival rates over time;** the arrival process of the travellers is shown in more detail by presenting the arrival rate. That is, the time derivative of the prior cumulative arrival graph. By plotting the arrival rate over time, we can discern how the arrival rates (as a proxy for network performance) evolves over time.

• **Relationship arrival rates – travel productions – network accumulation;** to get a better view on the traffic conditions and network performance, the arrival rates are evaluated against the travel productions and network accumulations. Travel production denotes the distance that all travellers together travel within a specific time interval (set here as one minute). Network accumulation is the network-wide traffic load. Scenarios which show higher arrival rates at equal network accumulation can then be said to perform ‘better’, in the sense that the way in which the (same amount of) traffic utilizes the network supply results in higher arrival rates. Finally, for a complete analysis, also the travel production is presented as a function of the network accumulation. This graph thus follows the shape of the macroscopic fundamental diagram\(^\text{11}\).

### 4.3 Trip generation

#### 4.3.1 Sensitivity range

The overall travel demand throughout the evacuation will depend on the number of people present in the threatened region and their participation. The former varies by the time of day, the day of the week, and the time of the year (following presence of workforce, shopping public, tourism, etc.). The evacuation participation is determined by the public perception of threat (based on, e.g., warning, information, and instructions) and the willingness to comply with a possible evacuation order. In the following, the number of generated trips is systematically varied between 80 % and 120 % of the default demand (i.e., 371,137 vehicles in total).

\(^{11}\) In a number of studies on the macroscopic fundamental diagram the dimension here termed as travel production is called network performance.
4.3.2 Numerical results

The results for the sensitivity analysis on trip generation are given by the key figures presented in Table 4.2 and the graphs presented in Figures 4.2-4.4. Note that the departure time profile is the same in all cases, i.e., the percentage of travellers departing over time is the same in all cases. However, as the total demand varies, so does the absolute number of departures. A larger number of departures causes the network load to increase, and increase more rapidly. This in turn can activate latent bottlenecks, respectively activate bottlenecks sooner. When a bottleneck becomes active, queues build up in front of it. As the queue discharge rate of a road section is typically lower than its free capacity, this yields a drop in the local throughput. The influence of this local capacity drop on the overall evacuation time will depend on the location of the bottleneck and the network topology. Generally speaking, bottlenecks further downstream tend to have a larger impact on the evacuation time. Bottlenecks further upstream will worsen the local traffic conditions, yet – as the network outflow rates are bounded by other capacity restrictions further downstream – these conditions may not affect the overall evacuation time.

This is indeed the case for the Rotterdam scenario. Increasing the trip generation (by 20 %) leads to a more than proportional increase in travel time (of 48 %) and delay time (of 54 %). This increase is caused by the more congested traffic conditions (as the queue time-length increases by 83 %). These worse traffic conditions however do not proportionally lead to longer evacuation times (which only increase by approximately 10 %). The reason for this is that the worsening of the traffic conditions leads to delays on the urban road network, however that the evacuation time is determined by the downstream bottlenecks on the motorways exiting the area. This can be discerned from considering Figures 4.2-4.4. The maximum arrival rates are comparable across the different scenarios, but are maintained longer in case of a larger trip generation. It is seen that the arrival rate remains constant independent of network accumulation, and that the relationship between travel production and network accumulation is similar for the various scenarios. This indicates that the arrival pattern is primarily determined by the capacity of (the routes towards) the motorways exiting the area, which is throughout most of the evacuation much lower than the rate with which travellers enter the network (i.e., the departure rate).

The reverse reasoning can be made for the case of decreasing the trip generation. Here, a (20 %) lower trip generation yields more than proportionally lower travel times (reduction of 44 %) and delay times (reduction of 49 %), due to less congested traffic conditions (reduction of 59 %). Yet, the evacuation time is only slightly reduced (by approximately 10 %) as the capacitating bottlenecks directly upstream of the exit points remain active.

Table 4.2: Key figures for trip generation sensitivity
### Chapter 4. Impact of Variations in Travel Demand and Network Supply Factors

#### Figure 8

<table>
<thead>
<tr>
<th>Figure</th>
<th>80 % (low)</th>
<th>100 % (base)</th>
<th>120 % (high)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Travel time</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>465,996</td>
<td>1,040,007</td>
<td>1,846,665</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(44.8 %)</td>
<td>(100.0 %)</td>
<td>(177.6 %)</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>1:34</td>
<td>2:48</td>
<td>4:08</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(56.0 %)</td>
<td>(100.0 %)</td>
<td>(147.6 %)</td>
</tr>
<tr>
<td><strong>Delay time</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>376,836</td>
<td>928,933</td>
<td>1,717,773</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(40.6 %)</td>
<td>(100.0 %)</td>
<td>(184.9 %)</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>1:16</td>
<td>2:30</td>
<td>3:51</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(50.7 %)</td>
<td>(100.0 %)</td>
<td>(154.0 %)</td>
</tr>
<tr>
<td><strong>Queue time-length</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- absolute [km-hours]</td>
<td>2,677</td>
<td>6,460</td>
<td>11,803</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(41.4 %)</td>
<td>(100.0 %)</td>
<td>(182.7 %)</td>
</tr>
<tr>
<td><strong>Distance travelled</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-km]</td>
<td>8,644,807</td>
<td>10,806,189</td>
<td>12,544,542</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(80.0 %)</td>
<td>(100.0 %)</td>
<td>(116.1 %)</td>
</tr>
<tr>
<td>- average [km]</td>
<td>29.1</td>
<td>29.1</td>
<td>28.2</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(100.0 %)</td>
<td>(100.0 %)</td>
<td>(96.9 %)</td>
</tr>
<tr>
<td><strong>Percentage arrivals after</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 16 hours</td>
<td>37.7 %</td>
<td>33.2 %</td>
<td>29.7 %</td>
</tr>
<tr>
<td>- 24 hours</td>
<td>94.7 %</td>
<td>78.9 %</td>
<td>67.9 %</td>
</tr>
<tr>
<td>- 32 hours</td>
<td>100.0 %</td>
<td>100.0 %</td>
<td>100.0 %</td>
</tr>
<tr>
<td><strong>Time to evacuate [hours:min]</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 60 %</td>
<td>19:07</td>
<td>20:41</td>
<td>22:21</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(92.4 %)</td>
<td>(100.0 %)</td>
<td>(108.1 %)</td>
</tr>
<tr>
<td>- 80 %</td>
<td>21:56</td>
<td>24:11</td>
<td>26:33</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(90.7 %)</td>
<td>(100.0 %)</td>
<td>(109.8 %)</td>
</tr>
<tr>
<td>- 95 %</td>
<td>24:03</td>
<td>26:49</td>
<td>29:45</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(89.7 %)</td>
<td>(100.0 %)</td>
<td>(110.9 %)</td>
</tr>
</tbody>
</table>
Figure 4.2: Cumulative departures (upper lines) and arrivals (lower lines): red solid, trip generation = 80%; green dashed, trip generation = 100%; blue dash-dotted, trip generation = 120%

Figure 4.3: Arrival rates: red solid, trip generation = 80%; green dashed, trip generation = 100%; blue dash-dotted, trip generation = 120%
Figure 4.4: Relationship arrival rates – travel productions – network accumulation: red solid, trip generation = 80%; green dashed, trip generation = 100%; blue dash-dotted, trip generation = 120%

Finally, we wish to make a note on the macroscopic fundamental diagram in Figure 4.4 (and following figures showing the same relationship for other scenarios). The pattern for the relationship between the travel production and arrival rates (TP-AR), and also between the network accumulation and travel production (NA-TP) starts in the origin and returns in the origin. This is because the road network is empty at the start of the simulation, and the simulation stops when the network is empty again (when everyone has arrived). Therefore, arrival rates, travel production, and network accumulation start at zero, then (gradually) build up, reach a peak, and finally diminish again to zero. However, the direction in which these graphs run is different. Where the TP-AR graph runs more or less counter clockwise, the NA-TP graph runs more or less clockwise. This is explained as follows. Towards the beginning of the evacuation, when more and more travellers depart, the increase in traffic (predominantly spread out across the urban road network) leads to an increase in network accumulation and travel production (defined as the distance travelled by all travellers together per time interval). Yet, arrival rates increase only gradually (and with a certain delay) as most travellers are still en-route. On the other hand, towards the end of the evacuation, most remaining traffic is caught up in (long) queues on (the onramps onto) the motorways. Hence, as traffic is arriving and exiting the network, and as a consequence the
network accumulation gradually decreases, the travel production is relatively low (due to the congestion), while the arrival rates are relatively high. Therefore, in the TP-AR graph, the lower branch originating at the origin belongs to the earlier phase, while the upper branch belongs to the later phase of the evacuation. And, in the NA-TP graph, the upper branch originating at the origin belongs to the earlier phase, while the lower branch belongs to the later phase of the evacuation.

### 4.4 Departure times

#### 4.4.1 Sensitivity range

The predicted departure times depend on contextual factors such as warning time, type of hazard, and time of evacuation (day/night). Here, travellers’ departure times are simulated according to the sigmoid curve. The half loading time is kept constant in all scenarios, since advancing or postponing (for all origins simultaneously) does not affect the network conditions. The traffic is loaded onto the road network with the same rate and therefore queue lengths and travel times are equal. However, different values for the response rate lead to different loading rates and hence also different traffic conditions. To quantify this impact, the response rate is varied between $\alpha = 0.35$ (slow response) and $\alpha = 0.80$ (quick response). This corresponds with travellers departing within a 16 to 32 hour time window, thus investigating the evacuation operations for different rapidity of travellers’ responses.

#### 4.4.2 Numerical results

The results for the sensitivity analysis on departure times are given by the key figures presented in Table 4.3 and the graphs presented in Figures 4.5-4.7. These results are similar to what is found and discussed in the previous section on trip generation. A quicker response leads to larger departure rates. As the network outflow rates are bounded by the network outflow capacity (determined by the bottlenecks directly upstream of the exit points), larger departure rates yield a higher network load. This higher network load in turn results in more traffic congestion and longer travel times. This is indeed what is seen in the Rotterdam case. Accelerating the departure times (represented here by increasing $\alpha$ from 0.5 to 0.65 and 0.8) yields a substantial increase in the queue time-length (increase of 38 % and 66 % respectively) as well as travel time (increase of 35 % and 60 %). The higher network load for a more rapid response is also seen from Figure 4.7, looking at the domain over which network accumulation is observed for the different scenarios. Although traffic conditions worsen and individual travel times increase, the overall evacuation time increases much less (with an increase of approximately 4 % and 7 %). This is again due to the fact that traffic conditions worsen mainly on the urban roads, thus affecting individuals’ travel time yet not so much the overall evacuation time, as the latter is more determined by the downstream bottlenecks located at (the onramps onto) the motorways exiting the area.
### Table 4.3: Key figures for departure times sensitivity

<table>
<thead>
<tr>
<th>Figure</th>
<th>$\alpha = 0.35$ (slow)</th>
<th>$\alpha = 0.5$ (base)</th>
<th>$\alpha = 0.65$</th>
<th>$\alpha = 0.8$ (quick)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Travel time</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>501,812</td>
<td>1,039,490</td>
<td>1,405,032</td>
<td>1,667,567</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(48.3 %)</td>
<td>(100.0 %)</td>
<td>(135.2 %)</td>
<td>(160.4 %)</td>
</tr>
<tr>
<td><strong>Delay time</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>395,249</td>
<td>928,235</td>
<td>1,296,182</td>
<td>1,560,085</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>1:03</td>
<td>2:30</td>
<td>3:29</td>
<td>4:12</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(42.6 %)</td>
<td>(100.0 %)</td>
<td>(139.6 %)</td>
<td>(168.1 %)</td>
</tr>
<tr>
<td><strong>Queue time-length</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- absolute [km-hours]</td>
<td>2,817</td>
<td>6,455</td>
<td>8,932</td>
<td>10,703</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(43.6 %)</td>
<td>(100.0 %)</td>
<td>(138.4 %)</td>
<td>(165.8 %)</td>
</tr>
<tr>
<td><strong>Distance travelled</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-km]</td>
<td>10,317,379</td>
<td>10,818,356</td>
<td>10,586,507</td>
<td>10,467,965</td>
</tr>
<tr>
<td>- average [km]</td>
<td>27.8</td>
<td>29.1</td>
<td>28.5</td>
<td>28.2</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(95.4 %)</td>
<td>(100.0 %)</td>
<td>(97.9 %)</td>
<td>(96.8 %)</td>
</tr>
<tr>
<td><strong>Percentage arrivals after</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 16 hours</td>
<td>41.1 %</td>
<td>33.2 %</td>
<td>27.9 %</td>
<td>24.1 %</td>
</tr>
<tr>
<td>- 24 hours</td>
<td>86.7 %</td>
<td>79.0 %</td>
<td>73.7 %</td>
<td>69.8 %</td>
</tr>
<tr>
<td>- 32 hours</td>
<td>99.6 %</td>
<td>100.0 %</td>
<td>100.0 %</td>
<td>100.0 %</td>
</tr>
<tr>
<td><strong>Time to evacuate [hours:min]</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 60 %</td>
<td>19:18</td>
<td>20:41</td>
<td>21:36</td>
<td>22:15</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(93.3 %)</td>
<td>(100.0 %)</td>
<td>(104.4 %)</td>
<td>(107.6 %)</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(94.4 %)</td>
<td>(100.0 %)</td>
<td>(103.9 %)</td>
<td>(106.7 %)</td>
</tr>
<tr>
<td>- 95 %</td>
<td>25:27</td>
<td>26:49</td>
<td>27:48</td>
<td>28:30</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(94.9 %)</td>
<td>(100.0 %)</td>
<td>(103.7 %)</td>
<td>(106.3 %)</td>
</tr>
</tbody>
</table>
Figure 4.5: Cumulative departures (upper lines) and arrivals (lower lines): red solid, $\alpha = 0.35$ (slow response); green dashed, $\alpha = 0.50$; blue dash-dotted, $\alpha = 0.65$; brown dotted, $\alpha = 0.80$ (quick response)

Figure 4.6: Arrival rates: red solid, $\alpha = 0.35$ (slow response); green dashed, $\alpha = 0.50$; blue dash-dotted, $\alpha = 0.65$; brown dotted, $\alpha = 0.80$ (quick response)
A slower response, corresponding to more uniformly distributed departure times (with $\alpha = 0.35$), substantially alleviates the traffic congestion (queue time-length decreases by 56 %) and shortens individuals’ travel times (reduction of 52 %) and delay times (reduction of 57 %). By the same reasoning as before, the time to evacuate say 60, 80, and 95 per cent of the population decreases much less (by approximately 6 %). However, the time for the complete evacuation takes longer, as seen from the percentage of arrivals over time reported in Table 4.3 as well as Figures 4.5 and 4.6. The lower response rate improves the traffic conditions which initially leads to a faster evacuation, yet may eventually cause (some) exit points to go under-utilized.

In conclusion, a quicker response and corresponding more peaked travel demand will always lead to a higher network accumulation (and more rapid onset of this high network load). However, as network outflow rates deteriorate due to congested traffic conditions, higher departure rates do not guarantee a faster evacuation. Vice versa, a more uniformly distributed slower response improves the traffic conditions and accelerates the evacuation. Therefore, in case of using a response curve, the appropriate curve should be carefully estimated, and preferably calibrated, to ensure realistic results.
4.5 Traffic information

4.5.1 Sensitivity range

Travellers may receive information on the present traffic state. Based hereon they may decide to change their route (and destination) en-route. Travellers will be able to reroute to the present (perceived) fastest route when they receive abundant information. Otherwise, travellers face the traffic conditions on their current route, unaware of the (possibly better) traffic conditions elsewhere on the network. In the extreme, the worst-informed case may represent, for example, travellers being only periodically updated on travel times and traffic conditions via radio, while in the best-informed case, for instance, radio and roadside or overhead variable message signs (VMS) are extensively used, and there is a high percentage of travellers using an in-car navigation system providing up-to-date traffic information.

We simulate a range of scenarios differing in the amount of traffic information that is provided to, or acquired by, travellers. To model this, we simultaneously vary the threshold with which travellers update their route between \( \tau_{\text{min}} = 0.1 \) (very sensitive) and \( \tau_{\text{min}} = 1 \) (relatively insensitive), and the logit scale parameter by which travellers select their (new) route between \( \mu = 20 \) (very informed) and \( \mu = 0.1 \) (relatively uninformed).

4.5.2 Numerical results

The results for the sensitivity analysis on traffic information are given by the key figures presented in Table 4.4 and the graphs presented in Figures 4.8-4.10. As discussed earlier, the arrival rate is bounded from above by the network outflow capacity (which is largely determined by the bottlenecks directly upstream of the motorways exiting the area). The network outflow capacity can be reached when all (roads towards the) exit points are optimally utilized. In case travellers are poorly informed and unfamiliar with the network, then certain exit points remain under-utilized, which can result in longer evacuation times compared to cases in which travellers are kept better informed on traffic conditions. For the Rotterdam case, this can be seen from the last column in Table 4.4 and the brown dotted graph in Figure 4.8. The travel times, delay times, and queue time-length increase and cumulative arrivals are lower at each time instant for the situation in which route flow rates are updated less often and route flows are most spread over alternative routes, thus indicating a low information level as discussed before. When we gradually increase the information level, we can expect that network outflow rates also increase up to a maximum approximating the network outflow capacity. This is because (more) exit points will then become (better) utilized. This is indeed seen by looking at the second column in Table 4.4, and considering the graphs representing the intermediate and reasonably high level of traffic information in Figure 4.9. Travel times, delay times, and queue time-length decrease substantially.
Table 4.4: Key figures for traffic information sensitivity

<table>
<thead>
<tr>
<th>Figure</th>
<th>$\tau_{\text{min}} = 0.1$, $\mu = 20$ (very informed)</th>
<th>$\tau_{\text{min}} = 0.3$, $\mu = 2$</th>
<th>$\tau_{\text{min}} = 0.5$, $\mu = 1$ (base)</th>
<th>$\tau_{\text{min}} = 1$, $\mu = 0.1$ (relatively uninformed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel time</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>425,018</td>
<td>314,341</td>
<td>576,333</td>
<td>1,428,572</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>1:08</td>
<td>0:50</td>
<td>1:33</td>
<td>3:50</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(73.7 %)</td>
<td>(54.5 %)</td>
<td>(100.0 %)</td>
<td>(247.9 %)</td>
</tr>
<tr>
<td>Delay time</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>351,675</td>
<td>204,531</td>
<td>407,199</td>
<td>1,098,263</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>0:56</td>
<td>0:33</td>
<td>1:05</td>
<td>2:57</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(86.4 %)</td>
<td>(50.2 %)</td>
<td>(100.0 %)</td>
<td>(269.7 %)</td>
</tr>
<tr>
<td>Queue time-length</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- absolute [km-hours]</td>
<td>2,483</td>
<td>1,512</td>
<td>2,986</td>
<td>8,005</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(83.2 %)</td>
<td>(50.6 %)</td>
<td>(100.0 %)</td>
<td>(268.1 %)</td>
</tr>
<tr>
<td>Distance travelled</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-km]</td>
<td>5,992,693</td>
<td>8,801,614</td>
<td>13,475,206</td>
<td>26,399,473</td>
</tr>
<tr>
<td>- average [km]</td>
<td>16.1</td>
<td>23.7</td>
<td>36.3</td>
<td>71.1</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(44.5 %)</td>
<td>(65.3 %)</td>
<td>(100.0 %)</td>
<td>(195.9 %)</td>
</tr>
<tr>
<td>Percentage arrivals after</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 24 hours</td>
<td>42.7 %</td>
<td>43.9 %</td>
<td>39.9 %</td>
<td>32.2 %</td>
</tr>
<tr>
<td>- 36 hours</td>
<td>97.2 %</td>
<td>97.1 %</td>
<td>96.9 %</td>
<td>82.4 %</td>
</tr>
<tr>
<td>- 48 hours</td>
<td>99.9 %</td>
<td>99.9 %</td>
<td>99.9 %</td>
<td>99.9 %</td>
</tr>
<tr>
<td>Time to evacuate [hours:min]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 60 %</td>
<td>27:15</td>
<td>26:48</td>
<td>27:45</td>
<td>30:11</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(98.2 %)</td>
<td>(96.6 %)</td>
<td>(100.0 %)</td>
<td>(108.8 %)</td>
</tr>
<tr>
<td>- 80 %</td>
<td>31:03</td>
<td>30:18</td>
<td>31:33</td>
<td>35:20</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(98.4 %)</td>
<td>(96.0 %)</td>
<td>(100.0 %)</td>
<td>(112.0 %)</td>
</tr>
<tr>
<td>- 95 %</td>
<td>34:13</td>
<td>34:05</td>
<td>34:37</td>
<td>39:38</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(98.8 %)</td>
<td>(98.5 %)</td>
<td>(100.0 %)</td>
<td>(114.5 %)</td>
</tr>
</tbody>
</table>
Raising the information level after a certain point (when the traveller information level is already reasonably high) leads to a lower network performance. The travel times, delay times, and queue time-length are all higher in case of very informed travellers (first column in Table 4.4), as compared to the fairly informed travellers (second column same table). Although this seems paradoxical, it follows from the principle of system optimality. More information (and/or network familiarity) may enable a few travellers to select a faster route and thus lower their travel time, yet consequently lengthen the travel time of many travellers already on this faster route, thus on average everyone is worse off. Hence, best results are obtained from travellers’ having near-perfect information (or only a large share of travellers, but not all, being well informed). Indeed the green dashed graphs in Figures 4.9 and 4.10 representing the scenario where travellers are fairly well informed has the highest arrival rates.

Figure 4.8: Cumulative departures (black upper line) and arrivals (coloured lower lines): red solid, $\tau_{\text{min}} = 0.1$, $\mu = 20$ (very informed); green dashed, $\tau_{\text{min}} = 0.3$, $\mu = 2$; blue dash-dotted, $\tau_{\text{min}} = 0.5$, $\mu = 1$; brown dotted, $\tau_{\text{min}} = 1$, $\mu = 0.1$ (relatively uninformed)

One might suspect, that increasing traveller information levels will stabilize the time-dependent arrival rates. The reason is that travellers select their route to the exit points based on the perceived travel times of the alternative routes. When travellers are fully
informed, then each traveller will continuously select the actual fastest route to the exit point. Hence, travel times on all used routes towards the exit points are equal. Therefore, the traffic flow on the routes feeding the exit points is steadier than in case of travellers being less informed and travel times and flows on alternative routes varying strongly over time. This principle is illustrated in Figure 4.10. On the one hand, it can be seen that the variations in the time-varying network outflow rates are smaller for higher information levels. On the other hand, generally speaking, a higher information level yields smaller travel production for equal network accumulation, and smaller travel production for equal arrival rates (or higher arrival rates for equal travel production). Basically, travellers are less ‘driving around’, and more ‘waiting in queues along the fastest routes’. The same can be concluded from looking at the distances that are travelled in the different scenarios. Relative to the base scenario, when travellers receive less travel information this leads to substantially longer average distances travelled (by 96 %), while better informed travellers can select shorter routes leading to a substantial decrease in the average distances travelled (of 35 % and 56 %).

In summary, the route flow rates have an impact on how (the routes feeding) the exit points are utilized, and thus on the arrival pattern. This impact is both non-linear and non-monotonic. As a result, providing more or better traffic information to travellers does not necessarily result in better traffic conditions and shorter evacuation times, and vice versa.

![Figure 4.9: Arrival rates: red solid, $\tau_{\text{min}} = 0.1$, $\mu = 20$ (very informed); green dashed, $\tau_{\text{min}} = 0.3$, $\mu = 2$; blue dash-dotted, $\tau_{\text{min}} = 0.5$, $\mu = 1$; brown dotted, $\tau_{\text{min}} = 1$, $\mu = 0.1$ (relatively uninformed)](image-url)
Figure 4.10: Relationship arrival rates – travel productions – network accumulation: red solid, $\tau_{\min} = 0.1, \mu = 20$ (very informed); green dashed, $\tau_{\min} = 0.3, \mu = 2$; blue dash-dotted, $\tau_{\min} = 0.5, \mu = 1$; brown dotted, $\tau_{\min} = 1, \mu = 0.1$ (relatively uninformed)

4.6 Traveller compliance

4.6.1 Sensitivity range

Evacuation conditions are determined by the collective of travellers’ departure time, destination, and route decisions. These decisions are influenced by deploying evacuation instructions. Up to what level travellers comply depends on how distinct these instructions are from their preferred behaviour, their willingness to conform and the enforcement executed by the regulating authority (e.g., police force, emergency services, and army). Little is known about travellers’ compliance towards evacuation instructions. Also, it may differ strongly by the (hazardous) situation. We therefore refrain from picturing various likely scenarios, but instead compare different scenarios in which the same instructions hold, yet compliance levels are systematically varied. To model this, we simultaneously vary the departure time compliance fraction between $\eta = 0.1$ (low compliance) and $\eta = 1$
(full compliance), and the relative route costs associated with non-compliance between \( \omega = 0.1 \) (low compliance) and \( \omega = 1 \) (high compliance). The scenario with \( \eta = 0.4 \) and \( \omega = 0.4 \), representing an intermediate level of compliance, is chosen as base case. The straightforward evacuation instructions that are deployed in all scenarios appoint travellers to their nearest exit point via the fastest route (under free conditions), and set departure times to obtain a uniform departure rate in order to limit congestion. These are likely not the best instructions. In Chapter 5, we discuss optimal evacuation instructions, and the role of traveller compliance therein.

### 4.6.2 Numerical results

The results for the sensitivity analysis on traveller compliance are given by the key figures presented in Table 4.5 and the graphs presented in Figures 4.11-4.13. The impact of travellers’ compliance behaviour strongly depends on how well the evacuation instructions perform with full compliance. When instructions are optimized and thus perform well with full compliance, then non-compliance will evidently worsen the evacuation. Arrival rates will decrease and evacuation times increase. However, when instructions are deduced from straightforward rules such as the ones considered here, non-compliance does not necessarily worsen the case.

---

**Figure 4.11:** Cumulative departures (upper lines) and arrivals (lower lines): red solid, \( \eta = 0.1, \omega = 0.1 \) (low compliance); green dashed, \( \eta = 0.4, \omega = 0.4 \); blue dash-dotted, \( \eta = 0.7, \omega = 0.7 \); brown dotted, \( \eta = 1, \omega = 1 \) (high compliance)
Table 4.5: Key figures for traveller compliance sensitivity

<table>
<thead>
<tr>
<th>Figure</th>
<th>$\eta = 0.1$, $\omega = 0.1$ (low compliance)</th>
<th>$\eta = 0.4$, $\omega = 0.4$ (base)</th>
<th>$\eta = 0.7$, $\omega = 0.7$</th>
<th>$\eta = 1$, $\omega = 1$ (high compliance)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel time</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>341,867</td>
<td>113,349</td>
<td>94,673</td>
<td>153,186</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>0:55</td>
<td>0:18</td>
<td>0:15</td>
<td>0:24</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(301.6 %)</td>
<td>(100.0 %)</td>
<td>(83.5 %)</td>
<td>(135.1 %)</td>
</tr>
<tr>
<td>Delay time</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>223,319</td>
<td>32,788</td>
<td>18,966</td>
<td>75,268</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>0:36</td>
<td>0:05</td>
<td>0:03</td>
<td>0:12</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(681.1 %)</td>
<td>(100.0 %)</td>
<td>(57.8 %)</td>
<td>(229.6 %)</td>
</tr>
<tr>
<td>Queue time-length</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- absolute [km-hours]</td>
<td>1,635</td>
<td>262</td>
<td>164</td>
<td>554</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(624.0 %)</td>
<td>(100.0 %)</td>
<td>(62.6 %)</td>
<td>(211.5 %)</td>
</tr>
<tr>
<td>Distance travelled</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-km]</td>
<td>9,483,533</td>
<td>6,531,555</td>
<td>6,154,177</td>
<td>6,300,868</td>
</tr>
<tr>
<td>- average [km]</td>
<td>25.6</td>
<td>17.6</td>
<td>16.6</td>
<td>17.0</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(145.2 %)</td>
<td>(100.0 %)</td>
<td>(94.2 %)</td>
<td>(96.5 %)</td>
</tr>
<tr>
<td>Percentage arrivals after</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 24 hours</td>
<td>46.3 %</td>
<td>57.9 %</td>
<td>66.4 %</td>
<td>73.8 %</td>
</tr>
<tr>
<td>- 36 hours</td>
<td>96.8 %</td>
<td>95.9 %</td>
<td>95.1 %</td>
<td>93.2 %</td>
</tr>
<tr>
<td>- 48 hours</td>
<td>99.9 %</td>
<td>100.0 %</td>
<td>100.0 %</td>
<td>100.0 %</td>
</tr>
<tr>
<td>Time to evacuate [hours:min]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 60 %</td>
<td>26:37</td>
<td>24:26</td>
<td>22:12</td>
<td>19:03</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(108.9 %)</td>
<td>(100.0 %)</td>
<td>(90.9 %)</td>
<td>(78.0 %)</td>
</tr>
<tr>
<td>- 80 %</td>
<td>30:27</td>
<td>28:33</td>
<td>28:01</td>
<td>26:48</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(106.7 %)</td>
<td>(100.0 %)</td>
<td>(98.1 %)</td>
<td>(93.9 %)</td>
</tr>
<tr>
<td>- 95 %</td>
<td>34:17</td>
<td>35:13</td>
<td>35:54</td>
<td>37:08</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(97.4 %)</td>
<td>(100.0 %)</td>
<td>(101.9 %)</td>
<td>(105.4 %)</td>
</tr>
</tbody>
</table>
Chapter 4. Impact of Variations in Travel Demand and Network Supply Factors

Figure 4.12: Arrival rates: red solid, $\eta = 0.1$, $\omega = 0.1$ (low compliance); green dashed, $\eta = 0.4$, $\omega = 0.4$; blue dash-dotted, $\eta = 0.7$, $\omega = 0.7$; brown dotted, $\eta = 1$, $\omega = 1$ (high compliance)

The evacuation instructions given here aim at removing the peak demand and leading to a more uniformly distributed travel demand pattern, which in principle helps to lower the network load. In general, this indeed occurs. This is seen in Figure 4.13 by considering the domain on which network accumulation is observed for the different scenarios varying in travellers’ compliance level, and indirectly by the queue time-length reported in Table 4.5. A higher compliance level leads to a more uniformly distributed travel demand, while a lower compliance level leads to a peaked demand and consequently also a shifted arrival pattern, see Figures 4.11 and 4.12. This peaked demand in turn results in higher network loads. The maximum network load for the lowest compliance level is clearly much higher than for higher compliance levels. The difference in network load for higher compliance levels is smaller, and is mainly due to the chosen evacuation routes.

The instructions assign travellers to the fastest routes under free conditions. Since these instructed routes are not optimal under the actually emerging evacuation conditions, traffic conditions may improve when a fraction of travellers deviate from the instructed route to under-utilized routes that are currently (believed to be) faster. This leads to travel time reduction for both non-complying travellers on the faster routes, and complying travellers who now face lighter traffic conditions. Indeed, travel times and delay times are lower for intermediate (reasonably high) compliance levels. When travellers fully comply and strictly follow the instructed routes, individual travel times are longer as well as the overall evacuation time. This because some routes towards the exit points are used, while
other attractive routes remain under-utilized. A reasonably high compliance level solves this by allowing travellers to deviate from their route in case of a faster alternative. Routes towards the exit points are better utilized and network outflow rates increase. This in turn lowers network load, as seen from the domain on which network accumulation is observed and the queue time-length which is lowest in case of reasonably high compliance. Hence, for the Rotterdam case, the ideal situation appears to be high compliance towards the instructed departure times, while fairly high towards the instructed destinations and routes. Decoupling the compliance level of departure time and route may lead to better results, but the latter is outside the scope of this chapter, and will be discussed in Chapter 5.

Figure 4.13: Relationship arrival rates – travel productions – network accumulation: red solid, $\eta = 0.1$, $\omega = 0.1$ (low compliance); green dashed, $\eta = 0.4$, $\omega = 0.4$; blue dash-dotted, $\eta = 0.7$, $\omega = 0.7$; brown dotted, $\eta = 1$, $\omega = 1$ (high compliance)

To conclude, the impact of compliance behaviour heavily depends on the evacuation instructions. This impact is likely to be non-monotonic and non-linear. Which is to be expected since the relation between travel decisions and the resulting traffic states and evacuation times is non-linear. As a higher compliance level does not necessarily improve
traffic conditions or fasten the evacuation, and vice versa, it is strongly recommended to incorporate traveller compliance behaviour in evacuation models such that evacuation plans can be tested for robustness regarding different compliance levels. More hereon, will be discussed in the next chapter.

4.7 Road capacities

4.7.1 Sensitivity range

We test the effect of varying road capacities between 80% and 120% relative to the base values, which are more or less similar to the road capacities in the calibrated network used by the municipality of Rotterdam for traffic management studies.

In can be noted that the 20% decrease of road capacity compared to ‘normal traffic flow conditions’ is in line with assumptions made in several studies by the Texas A&M University Hazard Reduction and Recovery Center (e.g., Ruch and Schumann 1997, 1998; Lindell et al. 2002). On the other hand, an increase in road capacity during an emergency evacuation may, at first hand, seem unrealistic. However, a small number of studies argue that emergency evacuation leads to more aggressive and anxious driving behaviour resulting in smaller headways and smaller gap acceptance (Hamdar 2004; Tu et al. 2010a). If true, then such driving behaviour would in turn yield higher road capacities. Hence, in the sensitivity analysis also the impact of higher capacities is tested for.

Within the sensitivity analysis, only network-wide variations in the road capacity are considered. These changes could be due to, for instance, changes in driving behaviour, due to the weather conditions or mentally-demanding evacuation circumstances. An analysis on the impact of local changes in network supply, for example due to incidents, is not part of the study here. For a discussion on the role of traffic incidents in evacuations, we refer to one of the few studies hereon by Robinson et al. (2009).

4.7.2 Numerical results

The results for the sensitivity analysis on road capacities are given by the key figures presented in Table 4.6 and the graphs presented in Figures 4.14-4.16. Road capacities directly determine the network capacity and thus the network throughput. Therefore, an increase in the network capacity yields less congested traffic conditions leading to lower average travel times (and delay times) and faster evacuation. Vice versa, a decrease in the capacity of the road network yields more congested conditions, higher travel and delay times and slower evacuation. These relations are disproportional. When road capacities are increased, on the one hand, some bottlenecks may become inactive (thus, avoiding the capacity drop associated with the activation of the bottleneck), while on the other hand, the persistence of internal conflicts on the network may refrain the higher capacities from being fully utilized. In the Rotterdam case, increasing the road capacities (by 20%) indeed
alleviates much of the traffic congestion (queue time-length decreases by 40 %) leading to much shorter travel times (37 % less) and delay times (41 % less). However, also true is that indeed internal conflicts persist which consequently limit the higher road capacities to yield proportionally higher arrival rates. The (cumulative) arrival patterns in Figures 4.14-4.16 show that an increase of 20 % in road capacity leads to an increase of 18 % in the maximum arrival rates. Hence, the 20 % capacity increase leads also to a decrease in evacuation time of only approximately 8 %.

In case the road capacities are decreased, some latent bottlenecks can become activated (or activated earlier), thus locally reducing the capacity to the queue discharge rate. In the Rotterdam case, the 20 % decrease in road capacity results in much more congested traffic conditions (queue time-length increases by 64 %) and hence longer travel times (59 % more) and delay times (67 % more). The worsened traffic conditions lead to a more-than-proportional decrease in arrival rates, where 20 % lower road capacities yield a 23 % decrease in maximum arrival rates. Again, this is due to internal conflicts on the road network and the activation of latent bottlenecks. However, the overall evacuation time increases by only approximately 12 %, since the peak arrival rates are maintained over a longer period of time (see Figure 4.15).

Figure 4.14: Cumulative departures (black upper line) and arrivals (coloured lower lines): red solid, road capacities = 120%; green dashed, road capacities = 100%; blue dash-dotted, road capacities = 80%
### Table 4.6: Key figures for road capacities sensitivity

<table>
<thead>
<tr>
<th>Figure</th>
<th>80 % (low)</th>
<th>100 % (base)</th>
<th>120 % (high)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Travel time</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>1,685,681</td>
<td>1,062,155</td>
<td>673,006</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>4:32</td>
<td>2:51</td>
<td>1:48</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(158.7 %)</td>
<td>(100.0 %)</td>
<td>(63.4 %)</td>
</tr>
<tr>
<td><strong>Delay time</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>1,553,865</td>
<td>933,170</td>
<td>548,898</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>4:11</td>
<td>2:30</td>
<td>1:28</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(166.5 %)</td>
<td>(100.0 %)</td>
<td>(58.8 %)</td>
</tr>
<tr>
<td><strong>Queue time-length</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- absolute [km-hours]</td>
<td>10,705</td>
<td>6,537</td>
<td>3,937</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(163.8 %)</td>
<td>(100.0 %)</td>
<td>(60.2 %)</td>
</tr>
<tr>
<td><strong>Distance travelled</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-km]</td>
<td>10,684,239</td>
<td>10,456,152</td>
<td>10,055,361</td>
</tr>
<tr>
<td>- average [km]</td>
<td>28.8</td>
<td>28.2</td>
<td>27.1</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(102.2 %)</td>
<td>(100.0 %)</td>
<td>(96.2 %)</td>
</tr>
<tr>
<td><strong>Percentage arrivals after</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 16 hours</td>
<td>28.7 %</td>
<td>32.8 %</td>
<td>36.5 %</td>
</tr>
<tr>
<td>- 24 hours</td>
<td>65.4 %</td>
<td>78.6 %</td>
<td>91.3 %</td>
</tr>
<tr>
<td>- 32 hours</td>
<td>100.0 %</td>
<td>100.0 %</td>
<td>100.0 %</td>
</tr>
<tr>
<td><strong>Time to evacuate [hours:min]</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 60 %</td>
<td>22:48</td>
<td>20:44</td>
<td>19:25</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(110.0 %)</td>
<td>(100.0 %)</td>
<td>(93.7 %)</td>
</tr>
<tr>
<td>- 80 %</td>
<td>27:12</td>
<td>24:15</td>
<td>22:21</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(112.2 %)</td>
<td>(100.0 %)</td>
<td>(92.2 %)</td>
</tr>
<tr>
<td>- 95 %</td>
<td>30:31</td>
<td>26:53</td>
<td>24:33</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(113.5 %)</td>
<td>(100.0 %)</td>
<td>(91.3 %)</td>
</tr>
</tbody>
</table>
The same conclusions can be deduced from looking at the macroscopic fundamental diagram in Figure 4.16. The graph presenting the situation for the reduced capacities is systematically lower than that for the default capacities, which is in turn lower than that for the case of higher road capacities. These lower network flows – for the case of reduced road capacities – lead to higher network loads as seen from the (higher) domain on which network accumulation is observed. While the situation for higher capacities shows higher network flows, leading to lower network loads. In principle, we can say that higher road capacities result in higher overall network capacity, and vice versa, confirmed by the maximal travel production in Figure 4.16 for different road capacities. And, lower road capacities result in higher network loads, confirmed by the maximal network accumulation for different road capacities. This is disproportional due to the reasons discussed above.

![Figure 4.15: Arrival rates: red solid, road capacities = 120%; green dashed, road capacities = 100%; blue dash-dotted, road capacities = 80%](image)

A final observation is on the distance travelled. Although the differences are small, less congestion (here due to higher road capacities) allows travellers to take the shorter route, while more congestion (here due to lower road capacities) leads to travellers diverting to longer routes which are (perceived) as still being faster. Here, increasing or decreasing the road capacities by 20% results in 4% decrease, respectively 2% increase, in the distance travelled.
4.8 Free speeds

4.8.1 Sensitivity range

In reality, the capacity of a road section depends on the free speed. Hence, variations in the free speed would yield changes in the road capacities. This is especially true for the urban roads where lower speed limits hold. However, these factors are here varied independently such that the impact of each factor can be quantified in itself. Therefore, we test the impact of varying free speeds between 80% and 120% of the default values (while the road capacities are unvaried and kept constant at their default values). Default values for the free speeds are set equal to the current local speed limits. These are 100 and 120 km per hour on the motorways, 80 km per hour on most of the main arterials, and 50 and 60 km per hour on most of the urban roads.
### Table 4.7: Key figures for free speeds sensitivity

<table>
<thead>
<tr>
<th>Figure</th>
<th>80 % (low)</th>
<th>100 % (base)</th>
<th>120 % (high)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Travel time</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>1,086,521</td>
<td>1,059,913</td>
<td>1,043,346</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>2:55</td>
<td>2:51</td>
<td>2:48</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(102.5 %)</td>
<td>(100.0 %)</td>
<td>(98.4 %)</td>
</tr>
<tr>
<td><strong>Delay time</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-hours]</td>
<td>931,795</td>
<td>931,099</td>
<td>932,229</td>
</tr>
<tr>
<td>- average [hours:min]</td>
<td>2:30</td>
<td>2:30</td>
<td>2:30</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(100.1 %)</td>
<td>(100.0 %)</td>
<td>(100.1 %)</td>
</tr>
<tr>
<td><strong>Queue time-length</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- absolute [km-hours]</td>
<td>6,597</td>
<td>6,521</td>
<td>6,482</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(101.2 %)</td>
<td>(100.0 %)</td>
<td>(99.4 %)</td>
</tr>
<tr>
<td><strong>Distance travelled</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- total [veh-km]</td>
<td>10,033,804</td>
<td>10,440,736</td>
<td>10,806,356</td>
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<tr>
<td>- average [km]</td>
<td>27.0</td>
<td>28.1</td>
<td>29.1</td>
</tr>
<tr>
<td>(relative to base)</td>
<td>(96.1 %)</td>
<td>(100.0 %)</td>
<td>(103.5 %)</td>
</tr>
<tr>
<td><strong>Percentage arrivals after</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 16 hours</td>
<td>32.5 %</td>
<td>32.9 %</td>
<td>33.2 %</td>
</tr>
<tr>
<td>- 24 hours</td>
<td>78.1 %</td>
<td>78.6 %</td>
<td>78.9 %</td>
</tr>
<tr>
<td>- 32 hours</td>
<td>100.0 %</td>
<td>100.0 %</td>
<td>100.0 %</td>
</tr>
<tr>
<td><strong>Time to evacuate [hours:min]</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- 60 %</td>
<td>20:48</td>
<td>20:44</td>
<td>20:41</td>
</tr>
<tr>
<td>(relative to base)</td>
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Figure 4.17: Cumulative departures (black upper line) and arrivals (coloured lower lines): red solid, free speeds = 120%; green dashed, free speeds = 100%; blue dash-dotted, free speeds = 80%

Figure 4.18: Arrival rates: red solid, free speeds = 120%; green dashed, free speeds = 100%; blue dash-dotted, free speeds = 80%
4.8.2 Numerical results

The indirect impact of variations in free speeds regarding the side-effect that it has on road capacities has been indirectly dealt with in the previous section (and hence will not be further discussed here). One might argue that an increase in the free speeds leads to an increase in the probability of traffic breakdown and traffic accidents, which in turn can substantially reduce network performance. Although true, these effects are not taken into account here. The results for the sensitivity analysis on free speeds are given by the key figures presented in Table 4.7 and the graphs presented in Figures 4.17-4.19.

In free flowing conditions, travel times are primarily determined by free speeds. Thus, travel times as well as the overall evacuation time decrease when free speeds increase, and vice versa. However, in case of congestion, travel times are determined by the network outflow rate, which is unrelated to the free speed (in this case). Travellers can drive faster from queue to queue, but still end up in the same queues with the same queue lengths, and thus exit the network at the same time. For the case of regional evacuation, large travel demand and congested traffic conditions are likely to occur. Therefore, variations in free

Figure 4.19: Relationship arrival rates – travel productions – network accumulation: red solid, free speeds = 120%; green dashed, free speeds = 100%; blue dash-dotted, free speeds = 80%
speeds (in themselves) will have no substantial impact on traffic states and evacuation times. This is confirmed by the results for the Rotterdam case. Travel times, delay times, the queue time-length, and the evacuation time are comparable across scenarios. The arrival pattern and network conditions are the same in all scenarios, as shown in Figures 4.17-4.19. While the network accumulation and arrival rates remain the same for all cases, only travel production differs across cases. This is to be expected for two reasons. First of all, in case of higher free speeds, travellers travel faster through the network leading to higher travel production (measured as the aggregated travelled distance per time interval), and vice versa. Second, because travellers base their route choice decisions on route travel times. When free speeds increase and queues build up, travellers select longer routes since these can now be travelled faster. Therefore, the total travelled distance increases (by 4%). Vice versa, when free speeds decrease, for the same reason the distance travelled decreases (by 4%).

Finally, although not in the considered setup, in other road networks (with ‘far-away’ exit points that are otherwise unattractive) higher free speeds may result in a better utilization of evacuation routes, and hence reduce evacuation times.

4.9 Discussion and practical implications

The factors of trip generation, departure times, traffic information, traveller compliance, road capacities, and free speeds have been tested regarding their impact on the evacuation process and network conditions. The results are presented in the previous sections. Here, we highlight the main findings from the Rotterdam case study and discuss how these are useful for evacuation planning studies in general.

- A higher travel demand (i.e., an increase in trip generation or a more peaked departure profile) or lower network supply (i.e., a decrease in road capacity) have an impact on the traffic conditions and evacuation process. The level of traffic congestion, travel and delay times, and the evacuation time all increase. Vice versa, these all decrease in case of a lower travel demand or higher network supply. For traffic congestion, and travel and delay times, this relation is non-symmetrical. Variations of the same magnitude (but in the reverse direction) yield increases in congestion level and travel times that can be on average 50% larger than corresponding decreases in congestion level and travel times. This non-symmetry in congestion levels and travel times is caused by the internal conflicts on the road network and the (earlier) activation of latent bottlenecks. Therefore, it is recommended to monitor the demand-supply-balance. This is done by either controlling the travel demand – e.g., by ensuring that departure times are more uniformly distributed and do not exceed the network outflow capacity – or extending the network supply – e.g., by opening peak lanes and hard shoulders, or applying contraflow operations.
• Continuing on the previous finding – the magnitude of the impact from variations in these aforementioned factors differs. The impact on the level of traffic congestion and travel times is on average about 6 to 7 times as high as on the overall evacuation time. This means that these demand and supply variations make a large impact of the road network conditions, yet a relatively much smaller impact of the evacuation progress. The reason for this is that the arrival rates (determining the evacuation progress) are somewhat independent from the network load (determining the congestion level and hence travel times), but instead are determined by the capacity of the bottlenecks upstream of the network exit points. Hence, the aforementioned measures to monitor the demand-supply-balance will improve the network-wide traffic conditions, but in order to accelerate the evacuation there needs to be a focus on increasing the capacity of the determining bottlenecks directly upstream of the network exit points. In the case of Rotterdam, these determining bottlenecks are located at the motorway onramps. Hence, the bottleneck capacity can be increased by, for instance, applying ramp metering or contraflow operations. The use of ramp metering can avoid the onset of congestion on the motorway, and thus ensure maintaining high (arrival) flow rates. The use of contraflow operations could increase the bottleneck capacity, and hence also the (arrival) flow rates, when it is applied across the stretch of the bottleneck. In other words, the contraflow starting point should lie upstream of the bottleneck (i.e., upstream of the motorway onramps, on the urban road network) and the contraflow termination point should lie downstream of the bottleneck (i.e., downstream of the motorway onramps, preferably sufficiently outside the evacuation area such that the congestion at the termination points does not spillback into the evacuation area).

• Controlling free speeds is advisable as this potentially reduces traffic breakdowns and accidents, although this is not quantified here. This is because the direct impact of free speeds – independent of the beneficial side-effects – on the traffic conditions and the evacuation process is negligible.

• Traffic information determines how the available network supply is used. Providing more (accurate) traffic information enables travellers to make better decisions on their destination and route, yielding substantially less congestion, lower travel times, and less distance travelled. Nevertheless, the impact of traffic information on the overall evacuation time is small, since the latter is predominantly determined by the capacity of the bottlenecks upstream of the network exit points. Traffic information is thus to be considered as an adequate measure to control the network-wide traffic conditions, as well as facilitate in travellers’ wish to be informed (as elaborated in Section 2.3).

• Continuing on the previous finding – the principle of system optimality (or price of anarchy) underlines that investing in more accurate traffic information is not always to be recommended. Network conditions are best – for the collective of evacuees – when travellers are fairly well informed. Also, deploying evacuation
instructions is most likely more efficient than providing traffic information (as here in the Rotterdam case the results from the situation of very low compliance to instructions that are generated from straightforward rules outperform the results from the situation of very well informed travellers).

- Deploying evacuation instructions can substantially improve traffic conditions. Even instructions generated from straightforward rules, such as those considered here, yield 3 to 10 times less congestion and delay times, and 2 to 4 times lower travel times (when comparing the cases of intermediate and high traveller compliance against the case of very low traveller compliance). Furthermore, also lower-intermediate levels of traveller compliance already lead to substantially better traffic conditions. The impact of evacuation instructions on overall evacuation time is less clear from this case study, yet justifies more detailed research (as will be done in Chapter 5).

- Continuing on the previous finding – when applying instructions that are generated from straightforward rules (and not optimized), traffic conditions will in most cases be best for intermediate to reasonably high levels of traveller compliance. This corresponds to the situation in which the majority of travellers complies and is ‘uniformly’ distributed across departure times, destinations, and routes, while at the same time a minority of travellers deviate to under-utilized non-prescribed routes and thus compromises for flaws in the original (sub-optimal) evacuation instructions.

### 4.10 Concluding remarks

In this chapter, we have used the evacuation model developed, implemented, and tested in Chapter 3, to conduct a sensitivity analysis on the evacuation plan and road network of the Dutch Rotterdam area. Within the discussion of the numerical results of each of the considered factors, some findings and conclusions were drawn. In the previous section the main findings are generalized and discussed as to their implications for evacuation planning studies. Future research following up on the findings found and elaborated here is suggested to investigate the impacts of cross-sensitivities. For example, how changes in road capacity due to dynamic traffic management measures correlate with changes in route flow rates due to traffic information.

The case study presented in this chapter confirms the stated need to further assess the impact of the (uncertain) travel demand and network supply factors in future evacuation planning studies. In particular, investigating the role of traffic information and evacuation instructions and compliance behaviour is interesting. This enables assessing the trade-off between the efforts associated with (collecting and disseminating) traffic information and enforcement of instructions, and benefits hereof in terms of less congestion, lower travel times, and faster evacuation. In the next chapter, a case study is performed in this direction where the evacuation model is placed in an optimization framework. Chapter 5 shows the
role of compliance behaviour with respect to optimal evacuation instructions, as well as the benefit of designing optimal evacuation instructions which specifically anticipate travellers’ partial compliance behaviour.
Chapter 5

Optimal Evacuation Instructions and the Role of Traveller Compliance

Evacuation planning – deploying instructions to travellers regarding their departure time, safe destination, and evacuation route – can lead to more efficient evacuation traffic flow operations. Empirical observations on evacuation behaviour, as discussed in Section 2.3, support the view that in practice a share of travellers decides not to comply, while current evacuation plan optimization techniques are limited to assessing mandatory evacuation under the assumption of full compliance. In this chapter, the evacuation model introduced earlier – in which travellers’ compliance behaviour is explicitly accounted for – is used within an optimization framework. The framework is applied to the case study describing the evacuation of the Walcheren peninsula in the Netherlands. It is shown how evacuation efficiency depends on the level of travellers’ partial compliance, and how this evacuation efficiency can be maximized when this partial compliance is anticipated. The method and application underline the relevance and importance of capturing the compliance behaviour of travellers while deciding on the most suitable evacuation instructions that are to be deployed, as this has a large impact upon the evacuation operations.

The current chapter is a natural follow-up from the discussion in Chapter 1 on the benefit of using transportation models in evacuation planning studies, the literature review in Chapter 2 looking into current practices, the evacuation model proposed, implemented, and tested in Chapter 3, and used to evaluate a real-life evacuation plan and road network in Chapter 4. In this chapter, the model is exploited to design optimal evacuation plans.

5.1 Introduction

It became apparent in the previous chapter, that one of the many factors determining the success or failure of an evacuation is the setup of the evacuation plan, regarding how evacuees are instructed to select their individual departure time, destination, and route. Optimizing these evacuation instructions has been researched extensively. One way to distinguish different methods to optimize instructions, is by whether an evacuation traffic simulation model is used. Optimization methods which do not make use of such a traffic model typically require restricting assumptions regarding, for instance, static travel times and link capacities (e.g., Fleischer and Skutella 2007; Lu et al. 2005), no dynamic queuing and spillback (e.g., Baumann and Kohler 2007; Liu et al. 2005; Opasanon and Miller-Hooks 2009), and static network characteristics. These same assumptions are evidently made when optimization is done using a static evacuation traffic model. These approaches lack a correct description of essential traffic flow characteristics regarding road capacity restrictions and queuing. These shortcomings clearly limit the applicability of the method to hypothesized cases. This is unfortunate since the merit of these methods is faster computation, due to the fact that time-consuming traffic simulations are avoided. Model-based optimization methods, on the other hand, exploit the simulation model to map evacuation instructions onto network outflow rates (e.g., Afshar and Haghani 2008; Chiu et al. 2007; Liu et al. 2006; Yuan and Han 2010; Xie and Turnquist 2010). Alternative evacuation instructions are then evaluated in an iterative manner until an (near) optimum is found. The main advantage of these model-based search methods is that more general situations can be addressed – within the features of the prediction model – in which are included factors such as traffic flow dynamics and time-dependent network characteristics representing the impact of the hazard’s spatial-temporal evolution and prevailing traffic regulations and control.

Model-based optimization methods principally also allow including the effect of traveller compliance. However, this has been lacking until now even though it is evidently more realistic (see the discussion on empirical observations on evacuation behaviour in Section 2.3) and has occasionally been identified as a promising future research direction (e.g., Abdelgawad and Abdulhai 2009b; Chiu 2004; Peeta and Hsu 2009). The main reason why compliance behaviour is not studied lies in the fact that the evacuation models, which are used as prediction model for the optimization process, are unable of adequately modelling travellers’ compliance behaviour. As a consequence, model-based optimization studies to date typically assume full compliance, and the evacuation operations under optimized evacuation instructions for full compliance are then presented as an upper bound for network performance. In this chapter, we generalize this approach to incorporate traveller compliance behaviour in order to (i) gain insight into the impact of traveller compliance on the evacuation, and (ii) enable making the trade-off made in real-life evacuation planning between the costs associated with ensuring a higher compliance level (determined by the way in which information and instructions are deployed) and the possible benefits hereof in terms of, for instance, less congestion, lower travel times, and faster evacuation.
This chapter starts with the next section discussing the few studies in which the impact of traveller compliance level on evacuation efficiency has been evaluated, and briefly recalls some empirical studies, earlier discussed in Section 2.3, which support the view of travellers’ partial compliance behaviour. After that, the optimization framework for testing the impact of (anticipating) partial traveller compliance behaviour is presented in Section 5.3. We use a heuristic optimization method based on ant colony optimization (Huibregtse et al. 2009) in combination with the evacuation model derived in Chapter 3, in which travellers’ compliance behaviour is explicitly incorporated. In the following Sections 5.4 up till 5.6, the optimization framework is applied to a real-life case study describing the evacuation of the Walcheren peninsula, the Netherlands. Subsequently, the case study description is given, experimental setup is discussed, and numerical results are presented. In this application, we numerically show and discuss I) the (negative) impact of partial compliance behaviour when assuming full compliance (Section 5.5), and II) the (positive) impact of anticipating on this partial traveller compliance behaviour (Section 5.6). Section 5.7 discusses the findings and makes a number of recommendations for evacuation planning studies. Finally, Section 5.8 concludes with some generalizing remarks on the illustrated benefits of applying an evacuation model, such as the one derived here in this thesis, within an optimization framework.

5.2 Studies on traveller compliance behaviour

Only few studies have investigated the impact of traveller compliance on evacuation efficiency. Yuan et al. (2007) evaluate the impact of a fixed compliance rate with respect to route choice on an existing evacuation plan. In this study using VISSIM, share \( x \) of the travellers complies, and is thus assigned to the prescribed evacuation routes, while the remainder share of travellers, that is \( 1-x \), is assigned to the nearest destinations and the routes following from the user-equilibrium assignment. The value of \( x \) is systematically varied between 1 (full compliance) and 0 (no compliance). One of the main conclusions of the study is that lower compliance levels may increase evacuation efficiency since partial compliance allows some travellers to deviate to under-utilized non-prescribed routes and thus compromises for flaws in the original evacuation instructions. The fixed compliance level and user-equilibrium assumption are relaxed in the evacuation model derived in this thesis (see Chapter 3), where travellers’ compliance behaviour is modelled as an explicit trade-off between following the prescribed evacuation routes and deviating to alternative routes which are (perceived as being) more attractive at each decision point (intersection) during their trip. This route switching choice process describing travellers’ compliance behaviour is modelled by applying the hybrid route choice model allowing for both pre-trip and en-route travel decisions (Pel et al. 2009). In the previous chapter, the perceived additional disutility for travellers to deviate from the instructed evacuation routes was systematically varied, thus modelling the instances of full compliance, no compliance, and intermediate states. The conclusions drawn in Chapter 4, on the impact hereof in case of applying straightforward evacuation instructions, are in line with the findings by Yuan et
al. (2007). That is, lower compliance levels may in some cases lead to higher evacuation efficiency. On the contrary, partial compliance towards optimized instructions cannot benefit the evacuation efficiency by definition. This is confirmed by Huibregtse et al. (2009) by testing the impact of variations in traveller compliance levels towards optimized evacuation instructions, where the evacuation instructions were optimized based on the full compliance assumption. In the presented case study application, evacuation efficiency - measured as the number of safe arrivals within the limited amount of time available - dropped by 5 to 15 percent in case of less than full compliance. It can be noted that, in this study by Huibregtse et al. (2009), the evacuation model developed here in this thesis was used, and hence travellers’ compliance behaviour is modelled in the same fashion as in the previous chapter and the current chapter.

The small number of studies referenced here shows how limited the research is on quantifying the impact of traveller compliance on evacuation efficiency. Yet, to the best of our knowledge, no evacuation optimization method has been proposed or applied to date in which traveller compliance behaviour is anticipated. This is unfortunate since the discussion in Section 2.3, building on the earlier socio-psychological studies by, for example, Leach and Campling (1982) and Quarantelli and Russell (1977), as well as the empirical observations on evacuation behaviour by, for example, Dash and Morrow (2001), De Jong and Helsloot (2010), Dow and Cutter (2000), Knowles (2003), and Rasid et al. (2000), strongly suggest that the full compliance assumption is too strict, and that in practice a share of travellers decides not to comply. Furthermore, evacuation efficiency can be improved in case of deploying evacuation instructions which anticipate this partial compliance. The latter is shown in the remainder of this chapter.

5.3 Optimization approach

In the case study following this section, evacuation efficiency is optimized by means of an evacuation traffic model and an optimization heuristic (based on ant colony optimization). Here, first a measure for evacuation efficiency is defined (Section 5.3.1), subsequently, the framework using the evacuation model and the optimization heuristic is presented and the general features of the optimization algorithm are described (Section 5.3.2).

5.3.1 Optimization objective

To optimize evacuation instructions basically means to design instructions which, once applied, maximize the evacuation efficiency. Various measures of evacuation efficiency can be thought of, depending on the evacuation objective and scenario constraints. Straightforward efficiency measures, such as network clearance time and system travel time, are used extensively. Other formulations evaluate, for instance, the risk exposure of evacuees both while being at home and en-route (Han et al. 2007, Yuan and Han 2009), or the number of arrivals thereby considering the possibility of a non-complete evacuation (Miller-Hooks and Sorel 2008). These efficiency measures are derived from the outcomes
of the evacuation model, simulating a specific scenario and set of evacuation instructions (i.e., the prescribed departure times, destinations, and evacuation routes). The uncertainty in the scenario – relating to hazard characteristics, traveller behaviour, road network supply, etc. – can be dealt with in two ways. One way is to evaluate all scenarios that are more or less likely to occur, and subsequently apply a probabilistic approach and a robust approach. A probabilistic approach maximizes the expected efficiency, where the efficiencies of all the individual scenarios are weighed by their predicted likelihood. A robust approach maximizes the minimal efficiency that is to be gotten from any of the individual scenarios, independent of their likelihood. Another way is to internalize the uncertainty into the optimization objective. This approach is used here where evacuation efficiency is defined as the weighted arrival rates integrated over time,

\[
\int_0^T e^{\beta t} f(t, E, X) dt
\]

Following (5.1), the evacuation efficiency \(w(E|X)\) of a specific set of evacuation instructions \(E\) is determined by the single representative scenario, denoted by \(X\). Thus, a specific set of evacuation instructions is evaluated only once, avoiding a multitude of computationally-intensive model runs to evaluate multiple probable scenarios. The uncertainty towards, for instance, the window of available evacuation time is instead incorporated through the parameter, \(\beta \geq 0\). For \(\beta = 0\), the value of \(w\) is equal to the arrival rates, integrated over time, \(\int f(t) dt\). In other words, the total number of arrivals. \(f(t, E, X)\) is determined by the evacuation model which is used to compute these time-dependent arrival rates, given a set of evacuation instructions, \(E\), and specific scenario, \(X\). When \(\beta > 0\), earlier arrivals are valued higher than later arrivals. In other words, given that the same number of travellers successfully arrives at their destination, evacuation instructions leading to a situation in which travellers arrive earlier are considered as more efficient. Hence, this formulation, adopted from Huibregtse et al. (2010), is able to internalize uncertainty in the window of available evacuation time.

### 5.3.2 Optimization framework

In the following, we maximize the evacuation efficiency as determined by (5.1). This is done by alternatingly calling the traffic model, which uses the evacuation instructions \(E\) (and certain parameter settings representing the level of travellers’ compliance behaviour) to compute the dynamic arrival rates \(f\), and calling the optimization heuristic which uses these arrival rates \(f\) to try improve the evacuation instructions \(E\). This iterative procedure is illustrated in Figure 5.1.

The optimization heuristic assigns instructions, regarding departure time, destination and route, to all travellers. The main concept of this heuristic is described in Appendix B, while a more detailed description of the optimization method can be found in Huibregtse et al. (2009) from where the approach was adopted. One note that should be made is that the heuristic used here assigns groups of travellers to evacuation instruction sets based on a stochastic procedure in order to iteratively improve the evacuation instructions. As a
consequence, the evacuation instructions found through applying this framework are, in most cases, likely not optimal (though highly efficient). Their efficiency however does approach optimality as the number of iterations increases. Also, the non-optimality due to the stochasticity in the procedure can be relaxed (up to a certain limit) by applying sufficient iterations and starting from different initial solutions, while the non-optimality due to the grouping of travellers can be relaxed by decreasing the group size.

This breaking apart of groups occurs also once we allow for partial compliance, as a share of the travellers belonging to a certain group then may divert to different departure times or routes (and destinations). This may principally allow for (slightly) more efficient evacuations in case of (slightly) less than full compliance. The effect of breaking apart of groups in case of partial compliance predicts that within early iterations, when evacuation instructions are likely still relatively far from optimal, higher evacuation efficiencies are found for the partial compliance levels compared to the full compliance level. This is due to (a larger share of) travellers not complying and thereby resolving some of the remaining flaws in the (clearly not yet optimal) evacuation plans, as they divert from the congested evacuation routes to under-utilized alternative routes. This mechanism has been mentioned in Section 5.2 and is indeed seen in the case study presented next.

![Figure 5.1: Optimization framework](image)

5.4 Case study

5.4.1 Case study description

In the following application of the evacuation model, we illustrate the impact of partial compliance behaviour on evacuation efficiency, in case the instructions are based on the full compliance assumption. Also, the impact of anticipating this partial compliance level is shown, and how this reduces the (negative) impact of travellers’ partial compliance. To this end, we will use the evacuation of the Walcheren peninsula as a case study. In this section, the considered case is briefly described.
The Walcheren peninsula is situated in the south-western part of the Netherlands. The population of approximately 120,000 inhabitants (excluding the few residential areas with less than 500 inhabitants) is largely concentrated in the two cities of Middelburg and Vlissingen, both clearly indicated on the map provided in Figure 5.2. Given the setting of the area, evacuation due to coastal flooding can be considered conceivable. Indeed, several programs on national and regional level have been initiated over the past years, dealing with the preparation for a possible flood. The flooding scenario determines the evacuation process characteristics in terms of warning time, scale of evacuation, safe destinations, possible network degradation, etc. Here, we choose a setting in which the available time to evacuate before the flood occurs is critical for complete evacuation, namely 8 hours. After 8 hours, further evacuation is considered no longer possible. It is assumed that everyone prefers to depart within these 8 hours where the departure time preferences follow the sigmoid curve pictured in Figure 5.3 (given by (3.2) with parameters $\alpha := 1.5$, and $h := 4$). Note that the realized departure times are determined by the interaction between travellers’ preferred departure times, instructed departure times, and travellers’ level of compliance, as discussed in Section 3.2. The designated exiting routes are a double lane motorway, and three single lane provincial roads in east and northeast direction, indicated in Figure 5.2. The road network used in the analysis consists of motorways, provincial and urban arterials, and collector roads, leading to 146 links and 61 nodes, including 23 origins and 4 safe destinations (i.e., exit points).
Figure 5.3: Preferred departure profile; green solid graph shows cumulative departures [travellers], and blue dash-dotted graph shows departure rate [travellers/hour]

5.4.2 Experimental setup

The case study consists of two related parts, both showing the relevance of incorporating travellers’ compliance behaviour in evacuation optimization. First, the (negative) impact of partial traveller compliance on the evacuation efficiency is shown when the instructions are optimized under the assumption of full compliance. Evacuation instructions that are optimized based on the assumption of full compliance are typically reported as an upper bound on evacuation efficiency. Here, the impact on evacuation efficiency is looked at when applying such optimized instructions while accounting for travellers’ (partial) compliance behaviour. To this end, first, evacuation instructions are optimized assuming full compliance, after which these instructions are applied to evacuation scenarios in which travellers’ compliance level is systematically varied. The impact of these variations in compliance levels on the evacuation operations and efficiency is then analysed.

Second, the (positive) gain in evacuation efficiency is shown when instructions are applied that anticipate the partial traveller compliance. The optimization framework described earlier allows searching for optimal instructions while anticipating on any traveller compliance level. This is done by iteratively searching for optimal instructions while simulating (the predicted level of) travellers’ compliance towards these instructions. The evacuation efficiency gotten from applying instructions that anticipate this partial
traveller compliance behaviour is compared with that from instructions assuming full compliance (i.e., not anticipating the predicted partial compliance level). First, evacuation instructions are optimized that anticipate a specific traveller compliance level. Then, the evacuation efficiency resulting from these instructions is compared against the efficiency resulting from the optimized instructions for full compliance that are applied to the scenario of the same specific traveller compliance level.

In the following analysis, the evacuation efficiency is maximized as computed by (5.1), where we set $\beta := 0.1$. The optimization framework and algorithm are implemented in Matlab (alongside with the evacuation model running in Matlab). Applying a time step of 30 seconds and group size of 200 travellers (resulting in about 380 groups), CPU running times on a Windows XP driven 2.2 GHz processor range from approximately 10 to 60 seconds for evaluating a single evacuation plan (with CPU time for the optimization algorithm to construct the plan being less than one second, and for the communication overhead being negligible). Evacuation instructions and compliance levels that lead to less congested road network conditions and shorter evacuation times result in lower CPU times, due to the way in which the traffic simulation model is implemented (and the fact that the simulation terminates once all travellers have either reached a safe destination or no longer have the possibility to do so). Also, full compliance leads to slightly lower CPU times since route flow rates do not need to be updated during the traffic flow propagation procedure (since travellers will not deviate from their route). Generally speaking, CPU times and memory usage are linearly proportional to the number of unique instruction sets that are assigned to traveller groups, since most link and node variables are computed and stored for groups of travellers with the same prescribed departure time or route.

To find efficient instruction sets for lower compliance levels, typically fewer iterations of the optimization routine are required, compared to higher compliance levels. This is because the remaining flaws in these evacuation plans are partially remedied by travellers deviating to different departure times or alternative routes (and destinations). The results presented next are obtained after 72 hours of computation, equivalent to the evaluation of approximately 30,000 possible evacuation plans for the full compliance setting (presented in Section 5.5) and 5,000 possible evacuation plans for each of the settings anticipating partial compliance (presented in Section 5.6).

### 5.5 Impact of full compliance assumption

#### 5.5.1 Analysis setup

In the following analysis, we investigate the impact of compliance behaviour towards departure time decisions, and towards destination and route decisions. Departure time choice compliance is modelled by a fixed compliance rate, according to (3.1) in Section 3.2.1. Here, we vary this compliance fraction between $\eta = 1$ and $\eta = 0$, thereby modelling the circumstances of full compliance, no compliance, and intermediate states of partial
compliance. Next, route choice compliance (implying destination choice compliance) is modelled by the minimum relative gain for travellers to deviate from the instructed route to an alternative route (with possibly another destination). This minimum relative gain, modelled by $\omega$ in (3.7) in Section 3.2.2, is varied between $\omega=\infty$ and $\omega=0$, thereby again leading to the circumstances of full compliance, no compliance, and intermediate partial compliance.

5.5.2 Numerical results

Deploying instructions, which are optimized under the assumption of full compliance, to the case of partial compliance, has a clear impact on the evacuation efficiency and number of arrivals. The effect of partial compliance towards the dedicated departure times (while fully complying with the instructed routes) is shown in Figures 5.4 and 5.5. These figures present the evacuation efficiency, respectively the number of arrivals, when applying the optimized instructions to a number of different compliance levels. The alternative case, showing the effect of partial compliance towards the dedicated destinations and routes (while fully complying with the instructed departure times) is plotted in Figures 5.6 and 5.7. Again, the evacuation efficiency and number of arrivals is shown for the optimized instructions (under the assumption of full compliance) being applied to a number of different traveller compliance levels. In all cases, a share of the travellers is not able to evacuate on time before the hazard causes the network to become inaccessible and the evacuation to come to a halt.

![Figure 5.4: Evacuation efficiency for instructions optimized on full compliance, tested for departure time compliance](image-url)
Figure 5.5: Arrivals for instructions optimized on full compliance, tested for departure time compliance

Considering the effect of departure time compliance, as expected, a lower compliance level has a larger negative impact on the evacuation efficiency and number of arrivals than a higher compliance level. The observed impact that the level of compliance has on the number of arrivals is similar to that on the evacuation efficiency, for which is optimized. Starting at full compliance and slowly moving over intermediate partial compliance levels to no compliance, both show a first gradual decrease followed by a stronger and growing decrease. The transition point, from where the efficiency/arrivals begins to be more affected by a further decreasing level of departure time compliance, lies around 40 to 50 per cent of the travellers complying. Before explaining the reason for this, let us first consider what happens in the two different cases of partial departure time compliance with full route compliance, and partial route compliance with full departure time compliance.

The optimized instructions maximize the weighted arrival rates. Maximum arrival rates are accomplished when all the evacuation routes are optimally utilized throughout the evacuation, including routes which are relatively slow because of, for instance, lower speed limits or larger route lengths. Basically, a route is optimally utilized when either a decrease or increase in the traffic flow that is assigned to this route would yield lower arrival rates. Lower arrival rates are due to under-utilization of the route when decreasing the route flow, while it is due to the onset of congestion, caused by over-saturated traffic conditions, when increasing the traffic flow assigned to a route. The consequence of travellers’ partial compliance is a combination of under-utilization and over-saturation, thereby reducing arrival rates and hence evacuation efficiency. However, the difference is that partial compliance with departure time instructions leads to all evacuation routes being under-utilized at the start of the evacuation, and being over-saturated later on. This
is due to the peaked dynamic travel demand, since with lower departure time compliance levels it more closely replicates the preferred departure profile (here following the sigmoid curve, shown in Figure 5.3). Another important factor is the assumption of full compliance towards the dedicated evacuation routes. Consequently, once a route become congested, the traffic congestion can easily spread throughout the network over time. On the other hand, partial compliance with destination and route instructions leads to some evacuation routes being under-utilized, while other routes are over-saturated. That is, travellers who are instructed to follow the slower (less attractive) evacuation routes now divert to the faster (more attractive) evacuation routes – thus moving away from system optimality, also discussed in Section 4.5. These faster evacuation routes are already critically loaded. Hence, this additional traffic flow results in over-saturated conditions. However, in the latter case, rerouting behaviour (which is now done by those travellers who choose not to comply) may limit queue spillback and confine the congested traffic conditions.

The latter is indeed seen from Figures 5.6 and 5.7, showing that the impact of partial compliance towards the destination and route instructions is much smaller. Another interesting observation, which may appear paradoxical, is the non-monotonicity of the impact of travellers’ level of route compliance. Starting again at full compliance and slowly moving over intermediate partial compliance levels to no compliance, both the graphs showing the evacuation efficiency and number of arrivals illustrate a direct and (relatively) strong decrease as soon as the compliance is not complete, followed by a slow incline, and a transition point after which the efficiency/arrivals gradually decline again. Recall that routes are expected to be best utilized when the optimized instructions are fully complied with. When the route compliance is slightly less than full, almost all (but not all) travellers comply. What is meant is, that the incentive to comply (the inverse of travellers’ minimum relative gain before deciding to deviate from the instructed evacuation route) is so high that the circumstances leading to rerouting are rare. This has two consequences. First, the travellers who will reroute (i.e., not comply, and deviate from their dedicated evacuation route) will be those initially assigned to a relatively slow (and hence unattractive from an individual’s point of view) route now deviating to a faster (and hence more attractive) route. However, most likely, congestion will set in on this faster route almost immediately since the traffic flow on this route was already critical (as it was ‘optimally utilized’). Second, and more important, as the incentive to deviate is still high, the travellers originally on this faster route, that has now become congested, are unlikely to reroute. The result is that the congested conditions can easily spill back and spread throughout the road network. Now, the size as to which these queues can spill back and spread depend on how soon the travellers on this (dedicated) evacuation route start to reroute. Basically, the sooner travellers will reroute, once congestion arises and spreads, the better. Hence, the increase in evacuation efficiency and number of arrivals when further lowering the level of route compliance (after the initial drop). At a certain level of compliance, this positive rerouting effect of a lower level of compliance is outweighed by the negative effect of more and more travellers deviating from their (optimal) dedicated evacuation route. This transition point, in this case study, lies at travellers expressing a minimum relative gain of 1.5 times the prevailing travel time, which appears fairly high.
Although the occurrence of such a transition point is most likely general, the location of this point along the compliance level spectrum depends, not only on the instructions (i.e., the dedicated evacuation routes) and road network topology (i.e., the alternative
routes), but also on the level of available traffic information. The exact effect of traffic information is, however, difficult to predict, since there are two mechanisms at work. The transition point lies where the benefits of more rerouting – corresponding to the lower compliance level – are outweighed by the costs of less travellers following the (optimized) evacuation plan, and vice versa in the direction of less rerouting. The actual benefits of rerouting however depend on how travellers reroute, which is largely dependent on the availability of traffic information. As elaborated in Section 4.5, better informed rerouting can in some cases increase the evacuation efficiency, and thus shift the transition point to a lower compliance level, while in other cases it can decrease the evacuation efficiency, and shift the transition point to a higher compliance level.

### 5.6 Impact of anticipating partial compliance

#### 5.6.1 Analysis setup

In the following analysis, evacuation instructions are optimized that anticipate a specific traveller compliance behaviour. The efficiency resulting from these instructions is then compared against the evacuation efficiency resulting from the optimized instructions for full compliance that are applied to the scenario of the same specific traveller compliance level. This is done for a higher and lower level of traveller compliance, represented by the parameter values $\eta = 0.7$ and $\omega = 0.5$ (high compliance level), respectively $\eta = 0.3$ and $\omega = 0.1$ (low compliance level). The impact of anticipating travellers’ partial compliance on the evacuation operations and efficiency is then analysed. For brevity, instructions that are optimized for the case of full compliance are denoted by OI-full. Likewise, OI-high denotes instructions optimized on the high compliance level, and OI-low denotes the optimal instructions in case of the low compliance level.

#### 5.6.2 Numerical results

In Section 5.5, it was shown how the evacuation efficiency decreases when travellers only partially comply with the instructions that are optimized under the assumption of full compliance (OI-full). The predicted traveller compliance behaviour may be anticipated while searching for optimal instructions. This leads to higher evacuation efficiency than when instructions are applied which are optimized based on full compliance, shown in Table 5.1, presenting the evacuation efficiency as computed by (5.1) for the various cases. A number of findings is made here. First of all, it holds by definition that, regardless of the compliance level, evacuation efficiency never decreases when partial traveller compliance behaviour is anticipated. This is also seen in the results here. Second of all, the increase of evacuation efficiency by anticipating the compliance level is larger in case of lower compliance levels than for higher compliance levels. This appears to be related to the fact that, for non-anticipating instructions, the impact of compliance level on evacuation efficiency is non-linear, where lower compliance levels lead to a more than proportionate
Chapter 5. Optimal Evacuation Instructions and the Role of Traveller Compliance 113

decrease in evacuation efficiency. Hence, since the negative impact of lower compliance levels is larger, also the positive impact of anticipating these lower levels of compliance can be larger. Third of all, the evacuation efficiency following from a scenario of low compliance where the instructions do anticipate hereon is higher than that in case of high compliance in combination with instructions not anticipating hereon. These three findings underline the relevance and potential of anticipating traveller compliance behaviour.

Apart from these findings, two other observations can be made. First of all, evacuation efficiency resulting from optimized instructions anticipating a specific compliance level cannot increase upon lowering the compliance level. This holds by definition. However, the evacuation efficiency may (in some cases) increase upon raising the compliance level. In other words, the compliance level that maximizes the evacuation efficiency that can be gotten from a set of evacuation instructions might be higher than the compliance level that this set of instructions is optimized on (but, to repeat, never lower). In our application, this is the case for OI-low (and, in general, is more likely to occur for instructions optimized on lower levels of compliance, since these place the largest restrictions on the ability to instruct, which are then relaxed once these instructions are applied under the conditions of a higher compliance level). Second of all, although not explicitly tested here, the results shown in Table 5.1 suggest that evacuation instructions which are optimized for lower compliance levels might be less sensitive to variations in traveller compliance levels. This shows from the fact that OI-high and OI-low outperform OI-full when either is applied to the case of low compliance, respectively high compliance behaviour.

Table 5.1: Evacuation efficiency for instructions that are optimized for full, high, and low compliance and applied to the cases of partial traveller compliance level. High compliance level: $\eta := 0.7$, $\omega := 0.5$; low compliance level: $\eta := 0.3$, $\omega := 0.1$.

<table>
<thead>
<tr>
<th>optimized for</th>
<th>applied to</th>
<th>high compliance</th>
<th>low compliance</th>
</tr>
</thead>
<tbody>
<tr>
<td>full compliance</td>
<td>77,754</td>
<td>73,411</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(110,340)</td>
<td>(108,468)</td>
<td></td>
</tr>
<tr>
<td>high compliance</td>
<td>81,428</td>
<td>76,080</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(114,598)</td>
<td>(112,406)</td>
<td></td>
</tr>
<tr>
<td>low compliance</td>
<td>80,817</td>
<td>80,437</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(112,780)</td>
<td>(114,852)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Values in table report the evacuation efficiency as computed by Formula (5.1). Values between parentheses report the number of successful arrivals. For instance, when applying instructions that are optimized for full compliance to the scenario of high compliance, then the efficiency of these instructions equals 77,754 while the number of arrivals equals 110,340 travellers.
Figure 5.8: Cumulative departures (upper lines) and arrivals (lower lines) for case of high compliance level: red solid, OI-high; green dashed, OI-full

Figure 5.9: Relationship arrival rates – travel productions – network accumulation for case of high compliance level: red solid, OI-high; green dashed, OI-full
Figure 5.10: Cumulative departures (upper lines) and arrivals (lower lines) for case of low compliance level: red solid, OI-low; green dashed, OI-full

Figure 5.11: Relationship arrival rates – travel productions – network accumulation for case of low compliance level: red solid, OI-low; green dashed, OI-full
The (differences in) traffic conditions for the different instructions and compliance levels are shown in Figures 5.8-5.11. The evolution of the total cumulative number of travellers that have departed from any one of the origins and that have arrived at any one of the safe destinations is plotted in Figures 5.8 and 5.10, for the level of high compliance, respectively low compliance behaviour. The relationship between arrival rates, travel productions, and network accumulations (thus depicting the macroscopic fundamental relation) is plotted in Figures 5.9 and 5.11, for the high compliance level, respectively low compliance level. Travel production denotes the distance that all travellers together travel within a specific time interval (set here as one minute). Network accumulation is the network-wide traffic load. Instructions leading to higher arrival rates at equal network accumulation are then to be preferred, in the sense that the way in which the (same amount of) traffic utilizes the network supply results in higher arrival rates.

For high compliance, the gain in evacuation efficiency for optimized instructions that anticipate the compliance level is primarily due to the (different) dedicated destinations and routes. This is seen from the fact that both instruction sets lead to a similar departure time profile (Figure 5.8), yet the ‘anticipating’ instructions yield higher arrival rates. These instructions anticipating partial compliance guide traffic flows more efficiently such that higher travel productions and arrival rates are maintained with similar network accumulation (Figure 5.9).

For low compliance, the larger evacuation efficiency in case of anticipating hereon is mostly because of the (different) instructed departure times. Anticipating the low traveller compliance level leads to instructing (possibly other) travellers to depart earlier than they would do otherwise (Figure 5.10). The larger departure rates at the start of the evacuation lead to larger network outflow rates in the first few hours of the evacuation. Instructing these travellers to evacuate earlier not only increases the evacuation efficiency, but also limits the network accumulation later on (since these travellers move out of the peak). This is seen from the domains on which network accumulation are observed in Figure 5.11. The arrival rate as a function of network accumulation is levelled off equivalently for both the instructions optimized for full compliance and low compliance, thereby showing that the instructions on destination and route choice play only a minor role here.

5.7 Discussion and practical implications

The role of traveller compliance behaviour has been tested regarding its impact on the evacuation process and network conditions for the cases of applying instructions that are optimized based on the assumption of full compliance and instructions that are optimized while accounting for partial traveller compliance. The results are presented in the previous sections. Here, we highlight the main findings from the Walcheren case study and discuss how these are useful for evacuation planning studies in general.

- With instructions that are optimized under the assumption of full compliance, the impact of partial compliance with the instructed departure times on the evacuation
efficiency is monotonic, however non-linear. That is, lower partial compliance, as compared to higher partial compliance levels, yields ‘more-than-proportional’ reduction in efficiency. For the Walcheren case, a decrease in traveller compliance from full compliance to 40-50 % compliance reduces the evacuation efficiency by 6 %, while a further decrease in travellers’ compliance from 40-50 % to no compliance reduces the efficiency by an additional 20 %. This non-linearity is explained as being inherent to the nature of road network performance, and thus holds is general. Although the exact relation between compliance and efficiency depends on the setting – in particular the distribution of travellers’ preferred departure times. As the impact of traveller departure time compliance is relatively large and non-linear, it is strongly advised that an evacuation strategy focuses on the adequate mobilization of the public and monitoring of the dynamic travel demand.

• With instructions that are optimized under the assumption of full compliance, the impact of partial compliance with the instructed destinations and routes on the evacuation efficiency is non-monotonic. Here, full compliance (where all travellers strictly follow their optimal route) yields the best results, followed by intermediate levels of partial compliance (where a number of travellers deviates to faster routes, leading to more congestion, however the spread of the congestion is limited by more rerouting), while worse results are gotten from the cases of very low compliance (where all travellers simply follow their preferred route to their preferred destination) and very high compliance (where a number of travellers deviates to faster routes, leading to more congestion, while at the same time this congestion can easily spread as most travellers mainly follow their dedicated route and rerouting is limited). For the case of Walcheren, the relative reduction in evacuation efficiency – compared to full compliance – for the case of intermediate compliance (as travellers express a minimum relative gain of 1.5 times the prevailing travel time) equals 3 %, while the reduction for the case of no compliance equals 4 %, and the reduction for the case of high compliance (as travellers express a minimum relative gain of 4 times the prevailing travel time) equals 7 %. Given the non-monotonic relation of the impact of partial compliance with the instructed destinations and routes, the following two recommendations can be made. First, prioritize the compliance of certain groups of travellers or at certain intersections. The impact of partial or non-compliance will differ across travellers and intersections where travellers choose to comply or not. Hence, these different impacts can be identified, and those groups of travellers or intersections where the partial or non-compliance leads to a larger negative impact on the evacuation efficiency should be more closely monitored with respect to their compliance. Second, traffic flows – and hence (the impact of) compliance – can be monitored during the evacuation, and instructions can be adjusted accordingly. The way instructions are to be adjusted is evidently not trivial and most likely requires an evacuation model, such as the one presented in this thesis, to be embedded in a decision support system for traffic management.
• When applying instructions that are optimized under the assumption of full traveller compliance, the impact of partial compliance behaviour is a reduction in the evacuation efficiency. At the same time, in case of partial traveller compliance behaviour, instructions which account for this are to be preferred as evacuation efficiency never decreases compared to deploying instructions optimized based on the full compliance assumption. Moreover, the benefits of such instructions are expected to be relatively large, in particular in case of low traveller compliance. In the Walcheren case study, accounting for partial compliance leads to 4% to 10% higher evacuation efficiency (and 2% to 6% more successful evacuations). Furthermore, the evacuation following from a scenario of low compliance with instructions which do anticipate on this partial compliance outperforms (by 4% higher efficiency and more successful evacuations) that in case of high compliance with instructions which do not anticipate hereon (but instead are based on full compliance). Therefore, it is strongly recommended to account for the (predicted) partial traveller compliance behaviour while designing evacuation instructions.

• Continuing on the previous finding – the compliance level that maximizes the evacuation efficiency that can be gotten from a set of evacuation instructions might be higher than the compliance level that this set of instructions is optimized on (but never lower). In the case study and in general this is more likely to occur for instructions optimized on lower levels of compliance, since these place the largest restrictions on the ability to instruct, which are then relaxed once these instructions are applied under the conditions of a higher compliance level. Therefore, upon predicting the traveller compliance behaviour to optimize on, a more conservative guess is to be preferred.

• Continuing on the previous finding – the gain in evacuation efficiency (and the number of successful evacuations) is for high compliance levels primarily due to the instructed destinations and routes, while being primarily due to the instructed departure times in case of low compliance. This means that in evacuation planning focus should firstly lie on ensuring a minimum level of compliance towards the instructed departure times, such that the dynamic travel demand is adequately distributed and peaks are avoided as much as possible. Secondly, focus should shift to ensuring a higher level of compliance towards the instructed destinations and routes, such that the traffic is well guided over the available evacuation routes.

5.8 Concluding remarks

Earlier studies on optimal evacuation instructions often assume full compliance, while the discussion on evacuation behaviour in Section 2.3 shows that this assumption is most likely inappropriate, as in practice a share of travellers will not comply. Therefore, the current chapter generalizes the design of optimal evacuation instructions to incorporate travellers’ compliance behaviour. First, the impact of partial compliance is illustrated for instructions which are optimized under the full compliance assumption. Second, the
impact of designing instructions which anticipate the level of partial compliance is shown. The case study results are presented and a number of findings are generalized as to their implications for evacuation planning studies in general.

The experimental setup chosen in the second part of this chapter aims at designing evacuation instructions which anticipate specific traveller compliance behaviour. That is, the efficiency of evacuation instructions was maximized for a single compliance level. The evacuation model and optimization framework used in this chapter are also applicable to designing optimal instructions which anticipate uncertain traveller compliance behaviour. Possible evacuation plans can then in the same fashion be constructed and tested against all likely traveller compliance levels, and a value for evacuation efficiency is computed by the weighted sum of the efficiencies for the individual levels. These weights may then, for instance, represent the predicted probability that the specific traveller compliance level is expressed (probabilistic approach), or more weight can be placed on traveller compliance levels leading to the lowest evacuation efficiency (robust approach). The latter was done in a study by Huibregtse et al. (2011) using the same evacuation model and optimization framework as in this chapter to design the evacuation instructions which maximize the minimum efficiency that is to be gotten from any likely level of partial traveller compliance.

The research on optimal evacuation instructions which account for the role of traveller compliance can be extended in a number of ways. As pointed out earlier, the model parameters describing compliance behaviour are influenced by the travellers’ willingness to comply and the authority’s enforcement to control. Hence, the authority can optimize the evacuation by deploying evacuation instructions and by enforcement to which the evacuees respond in their choice behaviour. By the latter we can discriminate the effect of giving discretionary advice (e.g., route guidance via road-side or overhead information panels) and mandatory orders (e.g., applying police force and road blocks to regulate the evacuating traffic flows). Within the application presented in this chapter, the focus was on optimizing evacuation instructions while anticipating a constant compliance (enforcement) level. This is a very straightforward approach, considering the more elaborate studies that can be done in this direction. Three extensions can be easily thought of. First, bivariate optimization. The desired level of enforcement, corresponding to a certain level of compliance, is then endogenously determined by the trade-off between the estimated costs associated with investing in ensuring a higher level of compliance on the one hand, and the benefits associated with the results from this higher compliance level (predicted by the evacuation model) on the other hand. This evidently requires a sufficiently accurate estimation of the costs of deploying different types of instructions, as well as a judgement on how the benefits hereof in terms of, for instance, a larger share of travellers being saved, or a lower evacuation time, can be monetized in order to find the optimal trade-off. Second, this line of research can be extended by allowing the desired enforcement level to be different at different locations and at different times. This makes sense as the benefits obtained from a higher compliance level as well as the costs of ensuring this higher compliance level will most likely differ across different locations and
times. Third, the optimization approach can incorporate the authority’s budget, in the sense that the amount of control measures that can be deployed to obtain the desired compliance is limited. The overall framework then ideally endogenously determines the best way to deploy the available police force, mobile information panels, road blocks, and all else that may help in instructing travellers on their evacuation.
Chapter 6

Synthesis, Implications, and Future Research Directions

Chapter 1 introduced the scope of this thesis, discussing the potential benefits of applying transportation models to evacuation planning studies, after which each subsequent chapter logically continued on the previous. Chapter 2 reviewed (observed) evacuation behaviour and its link with current practices in evacuation modelling. Chapter 3 used this literature overview while developing, implementing and testing a new evacuation model, relaxing some of the previously identified limitations. Subsequently, Chapter 4 applied the model to a sensitivity analysis on an evacuation plan for the road network of the Dutch city of Rotterdam. Finally, Chapter 5 embedded the model in an iterative optimization framework to study optimal evacuation planning and the impact of (anticipating) travellers’ response.

The purpose of this final chapter is threefold, elaborated in three sections. First, the thesis research is summarized from the perspective of its main contributions to evacuation modelling and planning studies. Second, the implications of the findings of the thesis are discussed. Third, the overall research approach and findings are reflected upon, leading to recommendations for future research directions.
6.1 Synthesis and main findings

This thesis deals with the development, potential role, and application of transportation models in evacuation planning studies. The theme is approached from different directions within the subsequent chapters, going from a literature review on evacuation behaviour and current modelling practices, to the development of a new model, to the testing and application of this model in a planning environment. The way in which the research discussed in the individual chapters fits together was set out in Section 1.3, and throughout the thesis briefly stated at the start of each chapter. Here, we recapitulate and synthesize the thesis research from a wider perspective, thereby focusing on its relevance to the fields of evacuation modelling and planning. The following discussion is thus structured around a number of contributions that can be attributed to the work in this thesis.

Rerouting and traffic information

Unanticipated conditions – from a traveller perspective – due to traffic control measures, the surge in travel demand, and possible impacts of the hazard on the road network will yield rerouting behaviour. This is logically deduced and empirically supported in Chapter 2. In the same chapter, the review of current assignment techniques shows the adequacy of hybrid route choice models to properly capture this rerouting behaviour. The principle and implementation of the hybrid route choice model is effectively established in this thesis, in Chapter 3. In short, the dynamic network loading procedure is executed only once (instead of many times within an iterative or incremental traffic flow convergence framework, commonly yielding a user-equilibrium assignment). Within this one-time execution of the dynamic network loading procedure (i.e., the traffic simulation), the impact of the prevailing available traffic information and road network dynamics are incorporated by combining pre-trip route assignment and en-route route switching, hence the term hybrid route choice modelling. In the pre-trip assignment, travellers are assigned to the prescribed evacuation routes to the prescribed safe destinations (coming from an evacuation plan). While en-route, travellers can decide to switch routes to any of the safe destinations, thereby responding to the information they receive about the changing (traffic) conditions (but not anticipating these conditions, as otherwise assumed by a user-equilibrium assignment).

The model characteristics of the hybrid route choice model are shown to give face-valid results, in the test example at the end of Chapter 3. The relevance of incorporating this rerouting behaviour is clear from the case study in Chapter 4, as well as from work done by Huibregtse et al. (2010, 2011) which exploits the model developed here and its unique advantageous flexibility towards road network dynamics. In the Rotterdam case study discussed in Chapter 4, the role of rerouting behaviour is endogenously tested by systematically varying the traffic information level (while it is analysed by variations in the hazard conditions in the studies by Huibregtse et al.). Two network-wide phenomena are observed. First, the level of traffic information does not strictly correlate with the network performance. Making more (accurate) information available generally improves the network performance, as it enables travellers to make better travel decisions, yielding
substantially less congestion and lower travel times. However, providing more (accurate) information than a reasonably high level causes the network performance to worsen. This is explained through the principle of system optimality. Second, the impact of traffic information on the overall evacuation time is relatively small. This is because the latter is predominantly determined by the capacity of the bottlenecks upstream of the network exit points. Traffic information is thus found to be an adequate measure to control the network-wide traffic conditions, as well as facilitate in travellers’ wish to be informed (as elaborated in Section 2.3).

In conclusion, the newly developed, implemented, and tested evacuation model and its applications strongly advance the understanding of the role of rerouting behaviour and network dynamics and how these can be adequately incorporated into evacuation models.

**Traveller compliance and optimal evacuation planning**

That the full compliance assumption is inappropriate is argued and empirically supported in Chapter 2. In that same chapter, as well as in Chapter 5, a literature review shows that travellers’ compliance behaviour and its impact on the performance of an evacuation plan is nevertheless seldom studied. The work in this thesis is a substantial contribution to this important factor in evacuation planning. The model developed in Chapter 3 formulates the departure time, destination and route decisions by travellers as the explicit trade-off that travellers make between complying with the prescribed travel behaviour (coming from the evacuation instructions) and following their preferred travel behaviour (i.e., the travel decisions that would be made in absence of an active evacuation plan). For the departure time choice, the level of compliance is here modelled exogenously (though in previous studies an endogenous approach was chosen, see Pel et al. 2008). For the destination and route choice, compliance behaviour is modelled endogenously by the hybrid route choice model and incorporation of an additional attribute representing the possible disutility that travellers associate with non-compliance. This approach enables modelling travellers’ full compliance, no compliance, and any intermediate state. This advantageous ability is unique to the evacuation model developed here in this thesis.

The impact of partial traveller compliance towards non-optimal instructions (derived from ‘common sense’) is non-linear and strongly dependent on the instructions that are given. At the same time, this impact is non-monotonic. A higher compliance level does not necessarily yield better traffic conditions or faster evacuation, and vice versa. This is due to the fact that the non-optimal evacuation instructions likely contain some ‘flaws’, which are then partially remedied when a share of travellers does not comply. This is shown in the Rotterdam case study in Chapter 4. Nevertheless, deploying evacuation instructions can substantially improve traffic conditions. Even instructions generated from straightforward rules, such as those considered here, yield a substantial reduction in traffic congestion and delay times.

On the other hand, partial traveller compliance towards optimized instructions (derived from a mathematical optimization heuristic) shows a different pattern, as discussed in the Walcheren application in Chapter 5. With respect to departure time compliance, partial
Transportation Modelling for Regional Evacuations

Compliance yields a monotonically decreasing network performance, while for destination and route compliance this relation is non-monotonic. In short, non-compliance with the instructed departure times leads to a more peaked demand leading to wide-spread congestion. Generally speaking, any further decrease in compliance level then further deteriorates network performance. We explain how this relation is non-linear, where lower compliance leads to ‘more-than-proportional’ reduction in evacuation efficiency. In the other case of non-compliance with the instructed evacuation routes, this leads to a spatial shift in travel demand, where some routes get congested while longer and less attractive routes (from a traveller’s perspective) are under-utilized. In short, full compliance (where all travellers strictly follow their optimal route) yields the best results, followed by intermediate levels of partial compliance (where a number of travellers deviates to faster routes, leading to more congestion, however the spread of the congestion is limited by more rerouting), while worse results are gotten from the cases of very low compliance (where all travellers simply follow their preferred route to their preferred destination) and very high compliance (where a number of travellers deviates to faster routes, leading to more congestion, while at the same time this congestion can easily spread as most travellers mainly follow their dedicated route and rerouting is limited). The location of these local minima and maxima in evacuation efficiency along the compliance level spectrum depends, not only on the instructions (i.e., the instructed routes) and road network topology (i.e., the alternative routes), but also on the level of available traffic information.

Optimal instructions that account for travellers’ partial compliance behaviour are to be preferred, as these improve the efficiency of the evacuation plan substantially. This is illustrated in Chapter 5. The beneficial increase in evacuation efficiency following from instructions which anticipate partial compliance appear to be larger in case of a lower compliance level. This likely relates to the fact that, for non-anticipating instructions, the impact of compliance level is non-linear, where lower compliance levels lead to a more than proportionate decrease in evacuation efficiency. Moreover, the evacuation efficiency following from the scenario of low traveller compliance with the use instructions which do anticipate hereon, is higher than that in case of high traveller compliance with instructions which do not anticipate hereon. These findings underline the relevance and potential of anticipating travellers’ compliance behaviour.

The research work done in this thesis provides a thorough understanding of the impact of travellers’ compliance behaviour on the performance of an evacuation plan, as well as the ability to design optimal evacuation instructions which anticipate partial compliance.

Factor sensitivity

Ideally, one chooses a model structure and mathematical formulation based on observed evacuation behaviour, checks its face-validity on synthetic test cases, and then calibrates and validates the model outcomes against real-life data. Many of the transportation models used in evacuation studies are not adequately validated in this sense – or are only validated against regular daily traffic conditions – and the proposed model in Chapter 3 is no
exception. There are basically two complementary approaches to address this validation problem, pointed out in Section 3.5. First, the limited amount of available evacuation-specific data can be appended with observations describing traveller behaviour in sufficiently equivalent conditions. The review on traveller behaviour in Chapter 2 indeed includes observations on, for example, route guidance and rerouting behaviour due to large-scale incidents on the road. Second, this validation problem can be anticipated by formulating the model structure and parameters such that these have a clear behavioural interpretation. This enables – with appropriate caution – exploratory simulations where model input and parameter settings are based on expert judgment or non-quantitative literature. The model formulation and applications in Chapters 3 and 4, respectively, are indeed along this line.

The structure and formulation of the model developed in Chapter 3 is strongly based on the literature review of observed traveller behaviour as well as modelling practices and their suitability (Chapter 2). Next, the newly-introduced model characteristics relating to travellers’ information and compliance are shown to produce face-valid results on a test network. Eventually, the consequences of possible errors between predicted values for model parameters and input on the one hand and the actual travel behaviour which these represent on the other, is further understood by the outcomes of the sensitivity analysis on these parameter and input values, as done in Chapter 4.

Factors relating to the departure rates and route flow rates are most sensitive. These have a substantial and non-linear impact, as faster response (i.e., higher departure rates) and better traffic information do not necessarily yield a faster evacuation. The former is due to the fact that an over-saturated network has a lower capacity, while the latter is due to the selfish and unilateral nature of travellers’ route choice behaviour. Factors resulting in a higher travel demand (i.e., an increase in trip generation or a more peaked departure profile) or lower network supply (i.e., a decrease in road capacity) have a negative impact on the traffic conditions and evacuation process. It is shown and discussed how this relation is non-symmetrical, where variations of the same magnitude (but in the reverse direction) yield increases in congestion level and travel times that are substantially larger than corresponding decreases in congestion level and travel times. At the same time, the magnitude of the impact from variations in these factors differs. The impact on the level of traffic congestion and travel times is many times higher than on the overall evacuation time. This means that these demand and supply variations make a large impact on the road network conditions, yet a relatively much smaller impact of the evacuation progress. Finally, the factor of free speeds is not sensitive at all, when disregarding its indirect effects on road capacity and the probability on traffic accidents. The free speeds may have a slight effect on route choice and exit choice behaviour, but this effect will most often be too small to have an overall effect on the evacuation traffic conditions. That is, congestion is likely to predominantly determine the evacuation time.

The analysis done in this thesis provides knowledge on the impact of variations in a number of travel demand and network supply factors, and hence on the consequences of possible errors in the parameter values and model input which are intended to represent
travellers’ behaviour during an evacuation. This insight into the sensitivity of different factors is helpful upon the process of model calibration and validation. Those factors that prove more sensitive are preferably calibrated and validated more precisely as remaining errors in these factors have larger relative impact on the model outcomes. Also, this insight helps when designing an evacuation plan. Plans which prove to be robust towards those factors which are uncertain, are to be preferred (see also next section).

6.2 Research implications

The evacuation model developed in this thesis, in Chapter 3, is applied in two case studies, both relating to evacuation planning. The Rotterdam case study (Chapter 4) evaluates the impact of variations in a number of travel demand and network supply factors. The Walcheren case study (Chapter 5) assesses the role of traveller compliance on optimal evacuation plans, and how evacuation plans can be optimized such that these anticipate the predicted traveller compliance behaviour. The findings from these studies have a number of (practical) implications for evacuation planning studies. These are discussed in Sections 4.9 and 5.7, respectively. Here, we highlight the main research implications from these model applications.

- The deterioration of network conditions – by traffic congestion and large delay times – causes further deterioration, and tends to be substantially larger than the improvement of network conditions due to antagonistic changes in the same underlying factors. Network-wide traffic conditions hence deserve attention. These can be improved by:
  - Controlling the travel demand, thereby ensuring that the dynamic travel demand is adequately distributed over time, such that it does not exceed the network (outflow) capacity. This could be done by instructing travellers on their departure times.
  - Extending the network supply, e.g., by opening peak lanes and hard shoulders, or applying contraflow operations.
  - Enabling better use of the available network supply, e.g., by providing traffic information – which at the same time meets travellers’ wish to be informed – or by instructing travellers on their destinations and routes.

- The evacuation progress – represented by the arrival rates and determining the overall evacuation time – is determined by the capacity of the bottlenecks upstream of the network exit points. Therefore, to accelerate the evacuation, the capacity of the determining bottlenecks directly upstream of the network exit points needs to be increased. This could be done by, e.g., applying ramp metering or contraflow operations.

- Controlling free speeds is advisable as this potentially reduces traffic breakdowns and accidents, while its direct impact on the traffic conditions and the evacuation
process is negligible.

- Providing traffic information is recommended as it facilitates in travellers’ wish to be informed. However, for an efficient evacuation, it is recommended to rely on an evacuation plan which instructs travellers on their departure times, destinations, and routes.

- When adopting an evacuation plan, the role and impact of traveller compliance behaviour is always to be incorporated, particularly considering the following:
  - When the instructions are not optimized (e.g., generated from ‘common sense rules’), intermediate to reasonably high levels of traveller compliance yield the best results, and should hence be aimed at.
  - When the instructions are optimized upon the assumption of full traveller compliance, it is strongly recommended that the implementation of the plan focuses on the adequate mobilization of the public and monitoring of the dynamic travel demand – as the impact of departure time compliance is relatively large and non-linear. At the same time, with respect to ensuring travellers’ compliance with the instructed destinations and routes, two recommendations are made. First, it is advised to prioritize the control of the compliance of those groups of travellers or at those intersections where the partial or non-compliance would otherwise lead to the largest impact on the evacuation efficiency. Second, it is advised to monitor traffic flows during the evacuation and adjust instructions accordingly – the latter by using an evacuation model, such as the one presented in this thesis, embedded in a decision support system for traffic management.
  - When the instructions are optimized accounting for the predicted partial traveller compliance, a more conservative guess on the compliance level is to be preferred. Upon implementation, focus should firstly lie on ensuring (a minimum level of) compliance towards the instructed departure times, such that the dynamic travel demand is adequately distributed. Second, focus should be on ensuring (a higher level of) compliance towards the instructed destinations and routes, such that traffic is well guided over the available evacuation routes.

- When designing an evacuation plan, it is strongly recommended to account for the (predicted) partial traveller compliance behaviour when optimizing the evacuation instructions.

### 6.3 Future research directions

One of the outcomes that almost any research will yield is that as the initial research questions are answered, new questions emerge. Along this line, a number of the findings
and conclusions from this thesis suggest potential future studies. These are identified and elaborated on within the previous chapters, and here briefly recapitulated.

- The synthesis on travel demand modelling practices (Section 2.4) suggests that the predictive power of the repeated binary logit model can be improved by estimating these models not on the dynamically prevailing conditions at the time instant that the decision is made, but on the dynamically predicted conditions. Where, as a proxy for these predicted conditions, the recently-past conditions that led up to the moment of the decision could be used.

- In the discussion on trip chaining due to household interactions (Sections 2.4 and 2.6), where car drivers pick up other household members to collectively evacuate, it is recommended to investigate the impact of intra-household communication and traffic information on drivers rerouting en-route to switch pick-ups by using the hybrid route choice model. It is suggested to let drivers’ rerouting decisions to be determined by minimizing not their individual generalized route costs, but the household generalized costs comprised of the (weighted) sum of the individual route costs of all drivers belonging to the household. This way pick-ups (and order and switches herein) are determined by the prevailing traffic conditions as perceived (collectively) by the drivers of a household.

- The review on the limited amount of research into evacuation destination choice (Section 2.5) and their largely common data source urges for more research in this direction. In this future research, it is recommended to use a dynamic modelling approach as this allows capturing the time-dependent destination availability, prevailing travel times, and prevailing risk threat on the routes towards these destinations.

- The review of literature on empirical observations of traffic volumes on different evacuation routes (Section 2.6) shows that future research is needed on identifying the route attributes which play a role in travellers’ route decisions. Related to this, more research is needed to identify the explanatory factors determining travellers’ willingness to comply with evacuation instructions (Section 3.1).

- Based on the findings from the sensitivity analysis in the Rotterdam case study (Sections 4.4 and 4.5), future research is recommended to extend the analysis to evaluate the impacts of cross-variations and cross-sensitivities in the considered travel demand and network supply factors. Here, cross-variations relate to, for instance, how changes in road capacity due to dynamic traffic management measures correlate with changes in route flow rates due to traffic information, while cross-sensitivities relate to, for instance, the combined impact of reducing departure rates and increasing road capacity.

- Travellers’ compliance is determined by their willingness to comply as well as the authority’s efforts in enforcing compliance (Section 5.7). Future research into evacuation plan optimization is suggested to look into estimating and incorporating the costs associated with enforcing compliance. This would allow endogenously
determining the optimal compliance level, where the costs of ensuring this level of compliance are justified by the benefits hereof. Subsequently, the optimization problem is to be extended to allow compliance levels to vary across time and network-location, as well as to account for the authority’s budget, in the sense that the amount of control measures that can be deployed to obtain the desired compliance is limited.

Within the past decade or so, there has been a substantial boost in research activity related to evacuation modelling and planning. The aforementioned potential future studies are derived from the synthesis and discussion of the contributions made in recent research and those contributions made in this thesis. Alongside these more specific research recommendations, in the ensuing of this section, we elaborate on a number of potential future research avenues from the wider perspective on the topic of this thesis, and propose a number of general directions for the research stream of evacuation modelling and planning. These are grouped as those directions aimed at understanding evacuation decision making behaviour, validating evacuation models, methodologically advancing evacuation models, and improving the use of models in evacuation studies.

A note can be made here on the first two directions, relating to evacuation decision making behaviour and the calibration and validation of evacuation models. The majority of the transportation models which are nowadays used in evacuation planning studies are not focused on a specific hazard (e.g., earthquake, flood, or hurricane), but instead aim to model the general travel behaviour during any such kind of disaster (see Section 2.2). Upon furthering the understanding of evacuation decision making behaviour and the calibration and validation of evacuation models, it might prove necessary to distinguish between different types of hazards, as it may show that each of these types of hazards requires different assumptions, frameworks, and behaviour tools to adequately describe the evacuation process.

**Understanding evacuation decision making behaviour**

An important direction for future research is the (empirical) analysis on how evacuation choice behaviour fits in with current theories on decision making behaviour, particularly decision making under risk and uncertainty. The assumption that travellers’ decisions can be adequately described (at an aggregated level) by expected utility maximization theory, as made in this thesis, may then prove to be less appropriate for evacuation conditions. Alternative theories may be hypothesized and tested, where the assumptions on rational maximization behaviour and utility-driven choice behaviour are relaxed. The former assumption, that travellers’ decisions can be described by a rational maximization of the expected utility, can be relaxed by considering, for instance, (cumulative) prospect theory or regret-minimization theory, where (cumulative) prospect theory incorporates the relativity and subjectivity of the utilities associated with alternatives, while regret-minimization theory incorporates the probability and disutility of choosing a dominated alternative. The latter assumption, that travellers’ decisions can be described by the utilities associated with the various alternatives, can be relaxed by considering decision
making theories where factors such as emotions, habit, and perceptual limitations play a (larger) role (e.g., following the somatic-marker hypothesis by Damasio where emotional processes can guide (or bias) decision making behaviour (Bechara and Damasio 2005)).

Calibrating and validating evacuation models
Transportation models used in evacuation studies would benefit from the calibration and validation of the model parameters relating to both demand (travel choice behaviour) and network performance (driver behaviour) under evacuation conditions. The rarity of mass evacuations prohibits collecting an adequate-sized database on revealed behaviour surveys and historical traffic flow observations (Wilmot et al. 2009). Three complementary approaches to address the validation problem are therefore recommended.

The first approach to the validation problem relates to hypothesizing about evacuation behaviour by making use of observations on traveller behaviour in sufficiently equivalent conditions. These equivalent conditions can be found in less rare and recurring exceptional events, where thus larger historical datasets are typically available. Examples are driving behaviour, and rerouting behaviour – possibly with route guidance – during large-scale incidents, organized parades, and sports, cultural or music events.

A second approach to the validation of evacuation transport models is by making use of synthetic observations coming from, for instance, stated preference surveys (for travel choice behaviour) and a driving simulator (for driver behaviour). Although the uncertainty in the behavioural realism of these observations should always be taken into account – as the conditions under which the travel choice experiment or driving simulator experiment are conducted will differ from real-life evacuation, and hence the expressed behaviour may differ too – nevertheless, findings from such experiments can be helpful to generate hypotheses on evacuation behaviour, and therewith aid model calibration.

A third and final way to deal with model validation is by anticipating the limited amount of data for calibration and validation ends and formulating the model structure and parameters such that these have a clear behavioural interpretation. Subsequently, sufficient exploratory simulations should be conducted where model input and parameter settings are based on expert judgment and non-quantitative literature. This allows for ensuring the face-validity and charting the uncertainty (i.e., stochasticity) of the model outcomes.

Methodologically extending evacuation models
Future research may aim at extending evacuation models by ‘broadening’ or ‘deepening’ the range of processes typically described within these models. A potential way in which evacuation modelling can be ‘broadened’, is by including other modalities, such as public and organized transport, alongside evacuation by car. Necessarily, such a model would incorporate travellers’ mode choice alongside (and possibly simultaneous with) their departure time choice, destination choice, and route choice. This extension will increase the applicability of the model to regions where a large share of the population is carless, or the evacuation plan dictates other modes of transport (e.g., for the sake of efficiency). Multimodal evacuation modelling is certainly not new, nevertheless still underdeveloped.
The few examples tend to be rather over-simplistic and lacking realism regarding the interaction of the various traffic modes on the road network, the representation of travellers’ mode choice, and multimodal trip chaining behaviour.

A potential way to ‘deepen’ evacuation models is by going from a trip-based approach to an activity-based approach. Activity-based modelling in the context of evacuation will mean modelling the process of how evacuees plan, schedule and reschedule activities such as “purchase emergency supplies”, “pick-up household member”, “evacuate area”, “return to safe-guard property”, etc. The main advantage of an activity-based modelling approach is the larger flexibility to include, for instance, the exchange between evacuees of warning and information through social interactions leading to the decision to evacuate (see, e.g., Hasan and Ukkusuri 2011), and the travel patterns due to interaction between household members (see also Bullet 2 in the list at the start of this section).

Enhancing the use of models in evacuation studies

The potential of transportation models in evacuation studies can be advanced – apart from by extending these models, as discussed earlier – by new ways in which these models are deployed. Two such new ways are mentioned here.

First of all, transportation modelling allows to test the sensitivity of an evacuation plan towards variations in model structure, parameters, and input. The results and findings from such sensitivity analyses, such as those elaborated in Chapter 4, can be used in evacuation planning. More specifically, the design of an evacuation plan can be assisted by a model. Iteratively, an alternative plan is postulated, inserted into the model and simulated, the simulation results are assessed, after which the plan may be adapted, and the evaluation starts again. This iterative process can be executed ‘manually’ (such as in the case of the design of the evacuation plan for the Dutch city of Almere, as described in De Jong et al. 2009, and Tu et al. 2010) or within an implemented optimization framework (such as in the case study in Chapter 5). Although the sensitivity of the eventual definite evacuation plan is typically checked in hindsight, this is not necessarily so, nor the preferred way. The sensitivity of an alternative intermediate plan can be checked and the plan can be adjusted accordingly throughout the design process. This yields evacuation plans that are more robust towards possible (uncertain) deviations within those factors that are shown to be most sensitive – that is, sensitive towards deviations between the actual influence of the factor and the factor as it is inserted into the model to represent the expected influence hereof.

Second of all, the research direction of evacuation plan optimization will benefit from a closer consideration of the balanced trade-off between a simpler transportation model formulation which facilitates the optimization process (or even allows for analytically solving the evacuation problem) and a more sophisticated model which extends the problem realism. As stated by Taylor and Freeman (2010), the simplicity of the model should not be achieved at the expense of reliable results and appropriate detail. However, in this context, we can add that model realism (or complexity) is preferably not achieved at the expense of computation time and optimization-ability. Hence, the problem
formulation which allows efficient optimization as well as describes the transportation system with adequate detail is a fruitful future research avenue.
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Appendix A

Traffic Assignment Model Implementation

Note. Chapter 3 gives the conceptual framework and mathematical formulation of the evacuation traffic simulation model EVAQ. For the test example in Section 3.3 and the model applications presented in Chapters 4 and 5 the model is implemented in Matlab. In the following appendix, we elaborate on some model implementation issues, particularly relating to the steps that have been made to solve the proposed destination and route choice model (i.e., traffic assignment model), and provide a step-wise algorithm.

Upon model implementation, first of all, the set of all alternative routes \( Q^n(t) \) is reduced to the set of all relevant routes which are likely to be chosen. Different route set generation models could be considered for this (for an overview see, e.g., Bekhor et al. 2006; Fiorenzo-Catalano 2007). Here, we adopt a stochastic route generation algorithm proposed by Bliemer and Taale (2006) (based on Bovy and Fiorenzo-Catalano 2007). This method applies Monte Carlo (MC) simulations in which the generalized link costs are assumed to be random variables with a mean related to the prevailing instantaneous link costs. In each subsequent MC simulation, the fastest routes from each origin to any of the destinations are determined using Dijkstra’s algorithm (Dijkstra 1959) and added to the route set (given that they show sufficient low overlap with existing routes in the route set). The dynamic route set is generated during the execution of the dynamic network loading model since we consider road infrastructure characteristics to be time-varying. In other words, some routes may be available and attractive during some time intervals, while being unavailable or unattractive during other time intervals.

Second, for the test example presented in Section 3.3 we choose to let the travel time error distributions be specified on link level (following (3.10)), while for the larger-scale applications described in Chapters 4 and 5 we use error distributions on route level.
In route choice modelling, typically the assumptions are made that (i) travellers’ generalized costs of a route consists of the sum of the generalized costs of the links on the route, and (ii) the error term in the generalized link costs – accounting for the subjective unobserved link costs – is the same for all routes using that link (meaning that the generalized costs of a specific link as perceived by a traveller, does not change depending on which route it is used by). This means that when error terms are defined on route level, we need to account for the effect of routes which partially spatially overlap (as these share the same link error term), basically meaning that the error terms are correlated. On the other hand, defining error terms on link level automatically accounts for this effect of spatially overlapping routes. However, the route flow fractions – determined as

$$\Pr\left(c_{pq}(t) \leq c_{pz}(t), \forall z \in Q(t)\right)$$

following (3.6) – then have no closed-form expression which necessitates solving these by means of simulation. A sufficiently large number of independent draws on the link-specific error terms is needed to replicate the error distributions. The route flow fractions then correspond to the relative number of draws in which the specific route $q \in Q(t)$ was the most attractive route compared to all alternative routes. That is, the number of times that $c_{pq}(t) \leq c_{pz}(t), \forall z \in Q(t)$ where $j$ denotes the draw.

To limit the required number of draws, low discrepancy sequences are used. Here the Modified Latin Hypercube Sampling (MLHS) method is applied to generate a sample of $J$ quasi-random draws (see Hess et al. 2005). In case the link travel time error terms are assumed to be identically and independently Normal distributed, i.e., $\varepsilon_a(t) \sim N(0, \sigma_a^2)$, this approach leads to the probit assignment model (Daganzo 1979; Sheffi 1985). Then, to obtain the link error terms, we evaluate the inverse of the cumulative error distribution function at the quasi-random draw $j$, $\lambda^{(j)}_a \in [0,1]$,

$$\varepsilon_a^{(j)} = \Phi^{-1}\left(\lambda^{(j)}_a\right)\sigma_a^2$$

(A.1)

where $\Phi$ is the cumulative distribution function of the standard normal distribution, and $\sigma_a^2$ corrects for the link-specific error variance. Recall that we assume the mean to be zero (no structural bias) and the variance ($\sigma_a^2 > 0$) to be related to the prevailing level of available traffic information. From (A.1) it is directly observable how a larger variance leads to a larger error and hence a larger difference between the actual travel times and the perceived travel times, thus implying a lower traffic information level.

Although the probit assignment technique is the preferred method for the (small-scale) example in Section 3.3, for the larger-scale applications presented in Chapters 4 and 5 we wish to avoid this computationally-intensive simulation-based method. This is possible by using the closed-form multinomial logit (MNL) model, assuming that the route error terms are identically and independently Extreme Value type 1 (Gumbel) distributed. The scale parameter in the MNL model is then related to the variance in the error distributions and thus represents the prevailing level of available traffic information. In this case, a route overlap factor can be included to account for the effect of spatially overlapping routes on the route flow fractions (see, for instance, the pathsize formulation by Ben-Akiva and Bierlaire 1999, or the commonality factor formulation by Cascetta et al. 1996). In the
model applications in Chapters 4 and 5, route fractions are determined by the pathsize logit formulation given by

$$\chi_{pq}(t) = \frac{\exp\left[\mu \tilde{c}_{pq}(t)\right]}{\sum_{z \in Q'(t)} \exp\left[\mu \tilde{c}_{pz}(t)\right]}$$

with

$$\mu = \frac{\pi}{\sigma_q \sqrt{6}}$$

(A.2)

where \(\sigma_q\) is the standard deviation in the Gumbel distributed error terms (assumed equal for all alternative routes), and the deterministic parts of the generalized route costs are computed as

$$\tilde{c}_{pq}(t) = \bar{c}_q(t)\left(1 + \xi_{pq}\omega\right) + \psi_q(t)$$

with

$$\bar{c}_q(t) = \sum_{a \in A} \left[\delta_{aq} \theta_a(t)\right]$$

(A.3)

and where the pathsize component, denoted by \(\psi_q(t)\) and accounting for spatial overlap on link level, is set as the weighted sum of the inverse of the number of alternative routes that overlap with the links on route \(q\) – the weights based on the individual link lengths – thus given by

$$\psi_q(t) = \ln \left[\sum_{a \in A} \left[\delta_{aq} l_{aq}^{-1}\right]\right]$$

with

$$Q'(t) = \{z \in Q'(t) | \delta_{nz} \neq 0\}$$

(A.4)

where \(l_q\) is the route length, computed as \(l_q = \sum_{a \in A} (\delta_{aq} l_{aq})\).

When applying route-based error terms, the relational effect between the level of traffic information and the variance in the error distribution is less directly observable. A larger variance leads to a smaller scale parameter \(\mu\) in (A.2), which – together with the exponential form of (A.2) – reduces the relative differences in the route costs based on the actual travel times, thus simulating the larger difference between actual travel times and perceived travel times corresponding to a lower traffic information level.

Below we present the step-wise algorithm corresponding to the destination and route choice model explained in Section 3.2. Here we use \(P\) to denote the full set of instructed evacuation routes from all origins to all destinations at all departure times, i.e.,

$$P = \bigcup_{r \in R, k \in T} P'(k).$$

**Destination and route choice algorithm**

**Input:** Road network with for each link, prevailing instantaneous travel times, \(\theta_a(t)\), and link lengths, \(l_a\), a set of safe destination, \(S\), and for each node \(n \in N \setminus S\) a choice set with relevant routes, \(Q'(t)\) (here generated using MC simulations and Dijkstra’s algorithm), their overlap with the prescribed routes, \(\xi_{pq}\), \(\forall p \in P, \forall q \in Q'(t)\), and the time instant when routes from this node \(n\) were last updated, \(\tilde{t}^n\).
\textbf{Parameters probit:} number of iterations (draws), J, link error variances, \( \sigma_a \), route updating threshold, \( \tau_{\text{min}} \), and costs of non-compliance, \( \omega \).

\textbf{Parameters logit:} logit scale parameter, \( \mu \) (following from route error variances), route updating threshold, \( \tau_{\text{min}} \), and costs of non-compliance, \( \omega \).

\textbf{Output:} Route fractions \( \chi_{pq}(t) \) for all relevant routes \( q \in Q^u(t) \) from all nodes \( n \in N \setminus S \), for all classes \( p \in P \).

\textbf{Step 1:} Compute node set for route updating, \( \tilde{N}(t) = \{ n \in N \setminus S | \exists q \in Q^u(t), \text{for which } \left( \tau_q(t) - \tau_q(t^*) \right) / \tau_q(t^*) \geq \tau_{\text{min}} \} \).

\textbf{PROBIT ASSIGNMENT:}

\textbf{Step 2:} Set \( j := 1 \). Set \( \chi_{pq}(t) := 0 \), \( \forall p \in P, \forall q \in Q^u(t), \forall n \in \tilde{N}(t) \).

\textbf{Step 3:} Compute (perceived) link travel times \( \theta_a^{(j)}(t) = \theta_a(t) \left( 1 + \left| e_a^{(j)} \right| \right) \), with \( e_a^{(j)} \sim \mathcal{N}(0, \sigma_a^2) \) (here using efficient MLHS draws).

\textbf{Step 4:} For all routes \( q \in Q^u(t) \), from all nodes \( n \in \tilde{N}(t) \), compute the (perceived) travel time, \( \tau_q^{(j)}(t) = \sum_{a \in A} \tilde{\delta}_{aq} \theta_a^{(j)}(t) \).

\textbf{Step 5:} For all routes \( q \in Q^u(t) \), from all nodes \( n \in \tilde{N}(t) \), and for all classes \( p \in P \), compute the travel costs, \( c_{pq}^{(j)}(t) = \tau_q^{(j)}(t) \left( 1 + \xi_{pq} \omega \right) \).

\textbf{Step 6:} For all routes \( q \in Q^u(t) \), from all nodes \( n \in \tilde{N}(t) \), and for all classes \( p \in P \), if \( c_{pq}^{(j)}(t) \leq c_{pc}^{(j)}(t) \), \( \forall z \in Q^u(t) \), then set \( \chi_{pq}(t) := \chi_{pq}(t) + 1 / J \).

\textbf{Step 7:} If \( j = J \), then stop. Otherwise, set \( j := j + 1 \) and continue with Step 3.

\textbf{LOGIT ASSIGNMENT:}

\textbf{Step 2:} For all routes \( q \in Q^u(t) \), from all nodes \( n \in \tilde{N}(t) \), compute the travel time, \( \tau_q(t) = \sum_{a \in A} \tilde{\delta}_{aq} \theta_a(t) \).

\textbf{Step 3:} For all routes \( q \in Q^u(t) \), from all nodes \( n \in \tilde{N}(t) \), and for all classes \( p \in P \), compute the travel costs, \( c_{pq}(t) = \tau_q(t) \left( 1 + \xi_{pq} \omega \right) \).

\textbf{Step 4:} For all routes \( q \in Q^u(t) \), from all nodes \( n \in \tilde{N}(t) \), and for all classes \( p \in P \), compute the route fractions \( \chi_{pq}(t) = \exp \left( \mu c_{pq}(t) \right) / \sum_{q \in Q^u(t)} \exp \left( \mu c_{pc}(t) \right) \).
Appendix B

Evacuation Plan Optimization Heuristic

Note. In Chapter 5, the evacuation model developed in Chapter 3 is used to show how the evacuation efficiency of an optimized evacuation plan depends on the level of travellers’ partial compliance, and how this evacuation efficiency can be maximized when this partial compliance is anticipated. To this end, the evacuation model is embedded within an optimization framework and applied to the case study describing the evacuation planning for the Walcheren peninsula in the Netherlands. In the following appendix, we elaborate on the main characteristics of the optimization heuristic which is used to design these optimized evacuation instructions (anticipating traveller compliance behaviour).

The ant colony based optimization heuristic assigns instructions, regarding departure time, destination and route, to all travellers. In sum, this entails first generating promising instruction sets, where each set consists of a prescribed departure time and route (where the route implies the destination), after which assigning these instruction sets to travellers. The first step of generating instruction sets is only performed once, while the second step of assigning these instruction sets to travellers lies within an iterative procedure executed a large number of times in which each iteration aims at improving the current-best solution, see Figure B.1. In short, Step 1 generates instruction sets, which are then assigned to travellers in Step 2 to form an evacuation plan. The evacuation plan is fed into the model EVAQ and simulated. The model outcomes are used to compute the efficiency of the evacuation plan (according to formula 5.1). Based on how well the evacuation plan performs, a new plan is formulated by re-assigning instruction sets. This new evacuation plan is fed into the model and simulated, to determine its efficiency. And so forth.

The optimization framework and heuristic applied here are used to design optimal evacuation instructions – possibly anticipating traveller compliance – in order to illustrate
the role of traveller compliance behaviour in (optimal) evacuation planning. For this purpose, they do well. However, the drawbacks of this optimization framework are in line with common disadvantages of model-based iterative optimization techniques and relate to the fact that the convergence towards a near-optimal solution tends to be computationally very intensive (depending on the applied heuristic), and no guarantee can be given on finding the optimal solution.

The main concept of each of the steps of generating instruction sets, and assigning these instruction sets to travellers is described in the ensuing. For a detailed description of the optimization method, we refer to Huibregtse et al. (2009) from where the approach was adopted.

![Evacuation plan optimization framework](image)

**Figure B.1: Evacuation plan optimization framework**

**Step 1: Generating instruction sets**

In the first step, instruction sets are generated. Due to dynamic traffic control measures and the hazard’s evolution over time and space, road infrastructure characteristics, such as the speed limit and flow capacity, can be time-dependent. Therefore, different routes will be appropriate for different departure time intervals. For example, a specific route might be an efficient evacuation route at the start of the evacuation, yet become an inappropriate evacuation route once a section becomes inaccessible due to flooding. To take this into account, for each origin we generate multiple route sets, where an individual route set
comprises of routes that are deemed efficient and available within a specific time interval. Available means that travellers departing within the associated departure time interval, \( k \), will safely arrive at their destination via these routes, \( P(k) \), under the condition of an predicted travel time (here, admittedly perhaps too naive, set equal to the travel time under free conditions). Since links become inaccessible at specific time instances (conditional to a certain disaster scenario) we can define route sets on departure time intervals in between the successive failure of two links in the road network. In the application in Chapter 5, these route sets (from all origins to all destinations) are generated using the same route set generation module as implemented in the evacuation model and explained in Appendix A (as the algorithm builds on the model). This way, time-interval specific route sets are generated (where such a route set contains routes from a specific origin to any of the safe destinations), containing departure time and route combinations that serve as possible evacuation instruction sets, and hence can be assigned to travellers. The latter is done in Step 2, described next.

**Step 2: Assigning instruction sets**

The second step assigns all travellers to any of the instruction sets that were generated in the previous step. To ensure practicality, first and foremost regarding computational costs, but arguably also for the real-life implementation of the evacuation instructions, travellers are not assigned individually, but in small groups. For instance, all inhabitants of a neighbourhood receive the same instructions. This is in accordance to current evacuation planning practices in the Netherlands and many other countries (see also the discussion by Lindell and Prater (2007) on so-called emergency response planning areas). Assigning (groups of) travellers to the generated evacuation instruction sets is done based on ant colony optimization. The concept of the procedure is as follows.

All instruction sets have a specific probability of being selected, where all these probabilities for all individual instruction sets belonging to a specific origin sum up to 1 (how these probabilities are computed is explained below). For each of the origins, we randomly select an instruction set – accounting for the selection probabilities – and assign this set to a group of travellers. We continue doing so until all (groups of) travellers have been assigned instructions. This procedure allows the same instruction set to be assigned to multiple groups of travellers, in contrast to the traditional ant colony optimization algorithm. The result is an evacuation plan, consisting of instructions for all travellers regarding departure time and route (implying destination).

In one iteration, multiple evacuation plans are generated (i.e., the arrow in Figure B.1 does not represent a single plan being fed into the model, but say 5 or 10 plans at the same time, which are all simulated and evaluated according to their efficiency). Each of these plans is evaluated using EVAQ, the evacuation model presented in Chapter 3. Applying EVAQ yields dynamic arrival rates, from which the evacuation efficiency is computed according to formula (5.1), for all evacuation plans in the current iteration. The evacuation plan in the current or previous iterations that leads to the highest evacuation efficiency is then selected. This overall-best evacuation plan is used to compute new probabilities of
selecting each of the individual instruction sets in the next iteration. More precisely, the probabilities of selecting the instruction sets which belong to the overall-best evacuation plan (and thus have shown to lead to high evacuation efficiency) are increased. Since all probabilities need to sum up to 1, as a consequence, the selection probabilities for all other instruction sets not belonging to the overall-best evacuation plan are reduced.

The increase and decrease in selection probabilities allows the search heuristic to converge towards the optimal evacuation plan which aims at maximizing the evacuation efficiency. A higher rate of increase/decrease in the selection probabilities over successive iterations, then results in more concentration of the search heuristic and less exploration, and vice versa. The iterative procedure is continued until no further improvement is made over a number of successive iterations or the procedure is terminated.

The initial selection probabilities, used in the first iteration, can be either all equal or based on the characteristics of the instruction sets. The latter is chosen in the following case study, where selection probabilities for instruction sets are initialized based on the earliness of the departure time (favouring earlier departure times) and the free travel time and capacity of the route (favouring lower free travel time and higher capacity).
Summary

Transportation Modelling for Regional Evacuations

The evacuation of a region due to the threat of a man-made or natural hazard is a complex and timely problem. One specific aspect is, planning how to best facilitate the evacuation of the population under threat. These planning studies can be assisted by a transportation model. Such a model, on the one hand, incorporates the effect of all kinds of measures, such as, traveller information systems, staged evacuation, route guidance, traffic control, etc. On the other hand, such a model predicts the evacuation process – i.e., travellers’ evacuation decisions, traffic conditions on the network, the arrival process at the safe destinations, etc. These model outputs then enable assessing alternative evacuation plans, optimising the evacuation plan (from a transportation point of view), and evaluating the robustness of an evacuation plan.

Modelling evacuation behaviour

The model application of regional evacuation planning sets certain requirements to the transportation model which is to be used. That is, the choice behaviour of travellers – regarding their decision to evacuate, when to depart, where to seek refuge, and which route to take – should sufficiently well replicate observed evacuation travel behaviour. Based on a literature review on observed evacuation choice behaviour, it is found that evacuees (once aware of the situation) tend to seek information, assess their personal risk, and make independent decisions. Therefore, the evacuation transportation model should account for dynamic hazard conditions, (traffic) information, and travellers’ compliance behaviour towards warnings, discretionary advice and evacuation orders.

Different travel demand models, destination choice models, and route choice models differ in their ability to adequately describe this behaviour. For a number of these models, recommendations are made for potential future model extensions (for the case they are applied in evacuation planning studies).

Pre-trip and en-route route choice

To describe travellers’ route choice behaviour, a new route choice model is developed. This is done by modelling a one-time dynamic network loading (DNL). Within this one-time execution of the DNL procedure, the impact of traffic information and infrastructure
dynamics are incorporated by combining pre-trip route assignment and en-route route switching. In the pre-trip assignment, travellers are assigned to the prescribed evacuation routes to the prescribed safe destinations (coming from an evacuation plan). While en-route, travellers can decide to switch routes to any of the safe destinations, thereby responding to the changing (traffic) conditions. This way, the realized destination and route decisions are a result of the trade-off that travellers make between complying with the prescribed travel behaviour and following their preferred travel behaviour (i.e., the travel decisions that are made in absence of an active evacuation plan). Travellers’ willingness to comply is then modelled by introducing an additional cost factor which represents the possible disutility associated with non-compliance. This approach allows modelling travellers’ full compliance, no compliance, and any state in between.

**Evacuation plan robustness and optimization**

The transportation model developed, implemented, and tested in this thesis (EVAQ) thus predicts the travel behaviour and traffic conditions in case of an evacuation, while accounting for the effect of traffic information, evacuation instructions, and traffic control measures. EVAQ is then used to quantify the determining (transportation-related) factors for a successful evacuation, and to investigate the role of travellers’ compliance behaviour in (optimal) evacuation planning. The first model application is conducted on the road network of the Dutch city of Rotterdam. A structured sensitivity analysis on the impact of variations in trip generation, departure times, traffic information, traveller compliance, road capacities, and free speeds, led to a number of findings and practical implications. It is shown how the deterioration of network conditions should be avoided by controlling the travel demand, extending the network supply, and enabling better use of the available network supply, by using traffic information and evacuation instructions. Also, it is shown how the evacuation time is determined by the capacity of the bottlenecks directly upstream of the network exit points.

The second model application analysing the role of travellers’ compliance behaviour in (optimal) evacuation planning is done on the road network of the Walcheren peninsula in the Netherlands. To this end, EVAQ is embedded within an optimization framework to heuristically design optimal evacuation instructions. It is shown how the efficiency of a set of evacuation instructions depends on the level of travellers’ partial compliance. Also, this evacuation efficiency can be maximized when this partial compliance is anticipated, and the instructions are adjusted accordingly. The method and application underline the relevance and importance of capturing the compliance behaviour of travellers while deciding on the most suitable evacuation instructions that are to be deployed, as this has a large impact on the evacuation operations.

**New insights on model-based evacuation planning**

Concluding, this thesis is on transportation models in evacuation planning studies. As such, this thesis first deals with evacuation modelling. It synthesises observed evacuation behaviour and the state of the art in evacuation modelling, identifies model requirements and current shortcomings, and provides a practical tool by means of the newly developed
evacuation transportation model EVAQ to assess evacuations and evacuation plans. Second, this thesis deals with model-based evacuation planning. It provides a framework for the model-based optimization of evacuation instructions while incorporating travellers’ compliance behaviour, and makes practical recommendations for evacuation planning.
Samenvatting (Dutch summary)

Transport modelering voor regionale evacuaties

Het evacueren van een gebied dat bedreigd wordt door een ramp – met een natuurlijke of menselijke oorzaak – is een complex en actueel probleem. Eén specifiek aspect hierin is het plannen van de wijze waarop het evacueren van de lokale bevolking het beste gefaciliteerd kan worden. Deze planning kan worden ondersteund door een transportmodel.

Een dergelijk transportmodel modelleert enerzijds de effecten van maatregelen zoals gefaseerde evacuatie, het informeren van reizigers, routegeleiding, verkeersmanagement, et cetera. Anderzijds voorspelt een dergelijk model het evacuatieproces – d.w.z., het keuzegedrag van reizigers, de verkeerscondities op het wegenennetwerk, de aankomst bij veilige bestemmingen, et cetera. Deze modeluitkomsten maken het vervolgens mogelijk om alternatieve evacuatieplannen te vergelijken, een evacuatieplan te optimaliseren (vanuit een transportperspectief) en de robuustheid van een evacuatieplan te onderzoeken.

Modelleren van evacuatiegedrag

Wanneer een transportmodel toegepast wordt voor grootschalige evacuatieplanning dan stelt dit bepaalde eisen aan het model. Het keuzegedrag van reizigers om te evacueren, alsmede hun vertrektijdstip, bestemming en route dienen (in voldoende mate) overeen te komen met eerder geobserveerd evacuatiegedrag. Op basis van een literatuurstudie naar geobserveerd evacuatiekeuzegedrag is gebleken dat evacuees (na zich bewust te zijn van de situatie) op zoek gaan naar informatie, hun persoonlijk risico inschatten en op basis daarvan onafhankelijk besluiten nemen. Daarom dient het evacuatietransportmodel rekening te houden met de effecten van dynamische rampcondities, (verkeers)informatie en de naleving van waarschuwingen, aanbevelingen en evacuatieorders.

Verschillende modellen voor het beschrijven en voorspellen van de vervoersvraag, bestemmingskeuze en routekeuze onderscheiden zich ten aanzien van de mate waarin deze geschikt zijn om dit geobserveerde reizigersgedrag adequaat te beschrijven. Voor een aantal van deze modellen worden aanbevelingen gedaan voor potentiële toekomstige modeluitbereidingen (wanneer toegepast binnen evacuatieplanningstudies).
Pre-trip en en-route routekeuze

Om het routekeuzegedrag van reizigers te beschrijven, is een nieuw routekeuze model ontwikkeld. Hierin wordt het verkeer eenmalig dynamisch toegedeeld aan het netwerk. Binnen deze eenmalige dynamische toedeling wordt het effect van verkeersinformatie en dynamische infrastructuur meegenomen door een combinatie van pre-trip route toedeling en en-route her-routeren. In de pre-trip toedeling worden reizigers toegedeeld aan de voorgeschreven evacuatieroutes naar de voorgeschreven bestemmingen (volgend uit een evacuatieplan). Eenmaal en-route kunnen reizigers van route wijzigen naar elk van de veilige bestemmingen, daarbij reagerend op de veranderende (verkeers)condities. Op deze manier zijn de gerealiseerde routekeuzen het resultaat van de afweging die reizigers maken tussen het naleven van de voorgeschreven routes (en bestemmingen) en het volgen van het geprefereerde reisgedrag (d.w.z. de reiskeuzen die gemaakt worden wanneer er geen evacuatieplan is). De bereidheid tot het naleven van het evacuatieplan wordt dan gemodelleerd door het introduceren van een extra kostenterm die de eventuele kosten van niet-naleven representeert. Met deze aanpak kunnen volledige naleving, geen naleving en alle tussenliggende situaties worden gemodelleerd.

Robuustheid en optimalisatie van evacuatieplannen

Het transportmodel dat ontwikkeld, geïmplementeerd en getest is, voorspelt het reisgedrag en de verkeerscondities tijdens een evacuatie, daarbij rekening houdend met het effect van verkeersinformatie, verkeersmanagement en evacuatie-instructies. Dit model – genaamd EVAQ – is vervolgens toegepast (1) om de maatgevende factoren voor een succesvolle evacuatie te kwantificeren en (2) om de rol van de naleving van het evacuatieplan te bestuderen. De eerste modelapplicatie is uitgevoerd op het Rotterdam-Rijnmond wegennetwerk. Een systematische gevoeligheidsanalyse naar het effect van variaties in de vervoersvraag, vertrektijden, verkeersinformatie, mate van naleving van instructies, wegcapaciteiten en vrije snelheden heeft geleid tot een aantal bevindingen en praktische implicaties. Zo is aangetoond hoe de netwerkcondities op peil gehouden moeten worden door het managen van de vervoersvraag, het uitbreiden van de netwerkcapaciteit en het beter benutten van de bestaande capaciteit door gebruik te maken van verkeersinformatie en evacuatie-instructies. Tevens wordt aangetoond hoe de evacuatieprestatie bepaald wordt door de capaciteit van de knelpunten direct stroomopwaarts van de netwerkuitgangen.

De tweede modelapplicatie die de rol van het naleven van instructies in een (optimale) evacuatieplanning bestudeert, maakt gebruik van het wegennetwerk van het schiereiland Walcheren. Hiervoor is EVAQ geïmplementeerd binnen een optimalisatie raamwerk om op heuristische wijze optimale evacuatie-instructies te bepalen. Zo wordt aangetoond hoe de efficiëntie van een set evacuatie-instructies bepaald wordt door de mate van naleving ervan door reizigers. Daarnaast kan de efficiëntie van een set instructies gemaximaliseerd worden wanneer ganticipeerd wordt op deze partiële naleving ervan en de instructies overeenkomstig aangepast worden. Deze methodiek en modeltoepassing wijzen duidelijk op de relevantie en het belang van het rekening houden met de wijze waarop instructies worden nageleefd.
Nieuwe inzichten in modelgebaseerde evacuatieplanning

Author’s Biography

Adam Pel was born on August 23, 1982 in Rangiora, New Zealand. The first half of his childhood was spent in New Zealand after which he moved to the Netherlands. In 2000, he graduated from high school and started an applied bachelor study Civil Engineering at the Avans Hogeschool in Tilburg. After receiving his BSc. degree in 2004, he switched to the Delft University of Technology for a master study in Transport and Planning. During his master thesis on the modelling of traffic flow operations during an evacuation, he spent three months at the Institute of Transport and Logistics Studies, affiliated to the University of Sydney, Australia. Adam obtained his MSc. degree in September 2007, and received a graduation medal for the innovativeness and excellence in his master thesis research.

In October 2007, Adam started his doctoral research at the Transport and Planning department at Delft University of Technology. His main research topic has been on the (mathematical) formulation of a dynamic traffic assignment model which is qualitatively validated with empirical observations on travellers’ choice behaviour during evacuation conditions as well as applicable to regional evacuation planning studies.

During his doctoral research, Adam was actively involved in education. He acted as daily supervisor for three master theses and one bachelor thesis. Also, he supervised a group of five bachelor students during their one-and-a-half year bachelor honours research project. Within the master course Transportation and Spatial Modelling he acted as instructor and oral examiner for the practical assignment. Within the master course Advanced Transportation Modelling and Network Design he gave multiple lectures on the topics of dynamic traffic assignment, evacuation modelling, and road pricing. Furthermore, he was one of the organizing lecturers in the four-day course Mathematics of Traffic held January 2009 at the TRAIL research school. He gave presentations at post academic courses on advances in traffic modelling, and traffic operations during large-scale events.
Adam spent several months from August 2008 till January 2009 working on a contract research project for the Maritime and Traffic Department (Dienst Scheepvaart en Verkeer) of Rotterdam, The Netherlands. Within this project, the simulation model he developed (EVAQ) was applied to study critical factors in the evacuation planning of the Rotterdam-Rijnmond area.

Adam Pel was one of the initiators and organizers of the 1st International Conference on Evacuation Modelling and Management (ICEM) held October 2009 in Scheveningen, The Netherlands, bringing together over 70 researchers and practitioners for a 3-day conference on the development of theory, models, and simulation tools to explain, predict, and control dynamic traffic flow operations in case of an emergency evacuation. He was one of the keynote speakers, and editor of the conference book published by Elsevier Procedia Engineering containing a high-quality selection of the conference proceedings.

Two special sessions pertaining to emergency evacuation modelling and planning were organised and chaired by Adam, at the 13th IEEE conference on Intelligent Transportation Systems held October 2010 in Madeira, Portugal, and at the 8th IEEE International Conference on Networks, Sensing and Control held April 2011 in Delft, The Netherlands. He acts as referee for more than twenty international journals and conferences.

Adam Pel aspires a continuation of his scientific career in the field of the analysis and modelling of traffic and travel behaviour. To this end, he submitted a research proposal for a personal (Rubicon) grant from the Netherlands Organisation for Scientific Research (NWO) for a postdoctoral study titled: “A resilient road network thanks to travellers’ response behaviour”. He plans to carry out this 2-year research project at the University of Canterbury, New Zealand.
Author’s Publications

The following publications by the author have been published or are under review for publication.

Journal publications


Book chapters

Immovers, L.H. (eds), *New Developments in Transport Planning, Advances in Dynamic Traffic Assignment*, Edward Elgar, Massachusetts, United Kingdom, pp. 293-302


**Editorship**


**Peer-reviewed conference proceedings**

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12th International Conference on Travel Behaviour Research, 13-18 December 2009, Jaipur, India


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Transportation Modelling for Regional Evacuations

Regional evacuation planning is complex and timely. These planning studies can be assisted by a transportation model. In this thesis, we investigate the requirements for such a model, and develop, implement, and test a new model, called EVAQ, which meets these requirements. Two case studies show how EVAQ can be used to assess the success and robustness of an existing evacuation plan, as well as design an optimal plan anticipating uncertainty in traveller compliance behaviour. The analyses yield a number of practical recommendations to improve evacuation planning.

About the Author

Adam Pel received his MSc. degree in Civil Engineering in 2007, after which he continued at the Delft University of Technology for his PhD research. His research focus is dynamic traffic assignment and its applications to evacuation modelling and planning.