Robust model-based optimization of evacuation guidance

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Delft University of Technology, 2013

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Preface

Prior to starting my master's thesis I had never before considered starting a PhD project. However, more than four years ago, when I had nearly finished, I felt that the research into my thesis subject was not finished yet. And so, a PhD-project was started. Now, four years later, this thesis is the result. I would like to take this opportunity to thank the people who have been most important to me during this PhD project.

First of all, I would like to thank my supervisors Serge and Andreas: both of you have contributed a lot by making valuable suggestions, discussing and challenging my ideas and commenting on my work. Andreas, thank you for your involvement, and Serge, thank you for your continuous enthusiasm. Not only did it make me start the project in the first place, it also motivated me during the years.

Of course, it is not all about work, and I have been really glad with my colleagues at the department. Especially, I really liked our group of PhD(-candidate)s and I am happy I have been sharing these years with you. You made this period a really enjoyable time, for which I would like to thank you. Thanks a lot for the chats, laughs, drinks, dinners, ideas, traveling, advises, runs, talks, games, stories, lunches, discussions, gossips, chocolate and friendship!

In 2011, I visited the group of Michel Bierlaire in Lausanne for a three months period. It was a valuable visit, as it resulted in Chapter 5 of this thesis, but above all, I really enjoyed my time there. Most of the 'thanks' for the group in Delft go to the group in Lausanne as well. Michel, thank you for providing me with the opportunity to visit EPFL and for being a member of my defense committee. I would also like to thank Cees Witteveen, Hani Mahmassani, Ira Helsloot and Satish Ukkusuri for being a member of the committee.

Special thanks must go to my parents and Elja, and finally, to you Stijn. Thank you for always being there for me, especially when I needed a little guidance myself.

Olga Huibregtse, January 2013

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Notation

1.	**Functions and constraints**
$B(\mathbf{T},\mathbf{U})$	Function that expresses the turning fractions $\mathbf{B}$ as function of the fixed time-dependent travel times $\mathbf{T}$ and the guidance $\mathbf{U}$ (p. 84)
$C(\mathbf{c})$	Function expressing the fixed-point (p. 88)
$H_1(\mathbf{B}^*, B(\mathbf{T}_A^*, \mathbf{U}))$	Distance function that expresses the difference between the optimal turning fractions $\mathbf{B}^*$ and the turning fractions resulting from the optimal advice $B(\mathbf{T}_A^*, \mathbf{U})$ (p. 88)
$H_2(\mathbf{c}, C(\mathbf{c}))$	Distance function that expresses the difference between the variables transferred between the subproblems of the fixed-point approach (p. 89)
$J(\mathbf{U}, \mathbf{X}_s)$	Objective function expressing the performance as function of the decision variables $\mathbf{U}$ and the states $\mathbf{X}_s$ (p. 10)
$Q(\mathbf{U})$	Function that expresses the link flows $\mathbf{Q}$ as function of the decision variables $\mathbf{U}$ (p. 82)
$T(\mathbf{Q})$	Function that expresses the fixed time-dependent travel times $\mathbf{T}$ as function of the link flows $\mathbf{Q}$ (p. 84)
$\hat{J}(\mathbf{Q}, \mathbf{x}(0))$	Objective function expressing the performance as function of the link flows $\mathbf{Q}$ and the initial state $\mathbf{x}(0))$ (p. 82)
$\phi, \tilde{\phi}, \bar{\phi}, \hat{\phi}, \breve{\phi}$	Equality constraints for the corresponding variables (p. 10)
$\psi, \tilde{\psi}, \bar{\psi}, \hat{\psi}, \breve{\psi}$	Inequality constraints for the corresponding variables (p. 10)
$\tilde{J}(\mathbf{U}, \mathbf{x}_s(0))$	Objective function expressing the performance as function of $\mathbf{U}$ and $\mathbf{x}_s(0)$ (p. 10)
$\tilde{Q}(\mathbf{B})$	Function that expresses the link flows $\mathbf{Q}$ as function of the turning fractions $\mathbf{B}$ (p. 84)
$f(\mathbf{x}_s(t), \mathbf{u}(t))$	Function that expresses the state $\mathbf{x}_s(t+1)$ as function of the state $\mathbf{x}_s(t)$ and the decision variables $\mathbf{u}(t)$ (p. 10)
.	
2.	**Sets and their indices**
A	Directed links indexed by $a \in A$ (p. 8)
A_n^{down}	Links downstream of node n, indexed by $j \in A_n^{\text{down}}$ (p. 15)
A_n^{up}	Links upstream of node n, indexed by $i \in A_n^{\text{up}}$ (p. 15)
A_D	Links directly upstream of the destinations D (p. 25)
D	Destinations indexed by $d \in D$ (p. 9)

$D^{\text{potential}}$	Potential destinations indexed by $d^{\text{potential}} \in D^{\text{potential}}$ (p. 20)
G	Groups indexed by $g \in G$ (p. 40)
K	Departure times, indexed by $k \in K$ (p. 46)
K_{r_e}	Departure times that are part of the elements that belong to r_e (p. 51)
L^{design}	Network design options, indexed by $l^{\text{design}} \in L^{\text{design}}$ (p. 20)
L_l^{link}	Patterns describing the link directions (p. 20)
L_o	Patterns for intersection o, indexed by $l \in L_o$ (p. 16)
M	Class of evacuees, indexed by $m \in M$ (p. 18)
N	Nodes indexed by $n \in N$ (p. 8)
O	Intermediate nodes indexed by $o \in O$ (p. 9)
$O^{\text{intersection}}$	Intersection nodes, i.e. the node between an on-ramp and a highway, indexed by $o^{\text{intersection}} \in O^{\text{intersection}}$ (p. 15)
P	Route set, indexed by $p \in P$ (p. 46)
P_r^{backup}	Origin r specific sets of backup routes (p. 46)
P_r^{overlap}	Origin r specific set of routes with limited overlap (p. 45)
$P_r^{\text{travel time}}$	Origin r specific set of routes with relatively short free flow travel times (p. 45)
P_m	Route set for class m travelers (p. 93)
P_r	Origin r specific route set, indexed by $p \in P_r$ (p. 46)
R	Origins indexed by $r \in R$ (p. 9)
R^{remove}	Origins for which holds that all routes starting in an origin which is part of this set should be removed from the route set (p. 46)
S	Scenarios indexed by $s \in S$ (p. 9)
T	Time instants indexed by $t \in T$ (p. 10)
U_r	Origin r specific search space indexed by $e \in U_r$ (p. 43)
$\mathbb{U}_S$	Search space for the set of scenarios S (p. 74)
$\mathbb{U}_s$	Search space for the decision variables $\mathbf{U}$ depending on scenario s (p. 10)
$\tilde{\mathbb{U}}(\mathbf{T}_A, \mathbf{B})$	Set of guidance derived from the turning fractions B and the travel times $\mathbf{T}$ (p. 85)
$\tilde{\mathbb{U}}^*(\mathbf{T}_A, \mathbf{B})$	Optimized set of guidance derived from the turning fractions B and time-specific travel times $\mathbf{T}_A$ (p. 85)

.

3.	**Parameters**
Δk	Fixed interval between the departure times (p. 43)
Δt	Size of the time step in between the time instants T (p. 23)
$\bar{n}^{\max}$	Number of iterations (p. 45)
χ_1	Weighting parameter for the objective function (p. 41)
χ_2	Compliance parameter (p. 42)
χ_3	Parameter influencing the pheromone trail (p. 50)
χ_4, χ_5	Parameters influencing the heuristic information (p. 51)

χ_6, χ_7	Parameters included in EAS (p. 52)
$\chi_8^{m_*}, \chi_9^{m_*}, \chi_{10}^{m_*}$	Class m_* specific parameters included in the route choice model (p. 93)
$\pi(r)$	Number of routes that can be added to P for origin r (p. 46)
ρ	Parameter influencing the pheromone trail (p. 50)
$\varphi_1^{\max}$	Maximum ratio with respect to the travel times (p. 45)
$\varphi_2^{\max}$	Maximum overlap of the routes (p. 45)
$\varphi_3^{\max}$	Maximum number of routes per origin (p. 46)
ξ	Number of evacuees per vehicle (p. 23)
.	
4.	**Others**
$\mathbf{B}$	Turning fractions (p. 84)
$\mathbf{B}^*$	Optimized turning fractions (p. 85)
$\mathbf{B}^{\text{lower}}, \mathbf{B}^{\text{upper}}$	Lower and upper bounds on the turning fractions respectively (p. 90)
$\mathbf{B}^{\text{pref}}, \mathbf{B}^{\text{adv}}, \mathbf{B}^{\text{real}}$	Preferred, advised, and realized turning fractions respectively (p. 91)
$\mathbf{Q}$	Time-dependent link flows (p. 82)
$\mathbf{Q}^*$	Link flows corresponding to the optimized turning fractions $\mathbf{B}^*$ (p. 85)
$\mathbf{Q}^{\text{in}}, \mathbf{Q}^{\text{out}}$	Time-dependent link in- and outflows respectively (p. 23)
$\mathbf{T}_A$	Time-dependent link travel times (p. 23)
$\mathbf{T}_A^*$	Travel times corresponding to the optimized turning fractions $\mathbf{B}^*$ (p. 85)
$\mathbf{T}_P$	Route travel times (p. 23)
$\mathbf{U}$	Decision variables, guidance (p. 10)
$\mathbf{U}_S^*$	Optimal guidance for the set of scenarios S (p. 74)
$\mathbf{U}_s^*$	Optimal values for the decision variables given scenario s (p. 10)
$\mathbf{U}^{\text{best}}$	Best-so-far guidance (p. 49)
$\mathbf{X}_s^*$	States corresponding to the optimized guidance $\mathbf{U}_s^*$ (p. 74)
$\mathbf{X}_s$	States of the system given scenario s (p. 10)
$\mathbf{Y}^{*(\tilde{n})}$	Optimized turning flows (p. 95)
$\mathbf{Z}_P$	Time-dependent route flows (p. 23)
$\mathbf{c}$	Variables transferred between the subproblems of the fixed-point approach (p. 88)
$\mathbf{u}(t)$	Decision variables at time instant t (p. 10)
$\mathbf{x}_s(0)$	Vector representing the initial state of the system (p. 10)
$\mathbf{x}_s(t)$	State of the system at time instant t (p. 10)
$c_{ij}(t)$	Aggregated compliance on the turn from i to j at t (p. 91)
d_r	Destination for origin r evacuees (p. 18)
e	Element of the search space: a combination of a departure time and a route (p. 43)
h_e	Probability that an ant assigns a group to element e (p. 49)
k^{earliest}	First departure time for the next route set (p. 46)

k_P	Last departure time for route set P (p. 46)
q_a	Flow at link a (p. 15)
$q_a(t)$	Flow at link a at t (p. 15)
$q_a^{\text{in}}(t)$	Inflow at link a at time instant t (p. 15)
$q_a^{\text{out}}(t)$	Outflow of link a at time instant t (p. 23)
$q_{a,d}^{\text{in}}(t)$	Destination d specific inflow at link a at t (p. 15)
$u_p^r(t)$	Fraction of travelers leaving origin r at time instant t advised to follow route p (p. 92)
$u_{g,r}$	Guidance given to group g belonging to origin r (p. 40)
$v_{ij}^o(t)$	Number of vehicles leaving upstream link i and entering downstream link j at time instant $t+1$ (p. 16)
$w_j^r(t)$	Number of vehicles leaving origin r and entering the unique downstream link j at time instant t (p. 16)
w_{kpd}^r	Number of vehicles leaving origin r to destination d at departure time k by route p (p. 18)
w_{kp}^r	Number of vehicles leaving origin r at departure time k by route p (p. 18)
$y_{ij}^{o^{\text{intersection}}}(t)$	Flow from on-ramp i entering the freeway j at entering point $o^{\text{intersection}}$ at time instant t (p. 16)
$z_p(t)$	Flow entering route p at time instant t (p. 23)
$E(N,A)$	Network consisting of nodes N connected by links A (p. 8)
$S_p(t)$	Size variable indicating the overlap between routes (p. 93)
$T^{\text{evacuation}}$	Evacuation time (p. 23)
$V_p^{m_*,\text{adv}}(t)$	Advice-related utility at t (p. 93)
$V_p^{m_*,\text{char}}(t)$	Characteristics-related utility at t (p. 93)
w_{kpd}	Number of evacuees departing at k to destination d by route p (p. 18)
$\Delta\mu_e$	Amount of pheromone deposited on the elements of the best-so-far guidance (p. 50)
$\alpha_j^n(t)$	Splitting rate: fraction of the traffic leaving node n that enters link j at time instant t (p. 16)
$\beta_{ij}^o(t)$	Turning fraction: fraction of the traffic leaving link i that enters link j (p. 16)
δ_l^o	Binary variable indicating whether pattern l is selected for intersection o (1) or not (0) (p. 16)
δ_{ij}^o	Binary variable indicating whether the turn from i to j is allowed for intersection o (1) or not (0) (p. 16)
$\delta^r(t)$	Binary variable indicating whether an instruction is given for origin r to depart at t (1) or not (0) (p. 19)
δ_l^r	Binary variable indicating whether pattern l is selected for the links directly connected to origin r (1) or not (0) (p. 20)
$\delta^{d^{\text{potential}}}$	Binary variable indicating whether the potential destination $d^{\text{potential}}$ is in use as destination d (1) or not (0) (p. 20)

δ_p^{rd}	Binary variable indicating whether the destination d specific demand from origin r is assigned to route p (1) or not (0 (p. 18)
$\delta_{l^{\text{design}}}$	Binary variable indicating whether network design option l^{design} is selected (1) or not (0) (p. 20)
ε_a	Random component for link a (p. 45)
η_e	Heuristic information for element e (p. 49)
γ_k^{rm}	Fraction of demand released at time instant t from origin r and class m (p. 18)
γ_{a^+}	Fraction of the combined original capacity of a^+ and a^- reserved for the flow in the direction a^+ (p. 19)
μ_e	Pheromone trail belonging to element e (p. 49)
ω^m	Proportion of class m travelers considering the advice (p. 93)
$\phi_p^m(t)$	Proportion of class m travelers selecting route p at t (p. 93)
$\tau_a^{\bar{n}}$	Travel time on link a at iteration $\bar{n}$ (p. 45)
τ_a^{free}	Free flow travel time on link a (p. 45)
$\tau_p(t)$	Travel time on route p when entering p at time instant t (p. 23)
$\varphi_2(1,2)$	Overlap between route 1 and route 2 (p. 45)
$\varpi(t)$	Weight at t (p. 25)
ϑ_{p_e}	Information about route p belonging to element e (p. 50)
ζ_{k_e}	Information about departure time k belonging to element e (p. 50)
$\bar{n}$	Iteration which is part of the generation of the search space (p. 45)
$\tilde{n}$	Iteration of the fixed-point approach (p. 88)
$\mathcal{N}(1,\sigma^2)$	Normal distribution with a mean equal to 1 and a variance σ^2 (p. 45)

Chapter 1

Introduction

1.1 Need for evacuation guidance

Large scale disasters such as floods and fires cause many casualties and economical damage. As stated in the World Disaster Report 2011, natural disasters have caused by estimation worldwide 111,030 casualties and 95,955 million dollar of economical damage on average per year over the period 2001-2011 (Knight, 2011). These natural disasters include among others tsunami's, floods, forest fires and storms. Technological disasters, like industrial and transport accidents, have caused by estimation 8,350 casualties and 1,510 million dollar of economical damage on average per year over the same period (Knight, 2011). The risk of disasters is characterized by these large consequences on the one hand, and low probabilities of occurrence on the other hand.

The risk of disasters is managed by risk mitigation. The risk is reduced by decreasing either the probability or the consequences. The probability is decreased by taking preventive measures. Examples are to raise the dikes or to raise the awareness of people about the way they can cause a bush fire. The consequences are reduced for example by building flood-resistant buildings or by preparing evacuation plans. Theoretically, applying a cost-benefit analysis will show the best way of risk mitigation. The effects of all types of risk mitigation are input for the analysis. The results have to be assessed with the utmost care given the risk of losing human life.

This thesis is about evacuation guidance as a way to mitigate the disaster risk. The guidance consists of instructions to the evacuees on when and how to travel over the transportation network, for example which route to take to a safe destination. Evacuating people from the threatened region reduces the casualty risk of the disaster. Guiding the people during this evacuation increases the effectiveness of the evacuation from a system perspective, for example in terms of the time needed to evacuate all people. The first explanation for this increase is that a lack of information about, and a lack of experience with the extreme situation are compensated by the guidance. This prevents for example that people choose a road which becomes impassable because of the disaster. Second, people can be steered in the direction of a system-optimal evacuation, which is needed because individually they would probably choose a route which is the best for themselves instead of the system.

The need for evacuation plans is recognized by the Dutch government. The Netherlands is prone to flooding, both from rivers and the sea. During the last decades, the policy in the Netherlands has been focused on flood prevention. After the disastrous flood of 1953, the government established the Delta committee which had to give advice on how to prevent future floods (Delta committee, 1961). This resulted in a strong system of dams and dikes. However, the focus has recently been expanded: the government established the 'Taskforce Management Overstromingen' which has to prepare the Netherlands for the consequences of floods. As a result, several projects were initiated to prepare the Netherlands on the organizational level, see, for example, Rijkswaterstaat (2010) and Projectgroep Dijkring 14 (2010). However, evacuation planning including traffic management needs further development (Taskforce Management Overstromingen, 2009).

Outside the Netherlands, the traffic management part of evacuation plans has received more attention. The USA uses plans that decrease the consequences of hurricanes by which they are affected practically each year. Usually, evacuation routes are identified and communicated to the public (U.S. Department of Transportation, 2006). The main approach to develop this plan is to select one based on practical or other judgment. Only a few cases use simulation models to evaluate the plans.

1.2 Objective of the thesis

The guidance which is suitable for a specific evacuation case can be selected based on evaluation studies like the ones presented by Hobeika & Kim (1998), Jha et al. (2004), Kolen et al. (2008) and Kolen & Helsloot (2012). In evaluation studies, the effectiveness of multiple predetermined evacuation plans is compared. A more advanced approach is to optimize the guidance. As will be discussed in Chapter 2, evacuation guidance is optimized in literature using several approaches, varying from rule-based approaches to optimization problems for which the global optimum can be found. The attention for uncertainty and compliance behavior is limited in existing optimization methods and the combination of these two elements even has never been incorporated before. This while these factors are of great importance for evaluating guidance in a realistic way.

The evacuation problem contains many uncertainties. For example, in case of a hurricane, the location of the disaster cannot be predicted exactly. Forecast errors in these locations are reported, for example, by Cangialosi & Franklin (2012). This type of uncertainty will influence the region that has to be evacuated. The population that has to be evacuated depends on these dynamics and is therefore uncertain too. If this uncertainty is not incorporated, but the guidance is developed for one specific situation instead, the guidance can be very ineffective if the real situation is not as expected.

Compliance behavior is the way that the population reacts to the guidance, varying from non-compliance to full compliance and everything in between. If this behavior is not incorporated, but full compliance is assumed instead, the real effectiveness of the guidance will probably be lower than expected. This shows that incorporating uncertainty and compliance behavior is important to evaluate possible guidance in a realistic way. If these aspects are not incorporated, the real effectiveness of the guidance will probably be lower than expected, which in the worst case will result in the loss of human life.

Incorporating uncertainty and compliance behavior makes the problem much more difficult and time consuming to solve. The time it costs to develop the guidance should fit the available time to prepare for the evacuation and should therefore be limited as far as possible. Important here is the trade-off between optimality and computational efficiency. Thus, a method is needed that develops guidance in an efficient way.

This brings us to the following research question, which is the central issue of this thesis: *How can evacuation guidance be optimized in an efficient way, while incorporating uncertainty and compliance behavior?*

1.3 Approach

The central research question will be answered by formulating the problem, both descriptive and mathematically, and developing solution approaches to solve this problem. The problem will be solved by a model-based optimization approach. In this optimization approach, simulation models are used to evaluate the effect of guidance. This section elaborates on the characteristics and the scope of the research.

The problem formulations and solution approaches presented in this thesis are generic, meaning that they are flexible with respect to the disaster situation and the corresponding modeling assumptions. It has to be possible to apply the approaches to any type of disaster for which a regional evacuation is desired. The behavior of people depends, among others, on the type of disaster. By making the approaches flexible with regard to the modeling assumptions, the behavioral model that will be included in the approach can be chosen based on the considered disaster.

The generic character makes the work applicable to all kinds of traffic streams characterized by autonomous propagation. Autonomous propagation means that the evacuees make their own decisions on how to travel along the transportation network. This implies that the problem formulations and solution approaches are applicable to the two main evacuation situations: evacuation by private car and pedestrian evacuation. To develop the guidance, models have to be chosen that describe traffic streams of the specific transportation mode. The applications in this thesis are all about private car traffic. In real evacuations, public transport will also play a part which is not described in this thesis. In a combined plan of private and public transport, for example investigated by Abdelgawad et al. (2010), this thesis can be used to guide the share of the people evacuating by private transport.

In this thesis, guidance will be developed for planning purposes. This means that so-called off-line guidance will be developed, which is guidance which is developed before the start of the evacuation. However, the resulting guidance can be extended by so-called online guidance, i.e., guidance which is updated during the evacuation. In this way, the guidance can be updated based on information which is not available before the start of the evacuation. Several methods exist to develop online guidance, see, for example, the method to develop online route guidance presented by Landman et al. (2012). Adding online guidance to off-line guidance has the advantage that the actual situation can be taken into account, which reduces the uncertainty. However, in practice online guidance requires more advanced means regarding the data availability and communication strategies. The availability of these means can be limited during an evacuation.

The evacuation guidance is part of a broader plan, mainly containing communication and operation strategies. Furthermore, the administrative process with respect to evacuations is important as well. The communication strategy deals with the question what the influence of a specific communication strategy is on the evacuation efficiency. Operational issues, of which an overview is given by Wolshon et al. (2005a) and Wolshon et al. (2005b), are, for example, the implementation of traffic measures, the distribution of fuel, and the provisioning of shelters. These issues have a big influence on the evacuation efficiency as turned out, for example, during the evacuation because of Hurricane Rita (Litman, 2006). An overview of evacuation planning and the corresponding administrative processes in the Netherlands is given by Helsloot et al. (2008). The formulations and approaches which will be presented in this thesis result in evacuation guidance. In order to use this guidance in practice, it needs to be combined with communication and operational strategies.

1.4 Scientific contributions

The main scientific contributions are summarized in this section. The information from previous sections is combined with more details from the rest of the thesis in order to make the contributions concrete.

Methodologically, this thesis contributes by presenting *approaches to incorporate compliance behavior and uncertainty in the evacuation problem* and an *approach to solve the evacuation planning problem efficiently*.

The specific contributions regarding the incorporation of compliance behavior and uncertainty are a problem formulation and a solution approach. A formulation of the basic evacuation problem is specified and extended to incorporate respectively compliance behavior and uncertainty. The proposed solution approaches are optimization methodologies that can be used to solve the introduced problems, resulting in optimized evacuation guidance.

The approach to solve the problem efficiently consists of a reformulation of the evacuation problem and a corresponding new and efficient solution approach. This contribution is not limited to the evacuation planning research field. The approach can be applied to optimize route guidance in general and does therefore contribute to the overall traffic management field.

Finally, the thesis contributes by giving *insight into the structure and performance of optimized evacuation guidance*. The solution approaches are used to optimize evacuation guidance, incorporating uncertainty and compliance behavior. This gives information on the structure of optimized guidance, i.e., which routes and departure times are advised and how does this deviate from non-optimized guidance. Furthermore, the optimization gives insight into the benefit of giving optimized guidance in terms of the evacuation efficiency.

1.5 Societal relevance

The methodological contributions and insights discussed in the previous section are of practical relevance. As discussed in Section 1.1, the Dutch government acknowledges the need for evacuation plans. This thesis gives new insights in how beneficial evacuations are and how realistic plans can be designed. These results show that the focus on decreasing the consequences of disasters instead of preventing them holds prospects: proper evacuation guidance does increase the evacuation efficiency.

The proposed problem formulations and solution approaches can be used for the actual development of evacuation plans. Incorporating uncertainty and compliance behavior is important because this enables to evaluate possible guidance in a realistic way, in the end resulting in the saving of human life. The efficiency reduces the time needed to generate the guidance which is important because of time constraints that are often involved in the evacuation issue.

One specific methodological contribution, i.e., the approach to solve the evacuation planning problem efficiently, is also of practical relevance in a wider scope. As mentioned before, the approach can be applied to all route guidance problems in the traffic management field. The approach has great potential and could for example be used in the struggle with the daily traffic jams.

The insights in the structure and performance of optimized evacuation guidance are of great benefit for the design of evacuation guidance in practice. The insights can be used to design the guidance in a direct way or to improve heuristics to design the guidance in an indirect, but automatic, way. An example of such an insight is the effectiveness of specific types of routes like the route with the shortest free flow travel time.

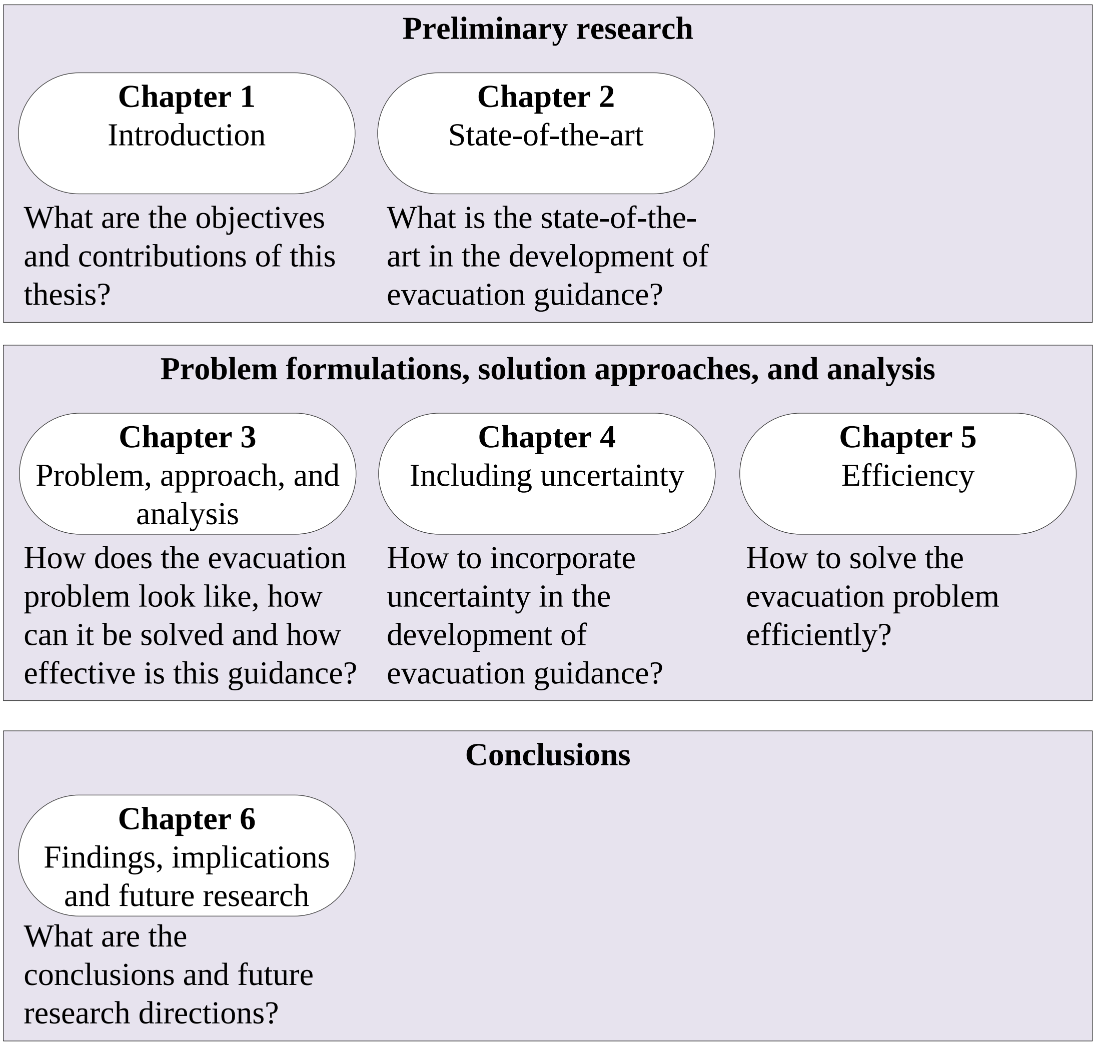


Figure 1.1: Content of each chapter and the relations between these chapters

1.6 Outline

Figure 1.1 gives an overview of the chapters, their relations, and the questions that will be answered in each chapter. Chapter 2 gives an overview of and discusses the methods proposed in literature to influence the evacuation efficiency. The chapter contains a discussion on the research gaps, laying the foundation for the rest of this thesis.

The problem formulation and a solution approach are given in Chapter 3. This problem formulation functions as basic formulation for the subsequent chapters: the formulation will be extended in Chapter 4, and reformulated in Chapter 5. Corresponding solution approaches are introduced in these chapters. Each chapter consists of a methodological part and an illustrative case study. Chapters 3 - 5 focus respectively on the effectiveness of guidance, the incorporation of uncertainty, and the efficiency of the solution approach. The thesis finishes with an overview on the findings, the corresponding conclusions, and their implications in Chapter 6. This chapter elaborates as well on future research directions.

Chapter 2

State-of-the-art evacuation problem formulations and solution approaches

In literature, several methods are proposed that aim to determine plans increasing the evacuation efficiency. This chapter gives an overview of the problem formulations and solution approaches that are part of these methods. The first objective of this chapter is to support the statement made in Chapter 1, i.e., that the attention for uncertainty and compliance behavior is limited in existing methods. This chapter describes the incorporation of these factors in existing approaches in order to accomplish this objective. Second, this chapter aims at giving insight into the parts of existing methods that can be used to fulfill the overall goal of this thesis which is introduced in Chapter 1, i.e., to incorporate uncertainty and compliance behavior in the development of evacuation plans. Therefore, the main characteristics of existing approaches are discussed.

The chapter starts with a generic description of the evacuation process and network in Section 2.1. Section 2.2 gives a generic formulation of the problem which will be used in the remaining sections of this chapter to discuss the existing studies.

A brief overview of the problem formulations and solution approaches proposed in literature is given in Section 2.3. Then, the elements of the problem formulations are further discussed in Sections 2.4 - 2.6. Each section discusses a specific part of the formulation, i.e., the decision variables, the objective function, and the travel behavior and traffic propagation model. Section 2.7 presents the solution approaches. All sections give an overview and discuss the incorporation of uncertainty and behavior as well as the usability of parts of the existing methods to incorporate the mentioned factors in the development of evacuation plans. Section 2.8 connects the discussions of all chapters and gives an overview of the main findings.

Acknowledgment. A journal article with similar contents as this chapter is under review.

2.1 Introduction of the evacuation process and network

This section introduces the evacuation process and network. The evacuation process is aimed to become more efficient as a consequence of the evacuation plan. As discussed in Chapter 1, this process describes the traffic flows on the network and is part of a bigger process that contains communication and operation processes. The evacuation process, which is visualized in Figure 2.1, consists of two parts. The starting point for the first part is the first stage that contains the components that influence the travel behavior, i.e. the network design, the population, the hazard scenario, the traffic situation, and possibly guidance. The network design represents, for example, the capacity of the roads. From the first stage, travel choices are determined by the travel behavior process. These choices describe people's travel choices, i.e., whether to depart, when to depart, the destination, and the route. From this second stage, the traffic flows over the network are determined by the traffic propagation process. The feedback included in the process represents updated travel choices based on other travel choices and traffic flows.

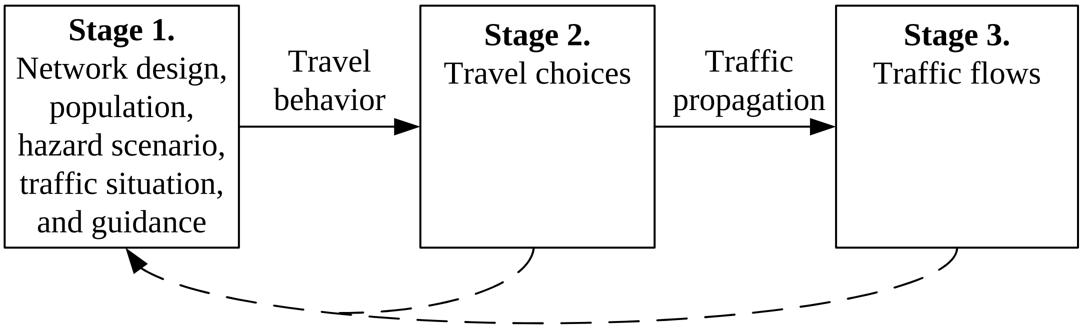


Figure 2.1: The evacuation process

In the evacuation problem, the process is modeled by a *travel behavior model* and a *traffic propagation model*, describing the two sub-processes respectively. In this thesis, the term traffic propagation model refers to any model that describes the propagation of traffic flows over the network. This term differs from the term *traffic flow model*, which is currently used in literature on traffic flow theory. Some traffic flow models describe the propagation on the network, but others are limited to the propagation on a single link. The term traffic propagation model differs from the term *dynamic network loading model* as well, which is a current term in literature related to dynamic traffic assignment models. Dynamic network loading models are time-dependent and consider congestion, while the term traffic propagation model refers to a broader scope of models as explained before.

The evacuees travel over the transportation *network* $E(N,A)$. This network, which is illustrated in Figure 2.2, consists of directed *links* A indexed by $a \in A$ which are connected by *nodes* N which are indexed by $n \in N$. The links represent roads and the nodes represent intersections or interchanges. Three node types exist: *origins* R indexed by

$r \in R$, i.e. the locations from where the evacuees depart, *destinations* D indexed by $d \in D$, i.e. the safe locations that the evacuees have to reach, and *intermediate nodes* O indexed by $o \in O$. In case destination guidance is considered, it is computationally convenient to add an artificial *super destination* such that all destinations can be considered together. The super destination is connected to all destinations by links with zero travel time and infinite capacity.

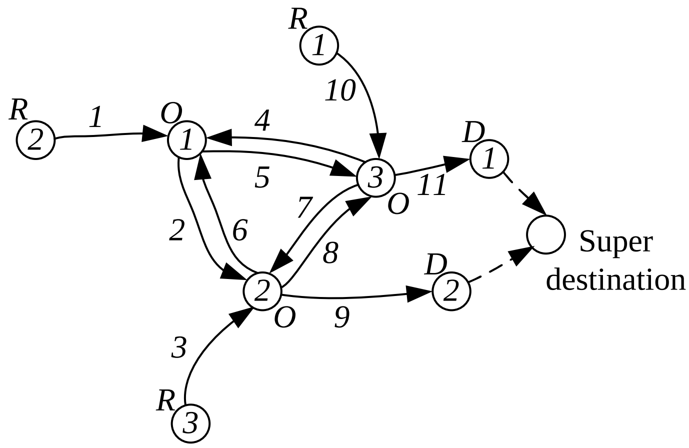


Figure 2.2: Network description: origins, destinations, and intermediate nodes, connected by directed links

2.2 Generic formulation of the evacuation problem

This section gives a generic formulation of the evacuation optimization problem. This formulation will be used throughout this chapter to discuss the formulations proposed in literature.

In operations research terms, a problem formulation consists of *decision variables*, an *objective function* and *constraints*, a structure described for example in Hiller & Lieberman (1990). The problem is to choose the values of the decision variables so as to maximize or minimize the objective function, subject to the constraints. The objective function expresses the performance, e.g. the total travel time, as a function of the decision variables, e.g. the route guidance. The constraints represent restrictions on the values that can be assigned to the decision variables, e.g., the restriction that people starting from the same origin are instructed to follow the same route.

Input like the demand, the network, and the hazard situation is described by a scenario indexed by s. The set S consists of the collection of scenarios that are indexed by s. In the current chapter, only one scenario is considered in the optimization. However, in Chapter 4 a set of scenarios is considered in the optimization representing uncertainty in the input.

According to this terminology, the optimal values for the decision variables given scenario s, $\mathbf{U}_s^*$, follow from the following formulation:

$$\begin{aligned} \mathbf{U}_s^* = \quad & \underset{\mathbf{U}\in\mathbb{U}_s}{\operatorname{argmin}}\, \tilde{J}(\mathbf{U},\mathbf{x}_s(0)), \\ \text{s.t.} \quad & \tilde{\phi}(\mathbf{U}) = 0, \\ & \tilde{\psi}(\mathbf{U}) \leq 0. \end{aligned} \tag{2.1}$$

where $\tilde{\phi}$ and $\tilde{\psi}$ represent equality and inequality constraint vectors respectively, $\mathbb{U}_s$ is the *search space* for the matrix of decision variables $\mathbf{U}$, and the vector $\mathbf{x}_s(0)$ represents the initial state of the system which is assumed to be known. The state contains that information that is essential to determine the future. The concrete interpretation of the state depends on the evacuation process but contains, for example and among other things, the traffic flows. The scalar objective function $\tilde{J}$ expresses the performance as function of $\mathbf{U}$ and $\mathbf{x}_s(0)$ by describing the evacuation process. The formulation is adapted by including this process explicitly, which lays emphasis on this process which is an important part of the evacuation problem. The process is described by a so-called state-space equation which is current in control theory, given here on the assumption of discrete time:

$$\mathbf{x}_s(t+1) = f\Big(\mathbf{x}_s(t),\mathbf{u}(t)\Big), \tag{2.2}$$

where the vector $\mathbf{u}(t)$ represents the decision variables at time instant t and the vector $\mathbf{x}_s(t)$ represents the *state* of the system at t given scenario s. The function f represents the state evolution which expresses the state at t as function of the state and the decision variables at the previous time instant. Including Equation 2.2 in Equation 2.1 gives:

$$\begin{aligned} \mathbf{U}_s^* = \quad & \underset{\mathbf{U}\in\mathbb{U}_s}{\operatorname{argmin}}\, J(\mathbf{U},\mathbf{X}_s), \\ \text{s.t.} \quad & \mathbf{x}_s(t+1) = f\Big(\mathbf{x}_s(t),\mathbf{u}(t)\Big),\ t\in T \\ & \phi(\mathbf{U},\mathbf{X}_s) = 0, \\ & \psi(\mathbf{U},\mathbf{X}_s) \leq 0, \end{aligned} \tag{2.3}$$

The objective function and constraints that are part of Equation 2.1 are replaced because of the explicit function f. The scalar function J expresses the performance as function of both the matrix $\mathbf{U}$, representing the decision variables, and the matrix $\mathbf{X}_s$, representing the states. The matrices $\mathbf{U}$ and $\mathbf{X}_s$ consist of the time-dependent variables $\mathbf{u}(t)$ and $\mathbf{x}_s(t)$ respectively. The vectors ϕ and ψ represent equality and inequality constraint vectors respectively, both on the decision variables and the states. The vector ϕ defines among others the initial state $\mathbf{x}_s(0)$. The set T represents the time horizon which consists of time instants indexed by $t\in T$. The function f and the constraints ϕ and ψ together represent the travel behavior and traffic propagation model.

The next sections discuss the components of this problem formulation as they are presented in literature. In this discussion, the term *complexity* is used. The most common use of this term in the area of optimization problems is the use within the theory of

NP-completeness, mainly founded by Cook (1971). This theory will be discussed in relation to the evacuation problem in Section 3.1.3. Throughout the rest of this thesis, the term complexity refers to the expected computational costs of solving the problem. Usually holds that the more decision variables or constraints are contained in the problem, the higher the costs of solving the problem are.

2.3 Overview of the literature

This section summarizes the problem formulations and solution approaches proposed in literature. It serves as reference for the overall picture in the detailed discussions of the formulations and approaches in Sections 2.4 - 2.7. The overview given in this chapter is complementary to the one given in Hamacher & Tjandra (2002), where network flow problems, like maximum flow problems, are discussed. In these problems, the objective is to find the flows that result in an optimal use of the capacity, with the assumption that the flow does not depend on the density. This chapter discusses the evacuation problem from a wider perspective. For example, the decision variables are not limited to flows, but travel choices and network design are considered as well. Furthermore, approaches that contain all kinds of traffic propagation models are included, including models in which the flow does depend on the density. By including this relation in the model, the dependency between the use of the network and the congestion is considered. This is important for the evacuation problem because it has a big influence on the performance of evacuation plans.

All methods included in the overview are mainly developed for vehicular traffic, except for the method presented by Saadatseresht et al. (2009) which is generic regarding the traffic mode. Methods that focus on other transport modes exist as well. For example, many methods exist to develop pedestrian evacuations plans: for regional evacuations, see e.g. Yamada (1996), but mainly for building evacuations, see e.g. Chalmet et al. (1982), Hamacher & Tufecki (1987), and Balkuli & Smith (1996). These and other methods focusing on non-vehicular traffic modes are not included in the overview. The reason for this is that they do not contain additional information relevant for this thesis, i.e. information on the structure of the methods and the incorporation of behavior and uncertainty, relative to the approaches that focus on vehicular traffic.

Table 2.1 summarizes the overview of formulations and approaches given in this chapter. The following components are included: the decision variables $\mathbf{U}$, the traffic propagation described by f, and the solution approach. The objective function J is not included because the consequence of the concrete objective function is limited for the problem structure as will be explained in Section 2.4.5. The travel behavior process is not included either because this process is hardly included in the existing problem formulations as will be discussed in Section 2.6. The constraints ϕ and ψ are not mentioned separately, but are discussed together with the components when of relevance.

Table 2.1: Overview problem formulations and solution approaches

Publication	**Problem formulation**						**Solution approach**		
	Decision variables			**Traffic propagation**					
	Stage 3: Traffic flows	Stage 2: Travel choices	Stage 1: Network design & guidance	Flow-independent	Linear model	Nonlinear model	Resulting in the global optimum	Metaheuristics	Problem-specific heuristics
Sherali et al. (1991)	x		x			x			x
Tuydes & Ziliaskopoulos (2004)	x		x		x		x		
Kim & Shekhar (2005)			x	x				x	x
Lu et al. (2005)		x		x					x
Liu et al. (2006)	x				x		x		
Sbayti & Mahmassani (2006)		x				x			x
Tuydes & Ziliaskopoulos (2006)	x		x			x		x	
Chiu et al. (2007)	x				x		x		
Liu et al. (2007)	x					x			x
Afshar & Haghani (2008)		x				x			x
Chiu & Mirchandani (2008)		x				x			x
Kim et al. (2008)			x	x					x
Miller-Hooks & Sorrel (2008)	x			x				x	
Abdelgawad & Abdulhai (2009b)		x				x		x	
Baumann & Skutella (2009)	x			x			x		
Dixit & Radwan (2009)	x				x		x		
Kalafatas & Peeta (2009)	x		x		x		x		
Saadatseresht et al. (2009)		x						x	
Stepanov & Smith (2009)		x			x		x		
Yao et al. (2009)	x				x		x		
So & Daganzo (2010)	x			x					x
Xie et al. (2010)	x		x			x		x	
Daganzo & So (2011)	x			x					x
Kimms & Maassen (2011)	x				x		x		
Bretschneider & Kimms (2012)	x		x	x					x

The formulations presented in literature are distinguished by the different interpretations of the elements. Regarding the *decision variables*, the approaches are distinguished by the stage in the evacuation process at which they influence the process. As visualized in Figure 2.3, the decision variables can represent traffic flows, travel choices, network design and guidance. This distinction is important because these different types of decision variables result in different structures of the problem formulations. For example, when the decision variables consist of network design variables, the travel behavior and traffic propagation need to be described such that the traffic flows are known. However, when the decision variables consist of travel choices instead, a travel behavior description is not needed but the traffic propagation description satisfies. Regarding the *traffic propagation model*, the approaches are distinguished by the accuracy of this model. This characteristic is typical for transportation problems in general and influences both the problem complexity and the representation of reality. The more accurate the description is, the more possibilities there are for an accurate representation of reality, but the more complex the problem is as well. This level of detail of the traffic propagation is represented by distinguishing the following types of descriptions, that increase in accuracy: a flow-independent, a linear, and a nonlinear description.

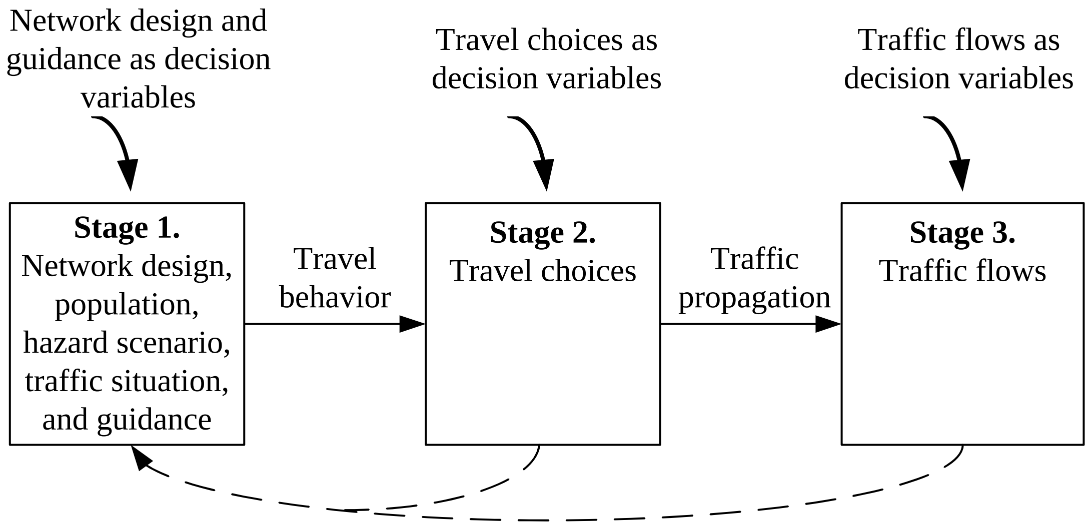


Figure 2.3: Influence of the decision variables on the evacuation process

The methods are distinguished by their *solution approaches* as well. Part of the approaches results in a global optimum, while metaheuristics and problem-specific heuristics result in an approximate solution. The approaches differ in the problems that can be solved: global optima can only be found for relatively simple problems, as will be discussed in Section 3.1.3. As illustrated in Table 2.1, global optima are only searched for when the problem formulation contains a flow-independent or linear descriptions of the traffic propagation. The table gives more insight into the structures of problem formulations. With respect to the decision variables, it shows that the network design variables are in most cases additional to decision variables representing traffic flows and travel behavior. The table shows as well that linear descriptions of the traffic propagation are mainly used in combination with decision variables representing traffic flows. This represents an often used combination in evacuation studies, i.e., turning flows as decision variables combined with a linear cell-transmission model. These variables and model are further explained in Sections 2.4.1 and 2.6.3 respectively. The rest of this chapter elaborates on the details of the problem formulations and solution approaches. The introduced terminology is consistent throughout the thesis. This means that, for example, the locations from where the evacuees depart are called origins, while in literature they may be referred to as sources, origins, and evacuation zones.

2.4 Decision variables

This section distinguishes three categories of decision variables **U**, i.e. traffic flow, travel choice, and input, e.g. network design, related decision variables. They differ in the stage at which they influence the evacuation process as visualized in Figure 2.3 and therefore result in different problem formulations as explained in Section 2.3.

The decision variables can also be distinguished by other criteria, like the operational function as done by Abdelgawad & Abdulhai (2009a). They distinguish contraflow, departure time, traffic signals, and routing. Such a criterion is less insightful for the overview given here which focuses on the structure of problem formulations. For example, both departure time and routing describe travel choices and do therefore result in comparable problem formulations. The details with respect to the problem formulations that are given in this section, e.g. the precise formulations of the decision variables, are not included in the overview given by Abdelgawad & Abdulhai (2009a).

Sections 2.4.1, 2.4.2, and 2.4.3 describe the decision variables related to traffic flows, travel choices, and network design and guidance, respectively. They are described in this order, i.e. from Stage 3 to Stage 1, because the decision variables in Stage 1 are usually complementary to decision variables in Stage 3 as will be discussed in Section 2.4.3. The decision variables are described but mathematical notations are given as well, such that the differences between the decision variables can be clearly stated. In order to make this distinction, the notations differ from **U**, the general notation for decision variables. The search spaces for the decision variables are explained in Section 2.4.4. The decision variables and their characteristics are discussed in Section 2.4.5.

2.4.1 Stage 3: Traffic flows

The decision variables related to traffic flow describe the propagation of traffic over the network. In some approaches, these decision variables are combined with decision variables related to network design. For example, both the turning flows and the capacity of the links are optimized. Section 2.4.3 elaborates on this. Figure 2.4 functions as basis for the discussion on the traffic flow related decision variables. Most of the decision variables describe the propagation of the traffic that is already loaded on the network, while there are also variables describing this loading process. In literature, the decision variables describing the loading process are always additional to decision variables that describe the propagation of already loaded traffic.

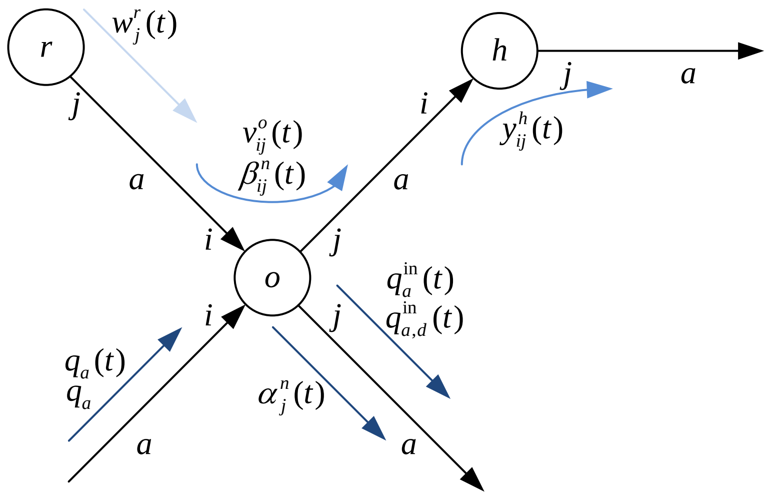


Figure 2.4: Decision variables describing traffic flows

To discuss the traffic flow related decision variables, the network terminology is extended. On node level, the links that are connected to node n are distinguished as *upstream links* A_n^{up}, indexed by $i \in A_n^{\text{up}}$ and *downstream links* A_n^{down}, indexed by $j \in A_n^{\text{up}}$. Furthermore, a new node type is introduced, i.e. the nodes $O^{\text{intersection}}$, indexed by $o^{\text{intersection}} \in O^{\text{intersection}}$, which is an intersection between the on-ramp i and the highway j.

Here, the decision variables that describe the propagation of the loaded traffic are distinguished based on whether they describe how the traffic *splits*, i.e. which downstream link j to enter when leaving node n, or *turns*, i.e. which downstream link j to enter when leaving the upstream link i. The decision variables that describe either turning or splitting movements are discussed together with their characteristics like whether the traffic is origin- or destination-specific.

First, the splitting movements are discussed. The decision variable in Baumann & Skutella (2009) and Bretschneider & Kimms (2012) is the scalar $q_a^{\text{in}}(t), a \in A, t \in T$, which represents the inflow at link a at t. The case study in Liu et al. (2007) contains the destination-specific version of this decision variable, i.e. the scalar $q_{a,d}^{\text{in}}(t), a \in A, d \in D, t \in T$, the inflow at link a at t with destination d. In other studies, the flows are not specific for the inflow, but are constant for the complete link. This holds for the scalar $q_a(t), a \in A, t \in T$, the flow on link a at time t, which is part of the formulation presented by Miller-Hooks & Sorrel (2008). A time-invariant version of this flow is the so-called *steady-state flow* $q_a, a \in A$, the flow at link a (Sherali et al., 1991). All variables introduced so far are flows with the unit of vehicles per unit of time. Contrary, the scalar *splitting rate* $\alpha_j^n(t), n \in N, j \in A_n^{\text{down}}, t \in T$, one of the decision variables in Daganzo & So (2011), represents the fraction of the traffic leaving node n that enters link j at t.

All introduced splitting movements have corresponding turning movements. For example, the variable corresponding to the splitting rate is the *turning fraction* $\beta_{ij}^o(t)$, $o \in O, i \in A_o^{\text{up}}, j \in A_o^{\text{down}}, t \in T$, the fraction of the traffic leaving link i that enters link j at t. This variable is proposed as decision variable by Liu et al. (2007), but it is not part of their problem formulation. The rest of this paragraph is limited to decision variables that are actually part of proposed formulations. The most often used decision variable is $v_{ij}^o(t), o \in O, i \in A_o^{\text{up}}, j \in A_o^{\text{down}}, t \in T$, the number of vehicles leaving upstream link i and entering downstream link j at $t+1$ (Tuydes & Ziliaskopoulos, 2004; Liu et al., 2006; Tuydes & Ziliaskopoulos, 2006; Yao et al., 2009; Dixit & Radwan, 2009; Chiu et al., 2007; Kimms & Maassen, 2011; Xie et al., 2010). In the approach presented in So & Daganzo (2010), which is specific for a network consisting of one freeway with on-ramps, the decision variable is $y_{ij}^{o^{\text{intersection}}}(t), o^{\text{intersection}} \in O^{\text{intersection}}, i \in A_{o^{\text{intersection}}}^{\text{up}}, j \in A_{o^{\text{intersection}}}^{\text{down}}, t \in T$, the flow from on-ramp i entering the freeway j at entering point $o^{\text{intersection}}$ at t. In Daganzo & So (2011), a network of freeways is considered using the decision variables $y_{ij}^{o^{\text{intersection}}}(t)$ and $\alpha_j^n(t)$. The units of $v_{ij}^o(t)$ and $y_{ij}^{o^{\text{intersection}}}(t)$ are vehicles and vehicles per time unit respectively.

Another type of turning related decision variable is presented by Kalafatas & Peeta (2009). At each intersection, at most one turn is allowed for the full time period. This is formulated by the binary decision variable $\delta_{ij}^o, o \in O, i \in A^{\text{up}}, j \in A^{\text{down}}$ indicating whether the turn from i to j is allowed ($\delta_{ij}^o = 1$) or not ($\delta_{ij}^o = 0$). Bretschneider & Kimms (2012) include a similar variable, but instead of allowing one turn per intersection, multiple turns are allowed as long as they are not conflicting. The decision variable is the binary variable $\delta_l^o, o \in O, l \in L_o$, indicating whether the so-called pattern l is selected for intersection o ($\delta_l^o = 1$) or not ($\delta_l^o = 0$). Each pattern contains a selection of turns at an intersection that are not conflicting. This variable sets the possible turns and the flows themselves are set by the $q_a^{\text{in}}(t)$ which is a decision variable in Bretschneider & Kimms (2012) as well as explained earlier in this section.

As mentioned earlier, some of the approaches contain additional decision variables describing the traffic loading. This holds for the approaches presented by Chiu et al. (2007) and Kimms & Maassen (2011), where the additional decision variables are $w_j^r(t), r \in R, t \in T$, the number of vehicles leaving origin r and entering the unique downstream link j at t. The decision variables describing splitting movements, i.e the different types of flows q and the splitting rates $\alpha_j^n(t)$, are all defined for all links in the network. Thus, the traffic loading is described by these variables as well. In Baumann & Skutella (2009) and Bretschneider & Kimms (2012), the traffic loading is decided by the settings of these variables. But in Sherali et al. (1991), Liu et al. (2007), Miller-Hooks & Sorrel (2008), and Daganzo & So (2011), the traffic loading follows directly from the assumed demand.

The difference between splitting and turning movements is not the only difference in traffic flow related decision variables. Part of the differences in the introduced traffic flow related decision variables are the consequence of *functional differences* in the problem formulation. These differences concern whether traffic loading is influenced or not, whether the traffic is destination-specific or not, and the type of nodes included in the network. These functional characteristics can either be enforced by the situation, e.g. traffic loading is not part of the decision variables because there are no means to influence this process in practice, or they can be chosen by the authority, e.g. traffic loading is not considered because the authority believes this process cannot be influenced.

Other differences, i.e. a splitting or a turning decision variable, a discrete or a continuous decision variable, and flows or fractions, influence the *problem complexity* and the *implementation possibilities*. Unlike the distinction made in this section, these differences receive usually little attention because they are not the obvious consequence of functional differences in the problem definition. Instead, these kind of choices are usually made when the problem is solved, consciously or unconsciously of the consequences of these choices. The differences and their consequences are discussed here, except for the difference between discrete and continuous decision variables. This difference holds as well for the decision variables in the other categories and is therefore discussed at once in Section 2.4.5.

A turning decision variable leads to a higher problem complexity than the corresponding splitting decision variable. In case of turning fractions, the upstream link plays a role which results in a higher number of variables and constraints, and because of that, a higher problem complexity. The search space for a splitting decision variable is a subset of the search space for the corresponding turning variable. Namely, when a constraint is added that equalized the turning variables belonging to the same downstream link, the effective search space for this turning decision variable is equal to the search space for the corresponding splitting variable. Considering a turning decision variable instead of the corresponding splitting variable results in probably more, but at least the same, freedom in the optimization and thus a probably higher, but at least equal, effectiveness of the optimal solution.

Whether turning or splitting movements are considered, influences the implementation as well. Measures have to be taken to reproduce the optimal values for the decision variables in practice. The implementation can be of any form: on a local level, for example, by variable message signs, traffic light settings, or ramp metering, or on a network level, for example, by departure time and route guidance. Usually, determining these measures based on the variables is non-unique. For example, multiple combinations of routes can result in the same flows. The extent of this freedom differs over the variables. When the problem is defined with splitting variables or with fractions, the freedom is bigger compared to the case of turning variables or flows respectively.

The choice between flows and fractions influences the solution feasibility and because of that the problem complexity. When the decision variables are equal to flows, infeasible solutions can arise. For example, when a turning flow at a certain node is bigger than 0 but there is no outflow at the corresponding upstream link, the solution is infeasible. This cannot happen in case the decision variables are equal to fractions: when in the same example the turning fraction is bigger than 0, the solution is still feasible.

There are more differences in the decision variables representing traffic flows, i.e. whether the flow is constant over the link or not, and whether the flow is time-dependent or not. This difference influences the model and thus the problem complexity.

2.4.2 Stage 2: Travel choices

The first way to distinguish the decision variables related to travel choices is by a functional difference, i.e. the choice that they represent. The decision variables represent the departure time choice (Abdelgawad & Abdulhai, 2009b), the route choice (Stepanov & Smith, 2009), the destination choice (Saadatseresht et al., 2009), or a combination of those. The combination of departure time, route, and destination choice is applied by Lu et al. (2005), Sbayti & Mahmassani (2006), Afshar & Haghani (2008) and Chiu & Mirchandani (2008). Another functional difference, which was introduced in Section 2.4.1, is whether the traffic is destination-specific, as is the case in Stepanov & Smith (2009), or not. The final distinction is that the decision variables can distinguish evacuation classes as done by Abdelgawad & Abdulhai (2009b). These classes distinguish evacuees, e.g by the level of guidance and information provision to these evacuees.

The same decision variables differ in the corresponding problem structure as well. This is related to the type of decision variable, of which the number of vehicles is the most common type. In Chiu & Mirchandani (2008), the decision variable is equal to the scalar $w^r_{kp}, r \in R, k \in K, p \in P$, the number of vehicles leaving origin r at departure time k by taking route p. The destination of the vehicles is explicitly included by Sbayti & Mahmassani (2006) and Afshar & Haghani (2008) by the scalar decision variable $w^r_{kps}, r \in R, k \in K, p \in P, d \in D$. Lu et al. (2005) express the decision variable in terms of evacuees instead of vehicles, i.e. by the scalar variable $w_{kpd}, k \in K, p \in P, d \in D$, the number of evacuees departing at k to destination d by route p.

Other types of decision variables are used as well. The decision variable in Abdelgawad & Abdulhai (2009b) is the scalar $\gamma^{rm}_k, t \in T, r \in R, m \in M$, the fraction of demand released at time instant t from origin r and class m. When all evacuees from a specific origin are assigned to the same, for example, departure time, numbers or fractions are irrelevant. In Saadatseresht et al. (2009), the decision variable is $d_r, r \in R$, the destination for origin r evacuees. The decision variable in Stepanov & Smith (2009) is $\delta^{rs}_p, r \in R, d \in D$, a binary variable indicating whether destination d specific demand from origin r is assigned to route p ($\delta^{rd}_p = 1$) or not ($\delta^{rd}_p = 0$).

Whether the decision variable is continuous, e.g. a fraction, or discrete, e.g. a number of vehicles, influences the problem structure. In principle, numbers of vehicles are discrete values. However, in Afshar & Haghani (2008), the variable is specified as continuous variable. In the solution approach presented by Sbayti & Mahmassani (2006), the decision variable is treated as continuous variable as well.

Other differences that are noticed in the travel choices related decision variables are whether the origin and destination are explicitly mentioned or not, and the difference between a number of vehicles and a number of evacuees. To explicitly include the origin and destination in the decision variable or not has no influence on the problem complexity, because they are specified by the route as well. The difference between vehicles and routes can be influential in case an approximate solution approach is used.

2.4.3 Stage 1: Network design and guidance

The decision variables discussed in this section influence the evacuation process in the first phase, as visualized in Figure 2.1. Both guidance to the evacuees and network design decision variables are discussed. Travel choices are derived from these variables in the evacuation process.

The incorporation of guidance as decision variable is limited. In Dixit & Radwan (2009), guidance is incorporated by the binary decision variable $\delta^r(t), t \in T, r \in R$, indicating whether an instruction is given for origin r to depart at t ($\delta^r(t) = 1$) or not ($\delta^r(t) = 0$). This decision variable is additional to the traffic flow related decision variable describing the propagation of the loaded traffic that is part of the approach as well, as described in Section 2.4.1.

Contrary, many approaches exist in which the decision variables describe the design of the network by means of capacity values. An example is a so-called contraflow approach which changes the driving direction of a link or lane. In most of the approaches, these decision variables are additional to traffic flow related decision variables that are introduced in Section 2.4.1. The decision variables are explained starting from the original network configuration that contains direction-specific links between each pair of nodes. The network terminology is extended based on the assumption that there are at maximum two links in between each pair of nodes. The links that are in between the same pair of nodes are coupled and distinguished as a^+ and a^-.

In Tuydes & Ziliaskopoulos (2004), the capacity of the links is set by the decision variable $\gamma_{a^+}, a \in A$, the fraction of the combined original capacity of a^+ and a^- reserved for the flow in the direction a^+. The capacity that is not used for a^+ is used for the direction a^-. Given this decision variable, the capacities can take all values and are not limited by a fixed capacity per lane, for example. The same problem is solved in a continuation of the research (Tuydes & Ziliaskopoulos, 2006). The solution approach used in this sequel results in more restricted but more realistic solutions: the capacity distribution is lane-based as is explained in Section 2.7.

The problem formulation given by Kim & Shekhar (2005) and Kim et al. (2008) contains a lane-based decision variable. Given a network where the directed links a^+ and

a^- all consist of one lane, the decision variable is the direction of each lane. The options are to keep the original configuration, or to change the direction from a^+ to the direction of a^- or vice versa. The approaches presented by Kim & Shekhar (2005) and Kim et al. (2008) decide on the traffic flows as well. However, no traffic flow related decision variables are introduced but several kinds of decision variables representing traffic flows are used in the solution approaches that focus on the network configuration. The traffic flow related decision variables are therefore not included in this overview. The decision variable in Xie et al. (2010) is lane-based as well. Given the number of lanes on an undirected link, the decision variables are the number of lanes in direction + and -, represented by integers.

The decision variables in Bretschneider & Kimms (2012) are related to the link directions, where the links can consist of multiple lanes. The problem formulation holds for a specific network type, i.e. all links that connect two intermediate nodes are interrupted by an unique origin. Patterns L^{link} are introduced that describe the directions of the links connected to that origin, see Figure 2.5. One of these patterns is selected for each of these origins. The decision variable is the binary variable $\delta_l^r, l \in L^{\text{link}}, r \in R$, indicating whether pattern l is selected for the links directly connected to origin r ($\delta_l^r = 1$) or not ($\delta_l^r = 0$).

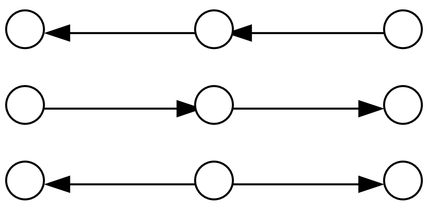


Figure 2.5: Patterns describing link directions in Bretschneider & Kimms (2012), based on Figure 3(b) in Bretschneider & Kimms (2012)

The previously introduced network design decision variables specify either the lane or link capacity or directions. Kalafatas & Peeta (2009) introduce a general decision variable, i.e. the binary variable $\delta_{l^{\text{design}}}, l^{\text{design}} \in L^{\text{design}}$ indicating whether the network design option l^{design} is selected ($\delta_{l^{\text{design}}} = 1$) or not ($\delta_{l^{\text{design}}} = 0$). This network design option represents a contraflow measure, but no exact definition is given.

In Sherali et al. (1991), another type of network design decision variables is introduced, i.e. the binary decision variable $\delta^{d^{\text{potential}}}, d^{\text{potential}} \in D^{\text{potential}}$, indicating whether the potential destination $d^{\text{potential}}$ is in use as destination d ($\delta^{d^{\text{potential}}} = 1$) or not ($\delta^{d^{\text{potential}}} = 0$). This variable is introduced such that a maximum on the available staff can be considered in the problem formulation.

The network design decision variables differ functionally from the guidance. The multiple types of network design variables differ functionally as well. Namely, whether decisions are made on the destinations or the capacity of the links, but also whether these last mentioned decisions are lane-based or link-based. This difference influences the problem structure and the implementation possibilities as well. A continuous variable defining the capacity, as introduced by Tuydes & Ziliaskopoulos (2004), leads to a low problem complexity but is hard to implement at the same time.

2.4.4 Search space

The search space $\mathbb{U}$ describes the values that can be adopted by the decision variables. The search space can consist of all possible values, e.g. all routes in the network in case of decision variables representing route choice. However, further restrictions on the search space exist as well. In case the decision variables are discrete but the variables they describe are continuous, restrictions are necessary. This holds for example for departure times choices that are represented by a discrete variable. Next to these necessary restrictions, the search space can also be bounded because of functional reasons. Another type of restriction is a restriction aimed to reduce the problem complexity, while possibly decreasing the efficiency of the evacuation as well. The restrictions on the bounds are discussed in this section given the distinction between necessary, functional, and additional restrictions.

The search space for decision variables related to the departure time is characterized in literature both by necessary and additional restrictions. The discrete decision variables in Sbayti & Mahmassani (2006) and Afshar & Haghani (2008), i.e., departure time choices, require a restriction which is realized by limiting the departure time choices to each minute. A restriction is required for the discrete origin-specific departure time instructions which are the decision variables in Dixit & Radwan (2009) as well. The restriction given by Dixit & Radwan (2009), i.e., the departure time instructions are limited to every six hours, can be classified as additional because of the order of magnitude of the time interval.

An additional restriction for route related decision variables is a limitation in the number of routes that are part of the search space. This restriction is applied in the case study in Afshar & Haghani (2008): the search space is limited to 10 routes. This limits the complexity of the problem. The restriction in the number of routes can be specialized to the problem such that the complexity is reduced in a smart way. Examples are the limitation to the kth-shortest paths (Stepanov & Smith, 2009), the limitation to cycle-free routes such that a node is not visited more than twice by the same traveler (Miller-Hooks & Sorrel, 2008), and the limitation to routes for which it is possible to reach safety based on the travel times and capacities (Miller-Hooks & Sorrel, 2008). These restrictions limit the search space to routes that probably affect the efficiency of the evacuation in a positive way which reduces the chance of decreasing the evacuation efficiency compared to a random selection of routes.

The search space for destination related decision variables is also characterized by additional restrictions. In Saadatseresht et al. (2009), the origin-specific destination search space is limited to a set of destinations selected based on the distance between origin and destination. A functional restriction is given by Bretschneider & Kimms (2012). One of their goals is to restrict merging conflicts and this is realized by limiting the possible patterns describing turning movements.

2.4.5 Discussion

The decision variables influence the evacuation process at different stages, as illustrated in Figure 2.3. Functional differences exist both between the decision variables at different stages, and between the decision variables within each stage. The type of decision variables influences also the implementation. As explained earlier, the implementation can be of any form: on a local level, for example, by variable message signs, traffic light settings, or ramp metering, or on a network level, for example, by departure time and route guidance.

Noticeably, almost all decision variables represent the resulting flows or fractions instead of these implementation measures themselves. Some decision variables can, under certain circumstances, be implemented directly. For example, when the traffic at an intersection is at full capacity level, optimized turning flows can be reproduced by the traffic light settings. However, this reproduction is impossible under different conditions. Furthermore, such direct reproductions are impossible for other implementation measures like variable message signs and route guidance. The implementation possibilities can be influenced via the search space as well. The search space can be limited to values of the decision variables with higher chances on compliance when they are used in practice. Examples are the limitation to the kth shortest paths (Stepanov & Smith, 2009) and the limitation to cycle-free routes (Miller-Hooks & Sorrel, 2008).

The type of decision variables influences the problem complexity as explained in the previous sections. One factor influencing the problem complexity is not yet discussed, i.e. whether the decision variable is discrete, e.g. a number of vehicles, or continuous, e.g. a flow or a fraction. This influence is illustrated by an example, i.e., a problem that contains only linear constraints. When this problem contains continuous decision variables, linear constraints are sufficient to model the problem. However, when the decision variables are discrete, linear constraints are no longer sufficient.

For some detailed characteristics of the decision variables holds that differences in these characteristics can influence the resulting solution. For example, different units of the decision variable could influence the stopping criterion. Another example with the same effect is whether the decision variable represents a flow or a fraction.

2.5 Objective functions

This section discusses the objective function J as part of the evacuation problem. The objective functions are distinguished based on a functional difference, i.e. the assumption about the arrival of evacuees. Either all evacuees arrive at a destination (Section 2.5.1) or only a part of the evacuees arrive at a destination (Section 2.5.2). Section 2.5.3 discusses ways to deal with multiple objective functions together in the evacuation problem. This overview on objective functions is complementary to those given by Løvås (1995) and Han et al. (2007). In this section, some objective functions are discussed that are not discussed in the previous overviews. Furthermore, some new relations between the objective functions and approaches to deal with multiple objectives are discussed.

The discussion aims at describing the differences between the objective functions themselves, independent on the choice of the variables and modeling assumptions. This because the influence of the objective function on the problem complexity is limited, because of which the objective function can easily be replaced. Therefore, the objective functions are described assuming one particular set of variables:

- The matrices of time-dependent *link in- and outflows* $\mathbf{Q}^{\text{in}}$ and $\mathbf{Q}^{\text{out}}$,
- The scalar $q_a^{\text{out}}(t)$, representing the outflow of link a at time instant t,
- The matrix of *route flows* $\mathbf{Z}_P$,
- The scalar $z_p(t)$, representing the flow entering route p at time instant t,
- The matrix of time-dependent *link travel times* $\mathbf{T}_A$,
- The matrix of *route travel times* $\mathbf{T}_P$,
- The scalar $\tau_p(t)$, representing the travel time on route p when entering p at time instant t,
- The parameter Δt, representing the *size of the time step* in between the time instants T,
- The parameter ξ, representing the *number of evacuees per vehicle*.

The route flows follow from the travel behavior process and the link flows follow from the traffic propagation process. The link travel times $\mathbf{T}_A$ can be approximated based on the link flows $\mathbf{Q}^{\text{in}}$ and $\mathbf{Q}^{\text{out}}$, and the route travel times $\mathbf{T}_P$ follow directly from these link travel times $\mathbf{T}_A$. The scalar variable evacuation time $T^{\text{evacuation}}$, i.e. the time from the start of the evacuation until the last arrival, can be derived from the link outflows $\mathbf{Q}^{\text{out}}$ and the population .

2.5.1 Objective functions assuming a complete evacuation

The time spent in the network by all evacuees individually is an often used objective function. Two different objectives exist, namely *minimization of the total travel time* (Tuydes & Ziliaskopoulos, 2004, 2006; Chiu & Mirchandani, 2008; Liu et al., 2007) and *minimization of the total trip time* (Sbayti & Mahmassani, 2006; Afshar & Haghani, 2008; Kalafatas & Peeta, 2009; Dixit & Radwan, 2009; Chiu et al., 2007). These objectives are formulated by the following objective functions:

$$J_1(\mathbf{Z}_P, \mathbf{T}_P) = \sum_{t \in T, p \in P} z_p(t)\tau_p(t), \tag{2.4}$$

and

$$J_2(\mathbf{Z}_P, \mathbf{T}_P, T, \Delta t) = \sum_{t \in T, p \in P} z_p(t)(\tau_p(t) + \Delta t \cdot t), \tag{2.5}$$

where J_1 represents the total travel time and J_2 represents the total trip time. J_2 is an extension of J_1, i.e. the sum of the waiting times is added to the sum of the travel times. The waiting time is the time spent by the traveler at the origin before departure. Minimization of the total trip time favors early arrivals. In case the decision variables do not contain a departure time related variable, or in case the travelers can always be directly loaded on the network, the ranking in different evacuation plans is independent on the particular objective considering these two objectives.

Sbayti & Mahmassani (2006) and Afshar & Haghani (2008) state that together with minimizing the total trip time, they also maximize the arrivals in each time period and minimize the evacuation time. They found this by referring to the triple optimization result given in Jarvis & Ratliff (1982). In Jarvis & Ratliff (1982), it is demonstrated that the following objective functions can be simultaneously satisfied in a maximal dynamic network flow problem: 1) maximization of the arrivals in each time period, 2) minimization of the evacuation time, and 3) minimization of the total trip time. However, this result holds for a particular kind of problems described in Jarvis & Ratliff (1982). The result does not necessarily hold for other problems like the problems proposed by Sbayti & Mahmassani (2006) and Afshar & Haghani (2008).

The objective functions in Sherali et al. (1991) and Xie et al. (2010) are adapted versions of the minimization of the total trip time. In Sherali et al. (1991), the measure is extended with a term that penalizes exceeding the considered destination capacity. Furthermore, only one time step is considered, because the travel time and the flows are constant over time in their model. In Xie et al. (2010), a penalty term is added which is a function of the number of conflicting flows at each intersection. In this way, the number of conflicts is limited which is one of the goals set.

An objective function that deals with the time pressure usually involved with evacuations is *minimization of the evacuation time* (Lu et al., 2005; Kim & Shekhar, 2005; Kim et al., 2008; So & Daganzo, 2010; Daganzo & So, 2011). The evacuation time $T^{\text{evacuation}}$ is equal to the time from the start of the evacuation until the latest individual arrives at a safe destination. This measure is usually applied together with the constraint that all evacuees arrive at the destination, which makes the performance strongly dependent on one specific individual. The second objective presented in Xie et al. (2010) is an adapted version of the minimization of the evacuation time. Namely, the introduced penalty term for conflicting flows at intersections is added to this objective. Another alternative is the *minimization of the weighted arrivals* (Bretschneider & Kimms, 2012), whereby the weight increases with time. This measure favors early arrivals. The corresponding function is equal to:

$$J_3(\mathbf{Q}^{\text{out}}, \xi) = \xi \sum_{t \in T, a \in A_D} \varpi(t) q_a^{\text{out}}(t), \tag{2.6}$$

where the scalar $\varpi(t)$ represents the weight at t that increases with time. The set A_D consists of the links directly upstream of the destinations D.

2.5.2 Objective functions assuming a partial evacuation

The time pressure can be so high that there is not enough time to evacuate all people. In that case, objective functions have to be used that do not assume that all people can arrive at a destination. A plan generated by applying such an objective function shows the potential of the considered way of evacuation, but should be extended to be applied in practice. Examples of extensions are the use of shelters in the region, transit-based evacuation, and vertical evacuation.

An objective function that assumes partial arrival is the *minimization of the time in which a certain percentage of the evacuees is evacuated*, one of the objectives proposed by (Han et al., 2007). This objective is closely related to the minimization of the evacuation time but makes the performance less dependent on the individual. Another objective is the *maximization of the arrivals* within a given time period (Miller-Hooks & Sorrel, 2008). The corresponding function is equal to:

$$J_4(\mathbf{Q}^{\text{out}}, \xi) = \xi \sum_{t \in T, a \in A_D} q_a^{\text{out}}(t), \tag{2.7}$$

where the time period T is input to the problem. A related measure is the *maximization of the arrivals at each point in time* (Baumann & Skutella, 2009). The corresponding function is equal to:

$$J_5(\mathbf{Q}^{\text{out}}, \xi) = \xi \sum_{a \in A_D} q_a^{\text{out}}(t), t \in T. \tag{2.8}$$

This measure is less generic, i.e. it requires specific traffic propagation models and behavior assumptions. Thus, this objective function cannot be used in all other approaches discussed in Chapter 2.

In Miller-Hooks & Sorrel (2008), different network states are considered representing uncertainty in the travel times and capacity values. The objective function is determined based on these states: it is the sum of the objective function value for the considered network states separately, weighted with their likelihoods, which are derived from the probabilities on the network states.

In the following measures, the arrivals or travelers on the network are weighted over time. A weighted version of the time spent in the network is the *minimization of the threat exposure* (Kimms & Maassen, 2011; Yao et al., 2009), defined as the weighted number of travelers over the network locations over time. The weight is both location- and time-dependent and represents the danger (which is equal to zero at the destination). In Yao et al. (2009), the destinations are not included and the weight in the latest time step is set to a positively large number such that an evacuation plan which leaves any evacuees behind at the end of the time horizon is penalized. An objective proposed by Han et al. (2007) is the *minimization of the evacuees that are not safe yet*, whereby the evacuees are weighted with a time- and location-specific risk factor.

Abdelgawad & Abdulhai (2009b) propose an objective function for which a partial evacuation is assumed as well. The proposed objective is the maximization of the total departures minus the sum of the percentage of evacuees en route over time. Given their constraint that all demand is released, the first term will be constant in all function evaluations.

2.5.3 Combined objective functions

This section discusses ways to deal with multiple objective functions simultaneously. These approaches integrate the measures, contrary to presenting multiple objectives from which one can be chosen as done by Xie et al. (2010).

The first approach is to assign priority levels to the performance measures. The plan is optimized for the measure with the highest priority, and if this does not result in a unique solution, the measure with the second priority level is considered for the resulting solutions. Priority levels are used in Liu et al. (2006): first, the number of arrivals is maximized, and in case there is enough time available to evacuate everyone, the total trip time is minimized.

The second approach is to use the weighted sum of multiple measures. By varying the weights, the importance of the different measures is varied. Stepanov & Smith (2009) minimize the weighted sum of 1) the ratio of the total traveled distance over the total traveled distance in case all travelers would follow the shortest route and 2) the ratio of the total travel time over the total travel time if all travelers would travel on the shortest route under free flow conditions.

The third approach is to look for a Pareto front as a solution to the problem. For this solution it holds that improving the value of measure leads to a decrease in the performance of another measure. A Pareto front is used by Saadatseresht et al. (2009) to combine the measures *minimization of the distance traveled* and *minimization of the overload of the destination capacity*, defined as the sum of the ratio of the population over the capacity of all destinations. A Pareto front offers many possibilities, like adding weak prioritization. An overview of the possibilities is given by Taboada et al. (2007).

2.5.4 Discussion

The differences in the objective functions are whether a full or partial evacuation is assumed and the use of one or multiple objective functions, see the overview in Table 2.2. The influence of the objective function on the problem complexity is limited. An example of a small influence on the complexity is that in case of a full evacuation, the problem contains a constraint guaranteeing that all evacuees reach a safe destination. In case of a partial evacuation, this constraint is not part of the formulation.

2.6 Travel behavior and traffic propagation models

This section describes the incorporation of the evacuation process in the evacuation problem. Section 2.6.1 describes the incorporation of behavioral models and Sections 2.6.2 - 2.6.4 describe the incorporation of traffic propagation. These sections differ in the accuracy with which the propagation is described by the model. Successively, flow-independent travel times, linear models, and nonlinear models are discussed. The more accurate the description is, the more realistic the traffic can be. However, the less advanced the description is, the easier the problem can be solved. The section finishes with a discussion in Section 2.6.5.

All literature included in Table 2.1 is included in this overview, except for the approaches presented by Saadatseresht et al. (2009), Kim & Shekhar (2005) and Kim et al. (2008). Travel behavior and traffic propagation are not described by Saadatseresht et al. (2009) because their approach is not specific for vehicular traffic. The approaches presented by Kim & Shekhar (2005) and Kim et al. (2008) are not included because no unique descriptions are given but several representations are used in the solution approaches that focus on the network configuration.

2.6.1 Travel behavior

Whether a travel behavioral model needs to be included in the problem formulation depends on the choice of the decision variables and any behavioral assumptions. The choices, i.e. departure time and route choice, that are set as decision variables are not described by a behavioral model. The same holds for the choices of which the corresponding flows, i.e. flows describing the traffic propagation or loading, are set as decision variables. Furthermore, departure time and route choice can be assumed because of which they do not need to be modeled as well.

All approaches with traffic flow related decision variables include decision variables representing the traffic propagation. Thus, route choice models are irrelevant for these approaches. However, the traffic loading is only part of the decision variables of the approaches presented by Chiu et al. (2007), Baumann & Skutella (2009), Kimms & Maassen (2011), and Bretschneider & Kimms (2012), given the literature listed in Table 2.1. For most of the approaches, the traffic loading is assumed (Sherali et al., 1991; Tuydes & Ziliaskopoulos, 2004; Liu et al., 2006; Tuydes & Ziliaskopoulos, 2006; Liu et al., 2007; Miller-Hooks & Sorrel, 2008; Kalafatas & Peeta, 2009; Yao et al., 2009; So & Daganzo, 2010; Xie et al., 2010; Daganzo & So, 2011). There is only one approach that needs a travel behavioral model: the approach presented in Dixit & Radwan

Table 2.2: Overview objective functions

Publication	**Complete or partial evacuation**		**One or multiple objectives**	
	Complete evacuation	Partial evacuation	One objective	Multiple objectives
Sherali et al. (1991)	x		x	
Tuydes & Ziliaskopoulos (2004)	x		x	
Kim & Shekhar (2005)	x		x	
Lu et al. (2005)	x		x	
Liu et al. (2006)		x		x
Sbayti & Mahmassani (2006)	x		x	
Tuydes & Ziliaskopoulos (2006)	x		x	
Chiu et al. (2007)	x		x	
Liu et al. (2007)	x		x	
Afshar & Haghani (2008)	x		x	
Chiu & Mirchandani (2008)	x		x	
Kim et al. (2008)	x		x	
Miller-Hooks & Sorrel (2008)		x	x	
Abdelgawad & Abdulhai (2009b)		x	x	
Baumann & Skutella (2009)		x	x	
Dixit & Radwan (2009)	x		x	
Kalafatas & Peeta (2009)	x		x	
Saadatseresht et al. (2009)	x			x
Stepanov & Smith (2009)	x			x
Yao et al. (2009)		x	x	
So & Daganzo (2010)	x		x	
Xie et al. (2010)	x		x	
Daganzo & So (2011)	x		x	
Kimms & Maassen (2011)		x	x	
Bretschneider & Kimms (2012)	x		x	

(2009) were departure time instructions are the decision variables. The departure times are assumed to be a deterministic function of the instructed departure time and the time of the day.

For the approaches with travel behavior related decision variables holds that the decision variables consists of both route and departure choices in Lu et al. (2005), Sbayti & Mahmassani (2006), Afshar & Haghani (2008), and Chiu & Mirchandani (2008). The departure times are assumed while the route choices are represented by the decision variables in the approach presented by Stepanov & Smith (2009). The departure times are assumed to follow a Poisson distribution. The routes are assumed while the departure times are represented by the decision variables in the approach presented by Abdelgawad & Abdulhai (2009b). The assumed routes are based on a user equilibrium.

2.6.2 Traffic propagation described by flow-independent travel times

The use of flow-independent travel times is the most straightforward way to describe the traffic propagation. In So & Daganzo (2010) and Daganzo & So (2011), the flow is assumed to be at a constant, i.e. time-independent, capacity level traveling at free flow speed. In Kim & Shekhar (2005), Kim et al. (2008), Baumann & Skutella (2009), and Bretschneider & Kimms (2012), time-independent travel times and capacities are assumed.

Time-dependency in the travel times and capacities is added by Lu et al. (2005) and Miller-Hooks & Sorrel (2008). The travel times in Lu et al. (2005) are restricted to preserve FIFO. In Miller-Hooks & Sorrel (2008), the travel times and capacities are discrete random variables with time-varying distribution functions, to reflect uncertainty in the situation. The time-varying capacities in both approaches can among other things be used to represent network degeneration caused by the hazard.

2.6.3 Traffic propagation described by a linear model

The model that is most often used is the so-called *cell-transmission model*, developed in Daganzo (1994, 1995a). This model is based on a macroscopic representation of traffic flow and incorporates moving queues and spill back. The main characteristic of the model is that the links are divided in homogeneous cells which length is such that the distance is traveled in one time step under free flow conditions. The cell-transmission model is reformulated to a linear system optimum dynamic traffic assignment problem by Ziliaskopoulos (2000). This linear problem formulation is adopted, sometimes in a modified way, by Tuydes & Ziliaskopoulos (2004), Dixit & Radwan (2009), Liu et al. (2006), Chiu et al. (2007), Yao et al. (2009), and Kimms & Maassen (2011). An example of a modification is the extension of the model to include lane reversal (Tuydes & Ziliaskopoulos, 2004).

A simplified version of the CTM is used by Kalafatas & Peeta (2009). They set the maximum density equal to the density at maximum flow and because of this they preserve free flow conditions. This further simplifies the model, since backward propagating traffic waves are not considered. Evacuees are allowed to exit the origin only if free flow is guaranteed along the entire route.

In Stepanov & Smith (2009), both a linear and a nonlinear queuing model are proposed. Both models limit blocking by using a fixed upper bound on the arrival rate for each link such that the blocking probability will not exceed a threshold value. The link travel time is a linear function of the arrival rate, the upper bound on the arrival rate, the free flow travel time and the travel time under capacity. Two different functions are proposed for this latest term: the travel time under capacity is a linear or exponential function of the free flow speed, the capacity, and the number of vehicles on the link.

2.6.4 Traffic propagation described by a non-linear model

Usually, non-linear models contain more details of the traffic propagation than linear models. This means that, for example, congestion is described more accurately. An example of a non-linear model is the so-called BPR function, that expresses the travel time as a non-linear function of the free flow travel time, the flow, and the capacity (Bureau of Public Roads, 1964). This function is part of the problem formulation presented by Sherali et al. (1991). Afshar & Haghani (2008) derive travel times from speed, which are determined by a version of Greenshield's model in which the speed on a link is a non-linear function of the free flow speed, the minimum speed, the density and the jam density. In Liu et al. (2007), the travel time is a function of the link in- and outflows and the number of vehicles present at the links. The function form is undefined.

In other papers, no details of the traffic propagation model are given but references to some standard models are given instead. Examples are the references to DynusT (Chiu & Mirchandani, 2008; Abdelgawad & Abdulhai, 2009b), DYNASMART-P (Sbayti & Mahmassani, 2006), VISTA (Tuydes & Ziliaskopoulos, 2006; Xie et al., 2010). Besides the traffic propagation, these packages can also describe the traffic assignment.

2.6.5 Discussion

The use of travel behavior models is limited in existing literature. So & Daganzo (2010) state that under their assumptions on how the population distributes over the on-ramps, the resulting situation is equal to a user equilibrium and therefore the chance on compliance is high. Same arguments could hold for other user equilibrium situations, like the situation in Xie et al. (2010).

The traffic propagation descriptions differ in the accuracy with which they represent the propagation. Kimms & Maassen (2011), Stepanov & Smith (2009), Liu et al.

(2007), Sherali et al. (1991), and Liu et al. (2006) see the solution of their problem as input for an evaluation with a more detailed traffic propagation model. In Kalafatas & Peeta (2009) it is stated that the used description is not meant for exact representation of traffic reality, but as an efficient mathematical programming transformation.

2.7 Solution approaches

The approaches that solve the evacuation problem can find the global optimum or an approximate solution. This section distinguishes: approaches resulting in the global optimum (Section 2.7.1), metaheuristics (Section 2.7.2), and problem-specific heuristics (Section 2.7.3). Both heuristic approaches result in an approximate solution, i.e. a solution whose performance approaches the performance of the optimal solution. Metaheuristics are general heuristics applied to all kinds of problems. Iteratively, the search space is explored while evaluating the solutions based on the objective function. The problem-specific heuristics are specially developed for the considered problem. Some of them consider the objective function explicitly, while others consist of rules which are assumed to result in a satisfying value for the objective function. The problems that are solved by the solution approaches differ in some cases from the given problem formulation. The appropriateness of a specific approach to solve a problem depends on the problem formulation. Approaches resulting in global optima are appropriate if the problem is not too complex, e.g. all linear functions, and the scale of the problem is reasonably small. Otherwise, heuristics need to be applied.

2.7.1 Approaches resulting in the global optimum

The linear problems that are based on the cell-transmission model are solved by approaches resulting in the global optima (Kimms & Maassen, 2011; Tuydes & Ziliaskopoulos, 2004; Dixit & Radwan, 2009; Liu et al., 2006; Chiu et al., 2007; Yao et al., 2009; Kalafatas & Peeta, 2009). These problems have similar constraints, i.e., flow conservation, capacity, initial and non-negativity constraints. As explained in Kimms & Maassen (2011), these problems have integer decision variables but this integer constraint can be relaxed in the solution approach. The impact of this relaxation, i.e. assuming continuous decision variables, was small in some computational tests for large instances. Most decision variables were automatically set to integers.

Kimms & Maassen (2011) use a decomposition procedure in order to accelerate the problem solving. This procedure starts by finding the solution for the inner circle of the network, than finding the solution for a bigger circle while adopting the solution from the first circle, and so on.

The problem in Baumann & Skutella (2009), known as the earliest arrival problem, is solved by an approach resulting in the global optimum which is based on the shortest paths. The linear problem introduced in Yao et al. (2009) and the integer problem introduced in Stepanov & Smith (2009) are also solved by an approach resulting in the global optimum.

2.7.2 Metaheuristics and other generic heuristics

Many types of metaheuristics are applied to solve evacuation problems. Genetic algorithms are used by Miller-Hooks & Sorrel (2008), Abdelgawad & Abdulhai (2009b) and Saadatseresht et al. (2009). The algorithms used are always specialized for the problem characteristics: a noisy genetic algorithm is used by Miller-Hooks & Sorrel (2008) to deal with the multiple considered network states and a genetic algorithm that deals with multi objectivity (Deb et al., 2002) is used by Saadatseresht et al. (2009). Tabu search heuristics are used by Tuydes & Ziliaskopoulos (2006) and Xie et al. (2010) and simulated annealing is used by Kim & Shekhar (2005).

2.7.3 Problem-specific heuristics

Many problems are solved using heuristics developed specially for the particular problem. Most of the heuristics contain a traffic behavior model and a traffic propagation model to evaluate solutions. This section presents some examples.

The heuristics differ in whether the values for the decision variables are determined together or separately. The heuristics proposed in Sbayti & Mahmassani (2006) and Afshar & Haghani (2008) determine the route, destination and departure time together as part of the assignment. The heuristic proposed in Sbayti & Mahmassani (2006) generates a new assignment in each iteration. This assignment is created by the method of successive averages out of the assignment from the previous iteration and a new assignment based on the least marginal travel costs. In Afshar & Haghani (2008), iterative heuristics are presented that consist of modules that either spread or squeeze the demand, respectively to minimize congestion or to minimize the last departure time. An example of decision variables whose values are determined separately is the heuristic presented by Tuydes & Ziliaskopoulos (2006). First, the lane directions are determined, after which this network design is evaluated by a system optimum traffic simulator.

Some heuristics are based on well-known algorithms like the shortest path algorithm or the max flow algorithm. In each iteration of the heuristic presented in Chiu & Mirchandani (2008), a traffic assignment is determined using a travel time based shortest path algorithm. This heuristic continues until the approach converges. The heuristic presented in Kim et al. (2008) is based on the maximum flow algorithm. In each iteration, the maximum flow and the corresponding network location limiting this flow are determined. Subsequently, the links across this location are flipped in the outgoing direction. This process is continued until the maximum flow does not improve anymore.

In So & Daganzo (2010) and Daganzo & So (2011), a strategy-based heuristic is presented. The flow from the on-ramps entering the freeway is determined based on an online strategy that gives absolute priority to travelers on the freeway, prioritizing upstream travelers. For each on ramp, this flow is equal to the difference between the downstream capacity and the directly upstream flow. An assumption is that the demand always exceeds the downstream capacity. In Daganzo & So (2011), split ratios are derived from the max-flow algorithm in addition to the flows.

2.7.4 Discussion

The main difference in the solution approaches is whether they result in a global optimum or an approximate solution. While approximate solutions can be found for all kinds of problems, global optima can only be found for problems with limited complexity, and related to that, limited accuracy.

Many papers give attention to the performance of the solution approaches in terms of the computational time and solution effectiveness. However, these results are highly case-dependent and the papers contain not enough information to be able to make a fair comparison. Because of this, the choice is made to limit this overview to the problem formulations and solution approaches themselves.

2.8 Conclusions

This chapter showed that the evacuation problem formulations proposed in literature differ in multiple ways. They differ in their functionality, for example by the choice to minimize the total travel time or to maximize the arrivals. Differences related to the problem complexity exist as well. For example, traffic flows can be described by flow-independent functions, or detailed traffic flow models can be used. The final difference is in the implementation possibilities. For example, traffic flows described by splitting movements leave more freedom for the implementation than the corresponding turning movements. The overview of the elements of the problem formulation with their characteristics and differences will be used in Chapters 3 - 5 to set up the problem formulations. The insights in the different solution approaches will be used in these chapters as well. An example is the choice for an approximate solution approach to solve the evacuation problem, see Chapter 3.

The chapter showed that the realization of the solutions gets little attention in literature. In some papers, this realization is not discussed. In part of the literature, it is recognized that optimized traffic flows are not automatically reproduced in reality (Tuydes & Ziliaskopoulos, 2004, 2006; Liu et al., 2007). The same holds for optimized travel choices (Sbayti & Mahmassani, 2006; Afshar & Haghani, 2008; Abdelgawad & Abdulhai, 2009b; Saadatseresht et al., 2009). However, none of the mentioned approaches take this into account in the problem formulation. This could be done, for example, by taking variable message signs as decision variable and include the compliance of people with variable message signs in the formulation. Instead, full compliance is assumed and the results are presented as explorations of the full potential or bounds on the system performance.

Studies often mention the importance of uncertainty and compliance behavior, yet they are hardly ever incorporated in the problem formulations. The importance of dealing with uncertainty is for example endorsed by Løvås (1995) and Han et al. (2007), who propose to deal with this in the objective function, e.g. by using expected values. However, uncertainty is only incorporated in two studies: Miller-Hooks & Sorrel (2008) consider multiple states and their probabilities to represent capacity and travel time uncertainty, and Yao et al. (2009) consider the maximum demand as representative scenario for uncertain demand. Instead of creating a plan that satisfies all uncertain factors, a plan can also be adapted during the evacuation. Such online approaches are proposed by Liu et al. (2007), Chiu et al. (2007), and Chiu & Mirchandani (2008).

The overview shows that uncertainty can be incorporated in different positions in the problem formulation, i.e. the objective function and the input to the problem. The compliance behavior can be incorporated in the travel behavior model. Incorporating uncertainty and compliance behavior makes the problem more complex, i.e., it becomes computationally more expensive to solve the problem. This problem will be dealt with in the following chapters.

Chapter 3

Problem formulation, solution approach, and analysis of the resulting guidance

This chapter presents the evacuation problem and a solution approach to solve this problem. Furthermore, the effectiveness of the resulting guidance is analyzed. Section 3.1 gives the problem formulation and discusses the complexity. Section 3.2 specifies the decision variables, objective function, models, and search space included in the formulation. As stated in Chapter 1, incorporating compliance behavior and uncertainty in the development of evacuation guidance is one of the main objectives of this thesis. The problem formulation incorporates this behavior and a specific type of uncertainty, i.e., uncertainty in the time available for the evacuation, in the travel behavior model and the objective function respectively. Section 3.3 presents an approach to solve the formulated problem.

Section 3.4 uses the formulation and approach to create guidance for a hypothetical case, a flood of part of the Netherlands. This comprehensive case study examines the effectiveness of the guidance and the efficiency of the specific approach in order to confirm the statement made in Chapter 1 that guidance increases the evacuation efficiency and to found the choice for an optimization approach to solve the problem. The main findings are discussed in Section 3.5.

Acknowledgment. The main contents of this chapter are based on Huibregtse, O., S. Hoogendoorn, A. Hegyi, M. Bliemer (2011) A method to optimize evacuation instructions, *OR Spectrum*, 33(3), pp. 595-627. The content of Section 3.4.8 is based on Huibregtse, O., A. Hegyi, S. Hoogendoorn (2012) Blocking roads to increase the evacuation efficiency, *Journal of Advanced Transportation*, 46(3), pp. 282-289.

3.1 Evacuation problem formulation and complexity

Section 3.1.1 gives an overview of the requirements on the formulation and the approach. These requirements are based on the objective of this thesis stated in Chapter 1 and the discussion on related literature given in Chapter 2. Section 3.1.2 gives the formulation of the evacuation problem and Section 3.1.3 discusses the complexity of the problem and the implications for the solution approach.

3.1.1 Requirements for the formulation and the approach

The main objective of this thesis, i.e. to develop evacuation guidance in an efficient way while incorporating uncertainty and compliance behavior, yields the main requirements for the formulations and approaches. Another requirement discussed in Chapter 1 is that the problem formulations are generic, i.e. flexible with respect to the network and modeling assumptions.

Given the objective, the *decision variables* that are part of the problem formulation represent the *guidance* given to the evacuees. This guidance consists of instructions that are intended to determine or influence evacuees' travel behavior, i.e. departure time, route, and destination instructions. Details, such as whether the guidance is given on a group or individual level, are not specified given the required generic character of the formulation. However, as discussed in Chapter 2, the precise definition of a decision variable influences the problem complexity and implementation possibilities. This should be considered when specifying the decision variables.

The *guidance* that is optimized in this thesis is required to be *effective*. Following the general structure of problem formulations discussed in Section 2.2, problem formulations describe the relation between the guidance and the corresponding effectiveness by means of an *objective function* and *models*. As discussed in Chapter 2, objective functions can easily be replaced with limited influence on the problem formulation. Therefore, no further requirements are set for the objective function. The requirements on the model are described later in this section.

The problem formulation is required to allow for the incorporation of *uncertainty* and *compliance behavior*. As discussed in Chapter 2, uncertainty is incorporated in literature either by multiple evaluations for varying input (Miller-Hooks & Sorrel, 2008) or by considering a worst case scenario (Yao et al., 2009). Furthermore, online methods exist that adapt the plan during the evacuation (Liu et al., 2007; Chiu et al., 2007; Chiu & Mirchandani, 2008). While the focus of this thesis is on evacuation planning, the problem formulation should be generic such that these different ways of incorporating uncertainty can be included. As discussed in Chapter 2, travel behavior related to the departure times is incorporated via a travel behavior model by Dixit & Radwan (2009). Here, the problem formulation should be able to incorporate different kinds of *travel behavior models* that determine travel choices like the departure time, route, and destination choice.

The problem formulation should be *generic*, i.e. flexible with respect to the network and the modeling assumptions. The flexibility regarding the *network* requires that the problem formulation is not limited to toy networks that can be used to demonstrate ideas. It should be possible as well to determine guidance for real-sized networks. The term real-sized networks refers to the road networks of real regions that can be threatened by a disaster like a flood or a fire, like the Walcheren peninsula that will be introduced in Section 3.4.

The flexibility regarding the *modeling assumptions* means that it should be possible to include any kind of travel behavior and traffic propagation model. This flexibility is important because of the high variety and development of these models. Perry & Mushkatel (1984) started to apply social knowledge to disaster management and since then many models have been developed. Overviews of these models are given in literature: an overview of travel behavioral models (Pel et al., 2012), an overview of the combination of travel behavior and traffic propagation models (Alsnih & Stopher, 2004), and an overview of driving behavior models (Hoogendoorn, 2012). The flexibility makes it possible to optimize evacuation guidance based on models presented in literature or any new developed models. The model of choice will depend, among other things, on the desired accuracy and computational costs.

As discussed in Chapter 2, *solution approaches* aim at either a global optimum or an approximate solution. Usually, solution approaches aiming at a global optimum are developed for concrete problem formulations. This while solution approaches aiming at an approximate solution are more flexible, for example, regarding the choice of the objective function. Given the required flexibility of the problem formulation, an *approximate solution approach* is required in this thesis. The solution approach has to solve the evacuation problem in an efficient way. The time available to develop an evacuation plan varies in practice. Therefore, a fixed time budget is not given, but the efficiency of the solution approach should be considered.

3.1.2 Evacuation problem formulation

This section gives the basic formulation of the evacuation problem based on the requirements discussed in Section 3.1.1. To summarize, the formulation is required to:

- include decision variables representing guidance,
- include an objective function and models to evaluate the effectiveness of this guidance,

and is required to be able to:

- include any kind of network,
- include any kind of model describing travel behavior and traffic propagation,

- include uncertainty.

The basic formulation of the evacuation problem is as follows. The optimal guidance for scenario s, $\mathbf{U}_s^*$, follows from the following formulation:

$$\begin{aligned} \mathbf{U}_s^* = \quad & \operatorname*{argmin}_{\mathbf{U}\in\mathbb{U}_s} J(\mathbf{U},\mathbf{X}_s) \\ \text{s.t.} \quad & \mathbf{x}_s(t+1) = f\Big(\mathbf{x}_s(t),\mathbf{u}(t)\Big),\ t \in T \\ & \phi(\mathbf{U},\mathbf{X}_s) = 0, \\ & \psi(\mathbf{U},\mathbf{X}_s) \leq 0, \end{aligned} \tag{3.1}$$

where the initial state $\mathbf{x}_s(0)$ is assumed to be known. The scenario s represents input like the demand, the network, and the hazard scenario. The function f represents the state evolution which expresses the state at t, $\mathbf{x}_s(t)$, as function of the state and the decision variables at the previous time instant. Thus, the function f contains the travel behavior and traffic propagation model by which the evacuation process is described. The scalar function J expresses the performance as function of both the matrix $\mathbf{U}$, representing the decision variables, and the set of matrices $\mathbf{X}_s$, representing the states. $\mathbf{U}$ and $\mathbf{X}_s$ consist of the time-dependent variables $\mathbf{u}(t)$ and $\mathbf{x}_s(t)$ respectively. The vectors ϕ and ψ represent equality and inequality constraints respectively. The set $\mathbb{U}_s$ is the *search space* for the matrix of decision variables $\mathbf{U}$.

Equation 3.1 will be used as generic formulation of the evacuation problem throughout this thesis. As mentioned before, the formulation will be applied, specified, and extended.

3.1.3 Complexity

This section discusses the complexity of optimization problems because this gives insight in the approaches that can be used to solve the evacuation problem. Usually, complexity is discussed based on the theory of NP-completeness. This theory, mainly founded by Cook (1971), classifies problems by their complexity. One of the classes distinguished by this theory is the class of NP-complete problems. While no proof exists, the problems in this class are most probably intractable (Garey & Johnson, 1979). This means that it is unlikely that the exact solution will ever be found by an efficient algorithm, e.g., solvable in polynomial time.

The complexity of a problem can be indicated by proving that a problem is NP-complete. In order to proof that a problem is NP-complete, it should be proved that 1) the problem belongs to the class NP, and 2) there exists an NP-complete problem that is polynomial reducible to the considered problem. A proof of this statement is given by, for example, Manner (1989). Another way to indicate the complexity of the evacuation problem is to prove that the problem is NP-hard. NP-hard problems are as difficult to solve as NP-complete problems, but are not necessarily in the class NP. In order to proof that the evacuation problem is NP-hard, it should be proved that there exists an NP-complete problem that is polynomial reducible to the considered problem (Manner, 1989).

If a proof of the NP-hardness or NP-completeness of the evacuation problem would be available, it would be certain that an exact solution could not be found efficiently. However, this proof is not available and difficult to deliver as well. The evacuation problem, as defined by Equation 3.1, is flexible in terms of the specifications of the decision variables, objective function and constraints. In order to prove the NP-hardness or NP-completeness, these specifications should be known or assumed. For specific realizations of the evacuation problem, it is possible to try to proof the NP-hardness or NP-completeness. However, given the desired flexibility of the formulation, this thesis will not go into details of proving that the evacuation problem is NP-hard or NP-complete.

While it is not certain that an exact solution for the evacuation problem cannot be found efficiently, it is chosen to use approximate solution approaches throughout this thesis. The models that are used to describe the travel behavior and traffic propagation are advanced to such an extent that it seems to be most unlikely that exact solutions can be found for the real-sized networks used in this thesis.

The discussion on approximate solution approaches in Section 2.7 contains generic heuristics, like metaheuristics, and problem-specific heuristics. Because of the required flexibility of the solution approach, generic heuristics are used in this thesis. It is possible to specialize such a heuristic for the evacuation problem. This can be realized for example by the parameter settings.

The heuristics used throughout this thesis have in common that they iteratively produce new solutions, based on the solutions of previous iterations and their performance. An ant colony based metaheuristic is used in Chapters 3-4, and a derivative-based heuristic is used in Chapter 5. These choices correspond to choices in the decision variables. The first mentioned heuristic is suitable to assign groups of evacuees to certain instructions, while the second type is suitable to assign fractions of evacuees to certain instructions. For the first type holds that the group sizes are fixed, while the fractions that can be assigned for in the second type of heuristics are real values.

3.2 Specification of the problem formulation

This section specifies the problem formulation that results in optimal guidance, which is given by Equation 3.1. The specifications concern all components of the problem formulation, i.e. the guidance $\mathbf{U}$, the objective function J, the model consisting of function f and constraints ϕ and ψ, and the search space $\mathbb{U}_s$. A part of the specifications in the guidance and the model is reflected by the revised formulation:

$$\begin{aligned} \mathbf{U}_s^* = \quad & \underset{\mathbf{U} \in \mathbb{U}_s}{\operatorname{argmin}} \, J(\mathbf{X}_s), \\ \text{s.t.} \quad & \mathbf{x}_s(t+1) = \begin{cases} f\Big(\mathbf{x}_s(0), \mathbf{U}\Big), & t = 0 \\ f\Big(\mathbf{x}_s(t)\Big), & t > 0 \end{cases} \\ & \phi(\mathbf{U},\mathbf{X}_s) = 0, \\ & \psi(\mathbf{U},\mathbf{X}_s) \leq 0, \end{aligned} \tag{3.2}$$

where $x_s(0)$ is assumed to be known. The guidance is given to the people at the start of the evacuation and is propagated over time by f via the states $\mathbf{X}_s$. The remainder of this section gives the details of the specifications by explaining all factors included in Equation 3.2.

3.2.1 Guidance

The guidance consists of a departure time, route, and destination instruction for each person. The people are divided in groups G indexed by $g \in G$ that are at least distinguished according to their origin. All people in the same group get the same guidance. The guidance $\mathbf{U}$ consists of the group-specific guidance $u_{g,r}, u_{g,r} \in \mathbf{U}$, where $u_{g,r}$ consists of the departure time and route guidance for group g. The destination is implicitly included via the route.

The guidance is created for groups of people in order to control the complexity of the problem and the feasibility of the resulting guidance. The smaller the group size is, the more complex the problem is in terms of computational demand. Furthermore, the harder it could be to implement the guidance in practice. The number of evacuees in each group is equal to a constant group size, except a possible rest group for each origin. By setting the group size equal to 1, each group consists of one evacuee and solving the problem would result in individualized guidance. As discussed in Chapter 1, the guidance will be developed for planning purposes. Thus, the guidance is determined off-line, i.e., before the start of the evacuation.

3.2.2 Objective function

The objective function used in this chapter deals with the uncertainty in the time available to evacuate the people. The objective function is a function of the number of arrived evacuees for each time period, where early arrived evacuees can be appreciated more than evacuees that arrived later. As there is a risk of not being able to evacuate everyone, it is preferred to evacuate people earlier than later:

$$J(\mathbf{X}_s) = \xi \sum_{t \in T, a \in A_D} \exp^{-\chi_1 t} q_{a,s}^{\text{out}}(t). \tag{3.3}$$

The variable $q_{a,s}^{\text{out}}(t)$, representing the outflow of link a at time instant t given scenario s, is part of the state $\mathbf{x}_s(t)$: $\mathbf{x}_s(t) = [..., q_{a,s}^{\text{out}}(t), ...]$. The higher the value of $J(\mathbf{X}_s)$, the more effective the guidance is. In the remainder of this chapter, the value of $J(\mathbf{X}_s)$ is referred to as the *effectiveness* of the guidance. For the weighting parameter χ_1 holds that $\chi_1 \geq 0$. When χ_1 is equal to 0, the moment of arrival is not considered which makes the objective function equal to maximizing the arrivals. The higher the value of χ_1 is, the higher the importance of early arrivals is that is reflected by the objective function. The appropriateness of the value for χ_1 depends on the horizon during which the evacuees actually arrive. A 24-hour evacuation requires a lower value of χ_1 than a 1-hour evacuation in order to let the late arrivals still influence the value of the objective function. The duration of the evacuation can be estimated based on simulation models or practical experience.

3.2.3 Travel behavior and traffic propagation model

The travel behavior and traffic propagation, included in Equation 3.2 by the function f and the constraints ϕ and ψ, are described by the model EVAQ developed by Pel et al. (2008). This model is specially developed for evacuations, which makes it suitable to use for the evaluation of evacuation guidance. It contains a travel behavior part and a traffic propagation part.

The *travel behavioral part* determines departure time and route flow proportions based on the guidance, a compliance level and preferences of the evacuees. The model starts with determining the departure time proportions. The idea is that each evacuee continuously has the opportunity to either evacuate or decide to postpone the decision to evacuate. The probability to evacuate multiplied with the population gives the departure time proportions. This probability is determined for each time period by a binary logit model and depends on the following factors: 1) the difference between the current time period and the time period the hazard strikes the origin and 2) the difference between the current time period and the instructed departure time. The evacuees can depart before or at the moment for which they are instructed to depart. This clarifies the representation of the function f in Equation 3.2. In the second part of the behavioral model, route flow proportions are determined by a multinomial logit model containing the following factors 1) the instantaneous travel time on the routes, 2) the overlap between the destination and the instructed destination, 3) the overlap between the route and the instructed route and 4) the overlap between the links in all routes. These route flow proportions are updated during the evacuation. A route choice set is generated using the algorithm presented by Bliemer & Taale (2006). The stochastic nature of the route choice generation process leads to a variance in the results over multiple runs.

Both parts of the behavioral model contain a *compliance parameter* χ_2. The value for this parameter can be varied from 0 up to and including 1. If the value is equal to 0, the instructed assignment has no influence. If the value is equal to 1, the evacuees will fully comply with the guidance, independent on the other factors. Increasing values between 0 and 1 have a non-linear increasing effect on the compliance. Namely, in the utility included in the binary logit model that determines the departure time proportions, the difference between the current time period and the instructed departure time is multiplied by $\chi_2/(1-\chi_2)$. In the utility included in the multinomial logit model determining the route flow proportions, both the overlap between the destination and the instructed destination and the overlap between the route and the instructed route are multiplied by $\chi_2/(1-\chi_2)$. The parameter is constant for all evacuees. More details on the compliance parameter can be found in Pel et al. (2008).

The *traffic propagation part* of EVAQ is similar to the model developed by Bliemer (2007). This dynamic model captures queuing and spill back and has a multi class structure. By incorporating queuing and spill back, i.e., the backward propagation of queues that cross intersections as well, the model contains the basic factors to represent traffic congestion. The multi class structure enables to represent traffic choices diversification, which is present in the evacuation problem. The in- and outflows of all links over time are the output of the model. From this information, the number of arrivals over time can be derived which is input for the objective function given by Equation 3.3. More details on the traffic propagation part can be found in Bliemer (2007). A difference between the models exist in the node model. In the application here, there is no traffic flow on an intersection of which one of the downstream links is completely occupied. This while according to the description given by Bliemer (2007), there could be traffic entering other downstream links.

EVAQ captures network degeneration caused by a hazard, a phenomenon that is not incorporated in the model developed by Bliemer (2007). Roads can become inaccessible during an evacuation, for example, if a storm washes away some land areas. Incorporating this network degeneration is important because network degeneration has a big influence on the effectiveness of the guidance.

3.2.4 Search space

The search space consists of all feasible solutions of a problem. Thus, the search space of the evacuation problem consists of all feasible guidance, i.e., all possible assignments of groups of evacuees to combinations of routes and departure times. Considering all feasible guidance in the optimization process gives the highest possible freedom in generating the guidance, which could theoretically result in the optimal guidance. However, the size of the search space would be enormous because of which it would be computationally very demanding to solve the problem. Here, the search space is limited to a subset of all feasible guidance in order to drastically reduce the computational costs.

The search space is limited by selecting part of all feasible combinations of routes and departure times. This selection is made as follows. A fixed interval between the departure times is set, i.e., Δk. The higher the value for Δk, the smaller the search space

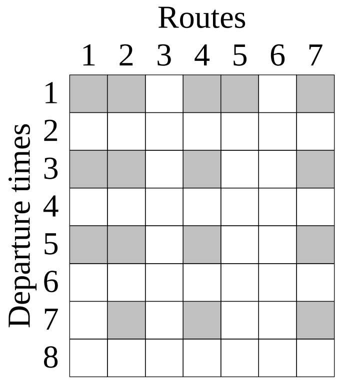


Figure 3.1: Example of a search space

is. The selected routes are set to routes that 1) are more likely to be used by the evacuees, i.e., routes with relatively short free flow travel times, and 2) are spread over the network, i.e, routes that have limited overlap. Routes can still be overlapping, but to a certain extent. This selection aims at a relatively high compliance and a relatively high performance of the resulting guidance. In the selection process, the combination of departure times and routes is considered as well. Only those combinations of departure times and routes are selected for which holds that it is possible to reach the destination under free flow conditions. An example of a search space is given in Figure 3.1. The search space consists of all gray blocks together.

The resulting search space is notated by $\mathbb{U}_s$. It consists of origin-specific sets U_r. Each set U_r consists of elements which are indexed by $e \in U_r$. Each element consists of a combination of a departure times and a route to which groups belonging to origin r can be assigned. In Figure 3.1, each element is illustrated by a gray block.

The search space $\mathbb{U}_s$ is generated by an algorithm that is based on one of the route set generation procedures that is common in route choice modeling, i.e., the so-called procedure of generating the *most probable routes*. This procedure, which is discussed by, for example, Bliemer & Taale (2006), generates a route set based on varying link travel times using Monte Carlo simulations. This procedure is preferred over another common procedure namely selecting the k-th shortest paths, because the last mentioned procedure will more probably result in unrealistic routes for specific origins as discussed by Bliemer & Taale (2006). As a consequence of the network degeneration caused by the hazard, which means that roads become inaccessible over time, the accessibility of routes varies over time. In order to incorporate this degeneration, different route sets have to be generated which can be combined with different departure times.

The search space is generated by the following steps:

1. Creating a route set given a totally accessible network, using the procedure of generating the most probable routes,
2. Combining the route set with departure times for which the routes in the set are still accessible,

3. Adapting the route set, i.e., removing and adding routes, such that the routes are accessible for the next departure time(s), and selecting the corresponding departure times. This step is repeated until it is no longer possible to reach any of the destinations for the next departure time.

In case network degeneration is not considered, only the first step is executed and the resulting routes are combined with departure times. In case network degeneration is considered, all steps are executed. The rest of this section gives the details of these three steps. The procedure has lots of details compared to a procedure of simply selecting the k-th shortest paths. However, these details contribute to the efficiency of the solution approach. Because the computational time of the generation of the search space is negligible compared to the computational time of the solution approach, it is worthwhile to use a detailed procedure as the one presented here.

Step 1: Generation of a route set using the procedure of generating the most probable routes

This step is based on the procedure of generating the most probable routes described by, for example, Bliemer (2007). The routes that result from this procedure are selected to become part of the route set based on the *overlap*, as done by Bliemer (2007). Furthermore, they are selected based on the *travel time* and the *number of routes per origin*. The reason for this selection process is that the generated route set will be used in an optimization context. Therefore, it is extra important that the route set is relatively small and that the routes in the set will be effective as part of the guidance. The number of routes is reduced by applying a maximum number of routes per origin. By selecting routes with relatively short travel times and limited overlap, the selection is expected to contain routes with a positive influence on the effectiveness of the guidance. The selection of routes with limited overlap aims at spreading the evacuees over the network in order to reduce the congestion level. While the overlap in Bliemer (2007) is based on the route length, here it is based on the route travel time instead.

Step 1 starts with the procedure of generating the most probable routes in combination with limiting the travel times of the routes (1.a). Then, part of these routes are selected based on the overlap (1.b). Finally, the number of routes is reduced and the non-selected routes are saved to be combined with future departure times potentially (1.c).

1.a Generation of routes with relatively short free flow travel times

The objective is to generate origin-specific route sets $P_r^{\text{travel time}}$, indexed by $p^{\text{travel time}} \in P_r^{\text{travel time}}$. Routes are generated by iteratively applying Dijkstra's algorithm (Dijkstra, 1959) based on iteration $\bar{n}$ -dependent link travel times $\tau_a^{\bar{n}}$. These travel times are created based on the free flow link travel times and a random component. Each resulting route is added to $P_r^{\text{travel time}}$ if the ratio between the free flow travel time of this route and the free flow travel time of the route with the lowest free flow travel time belonging to the origin is smaller than a maximum ratio $\varphi_1^{\max}$, $\varphi_1^{\max} > 1$. The details of Step 1.a are given by the following pseudocode, where $\bar{n}^{\max}$ denotes the number of iterations which are indexed by $\bar{n}$:

for $\bar{n}$:= *1* **to** $\bar{n}^{\mathsf{max}}$ **do**
  $\tau_a^{\bar{n}} \leftarrow \tau_a^{\text{free}}\varepsilon_a, \varepsilon_a \sim \mathcal{N}(1,\sigma^2)$;
  Apply Dijkstra's algorithm based on $\tau_a^{\bar{n}}$ to generate the shortest route per origin $p_r^{\text{travel time}}$;
  foreach r **do**
    if $\tau_{p_r}^{\mathsf{free}}/\tau_r^{\mathsf{free}} < \varphi_1^{\mathsf{max}}$ **then**
      Add $p_r^{\text{travel time}}$ to $P_r^{\text{travel time}}$;
    end
  end
end

In this pseudocode, τ_a^{free} represents the free flow travel time on link a, ε_a represents a link-dependent random component, and $\mathcal{N}(0,\sigma^2)$ represents a normal distribution with zero mean and a variance σ^2.

1.b: Selection of routes with limited overlap
The objective is to generate origin-specific route sets P_r^{overlap}, indexed by $p^{\text{overlap}} \in P_r^{\text{overlap}}$. This set is a subset of $P_r^{\text{travel time}}$, i.e., it consists of the routes in $P_r^{\text{travel time}}$ with limited overlap. The maximum overlap is notated by φ_2^{max}, $0 < \varphi_2^{\text{max}} < 1$. The overlap between route $p^{\text{travel time}}$ and route p^{overlap}, $\varphi_2(p^{\text{travel time}}, p^{\text{overlap}})$, is defined as the total free flow travel time of the links that both routes have in common divided by the free flow travel time of $p^{\text{travel time}}$. The details of Step 1.b are given by the following pseudocode:

foreach r **do**
  Remove the fastest free flow route from $P_r^{\text{travel time}}$ and add this route to P_r^{overlap};
  while $P_r^{\mathsf{travel\ time}} \neq \emptyset$ **do**
    Remove the fastest free flow route $p^{\text{travel time}}$ from $P_r^{\text{travel time}}$;
    if *For each route* $p^{\mathsf{overlap}} \in P_r^{\mathsf{overlap}}$ *holds that* $\varphi_2(p^{\mathsf{travel\ time}}, p^{\mathsf{overlap}}) < \varphi_2^{\mathsf{max}}$ **then**
      Add $p^{\text{travel time}}$ to P_r^{overlap};
    end
  end
end

1.c: Limit the number of routes
The objective is to generate origin-specific route sets P_r, indexed by $p \in P_r$. This set is a subset of P_r^{overlap}. Each route in the set P_r^{overlap} is either selected to be part of the set P_r or to be part of the set P_r^{backup} which will be used in Step 3. This selection is based on the maximum number of routes per origin φ_3^{max}. The details of Step 1.c are given by the following pseudocode:

foreach r **do**
  if $|P_r^{\mathsf{overlap}}| \leq \varphi_3^{\mathsf{max}}$ **then**
    $P_r \leftarrow P_r^{\text{overlap}}$;
  else
    Remove the $\varphi_3^{\max}$ shortest routes from P_r^{overlap};
    Set P_r equal to these shortest routes;
    $P_r^{\text{backup}} \leftarrow P_r^{\text{overlap}}$;
  end
end

Step 2: Select departure times
The objective is to generate the set of departure times K, indexed by $k \in K$. The set K consists of departure times that correspond to the route set P, indexed by $p \in P$. The set P consists of all origin-specific route sets P_r. The set K consists of the multiples of Δk from 0 up to and including k_P, which is equal to the last departure time at which it is possible to travel over all routes in the set from origin to destination, without being impeded by the hazard under free flow conditions. For each origin, the generation of the search space U_r is started. Each combination of a departure time $k \in K$ and a route $p \in P_r$ is denoted as element e of the search space U_r.

In Step 3, the route set P is updated after which corresponding departure times are selected. Step 3 is repeated until it is no longer possible to reach any of the destinations for the next departure time.

Step 3.a: Set the first departure time for the next route set
Set the first departure time for the next route set k^{earliest} equal to $k_P + \Delta k$.

Step 3.b: Update the network and the set of backup routes
Update the network by excluding all links that are inaccessible at k^{earliest} from the network. The set of backup routes is updated as well, by removing all routes from P^{backup} that are not completely included in the updated network.

Step 3.c: Remove routes from the route set based on the origins they belong to
Select the origins R^{remove} for which holds that all routes starting in an origin which is part of this set should be removed from the route set, either because the origin is inaccessible at k^{earliest} or because no destination can be reached anymore from the origin at k^{earliest} given the updated network. The possibility to reach any of the destinations from all origins is checked by registering all downstream links reachable from the aforementioned origins. All routes belonging to the origins R^{remove} are removed from P.

Step 3.c: Remove routes from the route set based on their accessibility
For each origin, the routes that are not completely included in the updated network are removed from P. The number of routes that can be added to P for origin r, notated by $\pi(r)$, is set equal to the number of removed routes for origin r.

Step 3.d: Update the route set by using backup routes
If there are backup routes belonging to the an origin for which holds that $\pi(r) \neq 0$, the set P is extended. As many as possible backup routes are added to P, the shortest backup route first. The used backup routes are eliminated from the set of backup routes and $\pi(r)$ is updated by subtracting the number of used backup routes for origin r.

Step 3.e: Update the route set with newly generated routes
New routes are generated in order to complete P. These routes are generated in the same way as routes are generated in step 1, based on the reduced network. For the overlap of the routes, both routes found in this step and routes in P are compared. The route set P is extended by adding a number of routes per origin r which is equal to or less than $\pi(r)$.

Step 3.f: Set the departure times that belong to the new route set
Departure times K are selected that belong to P. These departure times are equal to all multiples of $k*$ from k^{earliest} up to and including k^P, which is equal to the last departure time at which it is possible to travel over all routes in the set from origin to destination, without being impeded by the hazard under free flow conditions. The route set P is divided in origin-specific route sets P_r in order to update the search space. For each origin, the search space U_r is updated by adding each combination of a departure time $k \in K$ and a route $p \in P_r$ as element e of the search space U_r.

3.3 Solution approach

The problem, formulated by Equation 3.2, is solved by a metaheuristic that optimizes the departure time, route, and destination instruction for all groups simultaneously. In each iteration, multiple solutions to the problem are evaluated. A solution, i.e., guidance, is created by assigning each group of evacuees to an element e, containing a departure time and a route, from the origin-specific search space U_r. This search space follows from the approach presented in Section 3.2.4. The resulting guidance is evaluated using the travel behavior and traffic propagation model and the objective function.

The metaheuristic presented in this section, EAS$^+$-evacuation, is based on Elitist Ant System (EAS). EAS is a version of ant colony optimization (ACO) which is introduced by Dorigo & Stützle (2004). These metaheuristics are based on the communication behavior of ants. The evacuation problem differs from the usual applications of ACO like the Traveling Salesman Problem (TSP) and because of that, the metaheuristics differ as well. The differences between EAS$^+$-evacuation and EAS applied to the TSP (EAS-TSP) are discussed in Section 3.3.4. Othere metaheuristics could be used to solve the problem as well, as long as they are tailored to the evacuation problem.

EAS$^+$-evacuation, which is visualized in Figure 3.2, consists of two phases: *the construction phase* to generate solutions and the *update of pheromone trails* to update information based on the solutions and their performance, in order to give direction to the search process. These two phases are explained in Sections 3.3.1 and 3.3.2 respectively. Section 3.3.3 discusses the heuristic information, which determines the direction of the search process over the iterations.

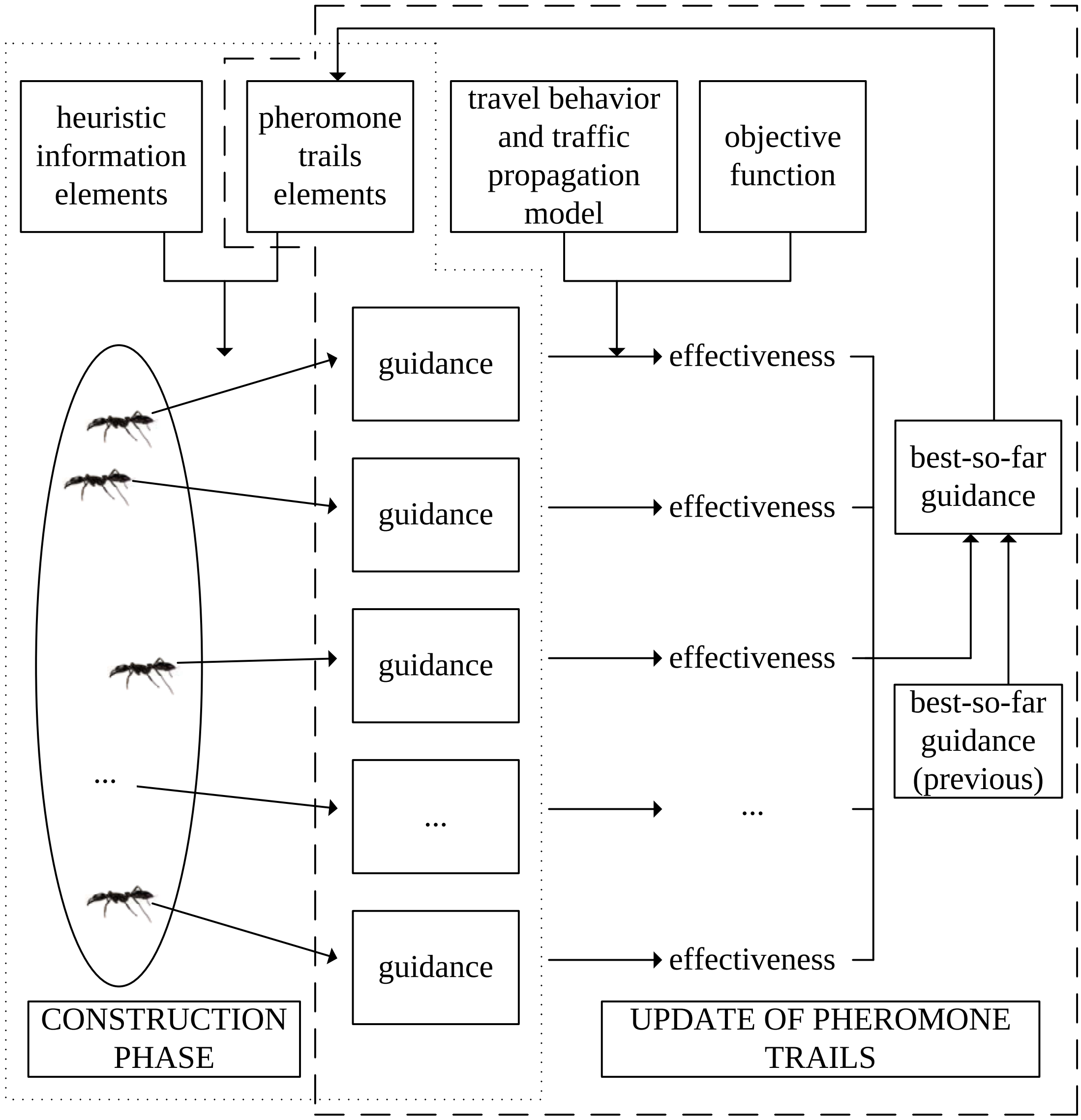


Figure 3.2: EAS$^+$-evacuation

3.3.1 Construction phase

In the construction phase, all ants concurrently build a solution. Thus, the number of solutions equals the number of ants. In EAS$^+$-evacuation, this solution is the guidance, i.e., a set of evacuation instructions. This set consists of all groups of evacuees assigned to an element of the search space, i.e., a combination of departure time and route. Multiple groups can be assigned to the same element.

The ants use a probabilistic action choice rule, called *random proportional rule*, to determine to which element each group is assigned. Random draws are used to select the elements, whereby the chance that an element is chosen is equal to the following probability. The probability with which an ant chooses to assign a group to element e is equal to:

$$h_e = \frac{\mu_e \eta_e}{\sum_{e \in U_r} \mu_e \eta_e}, 0 < h_e \leq 1, \tag{3.4}$$

where μ_e is the value of the so-called *pheromone trail* belonging to element e, η_e is a scalar for the so-called *heuristic information* for element e. By this probabilistic rule, the probability of choosing a particular element increases with the value of the associated pheromone trail and the value of the heuristic information. Heuristic information is constant for all iterations and gives elements which are expected to have a positive influence on the effectiveness of the evacuation instructions a relatively high selection probability. The heuristic information is specified in Section 3.3.3. Pheromone trails change over the iterations and give elements of good solutions of earlier iterations a relatively high probability. The pheromone trails are initialized at $\mu_e = 1, e \in U_r, r \in R$, in the first iteration and the update over the iterations is discussed in Section 3.3.2.

The construction of the solutions can either be parallel, i.e., at each construction step, all ants assign one group to an element, or sequential, i.e., an ant builds a complete solution before the next ant starts to build one. Here, parallel and sequential construction are equivalent: they do not influence the algorithm's behavior because the probabilities h_e are updated in the next iteration and not during the construction.

Each ant maintains a *memory* which contains the created solution. When all ants have created their solution, this memory is used to determine the effectiveness of each solution, i.e, the value of the objective function given by Equation 3.3. Based on these memories, the effectiveness values, and the *best-so-far guidance* determined in the previous iteration, the best-so-far guidance $\mathbf{U}^{\text{best}}$ and its effectiveness are known. This guidance is used in the update of the pheromone trails.

3.3.2 Update of pheromone trails

The pheromone trails are updated when all ants have created their solutions. This update starts with lowering the pheromone value of each element by a constant factor, which is called *pheromone evaporation*:

$$\mu_e \leftarrow (1-\rho)\mu_e, e \in U_r, r \in R \tag{3.5}$$

where $0 < \rho \leq 1$ is the *pheromone evaporation rate*. The range of μ_e is equal to $\langle 0, \infty \rangle$. The objective of the evaporation is to avoid unlimited accumulation of the pheromone trails and to enable to "forget" bad solutions constructed in earlier iterations. After the evaporation, pheromone is deposited on the elements to which people are assigned in the best-so-far guidance U^{best}:

$$\mu_e \leftarrow \mu_e + \chi_3 \Delta\mu_e \tag{3.6}$$

where χ_3 is a weighting parameter that indirectly influences the relative proportion of the exploration and concentration of the search process, and $\Delta\mu_e$ is the amount of pheromone deposited on the elements involved in the best-so-far guidance. For all other elements, $\Delta\mu_e$ is equal to 0. For the elements involved in the best-so-far guidance, $\Delta\mu_e$ is set equal to the product of 1) the effectiveness of the guidance divided by the total population, and 2) the population assigned to element e divided by the population of the origin belonging to element e. The first part of the product let $\Delta\mu_e$ increase by the effectiveness of the guidance and scales $\Delta\mu_e$ between 0 and 1. The second part makes $\Delta\mu_e$ dependent on the relative number of people that are assigned to element e. The higher the value of μ_e is, the more likely it is that this element will be part of a solution in the next iteration.

Appropriate values of the parameters ρ in and χ_3 depend on the search space: the larger the search space, the more exploration and therefore relatively low values for ρ and χ_3 are appropriate. An appropriate value of χ_3 depends on the time available to find evacuation guidance too: when the danger is critical, the value has to be relatively high to quickly find a solution. As mentioned by Dorigo & Stützle (2004), the search process is also influenced by the ratio between the initial values of the pheromone trails and the amount of pheromone with which the pheromone is updated.

3.3.3 Specification of the heuristic information

The heuristic information gives elements which are expected to have a positive influence on the effectiveness of the guidance a relatively high selection probability. In this chapter, these elements are the ones resulting in early arrivals given the objective function represented by Equation 3.3. The heuristic information of an element e depends on the departure time and the route belonging to the element:

$$\eta_e = \vartheta_{p_e} \zeta_{k_e} \tag{3.7}$$

where ϑ_{p_e} is a scalar representing information about route p belonging to element e, and ζ_{k_e} is a scalar representing information about departure time k belonging to element e. A relatively high value of η_e gives element e a relatively high selection probability. For η_e holds $0 < \eta_e \leq 1$, based on the boundaries of both information parts described hereafter.

An element with a relative short free flow travel time has a relative high value for the heuristic information:

$$\vartheta_{p_e} = \left(\frac{\min_{e \in E_r} \tau_{p_e}^{\text{free}}}{\tau_{p_e}^{\text{free}}} \right)^{\chi_4} \tag{3.8}$$

where χ_4 is a weighting parameter with $0 \leq \chi_4 \leq 2$. When $\chi_4 = 0$, the heuristic information does not depend on the travel times of the routes. The higher the value for χ_4 is, the larger the distinction in the heuristic information based on the differences in travel times is. The upper limit on the value of χ_4 avoids a selection probability becoming negligible. Given the boundaries for χ_4 and φ_1, it holds that $1/\varphi_1 \leq \vartheta_{p_e} \leq 1$.

An element with a relative early departure time has a relative high value for the heuristic information:

$$\zeta_{k_e} = 1 - \chi_5 \frac{k_e}{\max\{K_{r_e}\}} \tag{3.9}$$

where K_{r_e} is the set of departure times that are part of the elements that belong to r_e, the origin r belonging to element e. For ζ_{k_e} holds $0 < \zeta_{k_e} \leq 1$. For weighting parameter χ_5 holds that $0 \leq \chi_5 < 1$. When $\chi_5 = 0$, the heuristic information does not depend on the departure times. The higher the value for χ_5 is, the larger the distinction in the heuristic information based on the differences in departure times is.

3.3.4 Differences between EAS$^+$-evacuation and EAS-TSP

This section discusses all differences between EAS$^+$-evacuation and EAS-TSP (as described by Dorigo & Stützle (2004)). In the TSP, cities and distances between each pair of cities are given, and the objective is to find the shortest possible tour that visits each city exactly once. One of these differences changes the fundamentals of EAS. Namely, in EAS all ants deposit pheromone on the elements of their solution, and pheromone is deposited on the elements of the best-so-far solution. In EAS$^+$-evacuation, pheromone is only deposited on the elements of the best-so-far solution, to increase the influence of this solution and to avoid influence of bad solutions constructed by the ants. Relative to other ACO algorithms, EAS gives the elements of the best-so-far solution a high influence. Since this influence of the best-so-far solution is made stronger in the new algorithm, the name of the algorithm is changed from EAS to EAS$^+$-evacuation.

All other differences are the consequence of the application to the evacuation problem instead of the TSP. The first difference is in the solutions that are created by the ants. In EAS-TSP, a solution is a tour that takes the traveler through a given set of cities and then back home, while in EAS$^+$-evacuation, a solution is a set of instructions. The tour consists of arcs, while the set of instructions consists of numbers of people assigned to combinations of departure times and routes. Thus, in EAS$^+$-evacuation, elements are either part of the solution, or not, similar to the arcs in EAS-TSP, but for the elements that are part of the solution, there is also a number of people that is assigned to the element. This change in the solution automatically leads to a change in the memory: in EAS$^+$-evacuation, the memory of each ant contains the instruction set, while in EAS-TSP, the memory of each ant contains the visited cities in the order they were visited.

The second difference is in the use of the random proportional rule, i.e., Equation 3.4. One construction phase consists of multiple steps, and in each step one element is selected to be part of the instruction set of one of the ants. In EAS-TSP, Equation 3.4 *changes during the construction phase*, because possible arcs to be selected for the rest of the tour and their probabilities depend on the arcs that are already part of the tour. In EAS^{+}-evacuation, Equation 3.4 *does not change during the construction phase*, since possible elements to be selected for one group and their probabilities do not depend on the elements that are already selected for other groups.

The third difference is related to the *amount of pheromone deposited on the elements of the best-so-far solution*. In both metaheuristics, this amount is a function of the solution quality. Given that the applications, i.e., TSP and the evacuation problem, are completely different, the quality expressions are different as well.

The final difference is in the *parameters in the random proportional rule*. The rule as formulated by Equation 3.4 contains parameters α and β in EAS-TSP, representing the relative influence of the pheromone trail and the heuristic information respectively. With these parameters, Equation 3.4 changes in:

$$\tilde{h}_e = \frac{\mu_e^{\alpha}\eta_u^{\beta}}{\sum_{e \in E_r} \mu_e^{\chi_6}\eta_u^{\chi_7}}, 0 < \tilde{h}_e \leq 1. \tag{3.10}$$

In EAS+-evacuation, these parameters are not included, or equally, set to 1. The reason for this is that in EAS^{+}-evacuation, the relative influence of the pheromone trail is also influenced by the parameter ε in Equation 3.6, and the relative influence of the heuristic information is also determined by the flexible definition of the heuristic information. By not including χ_6 and χ_7, the number of parameters describing the same effect is limited.

3.4 Case study

This section analyzes the results of applying EAS^{+}-evacuation to solve the evacuation problem formulated in Section 3.2. The studied scenario is an evacuation as consequence of a hypothetical flooding of part of the Netherlands, which will be described in Section 3.4.1. The objectives of this case study are:

1. to support the statement made in Chapter 1, i.e., that guidance increases the evacuation efficiency, especially when this guidance is optimized,
2. to analyze the performance of the specific optimization method presented in this chapter,
3. to explore the applicability of the optimized guidance in a wider perspective.

Sections 3.4.2-3.4.4 analyze the evacuation efficiency in order to meet the first objective. Section 3.4.2 compares the efficiency of an evacuation with optimized guidance with the efficiency of an evacuation without any guidance. Section 3.4.3 compares the effectiveness of two types of guidance, i.e. optimized guidance and guidance set up by a set of simple, but computationally less demanding, rules. The difference between these two effectiveness values is analyzed more deeply by comparing the structure of these different types of guidance in Section 3.4.4.

The optimization method is applicable to optimize guidance for many kinds of evacuations, of which the Walcheren case is an example. In order to get insight into the results that will be obtained for other applications, the performance of the optimization method is analyzed. First of all, the near-optimality of the optimized guidance is analyzed in Section 3.4.5. Section 3.4.6 discusses the computational efficiency of the method. The influence of the parameter settings on the effectiveness of the resulting guidance is analyzed in Section 3.4.7.

Section 3.4.8 discusses the applicability of the optimized guidance in a wider perspective. It shows the effect of a new measure to increase the evacuation efficiency. This measure, i.e. the blocking of roads, is based on the optimized guidance.

The analysis presented in this section has an illustrative character. It is decided to analyze, discuss and explain several aspects of the optimized guidance and the corresponding effectiveness. Statements about the statistical significance of the results are not made. While these statements would strengthen the results for this specific case study, they would still not give any guarantees for other applications because of the use of a metaheuristic.

3.4.1 Scenario

The hypothetical flooding concerns Walcheren, a peninsula in the southwest of the Netherlands, see 3.3. Over 120,000 residents from an area of 216 square kilometers have to be evacuated, whereby the number of evacuees per vehicle is assumed to be equal to 2.5. Walcheren is flooded in four hours. The evacuation is assumed to start two hours before the flood, consequently the time available to evacuate is equal to six hours. The dashed lines in Figure 3.3 show which part of the network is flooded after 2, 3, 4, 5, and 6 hours. All data used in this case study, and in the case studies presented in the following chapters, are hypothetical.

The problem formulation is specified by setting the compliance parameter, which is introduced in Section 3.2.3, equal to 1. This means that the guidance is optimized under full compliance conditions. In this way, it is possible to compare the effectiveness of this guidance with the effectiveness of guidance created by a rule-based approach in Section 3.4.3. For this rule-based approach holds that it is impossible to consider guidance in the development. However, compliance is considered in the evaluation of the resulting effectiveness, as explained in Section 3.4.2. In the case study in Chapter 4, partial compliance is considered in the optimization of evacuation guidance. An analysis of the effect of incorporating guidance in the optimization approach can be found in Pel et al. (2009).

The parameter settings for the solution approach are given in Table 3.1. Section 3.4.7 analyzes the influence of these settings. The weighting parameter of the objective function, χ_1 is set to 0.1. This means that evacuees arriving at their destination after 6

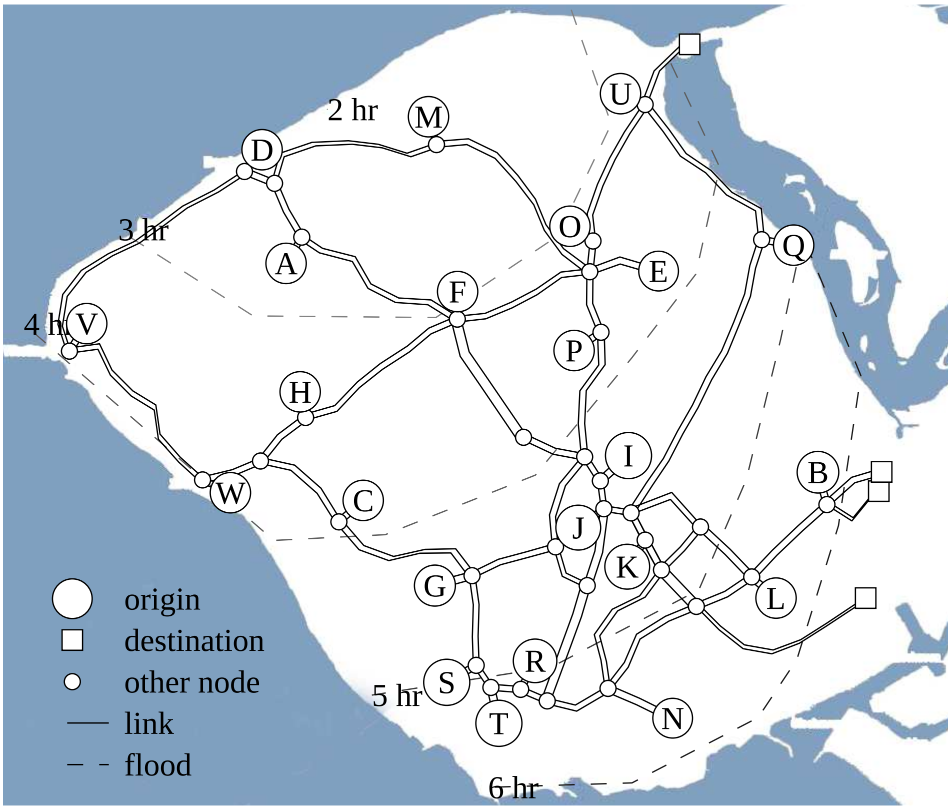


Figure 3.3: Walcheren network, consisting of 23 origins with a population size varying from about 1,500 to 17,000, 4 destinations, 34 intermediate nodes, and 142 unidirectional links connecting the nodes

hours of evacuation have a weight of 55% compared to 100% for evacuees arriving at their destination at the start of the evacuation.

The problem and the solution approach are programmed in Matlab, which is used for all case studies in this thesis. Other environments, which might solve the problems faster, could have been used as well. However, the current environment fits the illustrative purpose of the case studies. It gives insight in the relative difference in the computational time needed to solve the different problems. When the optimization methods presented in this thesis would be used in practice, more advanced techniques could be used. Examples are the use of other environments, parallel programming, and supercomputers.

3.4.2 Effect of guidance compared to no guidance

This section compares the effectiveness of the optimized guidance with the efficiency of an evacuation without any guidance. The guidance, optimized under full compliance conditions, has an effectiveness, i.e., the value of the objective function given by Equation 3.3, equal to 74,636. This value reflects the weighted number of arrivals. Here, the effectiveness of the optimized guidance is evaluated both under full com-

Table 3.1: Parameter settings

Symbol	Explanation	Value
Generation of search space		
Δk	Period between two consecutive departure times	0.5 hours
$\varphi_1^{\max}$	Maximum ratio with respect to the travel times	2
$\varphi_2^{\max}$	Maximum overlap of the routes	0.8
$\varphi_3^{\max}$	Maximum number of routes per origin	5
$\bar{n}^{\max}$	Number of iterations	100
σ^2	Variance of the normal distribution	$\left((\bar{n}-1)*0.05\right)^2$
-	Group size	10,000
EAS$^+$-evacuation		
χ_4	Parameter weighting the effect of the routes in the heuristic information	1
χ_5	Parameter weighting the effect of the departure times in the heuristic information	0.5
-	Number of ants	10
ρ	Pheromone evaporation rate	0.02
χ_3	Parameter influencing the exploration and concentration	0.1

pliance and under partial compliance. In the partial compliance case, the optimized guidance is evaluated by the model EVAQ introduced in Section 3.2.3 with the compliance parameter set to a value between 0.6 and 0.9. The efficiency of an evacuation without any guidance is obtained by evaluating the optimized guidance, or any other guidance, with the compliance parameter set to 0.

The evaluation resulted in the following range of effectiveness values, all reflecting the weighted number of arrivals:

- 74,636 (full compliance);
- 63,000 - 69,000 (partial compliance);
- 46,000 - 56,000 (no guidance).

Both the effectiveness of the optimized guidance evaluated under partial compliance and the efficiency of an evacuation without any guidance are expressed by ranges. The reasons are the stochastic nature of the route choice generation process for both evacuation types, and a varied value of the compliance parameter for the evaluation under partial compliance as explained before. The efficiency values indicate that guided evacuations are more efficient than an evacuation without any guidance. In addition to the efficiency values, the arrival patterns for the different evacuations are given in Figure 3.4. The figure shows that the number of arrivals in the final hour of the evacuation is limited. This is caused by the network degeneration as consequence of the hazard.

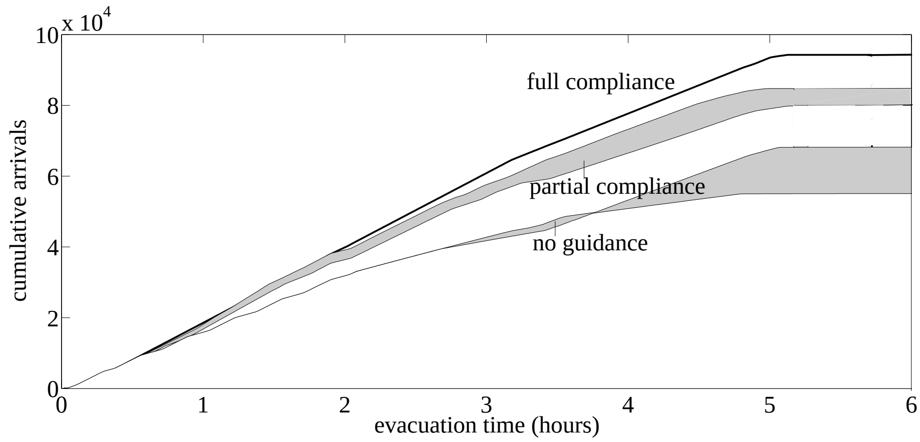


Figure 3.4: Arrival patterns of both the optimized guidance under partial and full compliance and an evacuation without any guidance

The stochastic nature in the route choice generation process resulted in a wide range of effectiveness values. For each intersection-destination pair, about 5 routes are considered in the process. In order to analyze the effect of this process, the efficiency of an evacuation without any guidance is analyzed as well for a situation in which all routes on the network are considered in the route choice generation process. This resulted in an effectiveness value equal to 63,700, substantially different from the range from 46,000 - 56,000 found for the small selection of routes. The combination of considering all routes in the network and updating the route choice during the evacuation means that the travelers are continuously aware of all possible routes and corresponding travel times. Interesting questions are whether it is more realistic to consider all possible routes or a selection of them, and eventually how many routes should be part of the selection. Because this thesis focuses on the incorporation of compliance and route choice behavior but not on the development of route choice models, these questions are not investigated here. However, this finding supports the development of an optimization method that 1) is generic regarding the modeling assumptions, and 2) incorporates uncertainty, e.g. regarding these assumptions.

3.4.3 Effect of optimized guidance compared to guidance created by simple rules

This section compares the effectiveness of the optimized guidance to the effectiveness of guidance set up by a set of simple, but possibly naive, evacuation rules. These rules are to instruct the evacuees to 1) go to the nearest destination, 2) follow the fastest free flow route, and 3) depart at a certain point in time. These instructed points in time are set in such a way that no congestion occurs, where evacuees whose origin will be flooded first are evacuated first. Similar rules are presented in literature, i.e. evacuees are guided over the shortest routes given an optimal distribution of the evacuees over the destinations (Saadatseresht et al., 2009). These type of rules are proposed to be used in practice as well.

The effectiveness of both evacuations, under assumption of full compliance, is equal to, approximately:

- optimized guidance: 74,636;
- guidance created by simple rules: 37,000.

Under assumption of partial compliance, whereby the compliance parameter is set to a value between 0.6 and 0.9, the range of the effectiveness of both evacuations is equal to, approximately:

- optimized guidance: 63,000 - 69,000;
- guidance created by simple rules: 49,000 - 53,000.

This indicates that optimized guidance performs better than guidance created by simple rules. Thus, application of an optimization approach like the approach presented in this chapter seems to be necessary to create evacuation guidance, and using simple rules to create evacuation guidance seems to be very ineffective. In addition to the effectiveness values, the arrival patterns for the evacuations under both kinds of instructions are given in Figure 3.5. Section 3.4.4 analyzes the structure of the optimized guidance in order to explain the relatively high difference in performance.

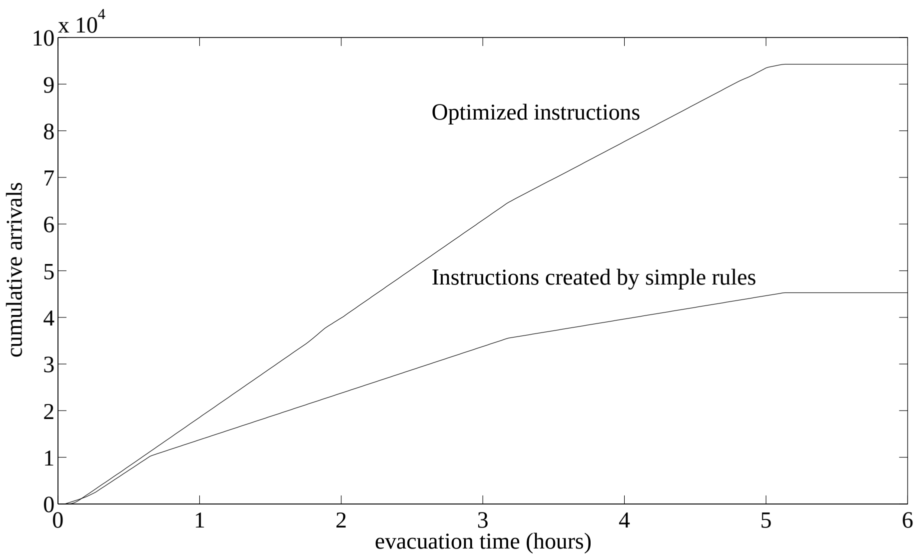


Figure 3.5: Arrival pattern of the evacuation by applying the optimized guidance and the guidance created by a set of simple rules

Comparing the effectiveness of the guidance created by simple rules, evaluated under the assumption of partial compliance, i.e., equal to 49,000 - 53,000, and the efficiency of an evacuation without any guidance, i.e., equal to 46,000 - 56,000, adopted from Section 3.4.2, gives an important insight: the performance of an evacuation without guidance is similar to an evacuation with guidance created by simple rules.

3.4.4 Analysis of the optimized guidance

Section 3.4.3 showed that optimized guidance performs better than guidance created by simple rules. Most likely, this difference in performance is caused by the relationship between the instructions in both sets. The results indicate that, for example, it is not effective to instruct all people to follow the shortest route. In this section, the optimized guidance is analyzed to see if there is a pattern in these departure time, route, and destination instructions explaining the relatively high performance.

The optimization of evacuation guidance is computationally much more expensive than the development of guidance by these simple rules. However, the consequences for the implementation of the resulting guidance are limited. Both approaches result in a route, departure time, and destination instruction for groups of evacuees. The only difference for the implementation relates to the size of the groups. In case of simple rules, these groups are set by the origins, while the groups can be smaller in case of optimized guidance.

For the departure time guidance holds that there is no indication of a relation between the instructed departure times and the moment the hazard strikes the origin, except the logical observation that no evacuees are assigned to a departure time later than the moment the hazard strikes their origin. Regarding the route guidance, the percentage of people assigned to the shortest free flow routes is equal to 36%, the other evacuees are spread over the rest of the routes. The percentage of people assigned to the nearest destination, based on the shortest free flow route, is equal to 55%, the other evacuees are assigned to other destinations. Because of the illustrative purpose of this case study, the analysis given here is limited to one case. The same analysis for other cases resulted in similar data as showed in Huibregtse et al. (2010).

There are both similarities and differences between the optimized guidance and the guidance created by simple rules, see Table 3.2 for an overview of this comparison. Apparently, it is efficient to instruct a part of the people to follow the shortest route and to travel to the nearest destination, but it is not efficient to give these instructions to all people. This can be explained by the fact that part of the network is unused when giving these instructions to all the people. The guidance created by simple rules guides 80% of the people to 1 out of the 4 destinations, and 20% of the people are guided to the other 3 destinations. For the optimized guidance, these values are equal to 48% and 52% respectively. The links directly upstream of the destinations have a big influence on the effectiveness as will be explained in Section 3.4.5. It is more efficient to use a bigger part of the network by spreading the evacuees over more routes and destinations. Another difference between the two types of guidance is that by applying the simple rules, evacuees whose origin will be flooded first, are evacuated first. Such a relation between the departure time and the moment the origin is flooded is not recognized in the optimized guidance.

Thus, it seems to be efficient to spread the people over the routes and destinations in the network such that part of the people are instructed to follow the shortest route and

Table 3.2: Comparison between the guidance created by simple rules and the optimized guidance

	Guidance created by simple rules	**Optimized guidance**
Departure times	Evacuees whose origin will be flooded first depart the earliest and the schedule is set up such that no congestion arises	No relation between the departure time and the moment the origin is flooded
Routes	100% of the people instructed to follow the shortest free flow route	36% of the people instructed to follow the shortest free flow route
Destinations	100% of the people instructed to travel to the nearest destination	55% of the people instructed to travel to the nearest destination

to travel to the nearest destination. Optimized guidance appears to have an advanced structure, which cannot be captured in simple decision rules. The structure of the optimized guidance shows as well that in case all evacuees prefer the nearest destination and the shortest route, part of the evacuees have to deviate from this preference under a full compliance assumption. In fact, not all evacuees will do so and therefore it is important to consider partial compliance.

3.4.5 Near-optimality of the effectiveness of the guidance

As showed in Sections 3.4.2-3.4.3, an evacuation with optimized guidance performs better than an evacuation without guidance, and the effectiveness of optimized guidance is higher than the effectiveness of guidance created by simple rules. However, so far it is unknown how close to optimal the optimized guidance is. This is analyzed in this section.

The best way to analyze the optimality of the optimized guidance is to compare the effectiveness with the effectiveness of the optimal guidance. However, this optimal guidance is unknown. Therefore, the effectiveness is compared to a theoretical upper bound from which it is unknown if this can be realized in practice. This theoretical bound is set equal to the maximal outflow of the links directly upstream of the destinations. This outflow represents the arrival rate for the given network, assuming that there are no internal bottlenecks. The capacity of the links directly upstream of destinations 1, 2, 3, and 4, see Figure 3.3, is equal to 5,000, 11,000, 5,000, and 5,000 evacuees per hour respectively. However, the links directly upstream of destinations 2 and 3 have the same upstream link which capacity is equal to 11,000 evacuees per hour. This limits the combined capacity of link 2 and 3 to 11,000 vehicles per hour. Furthermore, 4,790 evacuees from origin B (see Figure 2) can travel to destination 2 and 3 without making use of the mentioned upstream link. Combining this information, the maximal outflow is equal to 21,000 evacuees per hour plus 4,790 evacuees over the whole evacuation. Thus, the maximum outflow during the first three hours is equal to 67,790 evacuees. When applying the optimized guidance, the outflow during this period is equal to about 61,000. Thus, the outflow during this period is equal to 90% of the theoretical upper bound. Because of the illustrative purpose of this case study, the analysis given here is limited to one case. The same analysis for other cases resulted in similar data as showed in Huibregtse et al. (2010).

Figure 3.6 shows that during a substantial part of the evacuation period, the arrival rates at the destinations are equal to the maximal arrival rates. The figure illustrates that destination 2 and 3 share the capacity, as explained before. In the first moments of the evacuation no arrivals are possible since the evacuees have to travel from their origin to the destination. At the end of the evacuation, no arrivals are possible because of the network degeneration caused by the hazard. Other deviations from the maximal arrival rates, like the 'gap' in the arrivals at destination 4, could indicate sub-optimality of the guidance.

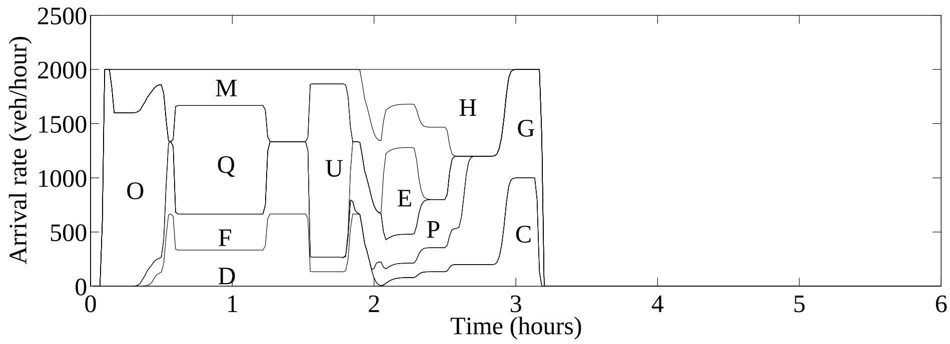
To conclude, the near-optimality of the guidance, expressed as the number of arrivals divided by the maximum outflow of the network, is equal to at least 90% during the analyzed period of the evacuation. This possibly indicates a sub-optimality of the optimized guidance. This sub-optimality can have several causes. It could be a direct consequence of the metaheuristic, but it could also be a consequence of the limitation of the search space or the used group size. A more deeply analysis would be needed to be certain about the cause. However, in case that the sub-optimality is caused by the limitation of the search space of the used group size, it could still be recommendable to use these settings. This because these settings limit the computational time. Furthermore, if the group sizes would become smaller, communication of the guidance could become more complicated as well.

The near-optimality of the optimized guidance is not a proof of the sub-optimality of the guidance. The maximum outflow of the network is an upper bound on the performance of the optimal guidance as mentioned before. It could be that this theoretical upper bound cannot be realized because of internal bottlenecks, the network design, the hazard pattern or the demand distribution.

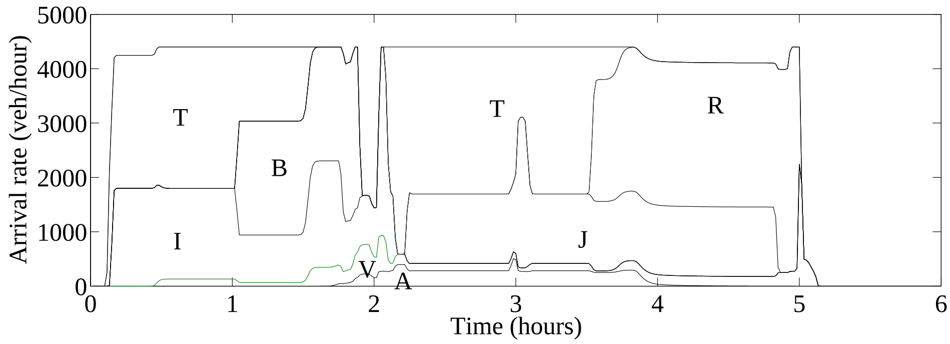
3.4.6 Efficiency of the solution approach

Figure 3.7 shows the convergence towards this guidance. Exploration is visible in the first iterations, i.e., the differences between the effectiveness of the iteration-best guidance are relatively large, and concentration in the last iterations, i.e., the differences are relatively small.

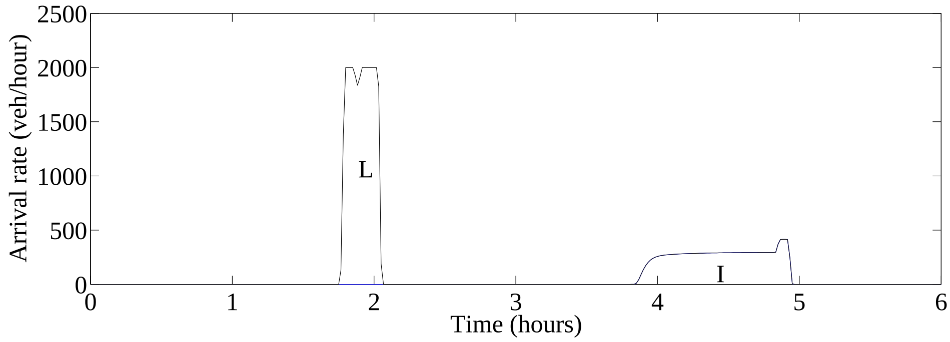
Solving the optimization problem took 12 hours computation time using a desktop computer with an Intel Pentium Core 2 Duo @ 2.5 Ghz and 2GB RAM. This computa-



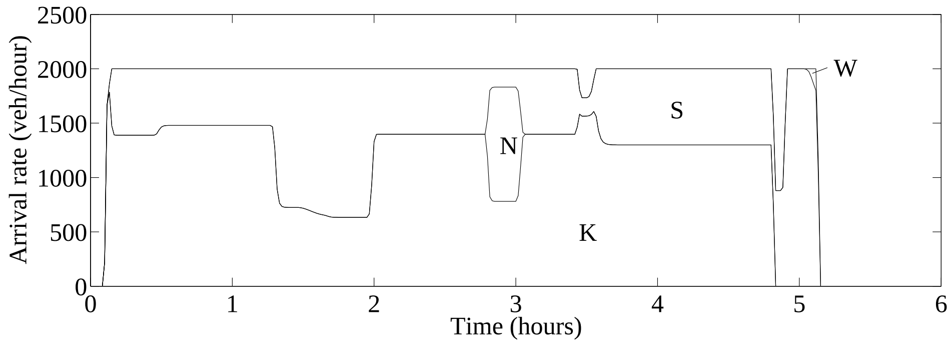
(a) Destination 1



(b) Destination 2



(c) Destination 3



(d) Destination 4

Figure 3.6: Arrival rates at the destinations of the Walcheren network. The letters indicate the origins of the evacuees.

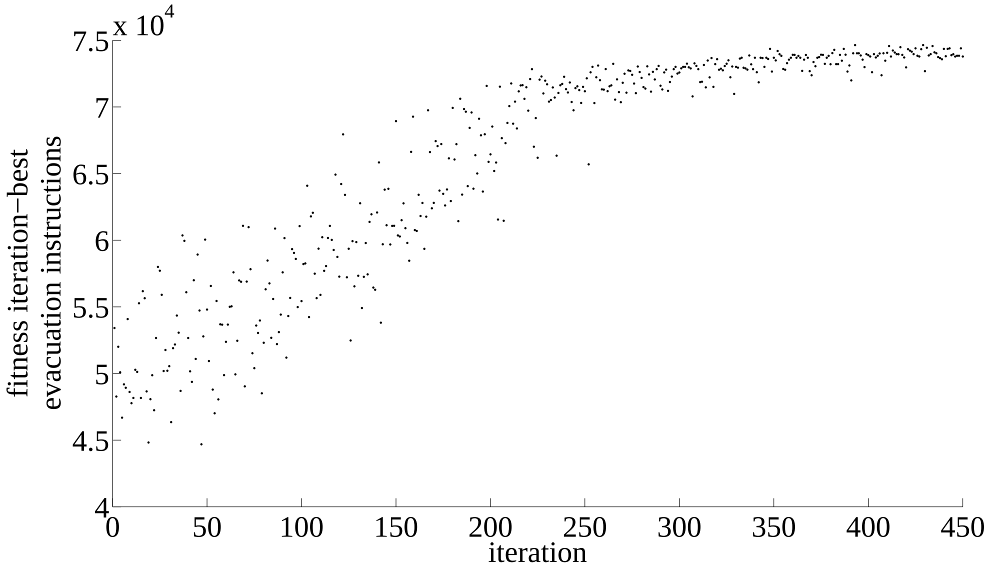


Figure 3.7: Effectiveness of the iteration-best guidance

tion time can be drastically lowered by parallel programming and using fast computers. The computationally most intensive part is the travel behavior and traffic propagation model.

3.4.7 Influence of the parameters and stochasticity

When applying the optimization method to another scenario, parameter settings have to be chosen. They can be set equal to the values chosen in this case study, but, most probably, better settings do exist because optimal parameter settings for ACO methods are problem-specific as showed by Gaertner & Clark (2005) and Wong (2008). This section serves as a guideline for the choice of the parameter values for other applications by showing the influence of the parameter settings on both the efficiency of the approach and the effectiveness of the resulting guidance. The influence of the stochasticity is investigated as well by analyzing different runs with the same parameter settings. The parameters of the generation of the search space are not analyzed here. These parameters influence the feasibility of the guidance and because of that, appropriate values of these parameters depend on the desires of the authority, e.g., the maximum number of different instructions.

The influence of the parameters is analyzed by applying EAS+ for different parameter settings. The following extreme situations are tested:

1. Same settings as before;
2. No heuristic information ($\chi_4 = 0$ and $\chi_5 = 0$);
3. Relatively high values for the heuristic information (relatively high values for χ_4 and χ_5);
4. Relatively low number of ants in the colony (relatively low value for $|Z|$);

Table 3.3: Parameter settings for EAS$^+$-evacuation

Symbol	**Test 1**	**Test 2**	**Test 3**	**Test 4**	**Test 5**	**Test 6**	**Test 7**
χ_4	1	0	2	1	1	1	1
χ_5	0.5	0	0.999	0.5	0.5	0.5	0.5
$\|Z\|$	10	10	10	5	15	10	10
ρ	0.02	0.02	0.02	0.02	0.02	0.1	0.2
χ_3	0.1	0.1	0.1	0.1	0.1	1	10

Table 3.4: Effectiveness of the guidance for the multiple runs of the different tests

	Test 1	**Test 2**	**Test 3**	**Test 4**	**Test 5**	**Test 6**	**Test 7**
Run 1	74,636	72,167	72,750	71,764	71,709	73,368	**70,574**
Run 2	**75,569**	70,353	72,779	73,641	74,734	73,136	65,769
Run 3	74,965	**74,976**	73,026	74,119	**75,176**	**73,922**	66,674
Run 4	75,548	73,163	**73,483**	**74,722**	71,928	68,334	68,461

5. Relatively high number of ants in the colony (relatively high value for $|Z|$);
6. Relatively small exploration (relatively high values for ρ and χ_3);
7. Small exploration, i.e., smaller than the exploration in test 6 (relatively high values for ρ and χ_3).

Table 3.3 gives the corresponding parameter settings. Each test is performed 4 times to analyze the influence of the stochasticity of the optimization approach. Table 3.4 gives the effectiveness of the optimized guidance for each run. The results show a limited influence of the stochasticity on the effectiveness values for Test 1 and 3, and more influence for the other tests. Regarding the effectiveness values, relatively high values were found for Test 1, and relatively low values for Test 6 and 7. However, optimized guidance with a low effectiveness value is also valuable compared to a situation without optimized guidance: the effectiveness of all optimized guidance in this section is higher than the efficiency of an evacuation without guidance and higher than the effectiveness of guidance created by simple rules, based on the analyses in Sections 3.4.2-3.4.3.

Table 3.5 shows in which iteration of the different tests certain effectiveness values are reached. For all tests, the run with the highest effectiveness of the optimized guidance is included. These runs are indicated by the bold values in Table 3.4. The biggest difference in the number of iterations needed to let the approach converge is the number of iterations needed by Test 1-5 on the one hand, and Test 6-7 on the other hand. Since the traffic simulation is the computationally most intensive part, the computational time for one iteration is approximately the same for the tests with same size of the ant colony (Tests 1-3 and 6-7). Contrary, one iteration of Test 4 and 5 needs respective half and double the time of one iteration of the other tests. This means that Test 7 needs the lowest amount of computational time, followed by Test 4 and 6, and Test 5

Table 3.5: Iterations in which the given effectiveness values are reached for all tests

Effectiveness	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7
55,000	1	11	3	32	2	1	4
60,000	60	130	8	57	57	19	6
65,000	135	157	76	159	100	30	11
70,000	191	244	147	213	159	39	27
75,000	309	-	-	-	251	-	-

is computationally the most expensive.

To conclude, different parameter settings lead to different results. However, also the optimized guidance with low effectiveness values are valuable because their effectiveness is higher than the efficiency of an evacuation without guidance and higher than the effectiveness of guidance created by simple rules as well. The settings do not only influence the effectiveness of the optimized guidance, they do also influence the efficiency of the solution approach. This means that the authority developing the guidance has to choose the parameter settings based on both the desired effectiveness of the guidance and the available computational time.

3.4.8 Applicability of the optimized guidance

In the previous sections, the optimized guidance is applied under the assumption of full or partial compliance. This section discusses a different approach to use the optimized guidance. Namely, the roads that have zero flows in case of applying the optimized guidance under a full compliance assumption are blocked, i.e. they are assumed to be made inaccessible. The travelers are free to choose any route that does not contain an inaccessible road. The idea behind this approach is that the travelers are forced to behave such that the resulting flows are close to the flows corresponding to the optimized guidance.

To analyze the effect of blocking roads, the optimized guidance presented in this chapter is used again. As discussed in Section 3.4.2, the effectiveness of this guidance is equal to 74,636 under the assumption of full compliance. Figure 3.8 shows the reduced network, that containing all links with nonzero flow is equal to zero for the full evacuation or not. The links that have nonzero flows are blocked. The efficiency of the resulting situation is analyzed by evaluating the effect of an evacuation without any guidance, given the reduced network. In this simulation, all routes on the network are considered in the route choice generation process. For the full network, the efficiency of an evacuation without any guidance is equal to 63,700 as discussed in Section 3.4.2.

The efficiency of the evacuation without any guidance given the reduced network is equal to 70,100. Thus, blocking roads turns out to be effective to increase the evacuation efficiency. A more detailed analysis on the effect of blocking links is given in

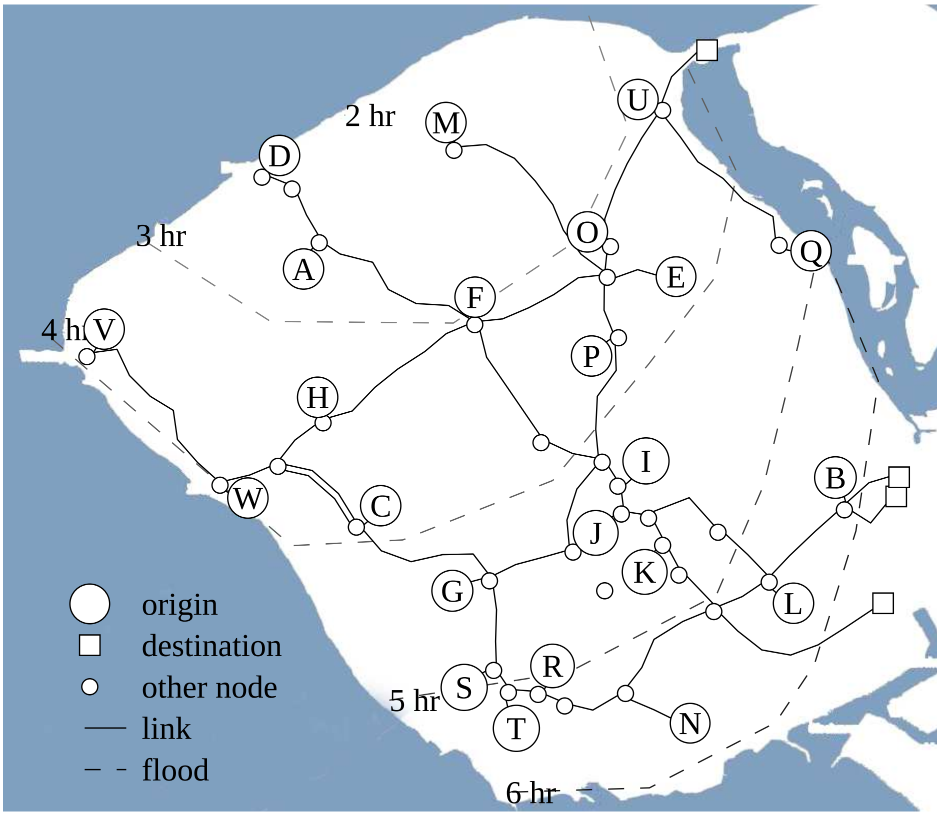


Figure 3.8: Reduced network, consisting of 23 origins, 4 destinations, 34 intermediate nodes, and 64 unidirectional links connecting the nodes

Huibregtse et al. (2012). This means that additionally to evacuation guidance, blocking roads can be considered as measure to increase the evacuation efficiency.

3.5 Conclusion

The application of EAS+ to a hypothetical flood of part of the Netherlands gives insight into the usefulness of optimized evacuation guidance. The case study shows that the efficiency of an evacuation with optimized guidance is higher than the efficiency of an evacuation without any guidance. Thus, instructions are needed. The case study shows as well that the guidance has to be optimized, construction of the guidance by simple decision rules results in a low effectiveness.

Further analysis shows that the near-optimality of the optimized guidance, expressed as the outflow of the network relative to the theoretical upper bound, is equal to 90%. This indicates a sub-optimality of the optimized guidance. However, the effectiveness of the unknown optimal guidance is most probably lower than the theoretical upper bound. Reasons for this deviation from the theoretical upper bound are, among other things, network degeneration caused by the hazard and internal bottlenecks. Thus, the deviation between the number of arrivals under optimized and optimal guidance is 10% at maximum.

The analysis of the parameter influences shows that different parameter settings lead to different values of both the effectiveness of the optimized guidance and the efficiency of the solution approach. Depending on the time available to generate the evacuation guidance and the desired effectiveness, suitable parameter values can be set.

Chapter 4

Robust optimization of evacuation guidance

This chapter incorporates uncertainty in the optimization of evacuation guidance, which is one of the goals of this thesis as formulated in Chapter 1. In Chapter 3, one specific type of uncertainty was dealt with, namely the time available to evacuate the people. This uncertainty was incorporated in the presented approach via the objective function. The approaches that are presented in this chapter are generic with respect to the type of uncertainty they can account for.

The general applicability of the approaches is important because the evacuation problem contains many types of uncertainty. The uncertainties are in the system, the hazard that causes the need to evacuate, and the evacuees using the network. The system uncertainty refers to the uncertainty in the road network, e.g, the capacity of the roads and the free flow speed, and the uncertainty in the traffic propagation over this network. With regard to the hazard, authorities may not be sure beforehand if the hazard will occur, when and where the hazard will occur, what the speed will be at which the hazard unfolds and what the impact of the hazard on the infrastructure will be. The uncertainty related to the evacuees concerns both the demand, e.g., the number of people and their location, and the behavior of the people, e.g., their preferred travel choices and their compliance to possible guidance. All these types of uncertainty can be incorporated in the optimization of evacuation guidance by the approaches that are presented in this chapter.

This chapter starts with a sensitivity analysis in Section 4.1, showing the influence of uncertainty on the effectiveness of guidance that is developed without incorporating the uncertainty. This analysis founds the need for uncertainty incorporation that is stated in Chapter 1. The analysis is followed by an overview of optimization approaches that can account for uncertainty presented in literature in Section 4.2. The approaches that are used to incorporate uncertainty in the evacuation problem in this chapter are introduced in Section 4.3. These approaches are presented by adapting the problem formulations and solution approaches presented in Chapter 3. Section 4.4 presents the results of the application of the approaches to the case of the Walcheren flood, introduced in Chapter 3. The main findings are given in Section 4.5.

Acknowledgement. Parts of the contents of this chapter are based on Huibregtse, O., A. Hegyi, S. Hoogendoorn (2011) Robust Optimization of Evacuation Instructions, Applied to Capacity, Hazard Pattern, Demand, and Compliance Uncertainty, in: *Proceedings of the 2011 IEEE International Conference on Networking, Sensing and Control*, Delft, the Netherlands, pp. 335-340.

4.1 Sensitivity analysis

In this section, the effectiveness of evacuation guidance is analyzed under varying input representing input uncertainty. The problem formulation and solution approach that are used to develop the guidance, which are similar to the ones introduced in Chapter 3, are discussed in Section 4.1.1. This is followed by an explanation of the set-up of the analysis in Section 4.1.2 and the actual analysis in Section 4.1.3.

4.1.1 Problem formulation and solution approach

The optimal guidance $\mathbf{U}_s^*$ follows from the following formulation:

$$\begin{aligned} \mathbf{U}_s^* = \quad & \underset{\mathbf{U}\in\mathbb{U}_s}{\operatorname{argmax}}\, J(\mathbf{X}_s), \\ \text{s.t.} \quad & x_s(t+1) = \begin{cases} f\Big(x_s(0),\mathbf{U}\Big), & t=0 \\ f\Big(x_s(t)\Big), & t>0 \end{cases} \\ & \phi(\mathbf{U},\mathbf{X}_s) = 0, \\ & \psi(\mathbf{U},\mathbf{X}_s) \leq 0. \end{aligned} \tag{4.1}$$

The difference with the formulation given in Equation 3.2 is the maximization instead of a minimization. The reason for this change is the following choice of the objective function:

$$J(\mathbf{X}_s) = \xi \sum_{t\in T, a\in A_D} q_a^{\text{out}}(t). \tag{4.2}$$

This function, which is equal to Equation 3.3 with $\chi_1 = 0$, maximizes the arrivals and does therefore not incorporate uncertainty in the available evacuation time directly. This objective function is used throughout this chapter in problems in which all types of uncertainty are incorporated as input instead. To obtain consistency between the sections, the objective function in the sensitivity analysis is equal to maximizing the arrivals as well. The travel behavior and traffic propagation are described by EVAQ, which is introduced in Section 3.2.3. In this chapter, the route choice set contains all possible routes on the network, such that the stochasticity that is coupled with a limited route set does not influence the analysis. The guidance and the search space specifications are as given in Section 3.2. Thus, the guidance consists of a departure time, route, and destination instruction for each person. The problem is solved with EAS^{+}-evacuation, the metaheuristic introduced in Chapter 3, with similar parameter settings as in Section 3.4 (Test 1).

4.1.2 Analysis setup

Guidance is optimized for varying input, i.e., varying demand, capacity, and compliance behavior. The following guidance is developed, whereby the situation considered in Section 3.4.1 is set as basic situation:

- Demand: $\mathbf{U}^{\text{D -20\%}}$, $\mathbf{U}^{\text{D -10\%}}$, $\mathbf{U}^{\text{D basic}}$, $\mathbf{U}^{\text{D +10\%}}$, $\mathbf{U}^{\text{D +20\%}}$, representing the guidance optimized for a demand that deviates from the basic level with -20% , -10%, 0%, +10%, and +20% respectively,
- Capacity: $\mathbf{U}^{\text{C -20\%}}$, $\mathbf{U}^{\text{C -10\%}}$, $\mathbf{U}^{\text{C basic}}$, $\mathbf{U}^{\text{C +10\%}}$, $\mathbf{U}^{\text{C +20\%}}$, representing the guidance optimized for a capacity that deviates from the basic level with -20% , -10%, 0%, +10%, and +20% respectively,
- Behavior: $\mathbf{U}^{\text{B 0.7}}$, $\mathbf{U}^{\text{B 0.8}}$, $\mathbf{U}^{\text{B 0.9}}$, $\mathbf{U}^{\text{B full}}$, representing the guidance optimized for a compliance level of 0.7, 0.8, 0.9, and 1, respectively. The full compliance situation corresponds to the basic situation.

The demand deviations are constant for all origins, the capacity deviations are constant for all roads. Other uncertainty representations are possible as well. An example is a minute-to-minute fluctuation in the capacity level. Since the objective in this thesis is to develop optimization approaches that incorporate uncertainty, relatively straightforward uncertainty representations are chosen that make it easier to interpret the results.

In the optimization, the uncertainty is considered per category. This means that, for example, when $\mathbf{U}^{\text{D -10\%}}$ is developed, the capacity and the compliance level are kept at basic level. As discussed in Chapter 3, solving the same problem multiple times results in different solutions and effectiveness values because of stochastic processes in the solution approach. However, the case study in Section 3.4.7 showed that the difference in effectiveness is small for the current parameter settings. Similar to the test in Section 3.4.7, each problem is solved 4 times and the guidance with the highest effectiveness is included in the analysis.

The sensitivity of the optimized guidance is analyzed by applying all optimized guidance to multiple scenarios on the following corresponding intervals:

- Demand: from -20% to +20% for all origins,
- Capacity: from -20% to +20% on all roads,
- Behavior: compliance level varying from 0.7 to 1 (full compliance) for all evacuees.

This shows the effectiveness of guidance when the situation deviates from what was expected. In the analysis, the scenario to which certain guidance is applied is notated in parenthesis. For example, $\mathbf{U}^{\text{D -20\%}}(\text{D -11\%})$ represents guidance optimized for a demand that deviates with -20% from the basic level, evaluated for a case with a demand that deviates with -11% from the basic level. The difference between two types of guidance applied to one scenario is expressed by the *relative effectiveness*. This term is defined as the effectiveness of some guidance divided by the optimal effectiveness, i.e. the effectiveness of the guidance optimized for the considered scenario. For example, the relative effectiveness of $\mathbf{U}^{\text{D -20\%}}(\text{D -10\%})$ is equal to the effectiveness of $\mathbf{U}^{\text{D -20\%}}(\text{D -10\%})$ divided by the effectiveness of $\mathbf{U}^{\text{D -10\%}}(\text{D -10\%})$.

4.1.3 Results and discussion

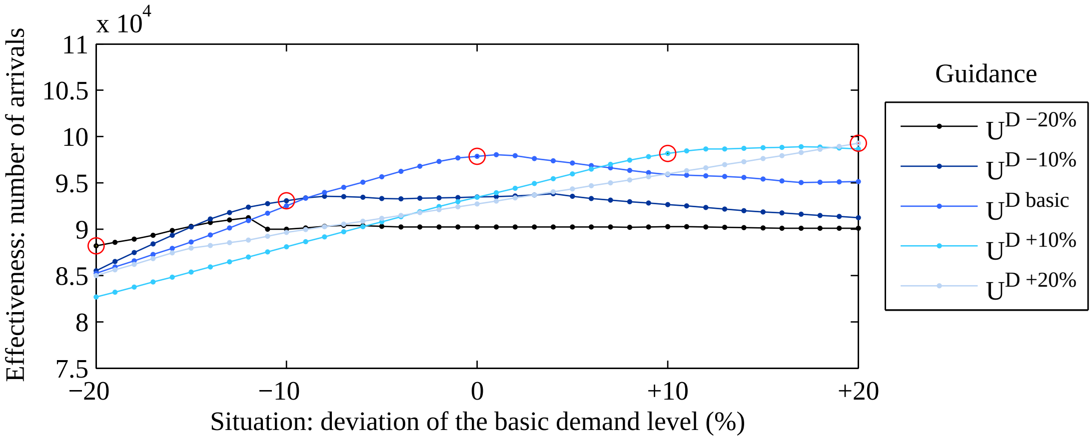
The sensitivity analysis results in the following values for the relative effectiveness:

- Demand: from 90.8 to 99.4%,
- Capacity: from 89.0 to 100.8%,
- Compliance: from 88.4 to 97.9%.

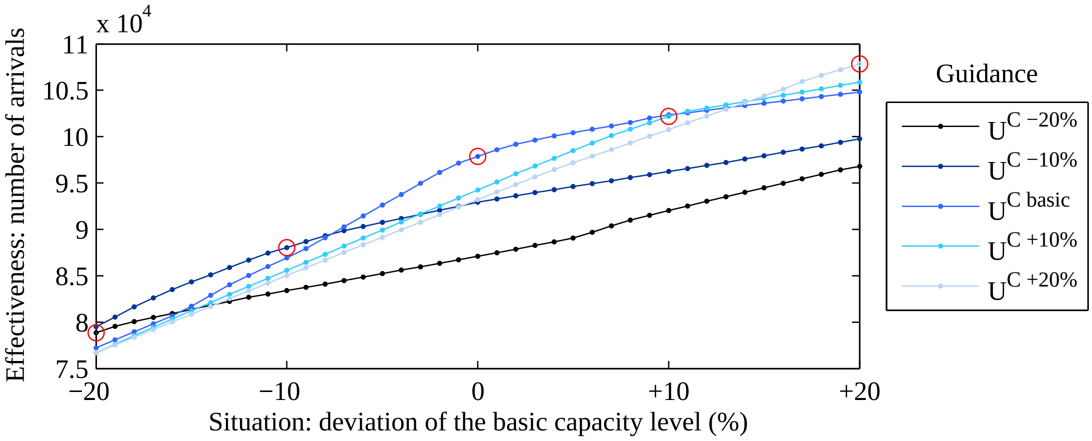
The lowest value of the relative effectiveness, i.e., 88.4%, indicates that when the real scenario deviates from the anticipated scenario in the optimization, the efficiency of the evacuation decreases with 11.6% in the worst case. To avoid this, the uncertainty needs to be incorporated in the optimization process. The relative effectiveness of 100.8% indicates the sub-optimality of $\mathbf{U}^{\text{C -20\%}}$, i.e. the effectiveness of $\mathbf{U}^{\text{C basic}}(\text{C -20\%})$ is higher than the effectiveness of $\mathbf{U}^{\text{C -20\%}}(\text{C -20\%})$. This sub-optimality is the consequence of an approximate solution approach but has no further influence on the analysis in this chapter.

The sensitivity analysis results in the effectiveness values presented in Figure 4.1. The effectiveness of guidance optimized for and applied to the same scenario is indicated by the circles. In all cases, except for $\mathbf{U}^{\text{C -20\%}}$, this effectiveness is higher than the effectiveness of any other guidance applied to that scenario. For the demand and the capacity uncertainty holds that when the scenario deviates slightly, i.e., plus or minus 1 percent, the effectiveness deviation is small as well. However, this does not hold for the behavior category. A possible explanation is the structure of the deviations. The route proportions change linearly with the demand variation, while for the behavior variation holds that some proportions will increase while others will decrease with this variation.

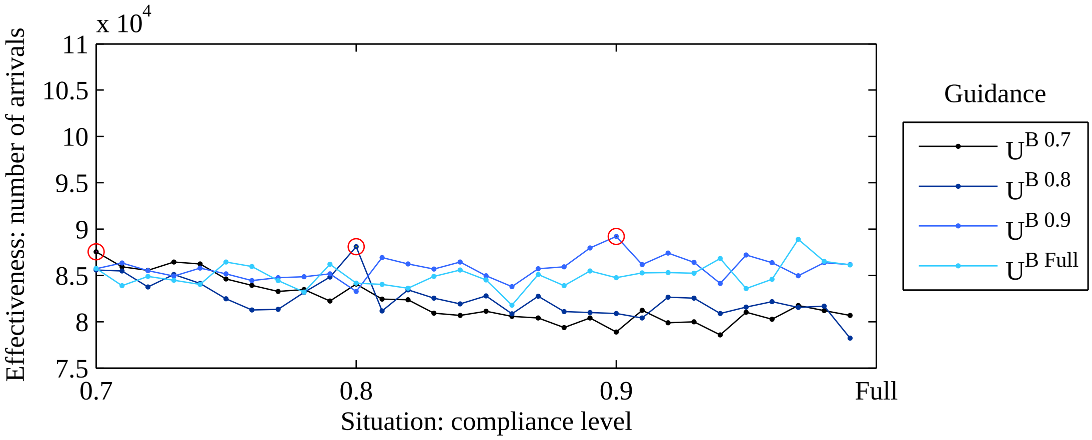
This section ends with a remark on the effectiveness values for full compliance applications that are not included in Figure 4.1(c). The reason for this is that in the model EVAQ, introduced in Section 3.2.3, the full compliance scenario deviates substantially from the scenario with high but not full compliance, e.g., compliance level 0.99. At full compliance, no deviation from the guidance is possible at all, no matter if the instructed route is accessible or not. If people are instructed to follow a route that is inaccessible, they will not arrive at a destination. At any compliance level lower than 1, the evacuees do deviate from guidance when the instructed route is inaccessible. An



(a) Demand



(b) Capacity



(c) Compliance

Figure 4.1: Sensitivity analysis per uncertainty category

instructed inaccessible route that is part of guidance optimized for a partial compliance level has therefore no influence for applications under partial compliance, but has drastic influence for the full compliance application. This unrealistic application of guidance optimized under partial compliance is therefore not included in the analysis.

4.2 Overview of optimization methods that incorporate uncertainty

Several approaches exist to formulate and solve optimization problems under uncertainty. An overview of them is given in Section 4.2.1 and approaches that are used for evacuation problems specifically are discussed in Section 4.2.2.

4.2.1 Generic approaches

An overview of robust optimization approaches can be found, for example, in Beyer & Sendhoff (2007). The main approaches used to deal with uncertainty in optimization problems are *stochastic programming* (e.g. Sahinidis (2004)) and *robust optimization* (e.g. Ben-Tal et al. (2009a)). The main characteristic of stochastic programming is to maximize or minimize the expectation of some value, while robust optimization focuses on the worst case. Most versions are developed to solve specific types of optimization problems, e.g. linear problems, and cannot be used to solve other problem types. However, the mentioned principles of the approaches are useful to solve all kinds of optimization problems under uncertainty: the choice between selecting a solution based on the expectation, or on the worst possible performance.

4.2.2 Approaches applied to the evacuation problem

Uncertainty is not incorporated in most of the evacuation optimization problems proposed in literature, but the problem is solved for one specific scenario instead. From all literature discussed in Chapter 2, the approaches that do incorporate uncertainty are the ones presented by Miller-Hooks & Sorrel (2008) and Ben-Tal et al. (2009b). Furthermore, uncertainty is incorporated in the online approaches presented by Chiu et al. (2007), Liu et al. (2007), and Chiu & Mirchandani (2008).

In Miller-Hooks & Sorrel (2008), uncertain capacity of the links and their travel times are taken into account, by considering the capacities and the travel times as discrete random variables with time-varying distribution functions. Each combination of possible values is referred to as a state. In each iteration, the solutions are evaluated on a randomly generated set of states resulting in an effectiveness value, equal to the sum of the effectiveness values over the different states weighted over their normalized probabilities. Using the terminology introduced in Section 4.2.1, Miller-Hooks

& Sorrel (2008) solve their problem using the stochastic programming principle and include probabilistic uncertainty represented by draws from this distribution. In Ben-Tal et al. (2009b), uncertainty in the demand is included by optimizing based on the highest possible demand. This approach is based on the principle of robust optimization. By selecting the demand representation that is the worst case according to their assumptions, no further specifications for the uncertainty representation are needed.

The approaches presented in this chapter contribute to this because they are generic regarding the type of uncertainty that is included and the model and network specifications. Furthermore, no assumptions are needed on the worst-case scenario as is needed in the approach presented by Ben-Tal et al. (2009b).

4.3 Approaches to optimize guidance under uncertainty

This section presents optimization approaches that can deal with probabilistic input representing many types of uncertainty. Examples of this uncertainty are uncertainty in the system, the hazard, and the evacuees. Because of the probabilistic nature of the uncertainty, the uncertainty input is assumed to be given by distribution functions. Given the complexity of the evacuation problem, these distributions cannot be incorporated directly but representations of the uncertainty are needed. These representations are called *scenarios*.

Section 4.3.1 presents the *absolute robust evacuation approach* (AREA) and Section 4.3.2 presents the *relative robust evacuation approach* (RREA). The absolute and relative robustness definition are derived from Kouvelis & Yu (1997). The performance indicator in the AREA is the worst-case performance over the scenarios. In the RREA, the performance indicator is a function of both this worst-case performance and the performance of the optimal solution for each specific scenario. Section 4.3.3 elaborates on the representation of uncertainty by scenarios.

4.3.1 Absolute robustness evacuation approach (AREA)

In the AREA, the optimal guidance for the set of scenarios S, indicated by $s \in S$, follows from the following formulation:

$$\begin{aligned} \mathbf{U}_S^* = \quad & \underset{\mathbf{U}\in\mathbb{U}_S}{\operatorname{argmax}} \Psi_n \Big\{ J(\mathbf{X}_s) \Big\}_{s\in S}, \\ \text{s.t.} \quad & x_s(t+1) = \begin{cases} f\Big(x_s(t), \mathbf{U}\Big), & t=0 \\ f\Big(x_s(t)\Big), & t>0 \end{cases}, \; s\in S \\ & \phi(\mathbf{U},\mathbf{X}_s) = 0, \; s\in S, \\ & \psi(\mathbf{U},\mathbf{X}_s) \leq 0, \; s\in S. \end{aligned} \tag{4.3}$$

where $\mathbb{U}_S$ represents the search space for the set of scenarios S and Ψ_n represents the n^{th} percentile. The percentile Ψ_5 represents a number such that 5% of the values of $J(\mathbf{X}_s)$ is smaller than this number, and 95% is bigger than this number. The specification of the search space $\mathbb{U}_S$ will be discussed in Section 4.3.3.

For the use in this chapter, the problem is specified as follows. The guidance consists of a departure time, route, and destination instruction for each person, equal to the guidance specification in Chapter 3. The objective function is equal to function 4.2. The specifications of the travel behavior model, the traffic propagation model, and the scenario-specific search spaces are equal to the specifications given in Chapter 3. The optimization problem is solved with the solution approach EAS$^+$-evacuation, the metaheuristic introduced in Section 3.3.

4.3.2 Relative robustness evacuation approach (RREA)

In the RREA, the optimal guidance follows from the following formulation:

$$\begin{aligned}
\mathbf{U}_S^* = \quad & \underset{\mathbf{U}\in\mathbb{U}_S}{\operatorname{argmax}} \Psi_n \left\{ \frac{J(\mathbf{X}_s)}{J(\mathbf{X}_s^*)} \right\}_{s\in S}, \\
\text{s.t.} \quad & x_s(t+1) = \begin{cases} f\Big(x_s(0), \mathbf{U}\Big), & t=0 \\ f\Big(x_s(t)\Big), & t>0 \end{cases}, \; s \in S \\
& \phi(\mathbf{U},\mathbf{X}_s) = 0, \; s \in S \\
& \psi(\mathbf{U},\mathbf{X}_s) \le 0, \; s \in S.
\end{aligned} \tag{4.4}$$

where $\mathbf{X}_s^*$ are the states corresponding to the optimized guidance $\mathbf{U}_s^*$. The problem specifications and the solution approach are equal to the specifications and approach discussed in Section 4.3.2.

4.3.3 Elaboration on the scenario selection procedures

The scenarios are representations of the uncertainty. Here, a *deterministic* and a *stochastic* scenario selection procedure are distinguished. The deterministic selection is constant over the iterations of the solution approach. Scenarios are selected that are assumed to be representative for the uncertainty distribution. The stochastic selection varies over the iterations: these scenarios consists of draws from the distributions. In both selection procedures, the probabilistic nature of the uncertainty can be considered because input representations with a higher probability can be given a higher chance to be part of the scenarios.

The deterministic scenario selection procedure can be used in combination with both the AREA and the RREA. Contrary, the stochastic selection procedure can only be used on combination with the AREA. The reason for this is that the optimal guidance for each scenario is input for the RREA. In the RREA, the number of scenarios can be infinite because of which this input cannot be delivered.

The search space $\mathbb{U}_S$ depends on the scenarios. For a deterministic scenario selection, this search space consists of the intersection of the scenario-specific search spaces. For a stochastic scenario selection, this search space needs to be approximated because of the infinite number of possible scenarios.

4.4 Case study

The goal of the case study is twofold. First, to compare the AREA and the RREA, and second, to compare the deterministic and stochastic scenario selection.

4.4.1 Comparison of the AREA and the RREA

The effectiveness of AREA and RREA is analyzed by solving the problems formulated by Equations 4.3 and 4.4 respectively. The approaches are applied to the flood of Walcheren introduced in Section 3.4.1. For both approaches, three problems are solved that incorporate either demand, capacity, or behavior uncertainty. The uncertainty is represented by the following distributions:

- Demand: demand that deviates from the basic level by a uniform distribution from -20% to +20%,
- Capacity: capacity that deviates from the basic level by a uniform distribution from -20% to +20%,
- Behavior: a compliance level that varies by a uniform distribution from 0.7 to 1 (full compliance).

The uncertainty is considered per category. This means that, for example, when the robust problem for demand uncertainty is solved, the capacity and the compliance level are kept at basic level. A deterministic scenario selection is chosen, consisting of the following scenarios:

- Demand: demand that deviates from the basic level with -20%, -10%, -0%, +10%, and +20%,
- Capacity: capacity that deviates from the basic level with -20%, -10%, -0%, +10%, and +20%,
- Behavior: a compliance level of 0.7, 0.8, 0.9, and to 1 (full compliance).

The percentile included in Equations 4.3 and 4.4 is set that low, for example, equal to 1, that all scenarios directly influence the solution.

Again, each problem is solved four times and the guidance with the highest effectiveness is included in this analysis. Solving the robust problems for the behavioral uncertainty took about 50 hours, the others about 20 hours. The computational time is limited by stopping the evaluation of certain guidance when the effectiveness of this guidance for a certain scenario was lower than the lowest effectiveness of the best guidance found so far. Because of this, only 27% of the combinations of the created guidance and the scenarios had to be tested.

The effectiveness of the guidance resulting from the AREA and RREA is given in Figure 4.2 which is an extension of Figure 4.1 that showed the results of the sensitivity analysis. The AREA is mainly useful when the worst case scenario is unknown beforehand. This holds in this case for the behavior uncertainty. The result could be seen as guidance that is reliable such that it will perform relatively well whatever the circumstances. In extension to this guidance, online measures could be taken. For example, when it is known that 5,000 people can be saved in any case while the population consists of 7,0000 people, supplementary measures can be taken to save the rest of the people. Examples of these measures are evacuation by public transport, vertical evacuation, or evacuation to shelters. In case that the worst case scenario is known, which seems to hold for the capacity uncertainty in this case, the guidance could be optimized for this worst case scenario instead.

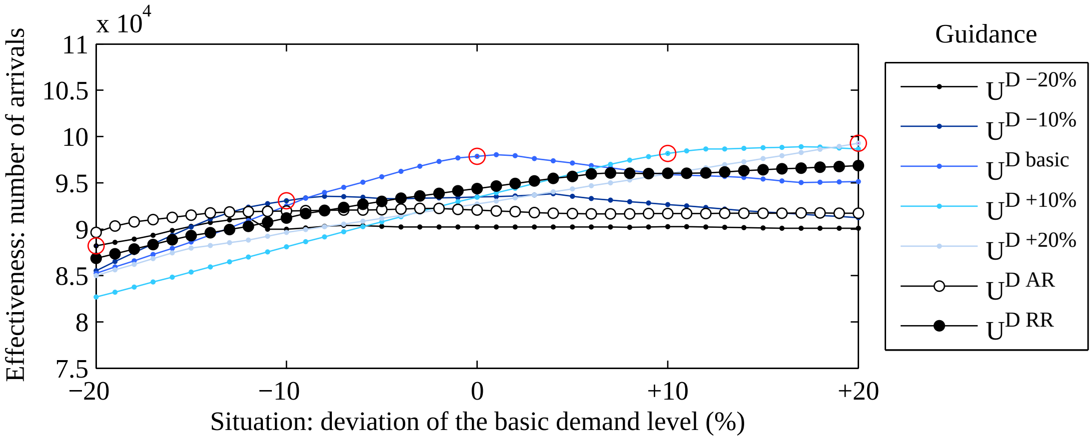
The effectiveness of the RREA is expressed by relative effectiveness values. As explained in Section 4.1.3, the *relative effectiveness* expresses the effectiveness of some guidance for a scenario divided by the effectiveness of the optimized guidance for that scenario. The intervals of the relative effectiveness for the RREA are as follows:

- Demand: 97.6 to 98.3%,
- Capacity: 97.4 to 98.8%,
- Behavior: 97.6 to 99.3%.

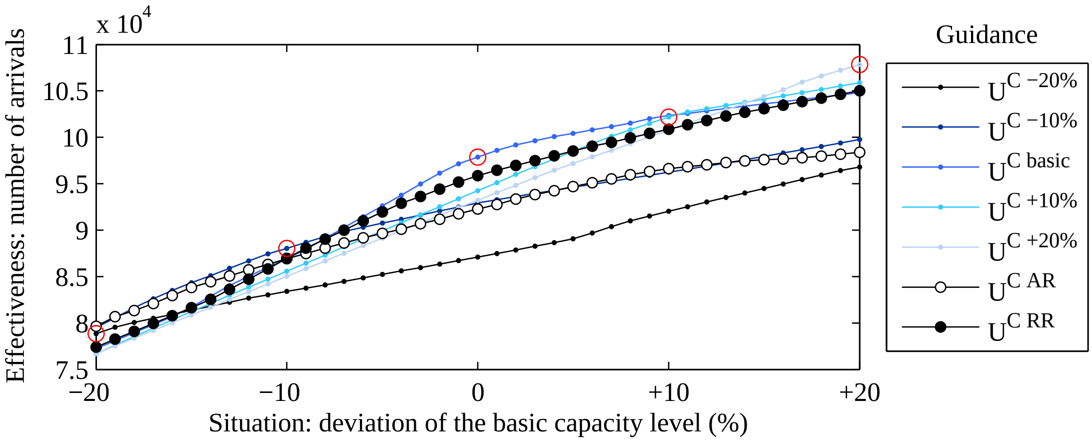
In Section 4.1, the relative effectiveness values were given of the guidance optimized per scenario. Comparing these two ranges of relative effectiveness values, up to 10.8% increase in the effectiveness can be obtained by implementing guidance optimized for the relative robustness problem.

4.4.2 Comparison of the deterministic and stochastic scenario selection

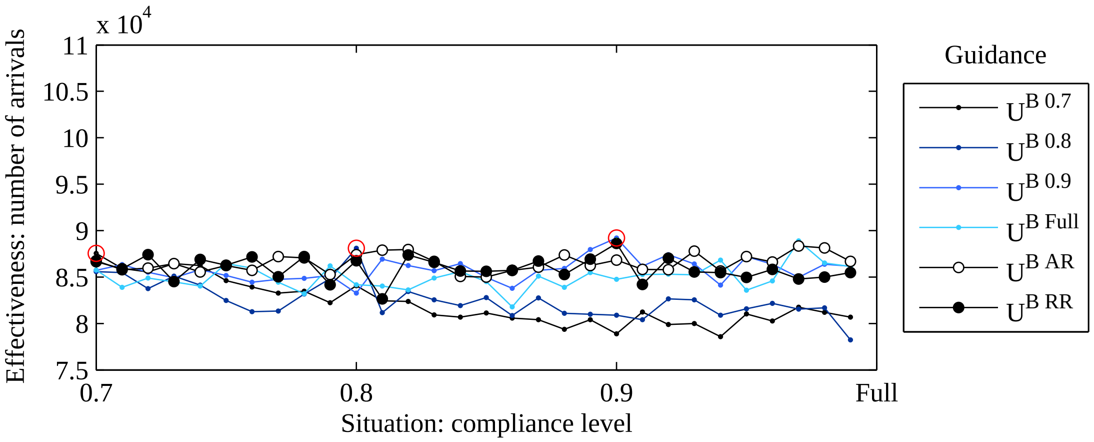
The influence of the scenario selection is analyzed by solving the AREA using both selection procedures. The approach is applied to the flood of Walcheren introduced in Section 3.4.1. The considered uncertainty is the combination of demand and capacity uncertainty: both are assumed to deviate with -20% to +20% from the basic level. Both selection procedures are illustrated in Figure 4.3. The deterministic scenario selection consists of fixed scenarios that are chosen to be equally spread over the uncertainty distribution. The selection of scenarios in the stochastic selection procedure is realized by latin hypercube sampling (LHS) (Iman, 2008). This selection is different in each



(a) Demand

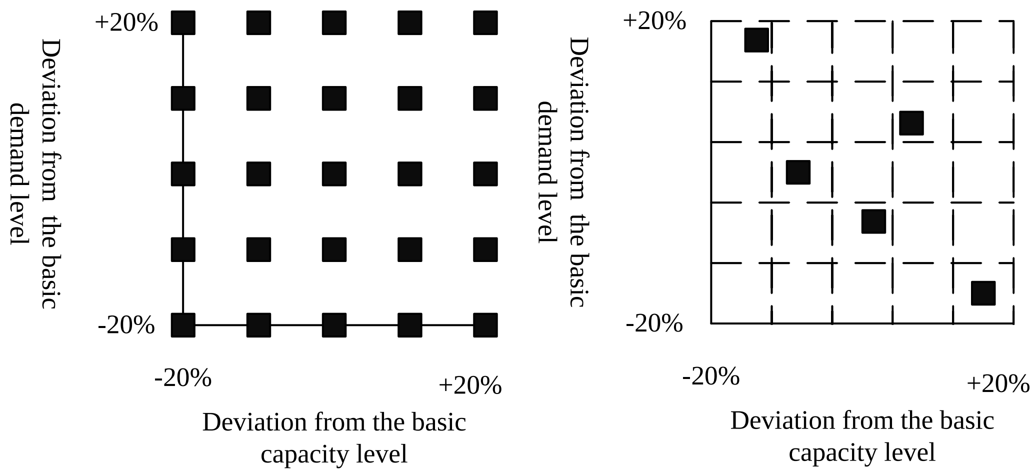


(b) Capacity



(c) Compliance

Figure 4.2: Robustness analysis



(a) Deterministic selection (b) Stochastic selection

Figure 4.3: Stochastic and deterministic scenario selection

iteration of the solution approach. Here, the selection of scenarios is 2-dimensional, but more dimensions can be added for case studies incorporating more uncertainties.

The problem with the deterministic selection procedure is applied with 25 scenarios, and the problem with the stochastic selection procedure is applied both with 5 and with 25 scenarios. Again, each problem is solved four times. All runs are included in this analysis instead of the runs resulting in the guidance with the highest effectiveness because of the variation in the results. Figure 4.4 gives the results. The figure shows that the stochastic selection overestimates the effectiveness of the guidance, especially in case of a small sample size. However, the effectiveness values are relatively close to the effectiveness values obtained by the deterministic selection. When applying the stochastic selection procedure, the sample size should be carefully chosen.

4.5 Conclusions

In order to incorporate uncertainty in the evacuation problem, the absolute robustness evacuation approach (AREA) and relative robustness evacuation approach (RREA) are formulated. The AREA is mainly useful when the worst case scenario is unknown beforehand. Application of the RREA for the Walcheren case study showed that by considering uncertainty in the optimization, the relative effectiveness is up to 10.8% higher for this case. This shows the usefulness of incorporating uncertainty in the evacuation problem.

The uncertainty is represented by scenarios. A deterministic and a stochastic scenario selection are compared. The deterministic selection is constant over the iterations of the solution approach, while the stochastic selection varies over the iterations. Both selection procedures were applied, whereby latin hypercube sampling was used for the stochastic selection procedure. The case study showed that the selections give similar

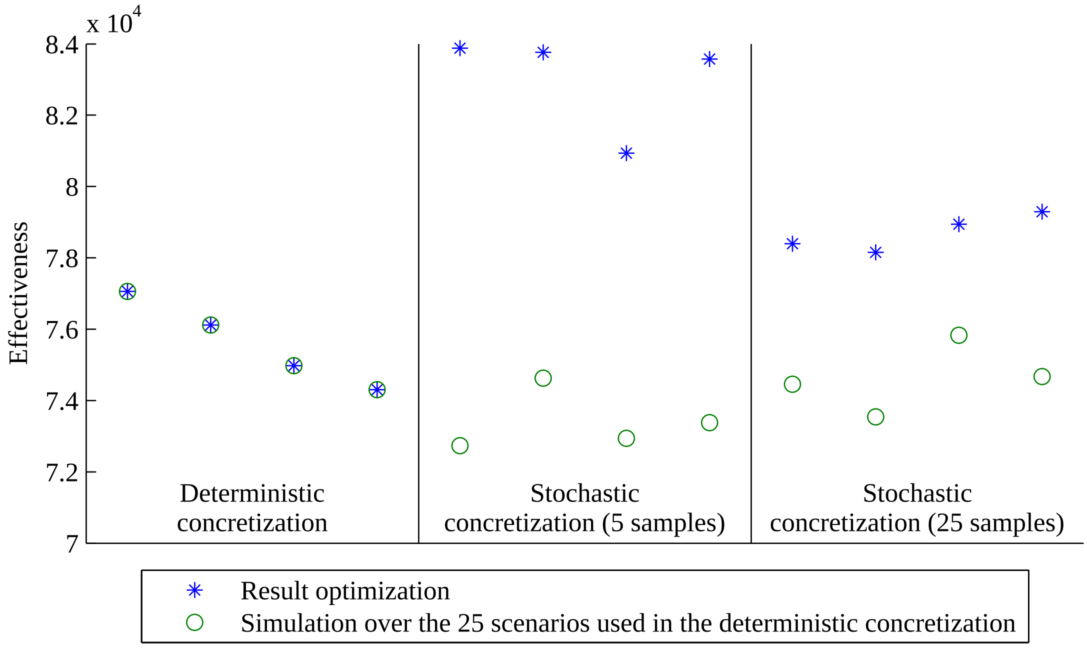


Figure 4.4: Effectiveness of the guidance resulting from the stochastic and deterministic scenario selection procedure

results, but the sample size of the stochastic selection procedure should be carefully chosen.

Incorporating uncertainty is computationally expensive. The applications discussed in this chapter took about 20 - 50 hours. When incorporating more uncertain factors in the optimization all together, the computational costs increase. In Huibregtse et al. (2011), the AREA optimization problem is solved based on a deterministic procedure containing 400 scenarios, representing uncertainty in the demand, capacity, behavior, and hazard. Solving this problem was computationally expensive, it took about 12 days. The high computational costs are the reason to search for more efficient approaches in Chapter 5.

Chapter 5

Reformulating the evacuation problem and solving it in an efficient way

This chapter presents an approach to optimize evacuation guidance efficiently, one of the objectives stated in Chapter 1. The need for an efficient approach is illustrated by the case studies in Chapters 3 and 4: solving the evacuation problem turned out to be computationally expensive, especially when considering compliance behavior and uncertainty. The new approach to optimize evacuation guidance consists of a reformulation of the problem introduced in Chapter 3 and the presentation of the corresponding solution framework. The basis of this approach is a new way to deal with compliance behavior.

Section 5.1 describes the difficulties of the original evacuation problem causing the high computational costs. Section 5.2 reformulates the problem and describes the proposed solution method. In Section 5.3, the efficiency of the fixed-point approach is illustrated by applying the approach to the hypothetical flood of Walcheren, introduced in Chapter 3. The approach presented in this chapter is not limited to evacuation problems but is an efficient approach to optimize route guidance for transportation problems in general. This is discussed in Section 5.4, after which the conclusions of this chapter are given in Section 5.5.

Acknowledgment. The main contents of this chapter are based on Huibregtse, O., G. Flötteröd, M. Bierlaire, A. Hegyi, S. Hoogendoorn (2012) A Fixed-Point Approach to System-Optimal Route Advice Considering Compliance Behavior, in: *Proceedings of the 90th Annual Meeting of the Transportation Research Board*, Washington D.C., USA. Furthermore, a journal article with similar contents as this chapter is under review.

5.1 Original evacuation problem and its difficulties

The original problem formulation, which is given by Equation 3.1, aims at optimal evacuation guidance subject to an objective function and a model describing route choice and traffic propagation. The problem formulation proposed in this section is equivalent to this formulation but the notation deviates. This new notation is convenient to be used for the reformulation in this chapter. One the one hand, the notation is made as compact as possible for convenience of comparison. On the other hand, more attention is given to the part of the formulation that plays a central role in the reformulation. In order to create a compact formulation, the state-space equation f is not explicitly included but Equation 2.1 is used instead. This equation is equivalent to Equation 3.1 as explained in Section 2.2. Furthermore, the explicit notation of situation s is removed. While the approach presented in this paper can be used to incorporate uncertainty as well, the reformulation given in this paper is expressed for one situation which makes the notation s redundant. The compact version of Equation 2.1 is equal to:

$$\begin{aligned} \mathbf{U}^* = \quad & \underset{\mathbf{U}\in\mathbb{U}}{\operatorname{argmin}}\, \tilde{J}(\mathbf{U},\mathbf{x}(0)), \\ \text{s.t.} \quad & \tilde{\phi}(\mathbf{U}) = 0, \\ & \tilde{\psi}(\mathbf{U}) \leq 0. \end{aligned} \tag{5.1}$$

The behavioral model and traffic flow model, represented by Q, are explicitly included in the formulation because the reformulation focuses on this model. The objective function J and the model Q are connected by the dynamic link flows $\mathbf{Q}$. Including the model Q in Equation 5.1 gives:

$$\begin{aligned} \mathbf{U}^* = \quad & \underset{\mathbf{U}\in\mathbb{U}}{\operatorname{argmin}}\, \hat{J}(\mathbf{Q},\mathbf{x}(0)), \qquad \text{(O-RAP)} \\ \text{s.t.} \quad & \mathbf{Q} = Q(\mathbf{U}), \\ & \bar{\phi}(\mathbf{U},\mathbf{Q}) = 0, \\ & \bar{\psi}(\mathbf{U},\mathbf{Q}) \leq 0, \end{aligned} \tag{5.2}$$

where the vectors $\bar{\phi}$ and $\bar{\psi}$ represent equality and inequality constraints respectively, both on the decision variables and the link flows.This formulation is from now on referred to as the *original route advice problem* (O-RAP). The objective function $\hat{J}$ is characterized in terms of the time-dependent link flows $\mathbf{Q}$, which result from some (complicated) function Q of the route advice $\mathbf{U}$. The function Q contains the route choice model, describing the route choice behavior of the travelers receiving the route guidance resulting in route flows, and a macroscopic dynamic traffic propagation model, describing the traffic propagation over the network as a function of the route flows. This traffic propagation model is required to distinguish multiple classes where each class represents a specific route flow. The search space $\mathbb{U}$ contains all possible values for $\mathbf{U}$. The demand is assumed to be fixed and time-dependent.

In this chapter, the evacuation guidance is limited to route guidance, which implicitly includes destination guidance. The problem can be extended to optimize departure time guidance as well, which is explained in Section 5.5.

The previous chapters showed that the O-RAP is a difficult problem to solve. The first source of this difficulty is the high number of decision variables. In the problem, the number of decision variables is a linear function of the number of routes, possibly multiplied by the number of departure time intervals. The second source of this difficulty are high evaluation costs. These high costs are caused by an evaluation of the advice based on route flows. A multi-class traffic propagation model is needed to evaluate these route flows, where the multiple classes represent the multiple routes.

5.2 Problem statement and solution framework

This section presents a fixed-point approach to optimize route advice efficiently. Fixed-point formulations were found to be successful for several other transportation problems, like the determination of the equilibrium assignment (Cantarella, 1997), the determination of dynamic network loading based on link travel time functions (Chabini, 2001), the estimation of an origin-destination matrix (Cascetta & Postorino, 2001), and the generation of anticipatory route guidance (Bottom et al., 1999). The approach in Bottom et al. (1999) also solves a route guidance problem; however, the fixed point does not aim at system optimality but merely at consistency between anticipated and resulting network conditions.

The fixed-point approach to route advice (FPA-RA) decomposes the O-RAP into simpler problems which are iteratively solved resulting in a solution to the original problem. The FPA-RA consists of the *fixed-point formulation of the route advice problem* (FPF-RAP) and a *fixed-point algorithm* to solve this problem. The FPF-RAP, which is given in Section 5.2.1, is a reformulation of the O-RAP that overcomes the computational difficulties that are associated with the O-RAP as discussed in Section 5.1. The algorithm solves this reformulated problem. Section 5.2.2 gives an intuitive step-by-step description of this algorithm and Section 5.2.3 formally derives this algorithm from the mathematical problem formulation. The components of the algorithm are further explained in Section 5.2.4.

5.2.1 Fixed-point formulation of the route advice problem (FPF-RAP)

The FPF-RAP overcomes the computational difficulties that are associated with the O-RAP as discussed in Section 5.1: the high number of decision variables and the high evaluation costs of the traffic propagation model. This is realized by turning fractions instead of route advice as decision variables, and a traffic flow representation that is less demanding regarding the number of classes.

The basis for the FPF-RAP is the replacement of the model $\mathbf{Q} = Q(\mathbf{U})$ by the following fixed-point formulation:

$$\mathbf{Q} = \tilde{Q}(\mathbf{B}) \text{ with } \mathbf{B} = B(\mathbf{T}_A, \mathbf{U}), \text{ and } \mathbf{T}_A = T(\mathbf{Q}), \tag{5.3}$$

where

- $\mathbf{Q} = \tilde{Q}(\mathbf{B})$ are the dynamic link flows that result from a propagation of the demand, which may, e.g., be represented in terms of an origin-destination matrix, given the turning fractions $\mathbf{B}$, by the traffic propagation model $\tilde{Q}$,
- $\mathbf{B} = B(\mathbf{T}, \mathbf{U})$ are the turning fractions, which describe what share of flow leaving a link enters which of its downstream links, obtained by determining route flows based on route advice by a route choice model and propagating these flows with fixed time-dependent link travel times $\mathbf{T}_A$,
- $\mathbf{T}_A = T(\mathbf{Q})$ are the travel times as function of the dynamic link flows, e.g., obtained from cumulative curves.

At a fixed-point, where the problem variables are self-reproducing, the flows following from Equation 5.3 are equal to $\mathbf{Q} = Q(\mathbf{U})$. This fixed-point approach separates the route choice model, that is part of B, from the traffic propagation model $\tilde{Q}$. The output of the route choice model, i.e., turning fractions, is input to the traffic propagation model. When propagating flows based on turning fractions instead of route advice or route flows, the traffic flow representation does not require multiple classes to distinguish route flows.

Equation 5.3 is used to reformulate the original problem (Equation 5.2). The model $\mathbf{Q} = Q(\mathbf{U})$ is replaced by the fixed-point formulation given in Equation 5.3.

$$\begin{aligned}
\mathbf{U}^* = \quad & \underset{\mathbf{U}\in\mathbb{U}}{\operatorname{argmin}}\, \hat{J}(\mathbf{Q}, \mathbf{x}(0)), \\
\text{s.t.} \quad & \mathbf{Q} = \tilde{Q}(\mathbf{B}), \\
& \mathbf{T}_A = T(\mathbf{Q}), \\
& \mathbf{B} = B(\mathbf{T}_A, \mathbf{U}), \\
& \hat{\phi}(\mathbf{U}, \mathbf{Q}, \mathbf{T}_A, \mathbf{B}) = 0, \\
& \hat{\psi}(\mathbf{U}, \mathbf{Q}, \mathbf{T}_A, \mathbf{B}) \le 0.
\end{aligned} \tag{5.4}$$

where the vectors $\hat{\phi}$ and $\hat{\psi}$ represent equality and inequality constraints respectively, on the decision variables, the link flows, the turning fractions, and the time-dependent travel times. Equation 5.4 limits the evaluation costs because the behavioral model is separated from the traffic propagation model, but does still contain a high number of decision variables. This difficulty is encountered by optimizing turning fractions instead of route advice, and determining the route advice based on the optimized turning fractions. Any advice $\mathbf{U}$ with corresponding travel times $\mathbf{T}_A$ results in unique turning fractions $\mathbf{B} = B(\mathbf{T}_A, \mathbf{U})$. However, deriving advice from turning fractions and corresponding travel times, which is expressed by $\tilde{\mathbb{U}}(\mathbf{T}_A, \mathbf{B}) = \{\mathbf{U} | \mathbf{B} = B(\mathbf{T}_A, \mathbf{U})\}, \mathbf{U} \in \tilde{\mathbb{U}}$, is possibly non-unique or possibly infeasible. The infeasibility is partly caused by non-compliance with the route advice. By limiting the turning fractions to those fractions that can be reproduced by route advice, represented by $\mathbb{B}$, determining route advice is feasible. This constraint is used to be able to replace the optimization of route advice by the optimization of turning fractions:

$$\begin{aligned}
&\tilde{\mathbb{U}}^*(\mathbf{T}_A^*, \mathbf{B}^*) &&= \{\mathbf{U}^* | \mathbf{B}^* = B(\mathbf{T}_A^*, \mathbf{U}^*)\}, \qquad \text{(FPF-RAP)},\\
&\mathbf{T}_A^* &&= T(\mathbf{Q}^*),\\
&\mathbf{B}^* &&= \underset{\mathbf{B}\in\mathbb{B}}{\operatorname{argmin}}\ \hat{J}(\mathbf{Q}, \mathbf{x}(0)),\\
&\text{s.t.} && \mathbf{Q} = \tilde{Q}(\mathbf{B}),\\
& && \hat{\phi}(\mathbf{U}, \mathbf{Q}, \mathbf{T}_A, \mathbf{B}) = 0,\\
& && \hat{\psi}(\mathbf{U}, \mathbf{Q}, \mathbf{T}_A, \mathbf{B}) \leq 0,
\end{aligned} \tag{5.5}$$

where $\mathbf{T}_A^*$ and $\mathbf{Q}^*$ are the travel times and link flows corresponding to $\mathbf{B}^*$ respectively. This problem is referred to as the *fixed-point formulation of the route advice problem* (FPF-RAP).

5.2.2 Description of the fixed-point algorithm

This section gives an intuitive step-by-step description of the algorithm that solves the FPF-RAP. The FPF-RAP is difficult to solve because determining $\tilde{\mathbb{U}}^*(\mathbf{T}_A^*, \mathbf{B}^*)$ is complicated. The reason for this is that route advice does not result in turning fractions directly, but results in route flows from which turning fractions are derived subsequently. The second difficulty of solving the FPF-RAP is that $\mathbb{B}$ cannot be identified in advance. The *fixed-point algorithm* proposed in this section encounters these difficulties.

In the fixed-point algorithm, the O-RAP is decomposed into three simpler subproblems:

1. Optimization of turning fractions,
2. Optimization of route advice,
3. Approximation of compliance behavior.

The first sub-problem aims at finding the turning fractions that result in the highest efficiency of the evacuation. The corresponding guidance and compliance behavior are not considered in this subproblem. The goal of the second subproblem is to reproduce the turning flows resulting from the first problem by guidance, incorporating compliance behavior. The third subproblem adapts the bounds of the decision variables of the first problem based on the extent of reproduction obtained in the second problem. The goal of this subproblem is to adapt the bounds such that the turning fractions can be reproduced by guidance given the compliance behavior. The subproblems are iteratively solved resulting in an approximate solution for the O-RAP. The remainder of this section elaborates on the subproblems, their relations, and their simplifications compared to the O-RAP. This is summarized in Figure 5.1.

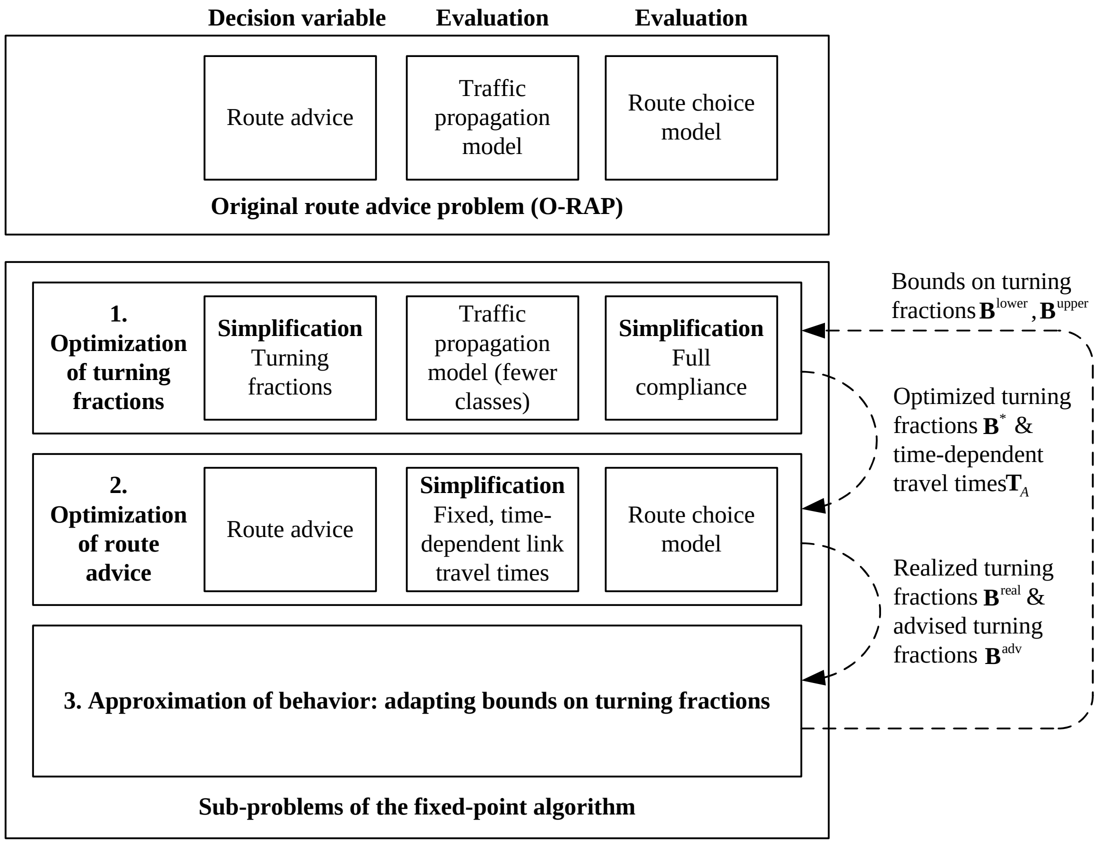


Figure 5.1: The subproblems of the fixed-point algorithm, their relations, and their simplifications compared to the O-RAP

The first problem is a simplification of the original problem in that turning fractions are optimized instead of route advice, and full compliance with these turning fractions is assumed instead of modeling this compliance by a behavioral model. Networks with a reasonable size have a high number of routes compared to the number of splitting rates or turning fractions. This is, for example, illustrated by Wisten & Smith (1997). These simplifications are justified because they are compensated, i.e. the components of the original problem are used, in other parts of the approach. In the second problem, the aim is to reproduce, as far as possible, the turning fractions obtained in the first problem by route advice. Compliance behavior is considered in this second problem. In the third problem, this behavior is translated into bounds on the turning fractions of the first problem based on the extent of reproduction. These bounds represent at an aggregate level behavior that could possibly be obtained through appropriate route advice. Because of the simplifications, the traffic propagation model needs fewer classes which limits the evaluation costs as well.

The second problem of optimally reproducing the turning fractions by route advice contains a simplified model compared to the original problem. Fixed, i.e. flow independent, time dependent link travel times are used which are derived from the first problem, instead of a macroscopic dynamic traffic propagation model embedded in the original problem. This simplification is justified since the fixed time dependent link travel times and the macroscopic dynamic traffic propagation model result in the same traffic propagation upon convergence of the complete procedure. The optimization is constrained by a behavioral model describing route choice. The reproduction can also be based on turning flows instead of fractions as will be explained in Section 5.2.4.

In the third problem, bounds on the turning fractions are updated based on the compliance encountered when solving the second problem. For turning fractions that could not be reproduced in the second problem, meaning that the optimization of turning fractions was too optimistic with respect to the travelers' compliance, tighter bounds are determined. For turning fractions that could be reproduced in the second problem, looser bounds are determined, increasing the freedom in the next optimization of turning fractions. All bounds are input for the optimization of turning fractions. The reproduction of turning fractions could also be limited because of other reasons, like turning fractions that are not matching with the destination-specific demand. These kinds of limitations in the reproduction are also automatically solved over the iterations.

Upon convergence to a fixed-point where turning fractions optimized in the first problem are reproduced in the second problem an approximate solution, i.e. route advice, to the original problem (Equation 5.2) is obtained. Consistency in the solution can be expressed in terms of any of the variables that are transferred between the three problems, e.g. the optimized turning flows.

5.2.3 Mathematical formulation of the fixed-point algorithm

This section gives a mathematical formulation of the fixed-point algorithm based on the FPF-RAP. The final result of this section consists of the three subproblems described in Section 5.2.2 and visualized in Figure 5.1. As discussed in Section 5.2.2, the FPF-RAP is difficult to solve because determining $\tilde{\mathbb{U}}^*_A(\mathbf{T}^*, \mathbf{B}^*)$ is complicated and because $\mathbb{B}$ cannot be identified in advance. In order to determine the guidance corresponding to the turning fractions in an easy way, an optimization problem is introduced that aims at finding the guidance that reproduces the optimized turning flows as close as possible. First, the turning fractions are optimized:

$$
\begin{aligned}
\mathbf{B}^* \quad &= \underset{\mathbf{B}\in\mathbb{B}}{\operatorname{argmin}}\, J(\mathbf{Q}), \\
\text{s.t.} \quad &\mathbf{Q} = \tilde{Q}(\mathbf{B}), \\
&\breve{\phi}(\mathbf{Q},\mathbf{B}) = 0, \\
&\breve{\psi}(\mathbf{Q},\mathbf{B}) \leq 0,
\end{aligned}
\tag{5.6}
$$

where the vectors $\breve{\phi}$ and $\breve{\psi}$ represent equality and inequality constraints respectively, on the link flows and the turning fractions. Subsequently, the guidance is optimized:

$$\begin{aligned}
\mathbf{U}^* \quad &= \underset{\mathbf{U}\in\mathbb{U}}{\operatorname{argmin}}\, H_1(\mathbf{B}^*, B(\mathbf{T}_A^*, \mathbf{U})),\\
\text{s.t.} \quad & \mathbf{T}_A^* = T(\mathbf{Q}^*),\\
& \hat{\phi}(\mathbf{U}, \mathbf{Q}, \mathbf{T}_A, \mathbf{B}) = 0,\\
& \hat{\psi}(\mathbf{U}, \mathbf{Q}, \mathbf{T}_A, \mathbf{B}) \leq 0,
\end{aligned} \tag{5.7}$$

where the variables $\mathbf{T}_A^*$ and $\mathbf{Q}^*$ represent the travel times and link flows corresponding to $\mathbf{B}^*$ defined by Equation 5.7 respectively. The distance measure H_1 expresses the difference between the optimal turning fractions and the turning fractions resulting from the optimal advice. The distance measure can, for example, be set equal to the root mean square error. When the distance expressed by H_1 is equal to 0, the guidance $\mathbf{U}^*$ defined by Equation 5.7 is equal to the guidance $\tilde{\mathbb{U}}^*(\mathbf{T}_A^*, \mathbf{B}^*)$ defined by Equation 5.5. In this case, the guidance resulting from Equation 5.6 is equal to the solution of the FP-RAP and the O-RAP. When the distance deviates from 0, the resulting guidance approximates the solution of the FP-RAP and the O-RAP.

In order to tackle the problem that $\mathbb{B}$ cannot be identified in advance, an approximation is made. This approximation consists of an iterative approach of optimizing $\mathbf{B}^{*(\tilde{n})}$ for a given $\mathbb{B}^{(\tilde{n})}$, where $\tilde{n}$ represents the iteration:

$$\begin{aligned}
\mathbf{B}^{*(\tilde{n})} \quad &= \underset{\mathbf{B}\in\mathbb{B}^{(\tilde{n})}}{\operatorname{argmin}}\, J(\mathbf{Q}), \qquad \text{(Subproblem 1)},\\
\text{s.t.} \quad & \mathbf{Q} = \tilde{Q}(\mathbf{B}),\\
& \breve{\phi}(\mathbf{Q}, \mathbf{B}) = 0,\\
& \breve{\psi}(\mathbf{Q}, \mathbf{B}) \leq 0,
\end{aligned} \tag{5.8}$$

optimizing $\mathbf{U}^{*(\tilde{n})}$ given $\mathbf{B}^{*(\tilde{n})}$:

$$\begin{aligned}
\mathbf{U}^{*\tilde{n}} \quad &= \underset{\mathbf{U}\in\mathbb{U}}{\operatorname{argmin}}\, H_1(\mathbf{B}^{*\tilde{n}}, B(\mathbf{T}_A^{*\tilde{n}}, \mathbf{U})), \qquad \text{(Subproblem 2)},\\
\text{s.t.} \quad & \mathbf{T}_A^{*\tilde{n}} = T(\mathbf{Q}^{*\tilde{n}}),\\
& \hat{\phi}(\mathbf{U}, \mathbf{Q}, \mathbf{T}_A, \mathbf{B}) = 0,\\
& \hat{\psi}(\mathbf{U}, \mathbf{Q}, \mathbf{T}_A, \mathbf{B}) \leq 0,
\end{aligned} \tag{5.9}$$

and updating $\mathbb{B}^{(\tilde{n}+1)}$ for the next iteration $\tilde{n}+1$ given the extent of reproduction of $\mathbf{B}^{*(\tilde{n})}$ by guidance (Subproblem 3). This exactly corresponds to the algorithm described in Section 5.2.2.

At a fixed-point, a consistent problem formulation has been obtained. At this fixed-point holds that $C(\mathbf{c}) = \mathbf{c}$, where $\mathbf{c}$ is a set of variables transferred between the different problems of the approach, e.g. the optimized turning flows. The function C is the combination of the *optimization of turning fractions*, *optimization of instructions*, and *approximation of compliance behavior*.

Convergence towards the fixed-point cannot be guaranteed. A gap function is defined for which holds that approximate convergence may be postulated once this gap function falls below a certain threshold value, i.e., $H_2(\mathbf{c}, C(\mathbf{c})) < \varepsilon$, where H_2 is a distance measure, and for ε holds that $\varepsilon > 0$. The fixed-point can be approximated in different ways. Results of one iteration can directly be included in the next iteration, results can be averaged over the iterations using the Method of Successive Averages (Liu et al., 2009), or more advanced methods can be applied, as the approach presented in Bierlaire & Crittin (2006). This approach can be chosen such that convergence to a solution is enforced. However, this approximate convergence should not be the main goal of the application because convergence gives no guarantee on the quality of the solution.

5.2.4 Elaboration on the components of the fixed-point approach

In this section, the *optimization of turning fractions*, *optimization of route advice*, and *approximation of compliance behavior* are further explained.

Optimization of turning fractions (Subproblem 1) The minimization problem formulated in Equation 5.8 results in optimized turning fractions $\mathbf{B}^{*(\tilde{n})}$, a matrix of time dependent turning fractions $\beta_{ij}(t)$ (from link i to link j at time t). The possible values for the turning fractions are elements of the set $\mathbb{B}^{(\tilde{n})}$ following from the *approximation of compliance behavior*, defining time-dependent lower and upper bounds on the turning fractions:

$$\beta_{ij}^{\text{lower}}(t) \leq \beta_{ij}(t) \leq \beta_{ij}^{\text{upper}}(t). \tag{5.10}$$

The optimized turning fractions $\mathbf{B}^{*(\tilde{n})}$ and the corresponding flows $\mathbf{Q}^{*(\tilde{n})}$ are used to determine the input for the *optimization of route advice*: time-dependent travel times $\mathbf{T}_A^{*(\tilde{n})}$ (the matrix of time-dependent link travel times $\tau_a(t)$, on link a at time t), and optimized turning flows $\mathbf{Y}^{*(\tilde{n})}$ (the matrix of time-dependent turning flows $y_{ij}(t)$, from link i to link j at time t). The fixed time-dependent link travel times follow from the time-dependent link in- and outflows under a first-in/first-out assumption. Alternative ways of extracting travel times from the network loading model can be equally well embedded in the framework. The optimized turning flows $\mathbf{Y}^{*(\tilde{n})}$ are derived from the optimized turning fractions $\mathbf{B}^{*(\tilde{n})}$ and corresponding link flows by the following relation between turning fractions, turning flows, and link flows:

$$y_{ij}(t) = \beta_{ij}(t) q_i^{\text{out}}(t), \tag{5.11}$$

where $q_i^{\text{out}}(t)$ is the outflow of link i at time t; it is contained in $\mathbf{Q}$. The reproduction of the turning fractions in Equation 5.9 is evaluated in terms of these turning flows rather than fractions. When evaluating based on flows, the importance of reproduction of specific turning fractions is distinguished by the amount of flow corresponding to the fractions.

The optimization is subject to the macroscopic traffic propagation model $\tilde{Q}$. As explained in Section 5.2.1, classes that represent multiple route flows are not needed because the decision variables are turning fractions. The origin-destination matrix can require multiple classes as well. When the demand is destination-specific, a multi-class model is needed that distinguishes the traffic by destination and class-specific turning fractions have to be used as well. When the demand is not destination-specific, a single-class model satisfies. Furthermore, the traffic propagation model is required to model the traffic that enters a node as mixed traffic with respect to the directions. This means that the links do not consist of direction specific lanes, but the traffic with a specific direction is distributed over the multiple lanes instead. In case of direction specific lanes, the model constraints could conflict with the lower and upper bounds on the turning fractions.

Optimization of route advice (Subproblem 2) The route advice $\mathbf{U}^{*(\tilde{n})}$ is optimized by Equation 5.9. The route advice should at least be origin and departure time specific, but could also be more detailed, e.g. at the level of (groups of) individuals, depending on the underlying demand representation. The optimization is subject to the model B, consisting of 1) a route choice model, e.g. based on discrete choice theory, describing route flows as function of route advice, and 2) the propagation of these route flows given the fixed time-dependent travel times, resulting in time-dependent turning fractions and (turning) flows. The distance measure H_1 expresses the difference between these turning fractions and the optimized turning fractions $\mathbf{B}^{*(\tilde{n})}$ resulting from the *optimization of turning fractions*. As discussed earlier in this section, the difference is expressed in turning flows instead.

The turning flows and fractions resulting from the optimization of route guidance are called the realized turning flows and fractions. The realized turning fractions $\mathbf{B}^{\text{real}}$ are, together with the advised turning fractions $\mathbf{B}^{\text{adv}}$, input for the *approximation of compliance behavior*. To determine the advised turning fractions, traffic is propagated again over the network whereby is assumed that the route flows are equal to the route advice.

Approximation of compliance behavior (Subproblem 3) In the third problem, bounds on the turning fractions are updated. Location- and time-specific compliance is determined based on the result of the *optimization of route advice*. Because the compliance behavior is a characteristic of the travelers, this location- and time-specific compliance does not hold in general, but is specific for the solution of the *optimization of route advice*. This compliance is used to update the bounds on the turning fractions.

The lower and upper bounds on the turning fractions, $\mathbf{B}^{\text{lower}}$ and $\mathbf{B}^{\text{upper}}$, represent the smallest and largest values that could, due to limited compliance, possibly be realized through guidance. For their computation, a model of approximate compliance at the turning fraction level is assumed. In this model, the realized turning fraction is a convex combination of the advised and the preferred turning fraction:

$$\beta_{ij}^{\text{real}}(t) = c_{ij}(t)\beta_{ij}^{\text{adv}}(t) + (1 - c_{ij}(t))\beta_{ij}^{\text{pref}}(t), \tag{5.12}$$

where $\beta_{ij}^{\text{pref}}(t)$ is the preferred turning fraction from link i to link j at time t, and $c_{ij}(t)$ is a compliance variable in [0,1], representing the aggregated compliance on the turning move level. The advised turning fractions result from an aggregation of the optimized route advice $\mathbf{U}^{*(\tilde{n})}$. The preferred turning fractions result from the population's route choice not considering route advice using the same route choice model as used in the *optimization of route advice*.

In order to identify the upper and lower bounds defining the set of reproducible turning fractions $\mathbb{B}^{(\tilde{n}+1)}$, Equation 5.12 is solved for $c_{ij}(t)$, which yields:

$$c_{ij}(t) = \frac{\beta_{ij}^{\text{real}}(t) - \beta_{ij}^{\text{pref}}(t)}{\beta_{ij}^{\text{adv}}(t) - \beta_{ij}^{\text{pref}}(t)}. \tag{5.13}$$

The compliance rates determine the possible deviation from the preferred turning fractions because of guidance. The lower and upper bounds on the turning fractions result from the insertion of the most extreme advice values (zero and one) into Equation 5.12, using the compliance values computed in Equation 5.13:

$$\beta_{ij}^{\text{lower}}(t) = (1 - c_{ij}(t))\beta_{ij}^{\text{pref}}(t), \tag{5.14}$$

$$\beta_{ij}^{\text{upper}}(t) = c_{ij}(t) + (1 - c_{ij}(t))\beta_{ij}^{\text{pref}}(t). \tag{5.15}$$

The compliance for a specific turn and time is unknown in case that the turning fractions for this turn and time are equal for the three simulated cases, i.e., advised, realized, and preferred. In this case, the corresponding bounds on the turning fraction are set equal to the preferred turning fraction. In the next iteration, this turning fraction can probably be reproduced by route advice, possibly resulting in looser bounds in the consecutive iteration. If the compliance value for a specific turn and time following from Equation 5.13 is negative, this value is set to 0. If the value following from Equation 5.13 is higher than 1, this value is set to 1.

5.3 Case study

The goal of the case study is to show the computational efficiency of the fixed-point approach, as well as the quality of the resulting solutions. In order to achieve this goal, evacuation route advice is optimized both by solving the O-RAP directly and by the fixed-point approach, and the results are compared. A discrete time setting is assumed. Section 5.3.1 describes the flood scenario. The common components of the original route advice problem and the fixed-point approach are specified in Section 5.3.2, and the additional components of the fixed-point approach are specified in Section 5.3.3. Section 5.3.4 describes the setup of the test and Section 5.3.5 analyzes the results.

5.3.1 Evacuation scenario

The scenario is the evacuation of the population of Walcheren, which is introduced in Section 3.4.1 and illustrated in Figure 3.3. Contrary to the case studies in Chapters 3 and 4, departure time advices are not optimized but demand is assumed instead. The demand at each origin is assumed to be uniformly spread over 6 hours. In this case study, it is assumed there is enough time to evacuate everyone. The evacuation ends when all people have arrived at a destination.

5.3.2 Specification of the common components of the O-RAP and the FPA-RA

This section specifies the components that the O-RAP and the fixed-point approach have in common: the variables route advice $\mathbf{U}$ and dynamic link flows $\mathbf{Q}$, the objective function J, the search space $\mathbb{U}$, and the route choice model and the traffic propagation model which are referred to by Q in the O-RAP and are part of B and $\tilde{Q}$ in the fixed-point approach.

Variables Route advice $\mathbf{U}$ is modeled by a real-valued vector that represents aggregated vehicle entry flows on the routes. The elements of $\mathbf{U}$ are values $u_p^r(t)$, the fraction of travelers leaving origin r at time instant t advised to follow route p. Thus, multiple fractions of travelers can be distinguished per origin, and each fraction receives its own advice consisting of 1 route to follow. The elements of the dynamic link flows $\mathbf{Q}$ are time-dependent link in- and outflows, $q_a^{\text{in}}(t)$ and $q_a^{\text{out}}(t)$ respectively, were $a \in A$ are the links in the network.

Objective function The objective function is equal to the function introduced in Section 3.2.2, i.e. a function of the weighted arrivals:

$$J(\mathbf{Q}) = \xi \sum_{t \in T, a \in A_D} \exp^{-\chi_1 t} q_a^{\text{out}}(t). \tag{5.16}$$

where J is the value of the objective function, and χ is a weighting parameter with $\chi > 0$. In this case study, χ is set to 0.1. In the remainder, $-J$ is referred to as the *effectiveness* of the evacuation.

Route choice model The route choice model is part of the model Q in the O-RAP and part of the model B in the fixed-point approach. It derives route flows from route advice $\mathbf{U}$. Similar to the model EVAQ presented by Pel et al. (2008) used in the previous chapters, a multinomial logit model is used to determine the route flow proportions. The model determines route flows, reflecting route choice decisions, as function of route advice. The model given here assumes that some evacuees will consider the advice in their decision process while others will not. Similar to the model EVAQ, it is assumed that the evacuees considering the advice will base their route choice both on this advice and on other characteristics of the route, e.g. travel time. Here, a generic definition of the corresponding utilities are given. The model is not published elsewhere and is therefore described in this section.

Consider a class of travelers, m, consisting of travelers receiving the same advised route. We assume that the people in the class either consider the advice (subclass m_1)

or ignore it (subclass m_2). The proportion of class m travelers choosing route p at time t is equal to the sum of the two subclass-specific proportions, weighted with the proportion of class m travelers that are part of the specific subclasses:

$$\phi_p^m(t) = \omega^m \phi_p^{m_1}(t) + (1-\omega^m)\phi_p^{m_2}(t), \tag{5.17}$$

where ω^m is the proportion of class m travelers considering the advice.

The route flow proportions are set equal to the probabilities that the routes are chosen. These probabilities follow from the route utilities by a path-size logit model adopted from Ben-Akiva & Bierlaire (1999), assuming that overlapping paths may not be perceived as distinct alternatives. The proportion of class m_* ($*$ being either 1 or 2) travelers selecting route p at t is equal to:

$$\phi_p^{m_*}(t) = \frac{\exp(V_p^{m_*}(t) + \chi_8^{m_*} \ln S_p(t))}{\sum_{p' \in P_m} \exp(V_{p'}^{m_*}(t) + \chi_8^{m_*} \ln S_{p'}(t))}, \tag{5.18}$$

where $S_p(t)$ is the so-called size variable, which has a value less than one if the path shares one or more links with the alternative routes (for the computation of the value of this variable, see Ben-Akiva & Bierlaire (1999)), P_m is the class-specific route set, and $\chi_8^{m_*}$ is a parameter. Since a macroscopic demand representation is used, the route flow proportions can be set equal to the probabilities that are modeled as continuous variables. $V_p^{m_*}(t)$ is the utility of class m_* travelers for route p at time t, and is equal to:

$$V_p^{m_*}(t) = \chi_9^{m_*} V_p^{m_*,\text{char}}(t) + \chi_{10}^{m_*} V_p^{m_*,\text{adv}}(t), \tag{5.19}$$

where $V_p^{m_*,\text{char}}(t)$ and $V_p^{m_*,\text{adv}}(t)$ are respectively the characteristics-related and advice-related utility at t, and $\chi_9^{m_*}$ and $\chi_{10}^{m_*}$ are parameters. Hereby holds $\chi_{10}^{m_1} > 0$ and $\chi_{10}^{m_2} = 0$, reflecting that travelers of any class m_2 ignore the advice, and $\chi_9^{m_*} < 0$, reflecting that travelers prefer routes with lower travel times.

For this case study, the characteristics-related utility $V_p^{m,\text{char}}(t)$ is set to the free flow travel time. Other realizations are possible as well. Given that the travelers are unfamiliar with the evacuation, free flow travel times are a reasonable realization. The advice-related utility $V_p^{m,\text{adv}}(t)$ is set to one if route p is instructed and to zero otherwise. To emphasize, this model specification is only given to illustrate the fixed-point approach. More research, out of the scope of this thesis, is needed to obtain a validated and calibrated model representing evacuation route choice behavior. Such a new model can easily be inserted in the fixed-point framework.

Traffic propagation model The traffic propagation model is part of Q in the O-RAP and represented by $\tilde{Q}$ in the fixed-point approach. The model applications differ for the two approaches in the input based on which the traffic flows are determined: this input consists of route flows in the O-RAP, and of turning fractions in the fixed-point approach. The traffic propagation model used here is the same as in Chapters 3 and 4, namely, the queuing model presented in Bliemer (2007) which is part of the model EVAQ presented by Pel et al. (2008). In this chapter, the original version of the node model proposed by Bliemer (2007) is used, which means that in case one of the downstream links is completely occupied, there could be traffic entering other downstream links. This while in the previous chapters the node model deviated as explained in Section 3.2.3. This difference is the consequence of adaptation of the traffic propagation model during the development of this thesis. However, this difference has no influence on the results because the case study in this chapter focuses on the efficiency of the approach, whereby the same traffic propagation model is used in both approaches, i.e. the model containing the original node model.

As explained in Section 5.2.4, the fixed-point approach needs a multi-class model when the demand is destination-specific, while a single-class model satisfies when this is not the case. The evacuation demand is assumed to be not destination-specific and because of that a single-class model satisfies. However, the O-RAP needs a multi-class traffic propagation model as explained in Section 5.1. The same model is used in both approaches and therefore a multi-class traffic propagation model is needed. The multi-class characteristic of this model is used only in the O-RAP.

Search space The search space $\mathbb{U}$ contains all route advice that can be given to the evacuees. This advice consists of routes to which fractions of people are advised. Here, a selection of all routes is used, and the fractions are continuous variables that can take all values between 0 and 1. The routes that are considered in the route choice model are limited to this selection of routes as well.

The search space, which is constant over the iterations, is generated as follows. First, a route set is generated using the procedure of generating the *most probable routes* as proposed, among others, by Bliemer & Taale (2006). As explained in Section 3.2.4, the resulting set consists of routes with relatively short free flow travel times and limited overlap between the routes. Here, this set is referred to as the initial route set. All turns, i.e. moves from up- to downstream links, are collected from the initial route set. All cycle-free routes that can be composed from these turns are part of the final route set. This adaptation is needed to ensure that the route selection is not limiting the feasibility of the *optimization of route advice* that is part of the solution approach for the FP-RAP. The turning fractions that are considered in the *optimization of turning fractions* are the fractions corresponding to the turns that are part of the initial route set. If the initial instead of the final set would be used when solving the FP-RAP, reproduction of the turning fractions through route advice could be unfeasible since routes could be needed that are combinations of parts of the routes in the initial set, but are not in the initial route set as a complete route.

5.3.3 Specification of the exclusive components of the FPA-RA

This section specifies the exclusive components of the FPA-RA: the variables turning fractions $\mathbf{B}$ and fixed time-dependent travel times $\mathbf{T}_A$, the distance measures H_1 and H_2, the function T and part of the function B, and the search space $\mathbb{B}$. Some approximations that are necessary because of the discrete time setting are discussed as well.

Variables The definitions of the variables turning fractions $\mathbf{B}$ and fixed time-dependent travel times $\mathbf{T}_A$ are given in Section 5.2.4, and repeated here: $\mathbf{B}$ consists of $\beta_{ij}(t)$, the fraction of traffic leaving upstream link i and entering downstream link j at time t, and $\mathbf{T}_A$ consists of $\tau_a(t)$, the travel time on link a at time t.

Route choice and traffic flow functions The function T derives fixed time-dependent link travel times $\mathbf{T}$ from the time-dependent link in- and outflows $\mathbf{Q}$. The travel times need to be approximated because of the time discretization. Interpolation is needed to determine these travel times based on the time-dependent link in- and outflows. In the case study, linear interpolation is applied.

The function B consists of the route choice model presented in Section 5.3.2 and the propagation of the resulting route flows given the fixed travel times. Because of the discretization of time, an approximation is needed in this propagation. The route flow in each time step is assumed to be linearly distributed over the time step, resulting in a platoon of vehicles. The tail and the head of this platoon are propagated over the route, constrained by the time-dependent link travel times, whereby a uniform distribution of the traffic is assumed at each location in between.

Distance functions As discussed in Section 5.2.3, the fixed-point can be approximated in several ways, e.g., by using the Method of Successive Averages. Here, results from one iteration are directly included in the next iteration. This resulted in fast convergence as illustrated in Section 5.3.5 because of which more advanced approaches are unnecessary. The distance measure that specifies the convergence is expressed in terms of the optimized turning flows $\mathbf{Y}^{*(\tilde{n})}$, using the RMSE to reflect the distance:

$$\begin{aligned} H_2\left(\mathbf{Y}^{*(n)}, C(\mathbf{Y}^{*(n)})\right) &= \mathrm{RMSE}\left(\mathbf{Y}^{*(\tilde{n})}, C(\mathbf{Y}^{*(\tilde{n})})\right) \\ &= \sqrt{\frac{\sum_{ij,t}\left(y_{ij}^{*(\tilde{n})}(t) - f(y_{ij}^{*(\tilde{n})}(t))\right)^2}{z}} < \varepsilon, \end{aligned} \tag{5.20}$$

where z is the number of data pairs. Other realizations of the distance function are possible as well, like the mean squared error. If the problem would be solved by a derivative-based exact approach, the RMSE could not be used because of the required differentiability.

The distance measure used in the *optimization of route advice* is expressed in turning flows. This measure defines the extent of reproduction of the optimized turning flows $\mathbf{Y}^{*(\tilde{n})}$ by the realized turning flows $\mathbf{Y}^{\mathrm{real}}$ and uses the RMSE as well:

$$\begin{aligned} H_1\left(\mathbf{B}^{*(n)}, B(\mathbf{T}_A, \mathbf{U})\right) &\approx \mathrm{RMSE}\left(\mathbf{Y}^{*(\tilde{n})}, \mathbf{Y}^{\mathrm{real}}\right) \\ &= \sqrt{\frac{\sum_{ij,t}\left(y_{ij}^{*(n)}(t) - y_{ij}^{\mathrm{real}}(t)\right)^2}{\tilde{n}}}, \end{aligned} \tag{5.21}$$

where the realized turning flows $\mathbf{Y}^{\mathrm{real}}$ are determined based on the realized turning fractions $\mathbf{B}^{\mathrm{real}}$ and the corresponding link flows $\mathbf{Q}$ using Equation 5.11. The value of $\mathrm{RMSE}\left(\mathbf{Y}^{*(\tilde{n})}, \mathbf{Y}^{\mathrm{real}}\right)$ will deviate from zero at the solution point since numerical imprecisions make an exact match of the quantities impossible. This numerical imprecision is caused by evaluating the turning fractions in the *optimization of turning fractions* with the traffic propagation model, and in the *optimization of route advice* based on the fixed travel times. The same set of fractions leads to slightly different traffic flows when evaluated either by the traffic propagation model or the derived travel times. These deviations happen infrequently but can become large.

Search space The search space $\mathbb{B}$ contains all values that can be assigned to the turning fractions $\mathbf{B}$. The specification of $\mathbb{B}$ is partly coupled to the specification of $\mathbb{U}$. All turns, i.e., moves from up- to downstream links, that are part of the route set included in $\mathbb{U}$ are selected. For the turning fractions corresponding to these turns, the possible values are on the continuous interval from 0 to 1, while the other turning fractions are set equal to 0. This part of the specification is equal for all iterations of the fixed-point approach. In each iteration, $\mathbb{B}$ is specified by Equations 5.14 and 5.15 for the turning fractions that are not limited to the value 0.

Turning fractions that are selected out of the search space $\mathbb{B}$ could require people driving in cycles in order to get the turning fractions being reproduced. However, cycles are eliminated from the route choice model thus exact reproduction is not possible for that case.

5.3.4 Test set-up

To show the efficiency of the fixed-point approach, route advice is optimized both by solving the O-RAP and the FP-RAP and the results are compared. Two test cases are set up that differ in the scale of the problem. The first test contains relatively few turning fractions and routes, called Test Small, and the second test contains relatively many turning fractions and routes, called Test Large. This difference is obtained by changing the number of Monte Carlo simulations used for the route choice set generation. Test Small contains 63 turning fractions and 43 routes, of which respectively 7 and 18 are decision variables and the other variables are dependent. The total number of optimization variables, accounting for different time horizons, is equal to 21 for the optimization of turning fractions and equal to 36 for the optimization of route advice. Test Large contains 71 turning fractions and 55 routes, of which respectively 10 and 32 are decision variables. The number of decision variables for the optimization of turning fractions is equal to 30, and for the optimization of route advice is equal to 64.

For each test, route advice is optimized both by solving the O-RAP and by applying the FPA-RA. Both tests are performed for three different parameter settings of the route choice model, A, B, and C. For each test holds that the values for the class-specific parameters vary by class. These parameter settings are obtained by drawing class-specific values from the following distributions:

- ω^m, the proportion of travelers considering the advice: uniformly distributed from 0.2 to 0.4;
- γ^m, the influence of the overlap in the routes: uniformly distributed from 0.4 to 0.6;
- μ^{m_*}, the influence of the route characteristics: uniformly distributed from -3 to -5;
- ν^{m_1}, the influence of the route advice: uniformly distributed from 1 to 3.

The FPA-RA is initialized by setting the compliance on all turns at each time step, $c_{ij}(t)$ in Equations 5.14 and 5.15, equal to 0.3. This value, together with the preferred turning fractions, results in bounds on the turning fractions that are input for the first instance of the *optimization of turning fractions* in the FPA-RA. The stopping criterion (Equation 5.20) is compared to a threshold value of $\varepsilon = 50$.

The length of the time step is set to 15 seconds and all models run at this resolution. In order to limit the complexity of the optimization problems, the route advice and the turning fractions that are optimized, are fixed at a larger temporal resolution of 3 hours. An exception is the final period in the optimization of turning fractions: this period starts after the last evacuee has departed, thus after 6 hours, and lasts until the last arrival. The bounds on the turning fractions follow from time-instant-specific compliance values (Equation 5.14 and 5.15) and are averaged over the same larger temporal resolution. As stated in Section 5.2.4, some bounds are unknown and are therefore set equal to the preferred turning fractions. Here, these assumed bounds are incorporated in the averaging only when not a single value is known in the considered time span for the specific turn.

The optimization problems that are part of the O-RAP and the FPA-RA are all constrained nonlinear minimization problems. Contrary to the problems solved in Chapters 3 and 4, the decision variables are continuous variables. This makes the solution approach EAS+, introduced in Chapter 3, unsuitable to solve the problem. Instead, MATLAB's fmincon optimization routine is used to solve the problems. This routine exploits differentiability. The settings of this solver, like tolerance constraints and the algorithm, used to solve the problem defined in Equation 5.2 are equal to the settings used to solve the upper optimization problem defined in Equation 5.5.

Upon incomplete convergence, the effectiveness values determined by the FPA-RA deviate from effectiveness values that would result from evaluation by the model Q. In addition to the evaluation incorporated in the FPA-RA, the optimized guidance resulting from each iteration of the FPA-RA is evaluated by the model Q as well. This gives insight in the improvement in the actual effectiveness over the iterations. From now on, effectiveness determined by the model Q is referred to as effectiveness, and the effectiveness determined by the FPA-RA is called *approximate effectiveness*.

For each test, the evacuation efficiency in case of no advice is determined as well. This effectiveness follows from the model Q with $\phi_r^{m_1} = 0$ and $\phi_r^{m_2} = 1$, where both proportions are constant over time. This shows the improvement in evacuation efficiency

Table 5.1: Results: No advice, advice resulting from applying the FPA-RA, and advice resulting from solving the O-RAP

(a) Test Small: Effectiveness (-J) and Computational time

	No advice	**FPA-RA**		**O-RAP**	
	Effectiveness	Effectiveness	Comp. time (number of iterations)	Effectiveness	Comp. time
A	78,937	85,402 (+8.19%)	0:27 (3)	85,433 (+8.23%)	22:58
B	78,956	85,554 (+8.36%)	0:31 (3)	85,603 (+8.42%)	40:01
C	78,983	85,579 (+8.35%)	0:27 (3)	85,795 (+8.62%)	38:29

(b) Test Large: Effectiveness (-J) and Computational time

	No advice	**FPA-RA**		**O-RAP**	
	Effectiveness	Effectiveness	Comp. time (number of iterations)	Effectiveness	Comp. time
A	79,368	87,371 (+10.08%)	1:42 (4)	87,458 (+10.19%)	124:50
B	79,407	87,853 (+10.64%)	2:18 (5)	87,941 (+10.75%)	208:19
C	79,426	87,573 (+10.26%)	3:17 (5)	87,844 (+10.60%)	103:39

obtained by the optimized route advice. While showing this improvement is not the main goal of this case study, it endorses the importance of optimized evacuation guidance and thus of creating this guidance efficiently by the FPA-RA.

5.3.5 Results and discussion

Table 5.1 gives the effectiveness values and computational times for the different tests. In addition to the effectiveness values, the effectiveness improvement relative to the no advice situation is given as well. The computational time, which is expressed in hh:mm, is the result of the use of 2 or less computational threads of a desktop computer with an Intel Core 2 Quad @ 2.83 Ghz and 4GB RAM. For the FPA-RA, the number of iterations is given in parenthesis.

The FPA-RA turns out to be an efficient approach to optimize route advice. Solving the FP-RAP is 32 to 91 times faster than solving the O-RAP, while the decrease in the relative effectiveness improvement is between 0.04 % and 0.34 %. Thus, the FPA-RA does substantially speed up the optimization of route advice, while maintaining a solution quality that is comparable to the solution of the O-RAP.

Figures 5.2 and 5.3 show the convergence of the FPA-RA for Test Small and Test Large respectively. For Test Large holds that the approach converges after a few iterations:

the distance between the turning flows decreases and the *approximate effectiveness* and the *effectiveness* become similar. The route advice with the highest effectiveness for Test Small is already found in the first iteration of the FPA-RA for each test.

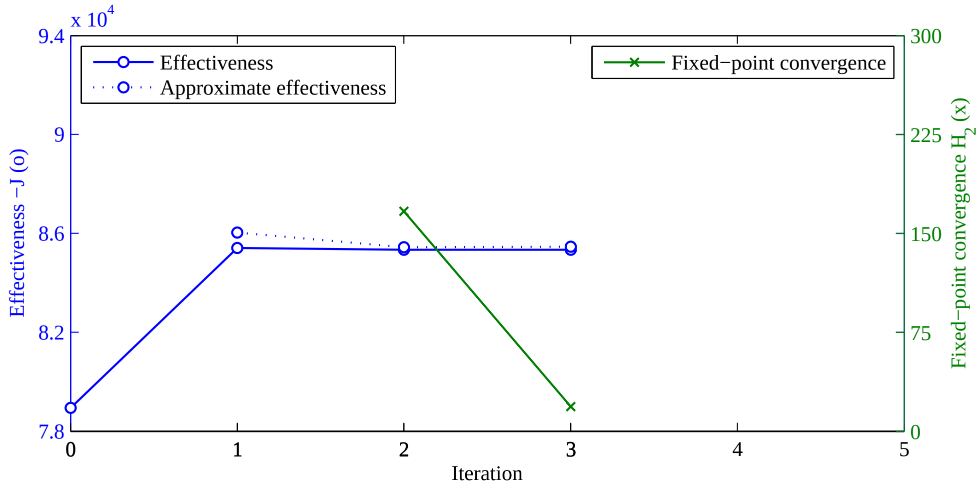
Both solution approaches, i.e. solving the O-RAP directly and applying the FPA-RA, are iterative processes. Figure 5.4 shows the effectiveness values of the evaluated route advice over the computational time. For the approach that solves the O-RAP directly is assumed that each evaluation took an equal part of the total computational time. The figure shows that when solving the O-RAP directly, route guidance with an effectiveness that approximates the highest effectiveness found for that test is found after 40% or 60% of the time for Test Small and Test Large respectively. As showed in Figures 5.2 and 5.3, for the FPA-RA holds that 1 iteration is sufficient for Test Small, while 2 to 3 iterations are needed for Test Large. Thus, comparing the intermediate results for both iterative approaches confirms that the FPA-RA does substantially speed up the optimization of route advice.

5.4 Applicability of the approach

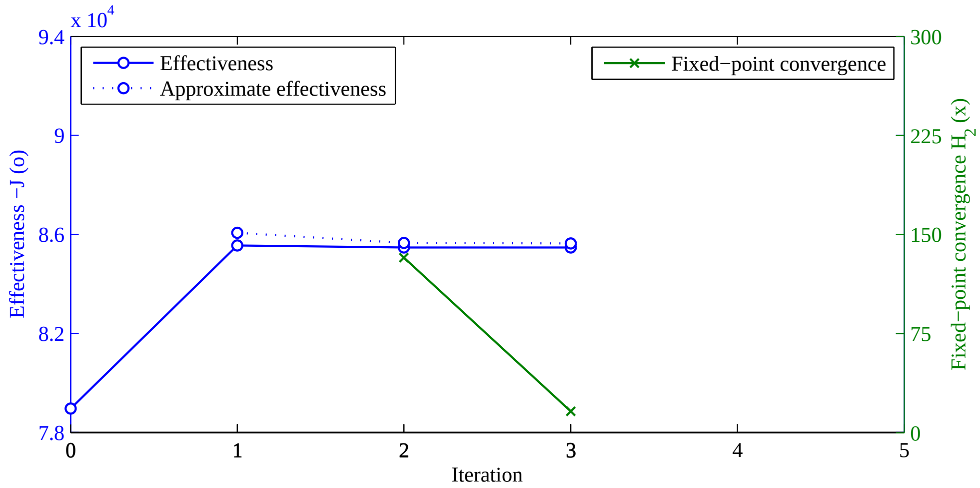
The fixed-point approach to route advice turned out to be an efficient approach to optimize route guidance for evacuation situations. However, this approach is not only useful to solve the evacuation problem, but can be used to solve any kind of route guidance problem efficiently. This is relevant because the importance of incorporating compliance behavior is often discussed but efficient approaches towards this goal are limited.

An overview on approaches to develop route guidance can be found in Herbert & Mili (2008) and Zuurbier (2010). Route guidance can be developed either from a system-optimal or user-equilibrium perspective. The appropriateness of these types is often discussed. System-optimal guidance is usually considered as being unrealistic. Complying with the guidance can decrease the performance from some users' perspective which in the end results in non-compliance. However, the user-equilibrium does probably lead to a low effectiveness from the system point of view. The difference in performance between system-optimal and user-equilibrium routing is compared analytically for relatively simple (static) traffic propagation models and networks (see e.g. Koutsoupias & Papadimitriou (1999) and Roughgarden & Tardos (2002)), and numerically for more advanced (dynamic) models and networks (see e.g. Mahmassani & Peeta (1993) and Wie et al. (1995)).

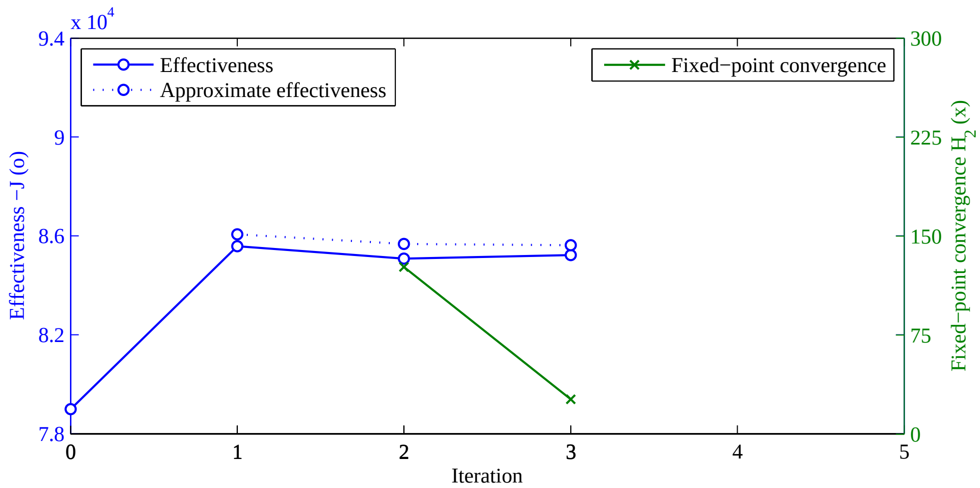
Compromises between pure system-optimal and user-equilibrium routing are developed. In Daganzo (1995b), a so-called uniformly fair strategy is proposed. This approach controls the flow through a bottleneck towards system-optimal performance, while allowing the people to choose the form of the penalty they must pay for using the bottleneck. The strategy consists of pricing and rationing, i.e. banning every individual from using the bottleneck a fraction of the days, indirectly influencing the route



(a) Test A

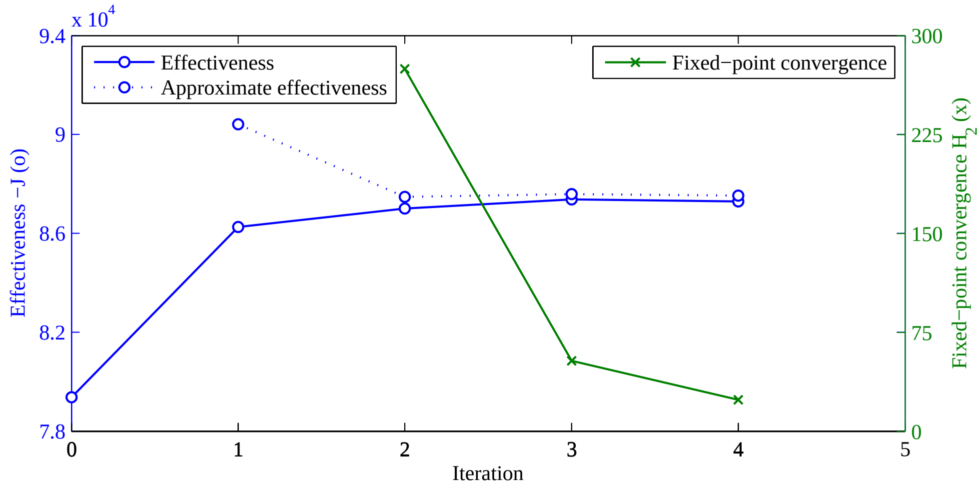


(b) Test B

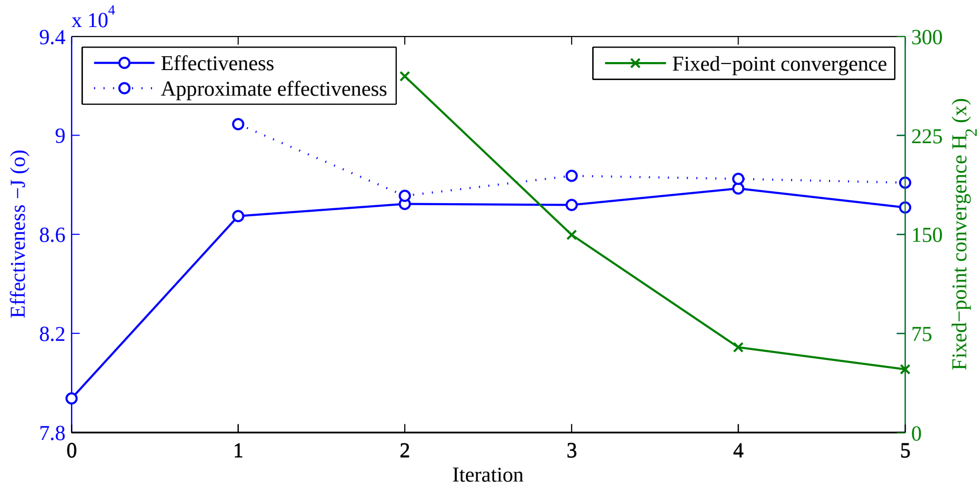


(c) Test C

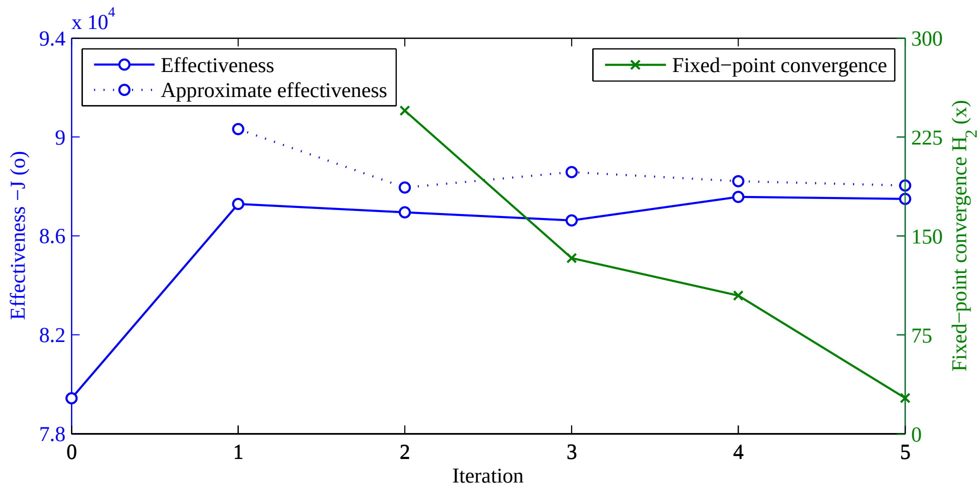
Figure 5.2: Results Test Small: the effectiveness (marked by circles) and the fixed-point convergence (marked by crosses) over the iterations



(a) Test A

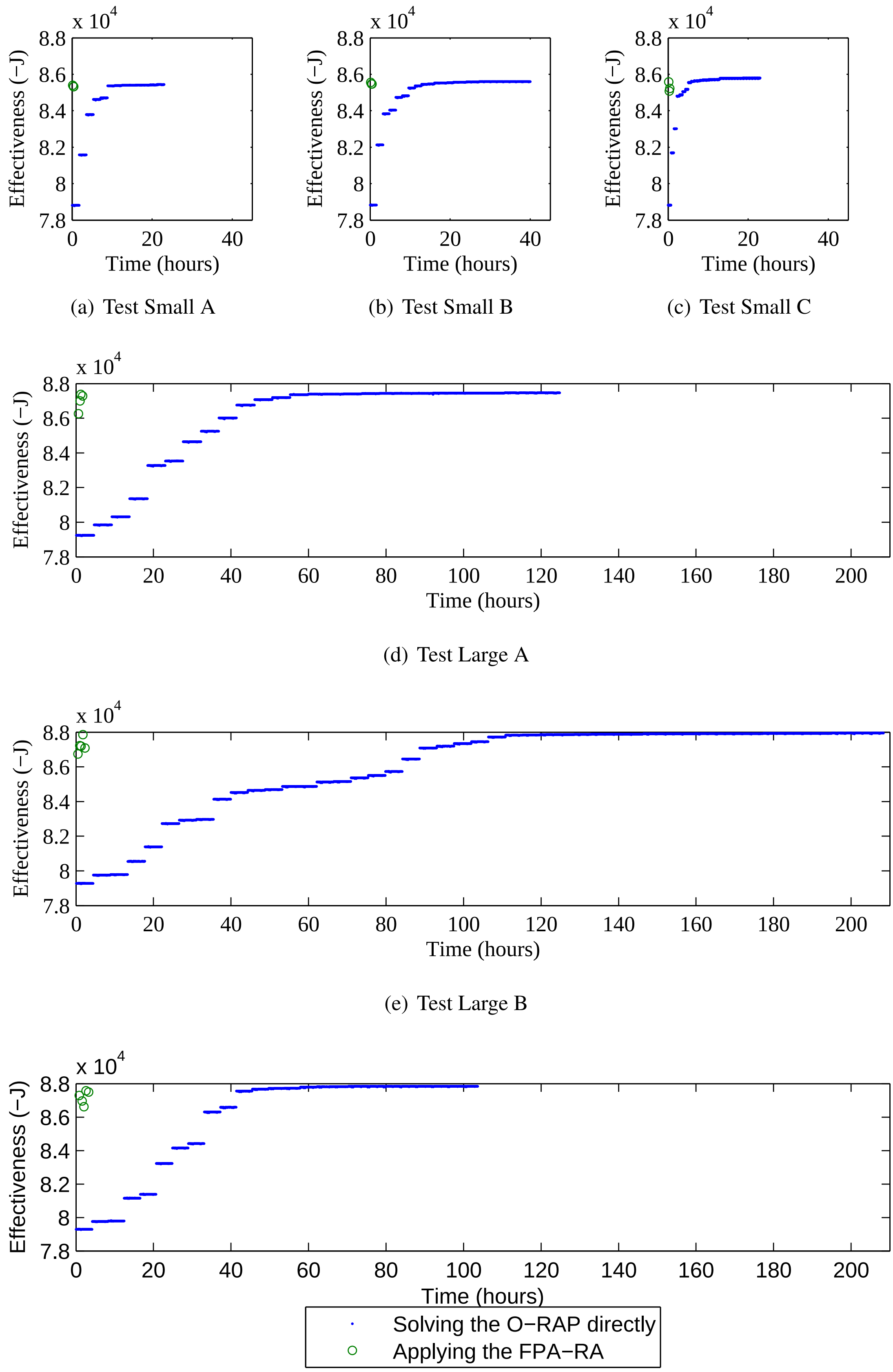


(b) Test B



(c) Test C

Figure 5.3: Results Test Large: the effectiveness (marked by circles) and the fixed-point convergence (marked by crosses) over the iterations



(a) Test Small A

(b) Test Small B

(c) Test Small C

(d) Test Large A

(e) Test Large B

(f) Test Large C

Figure 5.4: Effectiveness of the solutions over the computational time

choices. Another compromise is proposed by Jahn et al. (2005): routes are optimized from a system-optimal perspective with integrated user constraints. These constraints ensure that the suggested routes are not longer than a so-called normal length, e.g. defined by travel time. The discussion on the (dis)advantages of the system-optimal and user-equilibrium routing approaches and the development of compromises show the importance of both the system-optimality and the behavior of the travelers in the development of route guidance.

The fixed-point approach to route advice presented in this chapter combines system-optimality with the incorporation of travelers' behavior. Behavior can extensively be incorporated since route guidance is evaluated at route level in the fixed-point approach. A usual approach to evaluate route guidance is evaluation at node level, i.e. the use of compliance rates that reflect the fraction of travelers following the route guidance at a certain node, see, for example, Papageorgiou (1990). However, when travelers are advised to follow a certain route, or to take a certain road when they arrive at an intersection or interchange, their decision will depend on their total trip. To incorporate this behavior, route guidance has to be evaluated on route level, considering the route in its entirety. Incorporating this behavior by evaluation at node level is impossible.

The fixed-point approach is most beneficial for the evaluation of guidance given at route level. Advice given at route level is the advice to a traveler to take a certain route from origin to destination. Advice given at node level is the advice to take a certain road when arriving at an intersection or interchange. These types differ in their applicability. Route advice is easy to communicate, which is relevant when giving guidance prior to a trip, such that it needs to be memorized. Furthermore, an advice can consist of several alternative routes which can be compared by the traveler. Node advice can more easily be updated after the traveler has started the trip.

While the fixed-point approach is most beneficial for guidance given at route level, it is beneficial to optimize guidance given at node level as well. The fixed-point approach overcomes two difficulties of the O-RAP: the high number of decision variables and the high evaluation costs. This second difficulty belongs to a route advice problem that contains route advice given at node level as well. By applying the fixed-point approach, this difficulty is solved.

5.5 Conclusions

This chapter presents a new approach to optimize route advice from a system perspective, considering route choice and limited compliance to guidance in an explicit and generic way. This difficult problem is efficiently solved by a fixed-point approach that deals with the large number of decision variables and high evaluation costs by decomposing the problem.

This efficiency is shown in a case study, where the approach is applied to generate route advice during evacuations. The fixed-point approach turned out to be at least 32 times faster compared to solving the original route advice problem directly, while maintaining a comparable solution quality.

The fixed-point approach can be extended to include destination guidance as well. This can be realized by including origin-specific turning fractions. These fractions consider two downstream links: one link is the usual link by which traffic is loaded on the network and the other link is artificial and ends up in the origin again. By including these origin-specific turning fractions, combined departure time and route guidance can be developed. In this chapter, the application is limited to route advice because the computational gain depends on the determination of this specific advice.

Chapter 6

Findings, conclusions, implications, and future research directions

Evacuation guidance is needed for an efficient evacuation of people out of a region threatened by a disaster. The attention for uncertainty and compliance behavior is limited in literature on the optimization of evacuation guidance, while these factors are of great importance to be able to evaluate guidance in a realistic way. These findings where the reason to ask the following question: *How can evacuation guidance be optimized in an efficient way, while incorporating uncertainty and compliance behavior?* This question is answered in this thesis and this section summarizes these answers. Section 6.1 concentrates on the findings of this thesis and the corresponding conclusions. The implications of these conclusions for practice are discussed in Section 6.2. Since research is never finished but brings up new questions instead, this thesis concludes with suggestions on future research directions in Section 6.3.

6.1 Main findings and conclusions

The research question is answered by formulating mathematical optimization problems, developing solution approaches, and analyzing applications of these problems and formulations. A *problem formulation* is developed that contains decision variables, an objective function, and a model. The decision variables consist of evacuation guidance, e.g. departure time, route and destinations guidance. This guidance is optimized whereby the performance is expressed by an objective function that, for example, maximizes the arrivals. This performance follows from a model that describes the evacuation process, which consists of a travel behavior and a traffic propagation part. The problem formulation is generic with respect to the network and modeling assumptions. This means that the formulation can be used for any real-sized network and that any kind of travel behavior and traffic propagation model can be included. The problem formulation is specified throughout the thesis and corresponding solution approaches are developed. These solution approaches solve the problem iteratively and result in approximate solutions.

The applications of the problem formulations and solution approaches resulted in findings regarding the effectiveness of optimized guidance, the incorporation of uncertainty, and the efficiency of the solution approaches. All *findings* relate to a concrete case, i.e. the hypothetical flood of the real network of a peninsula in the Netherlands. *Conclusions* are drawn based on these findings that are, by definition, not specific for a case but have a generic character.

The research resulted in the following findings regarding the *effectiveness of optimized guidance*. The effectiveness of the optimized guidance turned out to be substantially higher than both the effectiveness of guidance created by simple rules and the efficiency of an evacuation without any guidance. While the creation of guidance by simple rules has the advantage that the computational costs are drastically reduced compared to optimized guidance, they substantially reduce the efficiency of the evacuation. The implementation possibilities of both approaches are similar, because they both result in departure time, route, and destination instructions for groups of evacuees. The relatively high efficiency of the optimized guidance is explained by the structure of this guidance. The optimized guidance resulted in the spreading of travelers over the network such that the parts of the network that are limiting the evacuation efficiency are efficiently used. The near-optimality of the guidance, which was based on a theoretical upper bound, was found to be equal to at least 90%. Based on these findings, it can be concluded that guidance is beneficial for the evacuation efficiency. Similar results are expected for other cases, given the structure of the guidance and the near-optimality.

Uncertainty is incorporated in the problem by a scenario-based approach, whereby both a deterministic and a stochastic scenario selection procedure are considered. The deterministic selection is constant over the iterations, while the stochastic selection varies over the iterations. Because of the scenario-based characteristic, all kinds of uncertainties can be included. This refers to uncertainty in the input like the demand and the network, but also to uncertainty in the modeling assumptions. The approach is applied whereby demand, capacity and behavior uncertainty were incorporated. Application of this approach resulted in the following finding regarding the *incorporation of uncertainty*. By considering uncertainty in the optimization, the relative effectiveness is up to 10.8% higher. The relative effectiveness expresses the effectiveness of guidance applied to a scenario relative to the effectiveness of optimized guidance for that scenario. Based on these findings it is concluded that uncertainty can be incorporated when optimizing evacuation guidance. Incorporating uncertainty is beneficial to guarantee a certain effectiveness considering the uncertainty in the evacuation problem.

The evacuation problem is a complex problem, i.e. it consists of consists of complex, nonlinear functions. The approximate solution approach that is needed is computationally expensive because of the large number of decision variables, i.e. routes, and high evaluation costs, i.e. behavioral and traffic propagation models. A new approach to route guidance is presented that decomposes the original evacuation problem in sub-problems that are iteratively solved resulting in an approximate solution for the original problem. The approach was applied resulting in the following findings regarding the *efficiency* of the solution approach. The new approach turned out to be at least 32 times faster compared to solving the original route advice problem directly, while maintaining a comparable performance. A comparable improvement in the efficiency is expected for other cases. This means that the computational complexity that is coupled with incorporating behavior and uncertainty can be reduced.

6.2 Implications for practice

This thesis gives new insights in how beneficial evacuations are and how guidance can be optimized efficiently. In the Netherlands, the focus has been expanded from preventing disasters only to decreasing the consequences of disasters as well. This thesis shows the potential of decreasing the consequences in terms of evacuation efficiency and gives a direction on how to establish this by preparing evacuation plans. The resulting solutions presented in this thesis gives insight in the structure of optimized evacuation plans. For example, it shows the advanced structure of the plans which indicates the benefits of spreading the evacuees over time and space.

The methods presented in this thesis can be used to develop guidance in practice. The application will give insight into the possible guidance and the corresponding performance. In other countries, like the United States of America, evacuation transport plans are developed and used on a regular basis. The existing plans can be compared to plans optimized for the specific case.

The methods presented in this thesis are ready for use in practice regarding the development of car-based evacuation guidance. The approaches are flexible regarding the specifications like the traffic propagation model. These specifications, including the parameter settings, have to be made by the plan developer. The insights from this thesis regarding the influence of model specifications and parameter settings, for example, the influence of the parameter settings on the computational speed, all helpful to make these choices. The evacuation guidance resulting from the approaches is limited to the planning of the vehicular traffic. The evacuation guidance will be part of a broader plan, mainly containing communication and operation strategies. These other parts of the evacuation plan cannot be developed by the approaches presented in this thesis.

The fixed-point approach to evacuation guidance, presented in Chapter 5, is relevant for other traffic flow problems as well. The approach can be applied to solve all kinds of route guidance problems in the traffic management field. The approach has great potential and could, for example, be used in the struggle with the daily traffic jams.

6.3 Future research directions

The first suggested future research direction focuses on combining the off-line guidance developed in this thesis with online guidance. Combining guidance which is developed before the start of the evacuation with updating guidance during the evacuation is not investigated yet while this could be an effective approach. The off-line part of the approach leads to a plan for the whole evacuation that is robust with respect to the uncertainty and coherent for the full time period. The online part steers the evacuation on a lower level of detail whereby the actual scenario and forecasts can be taken into account. A specific case wherein the mentioned direction is useful is when the performance of the robust solution is too low, for example, because not all people can be evacuated on time. When it is guaranteed that, for example, at least 75% of the people can be evacuated on time, online measures can be taken to evacuate the other people. The off-line part of the solution will probably simplify the online part, compared to an approach that is limited to an online part.

Second, the choice for the travel behavior and traffic propagation models included in the evacuation problem could be investigated. The set-up of the evacuation problem is flexible regarding the modeling assumptions. This means that it is possible to include more accurate or more simple models. Comparing these two models, accurate models have the advantage that, theoretically, the best representations of reality can be given. However, including such a model in an optimization problem is computationally dependent. Furthermore, the more parameters the model contains, the more data is needed. This while the availability of data with respect to evacuation is limited. The discussion on accurate or simple models could be held on all kinds of levels. Examples are the use of a macroscopic or microscopic representation of traffic, and the use of traveler-specific or constant behavioral parameters.

Another future research direction is to develop an extensive approach containing all kinds of evacuation measures. Possible extensions are evacuation by public transport, vertical evacuation, or evacuation to shelters. This combination of measures increases the possibilities and because of that the evacuation potential.

As stated in Section 6.2, the methods presented in this thesis are useful for developing evacuation plans in practice. In order to do so, evacuations need to be investigated from a wider scope. The evacuation transportation plan is part of a broader plan, mainly containing communication and operation strategies. The communication strategy deals with the question what the influence of a specific communication strategy is on the evacuation efficiency. Operational issues are for example the implementation of traffic measures, the distribution of fuel, and the provisioning of shelters. The evacuation traffic plan and the communication and operational strategies need to be combined to obtain the overall plan. The first part, i.e., the evacuation transportation plan, can be developed using the formulations and approaches presented in this thesis.

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Summary

Large scale disasters, such as floods and fires, cause many casualties. This risk of casualties is reduced by evacuating the people from the threatened region. By guiding these people, i.e. instructing them when and where to go, the efficiency of the evacuation is increased. This means that, for example, the time needed for the evacuation is reduced.

This thesis discusses the literature on optimization methods for car-based evacuation guidance. While many optimization methods are developed, the attention for uncertainty and compliance behavior in these methods is limited. This while these factors are of great importance for evaluating guidance in a realistic way. These findings are the reason to ask the following question: *How can evacuation guidance be optimized in an efficient way, while incorporating uncertainty and compliance behavior?*

This thesis answers this question by formulating problems, presenting solution approaches and analyzing the results of case studies. The problem formulations contain decision variables representing guidance, consisting of departure time, route, and destination instructions for all evacuees. An objective function expresses the performance of this guidance. A travel behavior model and a traffic propagation model are included in the problem formulation to evaluate the guidance resulting in the performance value. The formulations and approaches are flexible with respect to the modeling assumptions. This is important because of the high degree of development of evacuation models.

The first specific problem formulation presented in this thesis incorporates compliance behavior in the optimization of evacuation guidance. This problem is solved by a metaheuristic based on ant colony optimization. The method is applied to develop evacuation guidance for a hypothetical flood of part of The Netherlands. This case study shows that the optimized guidance increases the evacuation efficiency compared to no guidance or guidance developed by simple rules. This can be explained by the spread of travelers over time and space. The case study also shows that the solution approach results in a solution which effectiveness is close to the effectiveness of the optimal solution.

The problem formulation is extended such that all kinds of uncertainty, like uncertainty in the demand, the behavior and the capacity, can be incorporated. This formulation is based on scenarios, which are representations of the uncertainty. Two procedures to select these scenarios are proposed, i.e. a deterministic procedure which results in

a set of scenarios that is constant over the iterations of the solution approach, and a stochastic procedure that results in varying scenarios over the iterations. A case study shows the usefulness of incorporating uncertainty in the evacuation problem. For most cases holds that the efficiency of the evacuation increases when uncertainty is incorporated. The case study also shows that incorporating uncertainty is computationally demanding.

Solving the evacuation problem is computationally expensive because of a high number of decision variables and high evaluation costs. A fixed-point approach is presented that efficiently optimizes evacuation guidance, in particular route guidance. This approach decomposes the original problem into simpler problems that are iteratively solved resulting in an approximate solution to the original problem. This approach overcomes the difficulties associated with the original problem. A case study shows that the fixed-point approach substantially speeds up the optimization of route guidance, while maintaining a comparable effectiveness of the resulting guidance.

This thesis gives new insights in how beneficial evacuations are and how realistic plans can be optimized efficiently. The presented methods are ready for use in practice regarding the development of car-based evacuation guidance. Guidance can be optimized and, if available, it can be compared with existing plans. The guidance will be part of a broader plan that includes, for example, evacuation by public transport and communication and operation strategies.

Samenvatting

Grootschalige rampen, zoals overstromingen en bosbranden, veroorzaken veel slachtoffers. Het risico op slachtoffers kan worden verlaagd door het evacueren van mensen uit het bedreigde gebied. Door het instrueren van deze mensen wanneer waar naartoe te gaan wordt de effectiviteit van de evacuatie verhoogd. Zo wordt bijvoorbeeld de benodigde tijd voor de evacuatie gereduceerd.

In dit proefschrift wordt de literatuur op het gebied van optimalisatiemethodes die resulteren in evacuatie-instructies voor automobilisten bediscussieerd. Hoewel er veel optimalisatiemethoden ontwikkeld zijn, is de aandacht voor onzekerheid en nalevingsgedrag in deze methoden beperkt. Dit terwijl deze factoren erg belangrijk zijn om instructies op een realistische manier te kunnen evalueren. Deze vindingen zijn de reden om de volgende vraag te stellen: *Hoe kunnen evacuatie-instructies geoptimaliseerd worden op een efficiënte manier, waarbij rekening gehouden wordt met onzekerheid en nalevingsgedrag*?

Dit proefschrift beantwoordt deze vraag door middel van het wiskundig formuleren van problemen, het presenteren van oplossingsmethoden en het analyseren van de resultaten van toepassingen van deze optimalisatiemethoden. De formuleringen bevatten beslissingsvariabelen die de instructies representeren, bestaande uit vertrektijdstip-, route-, en bestemming-instructies voor alle evacuees. Daarnaast bevat elke formulering een doelfunctie die de effectiviteit van deze instructies uitdrukt. De instructies worden geëvalueerd met behulp van modellen die het reisgedrag en de verkeersstromen simuleren waaruit de waarde van de doelfunctie volgt. De formuleringen en methoden zijn flexibel zijn wat betreft de modelaannames. Dit is belangrijk gezien de hoge mate van ontwikkeling op het gebied van evacuatiemodellen.

De eerste specifieke probleemformulering die gepresenteerd wordt in dit proefschrift neemt nalevingsgedrag mee in de optimalisatie van evacuatie-instructies. Dit probleem is opgelost met behulp van een metaheuristiek die gebaseerd is op *ant colony optimization*. De methode is gebruikt om evacuatie-instructies te ontwikkelen voor een hypothetische overstroming van een gedeelte van Nederland. Deze toepassing laat zien dat geoptimaliseerde instructies zorgen voor een toename van de efficiëntie van de evacuatie in vergelijking met het niet geven van instructies of instructies gecreëerd met eenvoudige regels. Dit kan verklaard worden aan de hand van de mate van spreiding van de reizigers over de tijd en ruimte. Uit de toepassing blijkt ook dat de oplossingsmethode resulteert in een oplossing waarvan de effectiviteit dichtbij de effectiviteit van de optimale oplossing ligt.

De probleemformulering is uitgebreid zodat allerlei soorten onzekerheid, zoals onzekerheid in de vraag, het gedrag en de capaciteit, meegenomen kunnen worden in de optimalisatie. Deze formulering is gebaseerd op scenario's, die representatief zijn voor de onzekerheid. Twee procedures zijn gepresenteerd om de selectie van scenario's te maken, namelijk een deterministische procedure die resulteert in een constant set van scenario's over de iteraties van de oplossingsmethode, en een stochastische procedure die resulteert in verschillende scenario's over de iteraties. Een toepassing van de methode laat het nut zien van het meenemen van onzekerheid in het evacuatieprobleem. Voor de meeste gevallen geldt dat the efficiëntie van de evacuatie toeneemt wanneer onzekerheid wordt meegenomen. De toepassing laat verder zien dat het meenemen van onzekerheid veel rekentijd kost.

Het oplossen van het evacuatieprobleem kost veel rekentijd vanwege een hoog aantal beslissingsvariabelen en hoge evaluatiekosten. Een zogenaamde *fixed-point* aanpak is gepresenteerd die evacuatie-instructies, in het bijzonder route-instructies, op een efficiënte manier optimaliseert. Deze aanpak ontbindt het originele probleem in eenvoudigere problemen die vervolgens iteratief opgelost worden. Het resultaat van deze aanpak is een benadering van de oplossing voor het originele probleem. Hierdoor worden de moeilijkheden van het originele probleem aangepakt. Een toepassing van de aanpak laat zien dat de *fixed-point* aanpak de optimalisatie van route-instructies substantieel versnelt, terwijl een vergelijkbare prestatie behouden wordt.

Dit proefschrift geeft nieuwe inzichten in het nut van evacuaties en laat zien hoe instructies efficiënt geoptimaliseerd kunnen worden. De gepresenteerde methoden kunnen in de praktijk gebruikt worden voor de ontwikkeling van evacuatie-instructies voor automobilisten. De instructies kunnen geoptimaliseerd worden en, indien beschikbaar, vergeleken worden met bestaande plannen. Deze instructies zullen onderdeel zijn van een breder plan dat, bijvoorbeeld, evacuatie per openbaar vervoer en communicatie en operationele strategieën omvat.

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Olga Huibregtse was born on January 21st 1985 in Gouda, the Netherlands. In 2003 she started studying Civil Engineering at Delft University of Technology. In 2008 she obtained her Masters degree with a specialization in Transport and Planning.

In December 2008 Olga started her PhD research project which resulted in this thesis. During the four years she worked on the project, Olga also supervised students, taught courses and chaired discussion meetings within the department. Olga was a visiting scholar at École Polytechnique Fédérale de Lausanne in Switzerland and the University of Queensland and Swinburne University of Technology in Australia.

An overview of the publications of Olga Huibregtse:

Journal papers

Huibregtse, O., S. Hoogendoorn, A. Hegyi, M. Bliemer (2011) A method to optimize evacuation instructions, *OR Spectrum*, 33(3), pp. 595-627.

Huibregtse, O., A. Hegyi, S. Hoogendoorn (2012) Blocking roads to increase the evacuation efficiency, *Journal of Advanced Transportation*, 46(3), pp. 282-289.

The following papers are currently under review:

Huibregtse, O., G. Flötteröd, M. Bierlaire, A. Hegyi, S. Hoogendoorn. A fixed-point approach to system-optimal route advice considering compliance behavior.

Huibregtse, O., A. Hegyi, S. Hoogendoorn. State-of-the-art evacuation problem formulations and solution approaches.

Conference papers

Huibregtse, O., M. Bliemer, S. Hoogendoorn (2010) Analysis of near-optimal evacuation instructions, in: Hoogendoorn, S., A. Pel, M. Taylor, H. Mahmassani, eds., *1st International conference on evacuation modeling and management, Procedia engineering*, vol. 3., Elsevier, Amsterdam, pp. 189-203.

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