Guiding toward optimal route and parking choice of urban traffic

Development of an optimization model based on a trade-off between interests of specific stakeholders

MSc Thesis A.M. Rouwette

Witteveen+Bos

University of Twente
Enschede - The Netherlands

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This document presents the research performed for the completion of two Master studies in Civil Engineering & Management (discipline Traffic Engineering & Management) and in Applied Mathematics (discipline Operations Research), University of Twente, The Netherlands.
The research is performed at the consultant company Witteveen+Bos.

Author:
A.M. Rouwette

Committee:
Boucherie, Prof. Dr. R.J.
Goemans, Ir. J.W.
Hurink, Dr. J.L.
Korving, Dr. Ir. J.L.
Maarseveen, Prof. Dr. Ir. M.F.A.M. van
Zuilekom, Ing. K.M. van

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Summary

The amount of traffic all over the world is growing, together with its negative side effects. Especially in cities, problems caused by traffic growth are increasing rapidly. In the end, the only real solution to the traffic problems can be found in modal split changes and trip reduction. However, this is not a solution, which can be realized on the short term. Fortunately, with advanced guidance of road users, considerable changes in the traffic situation are possible.

Current route and parking guidance systems inform individual road users, but do not guide the complete traffic process. Therefore, these systems are not able to realize significant changes in the traffic situation. There is need for a central guidance system, which guides the complete traffic process, based on a trade-off between the interests of the stakeholders. With advanced guidance many interests can be served. The guidance can be used to spread road users over the parking stock, to relieve the most polluted parts of a city or to minimize congestion.

However, not all interests can be served equally. Therefore, in each situation a trade-off is necessary, between wishes and demands. There is no easy rule telling which guidance results in the optimal situation. Therefore, the objective of this study is to develop a generic model for the optimization of dynamic route and parking guidance, based on a trade-off between interests of specific stakeholders. The model is developed in four steps: conceptual model, theoretical model, implementation and testing. The following vision describes the future guidance:

The local government decides on the objective and constraints for the guidance, based on a trade-off between interests. For example, it is decided to minimize the emissions within the city center, but the maximum detour for road users is constrained to 10%. For every period of five minutes, the guidance model computes the optimal spread of traffic over the network. Based on this optimal spread, an individual route and parking advice is sent to each road user that enters the network. The road user receives the advice on his in car navigation.

The conceptual model

The conceptual model defines the traffic process, with guidance, based on the role, influence and interests of four specific stakeholders: the road user, the parking holders, air quality and the local government. The road user 'creates' the traffic process through route choice, parking choice and compliance with the guidance. The main interest of the road user is minimization of individual travel time. Furthermore, road users do not accept large detours or large walking distances from parking to destination.

The local government (LG) is the provider of the road network and regulations and manager of the guidance system. The LG is the stakeholder with the largest influence on the traffic process, through management tools and regulations. The LG establishes the guidance objective and constraints, based on a trade-off between the interests of all stakeholders. The parking holders provide the parking stock, but have limited influence on the traffic process. However, a fair competition between different parking holders is a constraint for the guidance optimization. An interest of the parking holder is reduction in queuing and searching at parking locations. This is possible by spreading the traffic over available locations.

The last stakeholder, air quality, is an output of the traffic process. The importance of and awareness on air quality are increasing all over the world. Air quality is one of the main triggers for efficiency improvements in the traffic process. Emission minimization is the main air quality interest.

The theoretical model

The conceptual model is translated to a theoretical (mathematical) model. This model consists of two levels. On the upper level the guidance settings are chosen. The guidance consists of a split of the traffic, per Origin-Destination (OD) relation and time period, over a set of available routes. The lower level comprises a model for the traffic assignment and propagation. Two traffic streams are distinguished: a stream of traffic that complies with the guidance and a stream of traffic that ignores the guidance. Furthermore, the traffic is split per parking type: public or private parking.

Three time steps are used to model the traffic process. The OD matrix (demand) varies per large time step (15 minutes). In every medium step (5 minutes) the route inflows of both guided and non-guided traffic are calculated, respectively based on the guidance settings and individual cost minimization. These inflows are distributed, per OD relation, over a set of available routes. In the smallest time step (20 seconds) the link inflows, outflows, occupancies and travel times are updated; the traffic is propagated through the network. For each medium period network performance measures are computed.

The optimization loop is run every medium period. In each iteration new guidance settings are fixed on the upper level; the traffic assignment and propagation are performed at the lower level. The guidance solution is valued, based on the network performance measures. A simulated annealing algorithm (mathematical search algorithm) is used to choose new guidance settings in every iteration and to search for the best guidance settings.

The implementation

The theoretical model is implemented in Matlab. For each model component a separate syntax (program) is written. The components are linked to perform all steps in the guidance optimization. The complete implementation uses link data, node data and a dynamic OD matrix as input. The outputs are guidance settings for every medium time period and network performance measures, such as link flows, travel times and occupancies. The objectives and constraints for the guidance optimization can be changed easily in the program, as well as the parameters.

Model testing

The guidance model is verified, calibrated and applied to a case study. In the verification, several tests are performed to check if the model works as it is intended to do and improvements are introduced. The tests show that the model functions correctly. The calibration is very limited, due to a lack of data. Therefore, it is mainly used to obtain plausible results. The traffic assignment is calibrated with results of the RBV (a Dutch traffic simulation model). For the guidance component, the calibration is used to find the parameter settings that lead to the best optimization, within the computational limitations.

The guidance model is applied to the city of Rotterdam (The Netherlands). Scenarios are studied to explore the possibilities of the guidance model and to study the effects of the guidance. The influence of different objectives, constraints and parameters, such as the compliance percentage, is studied. Furthermore, the model is applied to scenarios with demand varying from light to heavy and to the situation with a large demand peak for an event.

The case study gives a first indication of the possibilities of the guidance model and the effect of the guidance. The results are promising, especially for the parking guidance. However, it is not possible to conclude on the guidance effect with this case study. A small number of iterations is used in the optimization, because of computation time limitations. Since the solution is space is very large, the guidance model is not able to find good solutions for every period. Furthermore, it is difficult to conclude on the effect of changes in parameters and scenario settings, due to the large variability in the results. An extended calibration and optimization are necessary to be able conclude on the effects of guidance.

Discussion

The final product of this study is a flexible guidance optimization model. The current implementation can generate guidance related to four objectives: user equilibrium (with and without guidance), minimization of the average link travel time (weighted per user), minimization of average IC ratio (weighted per link or per user) and minimization of differences in parking occupancy. Furthermore, the model facilitates constraints related to maximum IC ratio, parking occupancy, walking distance and detours.

The main strengths of the guidance model are its flexibility and clear structure. The model components can easily be changed and extended. Furthermore, the model can be applied to every city and time period, without changes. The model is the first in its kind to generate guidance for a whole traffic process, based on objectives and constraints, which can be varied by the model user. The model fulfills in the need for central guidance of road users. The main model weakness is the large computational requirement. To enable a good calibration and online implementation, the model has to be translated to a faster programming language.

In the current version the guidance model is a very useful tool for analysis of the traffic process with and without guidance. When the model is translated to a fast program, the impact of guidance with different objectives, constraints and settings can be studied. This research is a start in the guidance model development and brings along many interesting follow-up studies.

Contents

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Notation

Network notation

G	The graph representation of the network $G = (N, A)$.
N	The set of network nodes n, including centroid nodes.
A	The set of network links a, including walking, connector and parking links.
Z	The set of centroid nodes z (the nodes where traffic enters and exits the network), $Z \in N$.
W	The set of walking links w, $W \in A$.
C	The set of centroid connectors c, $C \in A$.
N_p	Subset of network nodes that are the tail node of a parking link.
N_w	Subset of network nodes that are the tail node of a walking link (head of parking).
O	The set of origins o, $O \in Z$.
D	The set of destinations d, $D \in Z$.
D_{in}	The subset of destination nodes, located in the center of the study area.
D_{out}	The subset of destination nodes, located at the border of the study area.
P	The set of parking locations/parking links p, $P \in A$.
$A(n)$	Set of links, whose tail node is n.
$B(n)$	Set of links, whose head node is n.
$TL(a)$	Tail node of link a.
$HD(a)$	Head node of link a.
c_a	Capacity of a lane of link a in vehicles/hour.
cap_a	The total capacity of link a in vehicles/hour.
n_a	Number of lanes of link a.
V_a	Free flow speed of link a.
l_a	Length of link a.
t_a	Free flow travel time on link a (l_a/V_a).
τ_w	Walking time of walking link w (l_w/V_w).
V_c	Free flow speed on centroid connector c.
Q_a	Maximum departure rate during green from link a (for signalized links).
g_a	Green time for signalized link a, at the intersection at the head node.
Ct_a	Cycle time of the intersection at the head node of signalized link a.
cap_p	Capacity of parking location p, in number of parked vehicles.
c_p	Parking charge for parking location p, in charge per minute.
EPD_p	The expected average parking duration, for parking location p, in minutes.
ES_p	The expected service time at the entrance barrier of parking location p.
ce_p	The number of parallel entrances at parking location p.
τ_p^{min}	The minimum time spent in parking location p, from entering by car, till leaving by foot, toward the destination.

Flow variables

$R^{od}(t)$	The set of available routes r, for OD pair od, at time t.
$x_a(t)$	The total number of vehicles on link a at time t.
$x_{ar}^{od}(t)$	The number of vehicles at link a, traveling between origin o and destination d, via route r, at time t.
$u_a(t)$	The total inflow rate of link a, at time t.
$u_{ar}^{od}(t)$	The inflow rate (veh/sec) to link a, of vehicles traveling between origin o and destination d, at route r, at time t.
$v_a(t)$	The total outflow rate (veh/sec) of link a, at time t.
$v_{ar}^{od}(t)$	The outflow rate (veh/sec) of link a, of vehicles traveling between origin o and destination d, at route r, at time t.
$S_r^{od}(t)$	The cumulative (total) number of arrivals at destination d, of vehicles traveling from origin o, at route r till time t.
$s_r^{od}(t)$	The rate of arrivals at destination d, of vehicles traveling from origin o, at route r at time t.
$f^{od}(t)$	The departure flow rate from origin o, to destination d, at time t.
$f_r^{od}(t)$	The departure flow rate from origin o, to destination d at time t, at route r.
$\tau_a(t)$	The travel time on link a, at time t.
$\eta_r^{od}(t)$	The travel time/disutility of route r, between origin o and destination d, at time t.
$\pi^{od}(t)$	The minimal travel time/disutility, between origin o and destination d, at time t.
$\Omega_a^{oj^*}(t)$	The difference between the minimal travel time from o to j and the minimum travel time from o to j by routes including link a, with tail node i, at time t.
$C_r^{od}(t)$	Disutility of route r, between origin o and destination d, at time t.
$C_a(t)$	Disutility of link a at time t.
$\tau_p(t)$	Parking entrance time at location p, from reaching the access till leaving to the destination, at time t.
$OCC_p(t)$	Occupancy of parking location p, at time t.
$\varsigma_{ba}^{od}(t)$	Probability that traffic traveling between o and d, that leaves arc b at t, enters arc a.
$e_p(t)$	The exit flow rate of cars from parking location p, at time t.
γ_{ab}^{od}	The percentage of traffic, for relation od, on link a, that uses b as next link.
$q_a(t)$	$u_a(t - t_a)$, arrival rate at the queue at the end of link a, at time t.
$X_a(t)$	$\frac{q_a(t)/Q_a}{g_a/Ct_a}$, degree of saturation (flow to capacity ratio), of link a at time t.
$Dl_a(t)$	The average delay per vehicle (sec) at time t in link a.

Optimization variables

(Ω, f)	The instance of the minimization problem.
Ω	The set of feasible solutions.
$f : \Omega \to R$	The cost function, which values each solution.
$N : \Omega \to P(\Omega)$	The neighborhood function.
$N(\psi)$	Set of neighboring solutions, $\forall \psi \in \Omega$.
$*$	Asterisk, denoting the optimal value for the variable, with respect to the objective function.

User related notation

M	The set of user classes m.
Index m	The index m can be added to the flow variables to indicate the user class.
η_i	Percentage of users of group i complying with guidance.
df_{max}	Maximum detour factor for routes assigned to road users.
θ_d	Percentage of traffic, with destination d, using a public parking location.

Other notation

$\tilde{r}$	The set of remaining links of route r, after a certain link a.
C_{opt}	The optimal cycle time, calculated with Websters formula, for a signalized intersection.
T_v	The total internal delay within a cycle at a signalized intersection.
Y	The maximum conflict load at a signalized intersection.
T_f	The timespan for which the traffic intensity in the Akçeliks formula holds.
N_0	The size of the overflow queue at a signalized intersection.
X_0	The rate of saturation for which the overflow queue approximately equals zero.
Δ_A	Link-tail node incidence matrix (links a in rows, nodes n in columns).
$\delta^n_{A,a}$	Link-tail node indicator for link a and node n, 1 if node n is tail node of link a.
Δ_B	Link-head node incidence matrix (links a in rows, nodes n in columns).
$\delta^n_{B,a}$	Link-head node indicator for link a and node n, 1 if node n is head node of link a.
Δ^a_r	Link-route incidence matrix (routes r in rows, links a in columns).
δ^a_r	Link-route indicator for route r and link a, 1 if route r uses link a.

Abbreviations

AON	All-or-nothing (assignment)
DTA	Dynamic traffic assignment
DSO	Dynamic system optimum
DUO	Dynamic user optimum
EA	Evolutionary algorithm
FCTL	Fixed-cycle traffic-light (queue)
FW	Frank-Wolfe algorithm
GA	Genetic algorithm
IC	Intensity/Capacity (ratio)
MSA	Method of successive averages
MVA	Mean value analysis
OD	Origin Destination
PT	Public Transport
RBV	Regionale Benuttings Verkenner (regional traffic simulation model)
SA	Simulated annealing
UE	User equilibrium
VI	Variational inequality
VMS	Variable message signs

Preface

This document presents my graduation thesis, on which I have worked at the company of Witteveen+Bos, from August 2007 till June 2008. The thesis is a combined graduation project for two master studies at the University of Twente (the Netherlands): Civil Engineering and Management, in the field of traffic engineering and management, and Applied Mathematics, in the field of operations research.

Although, I finished my research exactly in the ten months I was supposed to spend on it, it did not always feel like a smooth running project. I was used to being busy with ten things at a time: sporting, coaching, study projects, working part-time at a traffic consultant, meeting friends, attending committee meetings, etcetera. Suddenly, I was sitting at a desk for 40 hours a week and I had to work on one research, on my own, for ten months. That was quite a change-over and not one that I liked at all times. Where I liked to be challenged by doing as many things as possible within the same period, the new challenge was to concentrate all my efforts on one project.

After the first month of getting used to this ‘new life’ and struggling with the start up of my research, I met a quite critical graduation committee at our first meeting. Although, I hoped for some positive discussion, I think the critical questions helped to get the research on track. From then on my study proceeded according to planning, without any significant problems. Now, 10 months later, I am proud of this final product, which you are about to read. I succeeded in independently developing a model for guiding urban traffic, of which I think that it meets an actual need and can really help to improve the traffic situation in cities.

During the 10 months, I learned to appreciate the critical questions of my graduation committee. Those questions kept me focused and helped to improve the research. Hans, Richard, Jan-Willem, Kasper, Johann and Martin: thanks a lot for supervising my graduation and guiding me toward this final product. Furthermore, I want to thank Witteveen+Bos and all my colleagues for providing me with a nice working environment and sometimes very welcome diversions. Last but not least, Maarten, thank you for your help during my research, for letting me use your computer and of course for listening to my complaints and uncertainties now and then.

Concluding, with this research, I think I succeeded in the challenge to concentrate my efforts on one project and I am looking forward to new challenges as a Master of Science!

Anke Rouwette

Enschede, June 2008

Report outline

Figure 1 presents the components of the study and the corresponding outline of this report. The report is split into four parts. The first part introduces the study and describes the conceptual model, which is the basis for the model development. Furthermore, this part gives background information on the theory, that is used throughout the research. The second part is the most technical part of the report. The model development is presented in detail. The theoretical model, the optimization model and the implementation aspects are discussed. An overview of the model development is given at the first pages of Part 2; reading this overview gives enough information to understand the other parts of the report. The third part presents the verification and calibration of the model. Furthermore, the scenario analysis for the case study is described. The model is tested and improved and the case study explores the possibilities for application. The fourth part of the report comprises a discussion on the final product. The model is reviewed in its strengths and weaknesses and recommendations for follow-up research are given. For several chapters, supporting information and figures are included in the appendices. These appendices can be found in the fifth part of the report.

PART I Introduction and concept

- Chapter 1 Introduction: Formulation of the study motive and objective.
- Chapter 2 Conceptual model: A delineation of the research and a conceptual description of the traffic process with guidance. The process is characterized in terms of influencing factors of the stakeholders and the relations between these factors. The conceptual model gives a framework to translate the problem into a theoretical formulation.
- Chapter 3: A brief introduction to the main theory, that is used in the research. Literature study is performed in various fields: traffic modeling, traffic simulation, optimization, route and parking choice modeling, behavioral aspects etcetera. This chapter presents theoretical background, which is necessary to understand the choices made in the development of the guidance model. References are given in the text and in the literature list for more information in various fields.

PART II Model development

- Model overview: A complete overview of the model, which introduces the components. The following chapters explain in detail the model structure and each of the components.
- Chapter 4 Theoretical model: The translation of the conceptual model of the traffic process into a mathematical traffic model.
- Chapter 5 Optimization model: Explanation of the optimization algorithm that is used to search for optimal guidance settings.
- Chapter 6 Implementation: Description of the implementation of the theoretical model, together with the optimization model, in a programming environment. The implementation is programmed in Matlab (a scientific computing language).

PART III Model testing

- Chapter 7 Verification and calibration: Description of the tests that are used to verify and calibrate the model and discussion on the results of these tests.
- Chapter 8 Case study: Introduction to the case study and the scenario analysis and discussion on the results.

PART IV Discussion and follow-up

- Chapter 9 Discussion: Evaluation of the final product of the study and review of its strengths and weaknesses.
- Chapter 10 Follow-up: Description of possible follow-up research and recommendations on further development of the model.

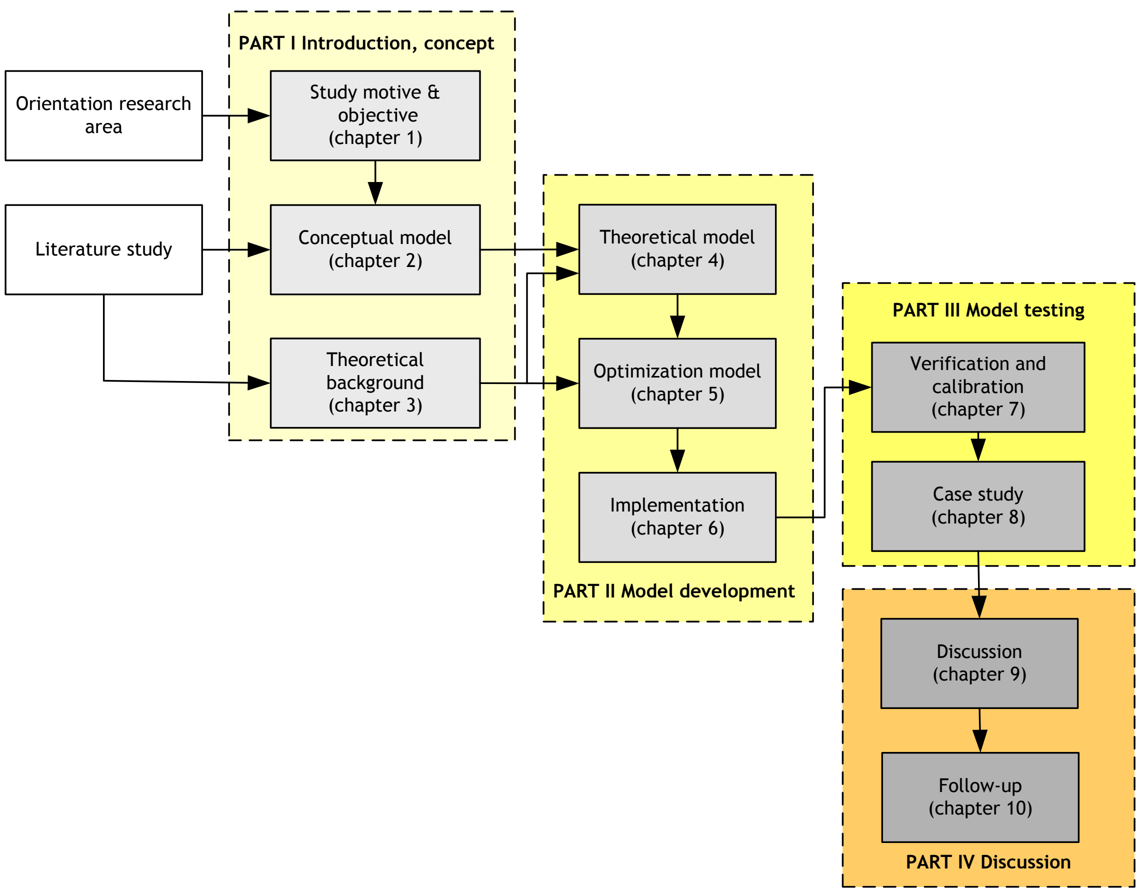


Figure 1: Research and report outline

Part I

Introduction and concept

Chapter 1

Introduction

1.1 Study motive

The amount of traffic all over the world is growing, together with its negative side effects. Especially in cities, problems caused by traffic growth are increasing rapidly. Road capacity is reaching its limit, congestion is growing and emission standards are exceeded. Recently, awareness on traffic related problems, like deteriorating air quality and climate change, is rising. Many actions are started in an attempt to (partly) solve the traffic related problems. Examples are road pricing, car pool stimulation, public transport improvement and promotion, traffic management, etcetera. In the end the only real solution to the traffic problems can be found in modal split changes and trip reduction. However, this is not a solution that can be realized on the short term, since people are not willing to leave their car at home or cancel trips. Fortunately, with advanced guidance of road users, considerable changes in the traffic situation are possible.

Road users choose a route and parking location in their own interest. They do not account for the effect on the total network situation and are not aware of the air quality conditions. The road user chooses the shortest route and the parking location closest to his destination. If the destination is full, he drives to a location nearby. According to research by Bonsall and Palmer (2002), 25-40% of the average total travel time, of journeys to central urban areas, is spent on the search for a parking space. The individual road user behavior enhances congestion and leads to an increase in the total distance driven in the city. These effects, in their turn, lead to extra emissions; both because more kilometers are made and because congestion causes the traffic flow to become less smooth. In many cities a start is made to reduce the searching traffic, by providing road users with actual information on available parking spaces (parking guidance information). Furthermore, information on congestion and traveltimes is provided to enhance the route choice. However, still road users will choose that route and that parking location, which is best in their own interest.

The current collective guidance systems focus on information provision, but leave the route and parking choice open to the individual road user. Furthermore, most in-car navigations systems recommend the shortest route, without accounting for occupancy of parking locations or the actual network situation. Each road user receives the same information or advice. The systems do not guide the complete traffic process. Therefore, these systems are not able to considerably change the situation on the network. For larger improvements, a central system is necessary, which spreads the traffic over the network and the parking locations, while accounting for the dynamics of the traffic process and the resulting network situation. Such a system can provide actual guidance to traffic streams or individual road users, by prescribing a route and parking location, based on the overall network performance. With this guidance many objectives can be served and considerable changes in the traffic process are possible.

Advanced parking and route guidance, combined with enforcement of compliance, can serve many interests. The guidance can be used to spread road users over the parking stock, to relieve the most polluted parts of a city or to minimize congestion. In the near future, developments will enable information supply on individual level, for example through in-car information. This enlarges the possibilities of directed guidance, compared to current methods with variable message signs (VMS). An advanced system can guide the route and parking choice behavior, both on individual or collective level.

However, the optimal guidance is difficult to determine and to realize, due to the large number of possible configurations and conflicting interests. Concerning air quality, for example, it is optimal to guide a part of the traffic over routes around the city center, to avoid heavy loads inside this area. However, this results in longer routes for the road user and pollution in other areas. There are many interests at stake and these are often conflicting. Air quality is already named as an important concern in cities, but there are several stakeholders with (possibly) other interests: the road users, local government and the parking holders. Not all interests can be served equally. Therefore, in each situation a trade-off is necessary, between wishes and demands. There is need for a model to find the optimal configuration of route and parking guidance, based on a trade-off between interests and the traffic dynamics.

Summarizing, the motive for this study is formulated as:

Current route and parking guidance systems inform individual road users, but do not guide the complete traffic process. Therefore, these systems are not able to realize large changes in the traffic situation. To be able to improve the traffic process, there is need for a central guidance system, which guides the complete traffic process, based on a trade-off between the interests of specific stakeholders.

1.2 Objective

The preceding section describes the need for a central system, that guides the complete traffic process, based on a trade-off between interests. However, there is no easy rule telling which guidance should be given to the individual road users, to realize the optimal situation. Therefore, the objective of this study is to develop a model for the optimization of the route and parking guidance. This should be a generic model, which can easily be adapted and applied to different cities. Furthermore, the model should support various objectives and constraints, to be able to serve both air quality as well as the interests of road users, local government and/or parking holders.

Road users, local government and parking holders (owners of parking locations) are the three most involved parties in a traffic process, subject to route and parking guidance. Air quality is added as fourth stakeholder, because of the importance of reduction in emissions for all citizens. Air quality is one of the main triggers for improvements in the traffic process. In most situations it is not possible to serve the, often contradictory, interests of all groups to the same extent. Therefore, a trade-off has to be made, per situation, to define which interests are the objective of optimization and which interests serve as constraints or are left out.

The objective of the research can be summarized as:

Development of a generic model for the optimization of dynamic route and parking guidance, based on a trade-off between interests of specific stakeholders.

This objective is translated into four main research parts:

- Development of a conceptual model, which describes the characteristics of the traffic process with guidance, based on the role, influence and characteristics of the stakeholders (the road user, local government, parking holders and air quality). The conceptual model gives a delineation of the research.
- Translation of the conceptual model into a theoretical model, which describes the traffic process and guidance optimization in mathematical terms.
- Implementation of the theoretical model in a programming environment. The implementation focuses on the model development and structure and does not have to be directly applicable online.
- Testing of the model: verification, calibration and application to a case study.

Chapter 2

Conceptual model

2.1 Introduction

This chapter presents the conceptual model of the urban traffic process with guidance. The objective is the development of a model to optimize guidance. Guidance settings are the output of the model: an assignment of routes and parking locations to the road users. The guidance interacts with the traffic process. To be able to find the optimal guidance, it is necessary to describe the underlying traffic process and the relation between the guidance and this process.

A conceptual model describes the general functional relationships between components of a system. The model gives a delineation of the research, a selection of influencing factors and the relations between the selected factors. The selected factors and the relations should give a correct description of the system, which can be translated into a solvable theoretical model. The system in this study is the urban traffic process. This traffic process is 'created' by the road users and those groups that can influence the road user: the local government, the parking location holders and air quality (the externalities). Furthermore, the traffic process is influenced by the guidance system.

The main purpose of the conceptual model is to give a description of the traffic process, in terms of the factors that determine this process and the relations between these factors. This description is used to translate the concept toward a theoretical model. Figure 2.1 gives a schematic representation of the basis for the conceptual model. The traffic process is defined as the outcome of the interaction between road user, government and parking holders. These are the three most important parties.

The local government is supplier and manager of the road network and associated regulations, the parking holders are supplier and manager of the parking stock and the user is the stakeholder that actually generates the traffic process. Air quality is a result of this traffic process and is chosen as a fourth 'stakeholder', because of the global importance of and growing awareness on this aspect. The object of optimization is the guidance system, which is managed by the local government. The trade-off between the interests of the four stakeholders is input to the optimization; it results in objectives and constraints, which can differ per city and situation.

The three parties and air quality are the only stakeholders considered in the model, although there are several other groups, with interests related to the traffic process. For example the citizens living alongside the network, companies providing private parking facilities and distributors of goods. However, these other parties do not have direct or large influence on the traffic process and are represented by the government. In order to simplify the problem situation only the four most important stakeholders are incorporated.

The conceptual model is developed from the perspective of the stakeholders. The position, influence and behavior of the stakeholders are the basis for the model. The basis for the conceptual model (Figure 2.1) is extended in the remaining part of this chapter. Section 2.2 introduces the aspects related to the road user. The local government is discussed in Section 2.3. In Section 2.4 the influence and role of the parking holders are described and in section 2.5 the same is done for the air quality. Based on these four sections the conceptual model is completed in Section 2.6.

The conceptual model is based on an extensive literature study. In literature numerous factors influencing the traffic process can be found. In the development of the conceptual model many of these factors have been considered, however only those factors that are included in the model are discussed in this chapter. For further information references are given in the bibliography.

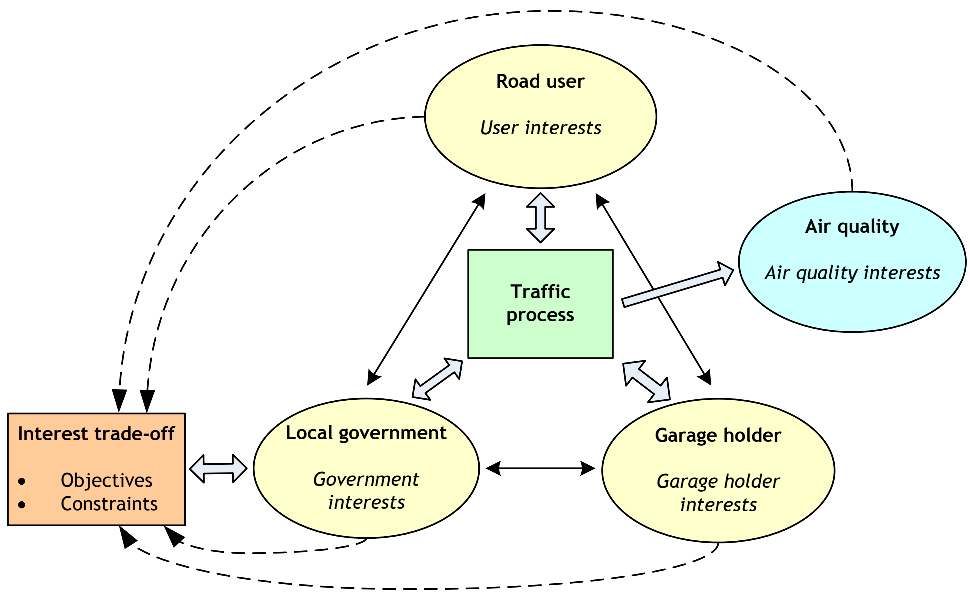


Figure 2.1: Basis for the conceptual model

2.2 The road user

The road user is the stakeholder that determines the traffic process most directly. The road user chooses where to go, when to go there, by which mode, by which route, with which driving behavior, where to park etcetera. Several aspects of the road user behavior are defined as fixed input to the model: destination choice (fixed OD-matrix), departure time choice, mode choice (fixed modal split) and driving behavior. There are three aspects related to the road user, which have large influence on the traffic process: route choice, parking location choice and behavior in the presence of guidance. These aspects are discussed in Section 2.2.1 to Section 2.2.3. In Section 2.2.4, the position, role and the interests of the road user are summarized. Figure 2.2 shows the traffic process from the road user point of view, based on the choices made in this section.

2.2.1 Route choice

Route choice is extensively discussed in literature. Almost all researches identify one main factor that determines route choice: the travel time (Cascetta et al., 2002; Bekhor et al., 2006; Lee et al., 2004; Ben-Akiva et al., 1991). The travel time can be expressed in different variables: free flow time, congested or equilibrium travel time and delays. Most route choice models use the congested travel time (including delays) as explaining variable. Other factors that are applied to describe route choice include:

- Link capacities and lengths;
- Gender, age;
- Income, value of time (VoT), occupation;
- Safety, comfort and scenery;
- Pavement type, road type, number of turns or traffic lights;
- Familiarity with the network (especially when diverting from initial choice);
- Habit, experiences and preferences.

Distance and value of time are factors, that are often used in route choice models. The other factors are only rarely incorporated, since their influence is small and/or data requirements are large. In this research, congested travel time is chosen as main factor in the description of route choice.

2.2.2 Parking choice

The literature on parking choice is limited. Most traffic models incorporate the traffic flows between origin and destination zone, but do not include the parking process. In the models that include parking (Bifulco, 1992; Bonsall, Palmer, 2002; Lam et al., 2005, Thompson et al. 2001; Waterson, 2001; Lambe, 1996) three factors, influencing the choice, are indicated to be most important: parking charge, travel time/distance from origin to parking location and walking time from the parking location to the destination. Two other important factors are the capacity of the parking location and the waiting/searching time at the location. These five factors are incorporated in the conceptual model.

Two methods can be distinguished to model parking behavior: network based modeling and the non-network approach. In the network based approach the transportation network is modeled as a graph and extra links are introduced to represent the parking facilities: parking links. A parking link can be characterized by parking charge, searching time for a parking space and walking time to the destination. In these models, parking is an integrated part of the route choice. In the non-network approach the route and parking choice are considered separately and the performances of the parking stock and of the transportation system are simultaneously calculated.

2.2.3 Behavior in the presence of information

The influence of dynamic information on route (and parking) choice is investigated in many studies. It is widely accepted that route guidance systems offer enormous potential for reducing delays and wasted mileage (Ben-Akiva et al., 1991). However, the research in this field, directed at investigating decision processes, underlying traveler behavior in the presence of real-time ATIS (advanced traveler information systems), is still in its infancy (Abdel-Aty and Abdalla, 2004). The decision processes are not sufficiently understood to predict the traveler behavior accurately.

Findings in literature (Arnott et al., 1991; Ben-Akiva et al., 1991; Abdel-Aty and Abdalla, 2004; Lee et al.,2004; Lam and Chan, 2001; Mahmassani, Liu, 1999; Waterson et al., 2001) show that user behavior, in the presence of dynamic information, is very complex. A part of the articles emphasizes that large improvements are possible with dynamic guidance, however the other part questions this. Numerous factors, which influence the compliance with information, can be found: familiarity with the network, reliability of information, type of information (prescriptive, descriptive), habit, personal characteristics, travel time differences between routes etcetera. However, there is no general agreement on the influence of these factors.

A distinction can be made between descriptive and prescriptive information. Descriptive information informs the road user on several routes and the driver can choose for himself which route is best. Prescriptive information tells the road user, which route to use. Especially the behavior in the presence of descriptive information is difficult to model. When the user receives information on several routes, he/she can either stay on the current route or switch to one of the other routes. With prescriptive information the options are limited: the user either does not comply and stays on the current route or complies and switches to the route that is prescribed by the information (if different). However, it is not clear which factors determine the compliance and what is the exact nature of the relations.

Concluding: more research is necessary to model compliance accurately. It is not possible to study compliance further, within the scope of this research. Therefore, it is decided not to incorporate a compliance model, but to use a compliance factor (percentage of users complying with guidance), which is varied in scenarios. Furthermore, prescriptive information is used, since the possibilities for guidance with this information type are larger (compared to descriptive) and also the expected compliance percentage is.

2.2.4 The road user position and interests

This section describes the way the road user is incorporated in the model. Four topics are discussed: the road user behavior, the influencing aspects fr this behavior, the road user interests and the position of the road user. Figure 2.2 illustrates the road users perception of the traffic process.

Road user behavior
The following concepts describe the behavior of the road user in the traffic process:

- Every road user makes an initial route and parking choice, when entering the network.
- The road user chooses route and parking location together in a rational way, minimizing personal perceived disutility. Parking and walking to the destination are incorporated in the route choice.
- Each road user either complies with guidance along the whole route or does not follow guidance at all.
- Scenarios with compliance rates are used to describe the compliance behavior.

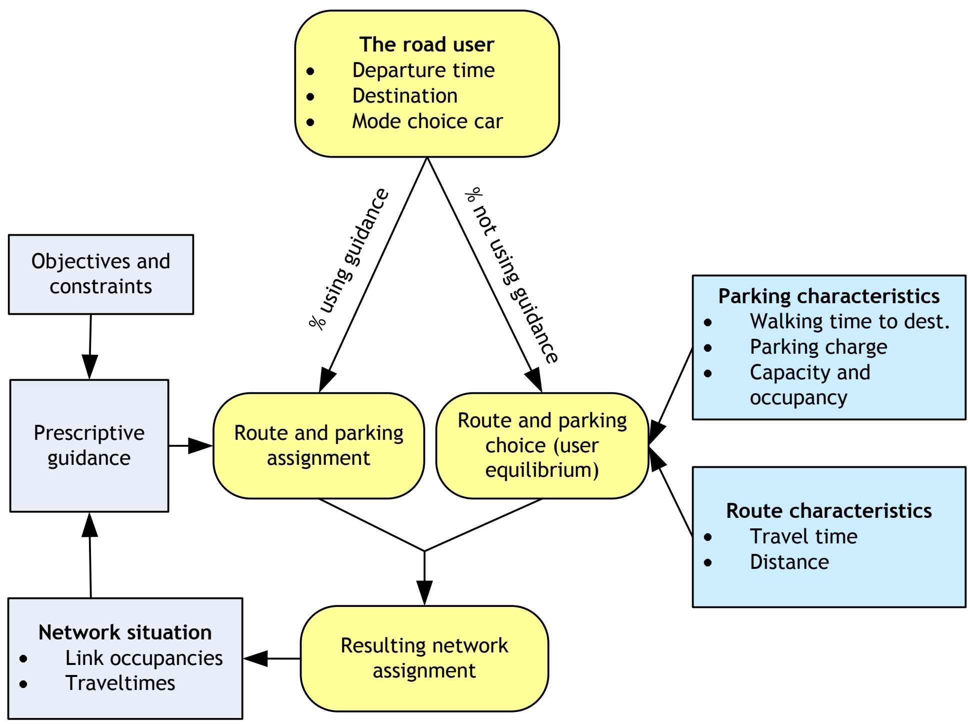


Figure 2.2: The traffic process from the road users perception

Influencing aspects
Route choice is explained based on the congested travel time, the walking time and the parking time. The influencing aspects for the parking choice are walking time to the destination, parking fares, capacity and waiting/queuing time at the entrance of the parking location.

Road user interests
The main interest of the road user is to reach the destination as fast as possible with the least costs. This results in the following objective:

- Minimization of the personal disutility for each road user ($\Rightarrow$ user equilibrium).

The interests of the road user can add the following constraints to the optimization:

- Walking distance within certain limits;
- Detour within certain limits;
- Parking fare within certain limits.

Road user position
The road user is the stakeholder that 'creates' the traffic process, however, the individual road user does not have a large influence. Each road user acts in his own interest and can not change the complete process. The aggregated road user behavior is guided by the infrastructure and regulations, which are provided by the local government.

2.3 The local government

The local government (LG) is the stakeholder with most tools available to influence the traffic process. The guidance system is the main management tool of the LG in this study. The configuration of the guidance system is discussed in Section 2.3.1. Section 2.3.2 describes the position and interests of the local government.

2.3.1 Configuration of the guidance

Guidance systems exist in many configurations, varying from signs with the number of free parking locations, to navigation systems that guide the user along the whole route. The guidance system in this research is defined with the following concepts:

- The guidance is dynamic. Every couple of minutes the guidance system calculates the optimal routes for the guided traffic according to the objective and constraints.
- The guidance consists of a split of traffic over the available routes for every OD-pair. For example, of traffic going from origin 1 to destination 2, 50% is assigned to route A and 50% to route B.
- The guidance gives individual advice for each road user, based on the optimal route split. This guidance can be translated to collective guidance. The VMS then advise each of the routes a certain percentage of time. However, a part of the guidance effect is lost with VMS, due to limitations in the number of routes and destination to guide to.
- The user can be guided to public parking locations as well as to zone centroids. The latter option is used for road users, that have private parking options at their destination. A parameter is used, per destination, to define the percentage of public parking.
- Guided users can switch routes during their trip. The optimal guidance is updated every few minutes. Users that are already in the network switch routes at every update instance, if that improves their route.

2.3.2 Government position and interests

The LG is the most influential stakeholder in the traffic process as manager of the road network and associated regulations. She has the possibility to change traffic light regulations, prohibit certain turning movements, change the network, introduce speed bumps, determine the settings of VMS, conduct campaigns, enforce air quality regulations, etcetera. In the end, the LG is the stakeholder, that largely determines the traffic process, by enforcing certain user behavior. In the guidance model, however, most influencing aspects of the LG are fixed input. The only aspect, that is varied, is the guidance. An interesting follow-up application of the guidance model is a study of the effects of changes in the other management tools.

The LG determines the guidance objectives and constraints and the guidance configuration. She is assumed not to choose the configuration out of own interest, but to perform a trade-off between interests of the four stakeholders. The local government interests are very diverse. The interests are often in line with the national policy, since this is the framework in which the LG works. However, the LG also has its own, city related, interests. In one city the LG might want to focus on air quality; in another city the focus can be the accessibility of the city center. The objectives differ per city. Possibilities are:

- Minimization of emissions;
- Minimization of vehicle kilometers or total travel time;
- Maximization of traffic flow through (minimization of stops, accelerations, decelerations);
- Minimization of traffic intensities within the city center area;
- Maximization of accessibility.

Each of these objectives can also serve as constraint by setting limits. Several objectives can be pursued together; except for the accessibility, the objectives have a lot in common. Together most objectives can be served by pursuing a system optimum (minimization of total travel time).

2.4 The parking holder

This section discusses the aspects related to the parking holders. Section 2.4.1 describes several parking aspects. Section 2.4.2 explains the position and interests of the parking holders.

2.4.1 Parking aspects

The parking aspects in the model are related to the physical infrastructure, including the location of the parkings, capacity and charges. These aspects are input to the model and are not changed to influence the traffic process. A possible application of the model is to study the effect of changes in the parking stock. An aspect of parking that can easily be varied in the model, is the number and type of parking locations included in the guidance optimization. This ranges from only including the large parking locations, to including all public parking locations. If more parking locations are included, more road users can be reached by the system.

Another important aspect is the number of different parking holders. One extreme is the situation in which all parking locations belong to the same garage holder. The other is the case where every parking location has a different owner. In the last case every owner wants to have as many revenues as possible and wants the cars to be guided to his location. In this case guidance is difficult, since guiding to one garage means taking revenues away from another. If all parking locations belong to the same owner more guidance alternatives are possible. The road users can be distributed over routes and parking locations to optimize the situation at the network and to prevent queuing at parking locations. If there is a small number of different owners, there are still many optimization possibilities. Per owner the distribution over parking locations can be optimized. An option to ensure fair competition is compensation of the parking holders, that are harmed by the guidance.

2.4.2 Parking holder position and interests

The influence of the parking holder is limited. The construction of a new parking garage has a large influence on the traffic process, however, this is not possible on the short term and is not considered in this research. Other possibilities of the garage holder are changing opening hours, interior design of the garage, protection, marketing or parking charges. The influence of these measures is limited. Reducing the charges can attract more cars, but this reduces profit and often there are regulations for parking charges in a city. The other measures have little influence on the road user.

The primary interest of the garage holder is to maximize revenues. However, this is not an interest that can be used as constraint or objective in the model, since the total parking demand is a fixed input. Another interest of the parking holder is to keep the customers satisfied and provide the road user with an attractive parking alternative. To keep the customers satisfied, queuing and searching should be minimized. If a parking holder owns/manages more than one location he can spread traffic over the locations. If there is always a queue at one location and another location is always half empty, the holder has an interest in directing road users from the first to the second location. Through spreading the traffic, he can increase the total number of customers at his locations and he can reduce queuing and searching. Furthermore, a good accessibility of the city center (and the parking locations there) is in the interest of the garage holder. This results in the following garage holder objectives:

- To spread the demand equally over the parking locations that are in his possession;
- Maximization of accessibility of the city center.

Furthermore, the garage holder can add two constraints to the optimization:

- Fair competition for each of the garage holders;
- No guidance to the parking location if the occupancy is above a certain percentage (for example 95%), because this results in queuing and searching.

2.5 Air quality

Air quality has no direct influence on the traffic process, it is a result. However, recently the awareness on air quality problems is rising and the willingness to improve air quality is increasing. The willingness and necessity to account for air quality is modeled in this research, by turning air quality into a stakeholder. As a stakeholder air quality has 'interests, wishes and demands'. The stakeholder air quality represents interests of the world population. Section 2.5.1 starts with a discussion on the aspects related to air quality. In Section 2.5.2 the position and interests of air quality in this model are presented.

2.5.1 Air quality aspects

The main relation between the traffic process and air quality are the vehicle emissions. Direct measurement of emissions is difficult. A large measurement network is necessary, which is not available in most cities. Therefore, emissions are often estimated with models. The literature on these kind of models is extended, however a simple, and at the same time accurate, emission model is not available. For many years, macroscopic models, based on average travel speed, were the most common methodology for estimating vehicle emissions (Int Panis et al., 2006). However, the accuracy of these kind of models is limited. The models are based on average speeds and give large scale estimations of emissions, which are only valid as a long term average. It is admitted that average trip speed is an important factor influencing emissions, however, instantaneous speed fluctuations have a larger impact.

Therefore, the attention shifted to microscopic emission models (used within microsimulation models). These models result in instantaneous emissions and account for the effects of driving style and vehicle dynamics. The disadvantage of these models is the large data requirement. Many factors are used in a microscopic model to calculate emissions (English, 1995):

- Flows (link loads);
- Resources (infrastructure, vehicles, road user expertise, attitudes);
- Road pricing;
- The specific fuel consumption of engines;
- Design factors related to vehicle size, shape and power;
- Factors affecting the marketing and age of vehicles in the fleet;
- The drive cycle (delays, acceleration, deceleration and stops).

If enough data is available, air quality can best be modeled with a microscopic emission model. However, if the data is limited, air quality indicators have to be used to relate the traffic process to air quality. Macroscopic emission estimation is not accurate enough for a dynamic model. Air quality indicators are mostly related to the flow through of traffic. If the traffic flows are smooth, emissions are low; if there are many accelerations and decelerations, the emissions increase. In this model several indicators are used to represent the air quality interests. These indicators are discussed in Section 4.6.

2.5.2 Air quality position and interests

Air quality is the result of the traffic process, however, that is not the only position of air quality in the guidance model. Air quality is representing the interests of stakeholders that are left out of the research: citizens and people all over the world and their health. Air quality gives binding constraints for urban traffic: emission limits. Furthermore, air quality can be chosen as objective in the optimization. The interests of air quality are easy to summarize: minimization of emissions. This minimization can be the objective of the optimization. Minimization of emissions is expressed with indicators and is closely related to the system optimum (minimization of total travel time). To improve local air quality the traffic load in parts of the city can be constrained. If emission measurements are available in cities, these can be used as input for the model instead of the indicators.

2.6 The final conceptual model

This section presents the final conceptual model that is based on Figure 2.1 and the choices in this chapter. The conceptual model gives the framework in which the theoretical model and implementation are developed. Figure 2.3 presents the complete concept. This figure shows how the interaction between the four stakeholders and the guidance results in the traffic process. The main components are:

- The four stakeholders, with the most important aspects describing their position and influence. The road user is entering the traffic process and air quality is resulting from this traffic process. The parking holders and the local government provide the infrastructure and regulations.
- Three 'infrastructure' elements: the guidance system, the parking stock and the road network. These elements are managed by the stakeholders and are fixed input for the guidance model.
- The interests of the stakeholders, as input to the trade-off, that provides the objectives and constraints for the optimization of the guidance system;
- The traffic process, which is a result of the interactions between the stakeholders and the infrastructure elements. The process is characterized by the network situation. The traffic process is the dynamic part of the conceptual model.

These components and the interactions, as described in this chapter, give a simplified description of the problem. This description is the framework for the formulation of the theoretical model, which translates the problem into a mathematical formulation.

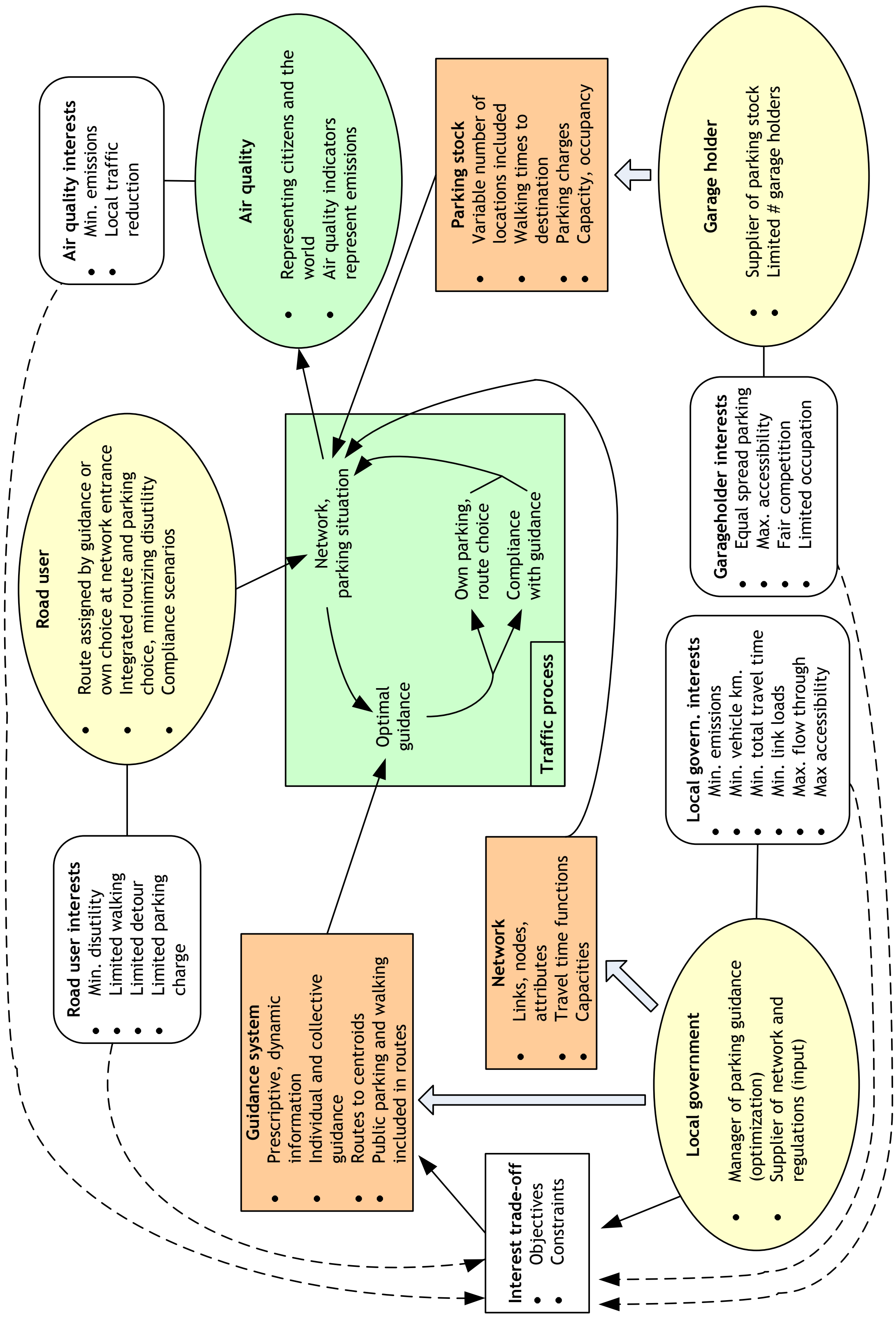


Figure 2.3: The final conceptual model

Chapter 3

Theoretical background

This chapter gives background information for the theoretical model and the optimization model. Section 3.1 introduces traffic models. Section 3.2 presents the traffic assignment formulation, which is the basis for the theoretical model. Section 3.3 discusses several optimization methods. Section 3.4 introduces formulations for calculation of delay on signalized links in a network. The information given in this chapter is a basis for the following chapters.

3.1 Traffic models

This section gives a basic introduction to traffic models and several components of these models. A complete introduction to traffic and transport modeling is provided in Ortúzar (2002).

3.1.1 Introduction to traffic modeling

Classic traffic models comprise four components:

- The trip generation: in this step the amount of traffic generated by and attracted to every zone of the study area is estimated. The estimation is based on zonal data like population numbers and amount of working places.
- The trip distribution: in this step, per origin, the traffic is distributed over the destinations, based on travel utility. The result is a matrix with the number of trips (per hour) per origin-destination (OD) pair.
- The modal split: in this step the trips per OD-relation are distributed over the available transportation modes.
- The traffic assignment: in this last step the traffic is assigned to routes through the network, resulting in route and link flows.

This research focuses on the last step: the assignment. An OD-matrix, for motorized traffic, is the input to the model and the modal split is fixed. The traffic assignment can be split into the assignment of traffic to routes and the actual propagation of traffic through the network. Both are discussed in this section.

3.1.2 Static and dynamic assignments

A traffic assignment can be either static or dynamic. A static traffic assignment (STA) assumes the OD demand to be constant over time. STA results in an equilibrium assignment to the network, with constant flows for all links. This kind of assignment assumes the travel times to be constant over the complete study period. Dynamic traffic assignment (DTA) uses dynamic demand as input: demand varying over time. DTA is more realistic in most situations, since demand differs between morning peak, off peak and evening peak and also within these periods. DTA gives a better representation of traffic realism. However, it results in a more complicated model than STA.

Since the guidance model provides dynamic guidance, it is necessary to adapt to the actual traffic situation. To be able to model this, the traffic dynamics have to be incorporated in the model. Therefore, a DTA model is used as basis for the guidance model.

3.1.3 Macro-, meso- and microscopic models

Traffic models are classified as microscopic, mesoscopic or macroscopic. Microscopic models model each vehicle individually and cover many vehicle characteristics like speed, position, accelerations, decelerations, etcetera. A well known class of microscopic models are the car following models. In these models the behavior of a vehicle is a response to the behavior of the preceding vehicle (the stimulus). In macroscopic models the vehicles are aggregated into flows. These models represent the traffic in terms of intensity, average speed and density. Macroscopic models can give a good representation of traffic dynamics in terms of queuing, delays and average speeds. These models do not give information on individual vehicles, but have the least computational requirements. Microscopic models are most useful to get insight in individual driver behavior, but have much larger computational requirements. A third class of traffic models are the mesoscopic models. These models use groups of vehicles in the assignment.

3.1.4 Analytic and simulation based models

DTA assignment models are classified into two categories: analytical models and simulation based heuristic models (Ziliaskopoulos et al., 2004). Analytic models use mathematical formulas to describe link in- and outflows and travel times. Three types of analytic models are distinguished: mathematical programming, optimal control formulations and variational inequality (VI) approaches (Peeta, Ziliaskopoulos, 2001; Boyce et al., 2001). Analytic models always use macroscopic formulations. The analytical formulations have two main disadvantages. First, these models are not able to capture the real dynamics in street networks, due to simplifications (necessary to keep the models tractable). An often occurring problem is to fulfill the FIFO (first in first out) requirement. Traffic that enters a link first, should also leave the link first (without overtaking possibility). Analytic models need extra constraints to ensure FIFO, which makes the models difficult to solve. A second problem is that analytic models tend to be intractable for real size networks.

VI formulations are the most used analytic approach. VI is more general and better equipped than the other two types. VI is a mathematical theory intended for the study of equilibrium problems. VI is especially fit to solve DTA to user equilibrium (UE), however, a model with VI formulation still faces the same problems as other analytic models. The simulation based heuristic approaches use a traffic simulator to replicate the traffic flow dynamics. The models use an analytic framework, but apply simulation for the traffic propagation. By simulating the complex traffic dynamics these models can give a realistic representation of the traffic process and avoid the need to introduce complex constraints. The main advantage of simulation is that the traffic dynamics are modeled realistically. However, simulation based models can not guarantee to result in an optimal solution and even do not always converge. Furthermore, simulation based models cannot give insight into the theoretical aspects of the problem. The main pro of the simulation based models is the fact that these are the only models that are currently applied to real size networks. There are very few examples in literature of analytical models that are applied to larger networks.

In practice, often macroscopic and microscopic simulation packages are used in traffic modeling. These packages use an OD-matrix and a network as input and can perform traffic assignment with one click in the menu. The disadvantage of these existing packages is that it is very difficult to add functionalities or change components; the models are black boxes, which are not easy to understand and to adapt. Furthermore, microscopic simulation packages have large computational requirements.

3.1.5 Route choice modeling

Most route choice formulations are composed of two parts: choice set generation and choice selection from the set. Both parts are introduced in this section.

Choice set generation

Route choice set generation can be divided into two main approaches (Cascetta et al., 2000): exhaustive or selective. In the exhaustive approach all loop-less paths connecting an OD-pair are included in the choice set and this choice set is the same for every road user. The selective approaches use a heuristic to create a choice set of routes with the largest chance to be used. Most used heuristics are the k-shortest path algorithm and link penalty and link elimination methods (Bekhor et al, 2006). The k-shortest path algorithm computes the k shortest routes for each OD-pair. By using this algorithm with large enough k all acceptable routes can be generated. The link penalty approach computes, in every step, the shortest route and then increases the cost of the links in this route to be able to find another shortest route in the next iteration. The link elimination approach works the same way, but eliminates a link in the shortest route from the network. By doing this, the approach ensures that another route is found in the next iteration.

Choice set generation for parking choice depends heavily on the walking distance. In practice all parking locations within a certain distance of the destination are included in the choice set. If the total number of parking locations is limited, all locations can be included.

Choice modeling

The number of methods for modeling route choices is very large. The most important approaches are shortly described in this subsection.

Deterministic choice models
Deterministic models assume that the road user has perfect knowledge on the network situation and minimizes a single variable. The shortest path problem is the best known model in this kind.

If all users are assigned to the same shortest path (not accounting for congestion), it is called an all or nothing (AON) assignment. One step further is the user equilibrium (UE). Again, each user uses the shortest path, but in this case the path with the shortest congested travel time. This means that each user accounts for the other users in the network. Also in the UE assignment perfect knowledge is assumed. This results in the situation, in which no user can decrease his travel time by changing routes: the so-called user equilibrium (or Wardrops first principle). For every OD-pair, all routes in use have the same, minimal travel time.

Stochastic models
The stochastic user equilibrium accounts for the heterogeneity between road users by introducing a random term into the route costs. Discrete choice (or logit) models are used to calculate the stochastic user equilibrium in the framework of random utility theory. In discrete choice models individuals select an option from a finite set of alternatives based on the perceived utility of each alternative. Individuals are assumed to choose the alternative that maximizes their personal utility. The personal utility consists of two components: a measurable systematic part (for example the actual travel time), which is the same for each user in a user group and a random part, which reflects the particular tastes and preferences of each individual. Often used discrete choice models are multinomial logit, C-logit and pathsize logit.

3.1.6 Traffic propagation

The traffic propagation is the actual movement of traffic through the network. Szeto and Lo (2005) give five requirements for the propagation:

- Flow conservation: the number of vehicles on a link at a particular time is equal to the number of vehicles that entered the link till that time minus the number of vehicles that left the link.
- First-In-First-Out (FIFO) requirement: the vehicle entering first, also leaves first (without overtaking possibility).
- Time-flow consistency: If the cumulative inflow (number of vehicles) on link a equals X on t_1 and the cumulative outflow equals X on t_2, the travel time of vehicle X on link a is t_2-t_1. This consistency holds when there is no overtaking possibility.
- Causality: the link travel time of a vehicle depends only on traffic entering the link before this vehicle.
- Queue spillback: if a queue grows larger than the link length, it blocks the junction at the beginning of the link and spills back to preceding links. To give a realistic representation of the traffic process a DTA model should incorporate spillback.

These five requirements complicate the formulation of traffic propagation. In many approaches not all requirements are fulfilled to be able to keep the model simple. The traffic propagation is the most difficult part of the dynamic traffic assignment and can be modeled in many ways. Helbing (2001) gives an extensive description of the modeling approaches for traffic propagation. Three models of traffic propagation are (Peeta, Ziliaskopoulos, 2001; Szeto, Lo, 2005):

- Exit functions (macroscopic, analytic): these functions compute the outflow based on the number of vehicles on the link and/or the inflow to the link. The outflow is a result of the flow conservation equations. Exit functions reflect aggregate behavior and do not track individual vehicle movement. The functions are often difficult to specify or measure. Without further constraints FIFO is violated.
- Travel time functions (macroscopic, analytic): a travel time function is specified for every link. This function can be based on link inflows and occupancy. The outflow is calculated from the travel times and inflows. Travel time functions suffer from drawbacks of realism and consistency and are often not able to capture traffic dynamics.
- The cell transmission model (simulation): this model uses a discretization of the study period into small intervals. The links are divided into small homogeneous segments: the cells. The length of each cell equals the distance traveled by free-flow moving vehicles in one time interval. The main advantages of this approach are the simplicity and the applicability to large networks. The major drawbacks are the, not very realistic, description of the traffic propagation on highly congested links and the precision errors.

3.2 Analytic, dynamic traffic assignment

This section presents a standard model for analytic, dynamic traffic assignment (DTA), based on the traffic assignment formulation developed by Boyce, Lee and Ran (2001). In the theoretical model (Chapter 4) this model type is used as basis for the dynamic traffic assignment and the traffic propagation. The analytic DTA describes traffic assignment and propagation (without guidance) in terms of link in- and outflows and travel time functions. Traffic (without guidance) is assumed to behave according to a user equilibrium (UE). In most models the route choice according to UE is described with a variational inequality (VI) formulation. First the model framework is described and second the VI formulation for the UE.

Model framework

The model framework is based on the DTA-VI formulation developed by Boyce, Lee and Ran (2001). This section defines the flow constraints, flow conservation, propagation and the non-negativity and boundary constraints. All constraints are route based. Flow that starts on a route stays on that route. There is no route switching.

The network flow constraints
These constraints describe the relation between the number of vehicles on a link and the in- and outflow. The rate of change of vehicles at a link equals the difference between the inflow and the outflow rate (Equation 3.1). The rate of change of the cumulative number of arrivals at the destination equals the arrival rate (Equation 3.2).

$$\frac{dx_{ar}^{od}}{dt} = u_{ar}^{od}(t) - v_{ar}^{od}(t) \quad \forall a, r, o, d, \tag{3.1}$$

$$\frac{dS_r^{od}(t)}{dt} = s_r^{od}(t) \quad \forall r, o, d \neq o, \tag{3.2}$$

where

$x_{ar}^{od}(t)$ the number of vehicles at link a, traveling between origin o and destination d, via route r, at time t;
$u_{ar}^{od}(t)$ the inflow rate (veh/sec) to link a, of vehicles traveling between origin o and destination d, at route r, at time t;
$v_{ar}^{od}(t)$ the outflow rate (veh/sec) of link a, of vehicles traveling between origin o and destination d, at route r, at time t;
$S_r^{od}(t)$ the cumulative (total) number of arrivals at destination d, of vehicles traveling from origin o, at route r till time t;
$s_r^{od}(t)$ the rate of arrivals at destination d, of vehicles traveling from origin o, at route r at time t.

Flow conservation constraints
These constraints describe the conservation of flow between links. The sum of inflows, to the links emanating from a certain origin o, equals the departure rate from that origin, for each destination (Equation 3.3). The total arrival rate, to node n, equals the total departure rate from node n (per o,d,r combination): traffic can not remain in a node (Equation 3.4). The departure rate from each destination node equals the arrival rate at the destination, per o, d, r combination (Equation 3.5).

$$f^{od}(t) = \sum_{a \in A(o)} \sum_r u_{ar}^{od}(t) \quad \forall o, d, \tag{3.3}$$

$$\sum_{a \in B(n)} v_{ar}^{od}(t) = \sum_{a \in A(n)} u_{ar}^{od}(t) \quad \forall n, r, o, d; n \neq o, d, \tag{3.4}$$

$$\sum_{a \in B(d)} \sum_r v_{ar}^{od}(t) = s^{od}(t) \quad \forall o, d; d \neq o, \tag{3.5}$$

where

$f^{od}(t)$ the departure flow rate from origin o, to destination d at time t;
$A(o)$ the set of links, whose tail node is o;
$B(n)$ the set of nodes, whose head node is n.

Flow propagation
These constraints describe the relation between the inflow, outflow and travel times of links. Equation 3.6 describes the propagation of traffic that is at link a at time t. This traffic propagates to the remaining links in the route ($b \in \tilde{r}$) or to the destination, during the period equal to the travel time of link a. Equation 3.7 describes the relation between the inflow and the outflow of a specific link. If the travel time is constant, the outflow rate at $t + \tau_a(t)$ equals the inflow rate at t. If the travel time decreases, the outflow is larger; if the travel time increases the outflow is smaller.

$$x_{ar}^{od}(t) = \sum_{b \in \tilde{r}} \{x_{br}^{od}[t + \tau_a(t)] - x_{br}^{od}(t)\} + \{S_r^{od}[t + \tau_a(t)] - S_r^{od}(t)\} \quad \forall a \in B(n); n \neq o; r, o, d, \tag{3.6}$$

$$v_{ar}^{od}(t + \tau_a(t)) = \frac{u_{ar}^{od}(t)}{\frac{d\tau_a(t)}{dt} + 1} \quad \forall a, r, o, d, \tag{3.7}$$

where

$\tilde{r}$ the set of remaining links of route r, after link a;
$\tau_a(t)$ the travel time on link a, at time t.

Definitional, non-negativity and boundary constraints

$$\sum_{odr} u_{ar}^{od}(t) = u_a(t) \quad \forall a, \tag{3.8}$$

$$\sum_{odr} v_{ar}^{od}(t) = v_a(t) \quad \forall a, \tag{3.9}$$

$$\sum_{odr} x_{ar}^{od}(t) = x_a(t) \quad \forall a, \tag{3.10}$$

$$x_{ar}^{od}(t), \quad u_{ar}^{od}(t), \quad v_{ar}^{od}(t), \quad s_r^{od}(t), \quad S_r^{od}(t) \geq 0 \quad \forall a, r, o, d, \tag{3.11}$$

$$S_r^{od}(0), \quad x_{ar}^{od}(0) = 0 \quad \forall a, r, o, d, \tag{3.12}$$

where

$u_a(t)$ the total inflow rate (veh/sec) of link a at time t;
$v_a(t)$ the total outflow rate (veh/sec) of link a at time t;
$x_a(t)$ the total number of vehicles on link a at time t.

The VI formulation

The model framework can be used in a route-time-based or a link-time-based model. Both models result in the same assignment. The difference is the use of route flow variables in the route-based model and link flow variables in the link-based model. The route and link variables are related through the model framework. For the route-based model the VI formulation for UE can be expressed with the following constraints:

$$\eta_r^{od^*}(t) - \pi^{od^*}(t) \geq 0 \quad \forall r, o, d, \tag{3.13}$$

$$f_r^{od^*}(t)[\eta_r^{od^*}(t) - \pi^{od^*}(t)] = 0 \quad \forall r, o, d, \tag{3.14}$$

$$f_r^{od^*}(t) \geq 0 \quad \forall r, o, d, \tag{3.15}$$

where

$f_r^{od}(t)$ the departure flow rate from origin o, to destination d at time t, at route r;
$\pi^{od}(t)$ the minimal travel time, between origin o and destination d, at time t;
$*$ asterisk, denoting the optimal value for the variable, with respect to the objective function.

These constraints ensure a dynamic user equilibrium. Only those routes, that have a travel time equal to the minimal travel time, are in use. These constraints can be written in one VI formulation. The following VI equations can be found for respectively the route and the link based model:

$$\int_0^T \sum_{od} \sum_r \eta_r^{od^*}(t)[f_r^{od}(t) - f_r^{od^*}(t)]dt \geq 0, \tag{3.16}$$

$$\int_0^T \sum_{od} \sum_a \Omega_a^{oj^*}(t)\{u_a^{od}[t + \pi^{oi^*}(t)] - u_a^{od^*}[t + \pi^{oi^*}(t)]\}dt \geq 0, \tag{3.17}$$

where

$\Omega_a^{oj^*}(t)$ difference between the minimal travel time from o to j and the minimum travel time from o to j by routes including link a, with tail node i, at time t.

3.3 Optimization

The guidance model, developed in this research, uses global optimization to search for optimal guidance settings. This section gives an introduction to optimization problems and methods. Section 3.3.1 gives a general introduction to optimization problems. Section 3.3.2 discusses several probabilistic optimization methods.

3.3.1 Introduction to optimization problems

Global optimization is a branch of applied mathematics and numerical analysis, that deals with the optimization of a function or a set of functions to some criteria (Wikipedia, 12-2007). Weise (2007) gives an extensive overview of global optimization methods and uses the taxonomy shown in Figure 3.1. Optimization methods are divided into deterministic and stochastic methods.

Deterministic algorithms have a fixed progression. In every step there is only one way to proceed and if there is no possibility to proceed the algorithm terminates. Deterministic algorithms are used, when there is a clear relation between the solution characteristics and the objective function values. The solution space can be efficiently explored by going from solution to solution, based on the relations between solutions and the objective function. Figure 3.2 shows possible relations between solution characteristics and the objective value score. The smooth function (a) can be solved with deterministic algorithms, because it is clear how the optimal value can be found, without checking all solutions. For less smooth functions (like d in the figure) deterministic algorithms are not applicable, since there is no clear relationship between the solution characteristics and the corresponding objective function value. To find the optimal solution with a deterministic algorithm almost all solution possibilities have to be checked. If the solution space is large, this leads to enormous computation times. Furthermore, the chance to end in a local optimum instead of the global optimum is large for most deterministic algorithms.

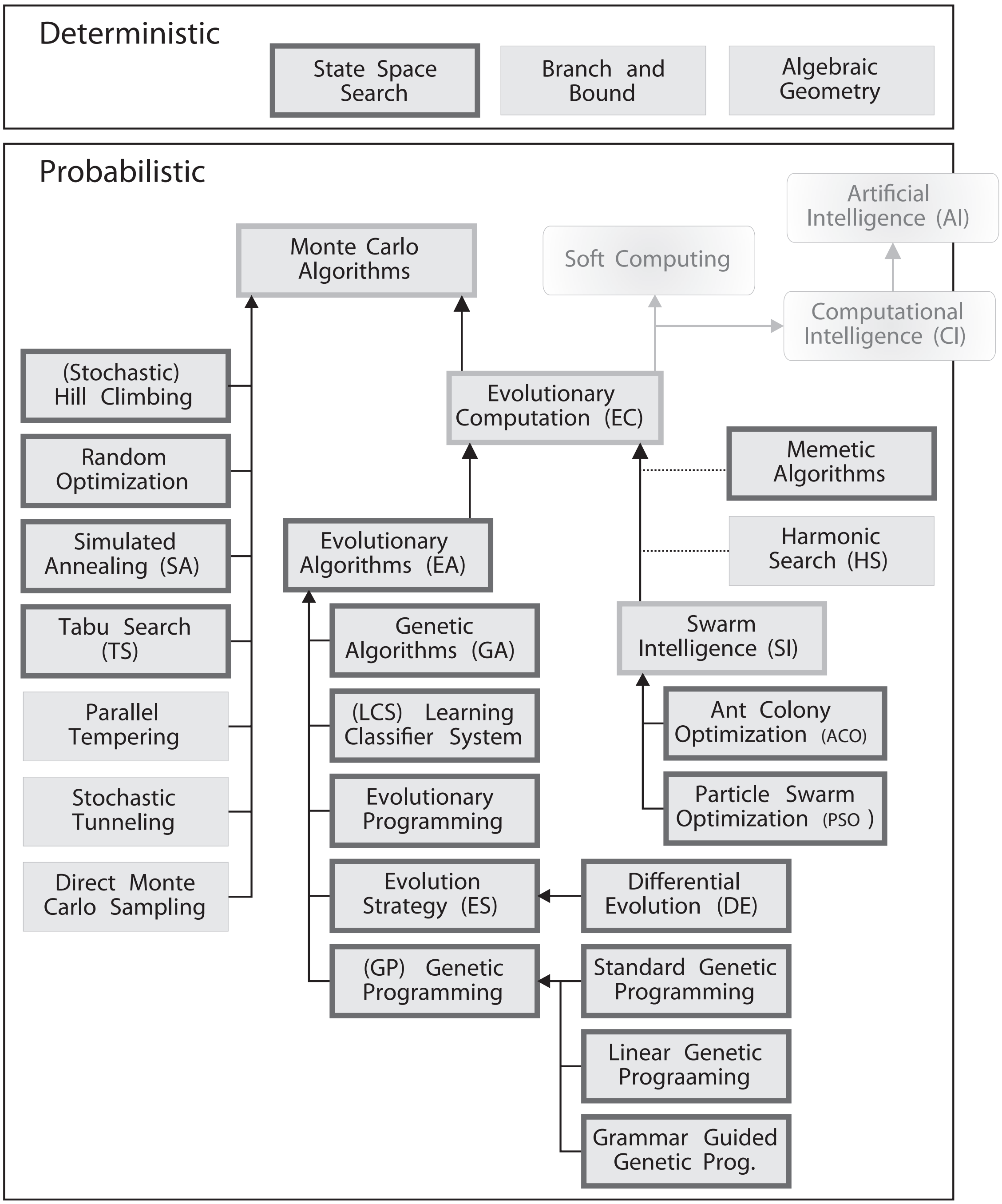


Figure 3.1: Taxonomy of global optimization methods (Weise, 2007)

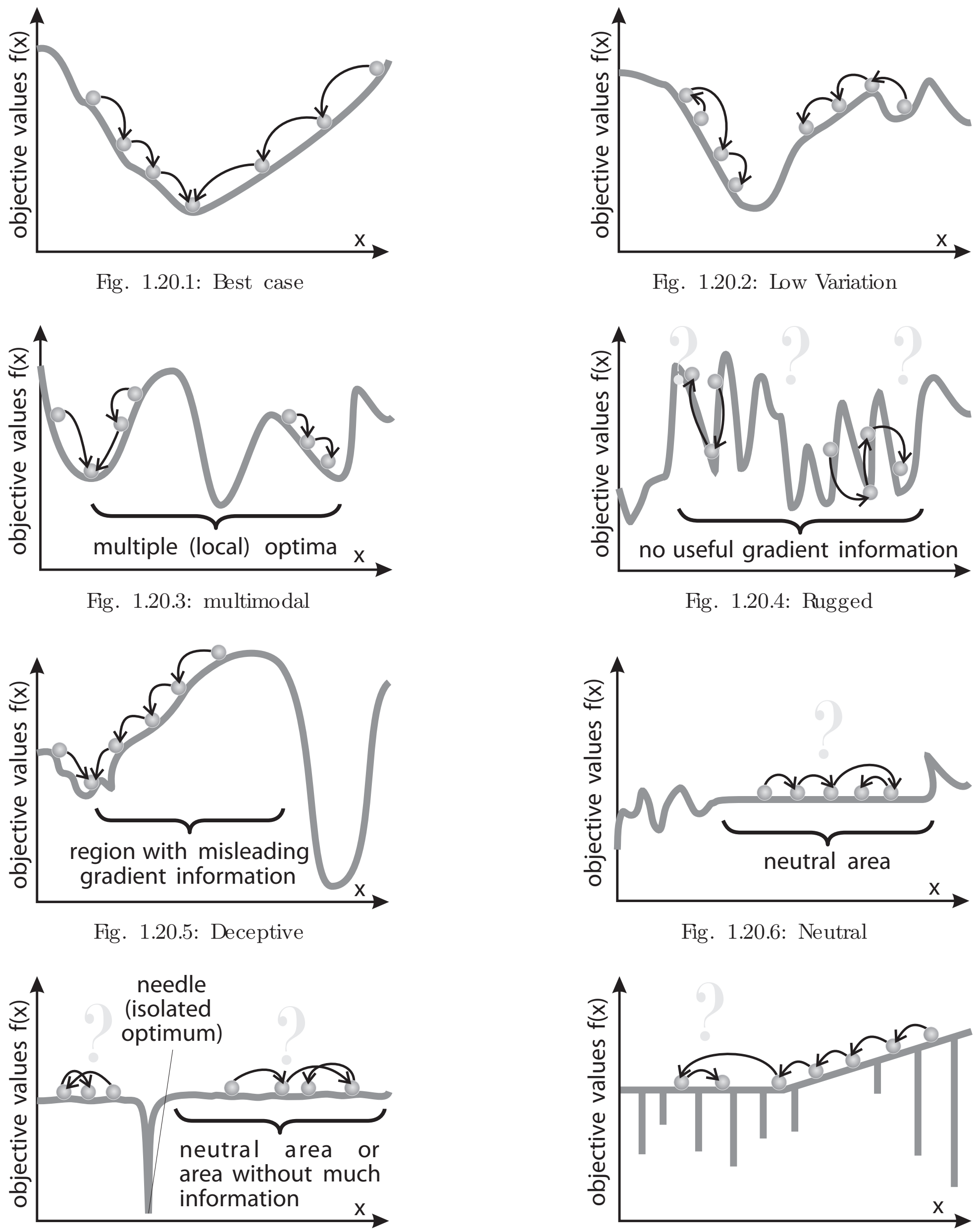


Fig. 1.20.1: Best case

Fig. 1.20.2: Low Variation

Fig. 1.20.3: multimodal

Fig. 1.20.4: Rugged

Fig. 1.20.5: Deceptive

Fig. 1.20.6: Neutral

Fig. 1.20.7: Needle-In-A-Haystack

Fig. 1.20.8: Nightmare

Figure 3.2: Different objective function forms (Weise, 2007)

If the solution space is very large or if the relation between solutions and their objective value is unclear, probabilistic algorithms are used. These algorithms do not ensure the global optimum to be found, however, the algorithms are better suited to search through a large solution space, than deterministic ones. For several probabilistic algorithms it is shown that these find the optimal solution, with probability 1, if the allowed computation time is infinite and if the problem characteristics fit certain requirements. Probabilistic algorithms use heuristics (functions) to choose solutions from the solution space, to be examined. Most important in these algorithms is to use a heuristic that minimizes the number of possible solutions, that have to be examined, to find a satisfactory solution.

In this research, the solution space is not smooth and the relation between solution characteristics and the objective function value is complex. Therefore, deterministic algorithms are not fit to solve the problem. The following subsection introduces several probabilistic algorithms.

3.3.2 Optimization methods

This section introduces several optimization methods, that can be applied to the problem studied in this research.

Evolutionary algorithms
"Evolutionary algorithms (EA) are generic, population-based, meta-heuristic optimization algorithms that use biology-inspired mechanisms like mutation, crossover, natural selection and survival of the fittest" (Weise, 2007). A solution is an individual in the population. Solutions combine to create offspring (a new generation). Individuals are valued based on the fitness function (objective function). The chance to be selected for crossover/combination depends on this fitness value. The selection leads to survival of the fittest: survival of the best solutions. Also random mutations happen, which keeps the population diverse. The evolutionary algorithms try to copy Darwinian evolution to find optimal solutions for complex problems.

The main advantage of evolutionary algorithms is that no information is needed on the relation between solution characteristics and the objective function value: the fitness landscape. For example, in the context of this study, it is not necessary to have information on the functional relation between the guidance settings (the genotype) and the resulting network performance (the phenotype). Evolutionary algorithms do not need information on slopes (no differentiability needed) and the function does not have to be continuous. EA is used in many fields: engineering, art, biology, economics, genetics, operations research, robotics, social sciences, physics and chemistry.

Evolutionary algorithms proceed in general according to the following steps:

- A population of solutions (individuals) with random characteristics (genome) is created.
- All solutions are tested. A model run is performed for each solution to find the corresponding fitness value.
- Each solution is valued according to the fitness function. In a transport context, this can be for example the average link travel time, resulting on the network, with certain guidance settings.

- In the selection process the solutions with the lowest fitness are filtered out and the solutions with higher fitness can enter the pool for combination, with a higher probability.
- In the reproduction phase, offsprings are created by combining or crossing the solutions in the pool and by applying random mutations. The offsprings are added to the pool of solutions and the solutions with lowest fitness value (that were already in the pool) are removed.
- If a termination criterion is met (small improvement in fitness values for example), the evolution stops. Otherwise the algorithm returns to step 2.

Several types of evolutionary algorithms can be distinguished: genetic algorithms, evolution strategy, genetic programming, learning classifier systems and evolutionary programming. All evolutionary algorithms use the same basis. Genetic algorithms (GAs) are the most used subclass. GAs code a complete solution into one string of binary or real numbers. Each number represents an allele (single gene value) that is subject to mutations. Furthermore, cross-over points between the alleles can be defined, where genes split to combine with other genes. Through cross-over and mutation of the fittest (best) solutions offspring is created in every iteration.

Hill climbing
Hill climbing is a simple, local search method. The algorithm proceeds in a loop; the currently best solution is used to produce one offspring. If the offspring is better than its parent, it replaces it. This process is repeated till, in a prespecified number of iterations (in row) no improvement, in the objective function value, is found. This does not mean that the global optimum is found, the algorithm can easily end in a local optimum. Getting stuck in a local optimum can be prevented by starting randomly in another point after a certain number of iterations and searching from that point. If the random start is repeated several times a larger part of the solution space is explored. Hill climbing with random restarts is also called stochastic hill climbing.

Random optimization is very close related to hill climbing. The difference is that in this algorithm the offspring of the current best solution does not have to be closely related to its parent. A close relation is probable, but there is also a chance that the offspring differs largely. The problem with hill climbing for non-smooth functions is that many restarts are necessary to ensure a good approximation of the global optimum. The fitness function can have many local optima and therefore, the hill climbing can get stuck several times.

Simulated annealing (SA)
This method is used to approximate the global optimum of a function in a large search space. The method is based on annealing in metallurgy, which involves heating and controlled cooling to improve the structure of the material. During heating, atoms can move freely (easily move from solution to solution), during cooling the structure becomes more rigid (not all changes in the solution are allowed). The SA algorithm uses a 'temperature'. In every step the current solution is replaced by a random (close by) solution, which is accepted with a probability based on the difference in the objective function value and the parameter T (the temperature).

At the beginning of the process T is high and the current solution can almost randomly change (all other solutions have a high probability of being accepted). During the process the temperature is reduced according to a rule (cooling scheme). If the temperature decreases, the probability that solutions, with a lower objective value (less good solutions), are accepted reduces. At the beginning the algorithm can wander around freely, moving toward better and worse solutions. This prohibits the algorithm getting stuck in a local minimum. Toward the end almost only improvements in the solution are accepted. (Wikipedia, 2007)

There exist many SA algorithms that differ in the annealing schedules (cooling down schedules). Furthermore, some algorithms use a start-over option to go back to an old solution. SA is proved to reach the global optimum with probability 1 (if the problem structure fits certain requirements), however, an extended annealing schedule is necessary in that case, which leads to almost complete enumeration of the solution space. With large solution spaces this is no option. For larger solution spaces the algorithm can give an approximation of the optimum.

3.4 Link delays

In urban areas the travel time is largely determined by delays at intersections. Therefore, the estimation of these delays is important for the correct representation of the traffic process. This section introduces formulations that are used to describe delays at signalized intersections.

3.4.1 Websters delay model

A model that is often used to describe delays for fixed cycle time traffic lights is the FCTL (fixed cycle traffic light) queue. This queue is based on a Polling model: a model in which one server is available to serve several queues and one queue is served at a time. At a signalized intersection the different traffic streams, are served each in turn for a time equal to the green time for the direction. The FCTL model calculates the average delay for each of the traffic streams. Most research for the FCTL queue assumes that vehicles arrive to an intersection according to a Poisson process. For this case an often used result is Websters formula, which is partly based on queuing theory and partly on simulation (Rouphail et al., 1996):

$$Dl_a(t) = \frac{Ct_a(1-g_a/Ct_a)^2}{2[1-(g_a/Ct_a)X_a(t)]} + \frac{X_a(t)^2}{2q_a(t)(1-X_a(t))} - 0.65\left(\frac{Ct_a}{q_a(t)^2}\right)^{\frac{1}{3}} X_a(t)^{2+5(g_a/Ct_a)}, \quad (3.18)$$

where

$Dl_a(t)$	average delay per vehicle (sec) at time t in link a;
Ct_a	fixed cycle length (sec) for the intersection at the end of link a;
g_a	fixed effective green time (sec) for link a;
$X_a(t)$	degree of saturation (flow to capacity ratio) of link a at time t;
$q_a(t)$	arrival rate (veh/sec) from link a to the queue at the intersection at time t.

The main advantages of this model are the compatibility with a macroscopic, analytic environment and the limited data requirements. The main disadvantage is the fact that the model is only accurate for loads below 80% (inflow to the intersection smaller than 80% of departure capacity).

Furthermore, the model assumes Poisson arrivals, fixed signal times and green per link instead of per direction. A possibility to improve the delay model, is to incorporate adaptive cycle and green times, based on the current network situation. Webster gives the following formula for calculation of the optimal cycle time (Maarseveen et al., 2001):

$$C_{opt} = \frac{1.5 \cdot T_v + 5}{1 - Y}. \tag{3.19}$$

In this formula T_v is the total internal delay of the maximal conflict group (seconds). A conflict group is a group of turning directions that can not have green at the same time. Y is the total load of the conflict group (sum of the loads of the directions in the group). The internal delay is the part of the cycle time that can not be assigned to a direction, to prevent collision between two directions that have subsequent green periods. With the optimal cycle time, the available time (minus internal delay) can be divided over the directions in the conflict group. The other directions get green periods together with one or more of the directions in the maximal conflict group.

The advantage of the use of the cycle time formula, is that the cycle and green times can be adapted to the actual situation. However, this formula is based on a description of the intersection flows per direction. To be able to use this description, traffic flow per link should be split into traffic flow per direction. This increases the problem size (especially in the traffic propagation) several times.

3.4.2 Akçeliks formula

Akçelik developed a formula for the average delay that is also applicable for loads above 80%. The first component of the formula is the same as the first component of Websters formula (Equation 3.18); in the second component the overflow queue is introduced. This is the queue that remains, on average, after a green period, due to insufficient time for all vehicles to cross the intersection. Akçeliks formula is given by Van Maarseveen et al. (2001):

$$Dl_a(t) = \frac{Ct_a(1 - g_a/Ct_a)^2}{2[1 - (g_a/Ct_a)X_a(t)]} + \frac{N_0(t,a) \cdot X_a(t)}{q_a(t)}, \tag{3.20}$$

where N_0 is the overflow queue, which can be calculated, for all $X_a(t) > X_0$, as:

$$N_0(t,a) = \frac{(g_a/Ct_a) \cdot cap_a \cdot T_f}{4} \cdot \left((1 - X_a(t)) + \sqrt{((1 - X_a(t))^2 + \frac{12(X_a(t) - X_0)}{(g_a/Ct_a) \cdot cap_a \cdot T_f})} \right), \tag{3.21}$$

X_0, the rate of saturation for which the overflow queue equals zero, is approximated as:

$$X_0 = 0.67 + \frac{Q_a \cdot g_a}{600}, \tag{3.22}$$

where

T_f the timespan for which the traffic intensity in the formula holds;
cap_a the capacity of link a;
X_0 the rate of saturation for which the overflow queue approximately equals zero;
Q_a the maximum departure capacity of link a during green.

The main advantage of this formula is the applicability to situations with large loads. The disadvantages are the Poisson arrival assumption, the fixed cycle times and the green times per link instead of per direction. The formula of Webster (Equation 3.19), for calculation of optimal cycle and green times, can also be used as extension to Akçeliks formula, to overcome the disadvantage of fixed signal times.

3.4.3 Exhaustive and gated polling

Winands (2007) uses exhaustive and gated polling systems to find delays in manufacturing systems, with N stations and one server. An intersection can be seen as a system with four stations (if four legged and green per link) and one station has a green light (is served) at a time. The green periods are separated by set-up times. In an exhaustive polling system one station is served till the queue is empty. Also customers, that arrive while the server is at their station, are served. In a gated polling system, only those customers, that were in the queue, when the server arrived, are served. The customers arriving during service, have to wait till the next cycle. These system descriptions correspond to traffic responsive signal settings: signals that are adapted to the actual traffic flows.

The following notation is used.

ρ_i	The fraction of time the server spends at station i.
S_i	The setup time at station i.
C	The cycle time (time in which all stations are served once).
θ_i	The time the server spends at station i, including setup time: $E[\theta_i] = \rho_i E[C] + E[S_i]$.
$\theta_{i,j}$	(i,j)-period: the sum of j consecutive station times starting in queue i: $\theta_{i,j} = \sum_{n=i}^{i+j+1} E[\theta_n]$.
B_i	The service time of one customer at queue i.
Q_i	The queue length (number of customers waiting) at queue i.
$R_{variable}$	Residual value of the variable in the index.
$Q_{i,n}$	The queue length at queue i, at an arbitrary epoch in which the server is at queue n: $E[Q_i] = \sum_{n=1}^{N} E[Q_{i,n}]$.
$q_{i,j}$	The fraction of time the system is in an (i,j)-period: $q_{i,j} = E[\theta_{i,j}]/E[C]$.
λ_i	The arrival rate at station i.

By using mean value analysis (MVA), the following set of equations can be found, for calculation of the queue lengths (with exhaustive service), for $i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, N-1$

$$\sum_{n=1}^{N} q_{n,1} E[Q_{i,n}] = \frac{\lambda_i}{1-\rho_i} \left(\rho_i E[R_{B_i}] + \frac{E[S_i]}{E[C]} E[R_{S_i}] + (1 - q_{i,1})(E[R_{\theta_{i+1,N-1}}] + E[S_i]) \right), \quad (3.23)$$

$$\lambda_i E[R_{\theta_{i+1,j}}] = \sum_{n=i+1}^{i+j} \frac{q_{n,1}}{q_{i+1,j}} E[Q_{i,n}], \tag{3.24}$$

$$E[R_{\theta_{i,1}}] = \frac{1}{1-\rho_i} \left(E[Q_{i,i}]E[B_i] + \frac{\rho_i E[C]}{E[\theta_{i,1}]} E[R_{B_i}] + \frac{E[S_i]}{E[\theta_{i,1}]} E[R_{S_i}] \right), \tag{3.25}$$

for $j = 2, 3, \ldots, N-1$

$$E[R_{\theta_{i,j}}] = \frac{q_{i,1}}{q_{i,j}} \left(\frac{E[R_{\theta_{i,1}}]}{\prod_{n=1}^{j-1}(1-\rho_{i+n})} + \sum_{n=1}^{j-1} \frac{E[S_{i+n}] + E[Q_{i+n,i}]E[B_{i+n}]}{\prod_{m=n}^{j-1}(1-\rho_{i+m})} \right) + (1 - \frac{q_{i,1}}{q_{i,j}}) E[R_{\theta_{i+1,j-1}}]. \tag{3.26}$$

With these equations $E[R_{\theta_{i,j}}]$ can be eliminated from the first two equations (replaced by the last two equations). The resulting set has N^2 linear equations. The corresponding waiting times for the queues can be found with Little's formula:

$$E[Q_i] = \lambda_i E[W_i]. \tag{3.27}$$

A similar set of equations can be found for systems with gated service.

To be able to use these equations for the calculation of delays at intersections, the following input is needed:

- The flow arriving to the end of each of the links connected to the intersection;
- The fraction of time the server is working on queue i; this is equal to the variable (!) green time for the queue, divided by the cycle time; the fraction can be calculated with the relative load of each of the queues (related to the total load);
- The expected cycle time for the intersection;
- The expected setup time for every link connected to the intersection (the loss time between two consecutive green periods);
- The expected service time of one car; this equals the inverse of the green rate (departure rate during green);
- The expected residual service time of one car (can be calculated if the first and second moment of the service time distribution are known);
- The residual setup time for each link (can be calculated if the first and second moment of the setup time distribution are known).

The main advantage of this approach is that actuated signal controls can be modeled. However, the model still assumes Poisson arrivals and loads smaller than 1. Interesting is to study the relation between the Polling models, described in this section, and the signal settings that are computed with Websters formula. The minimal fixed cycle length, according to Webster, equals the average cycle time in a Polling system. The effective green times assigned to each direction equal the average time spent per station in a Polling system. These relations are explained in Appendix A.

Part II

Model development

Model overview

The chapters in this part of the report describe in detail the model, that is developed to generate optimal route and parking guidance for urban traffic. This introduction gives an overview of the complete application. The model development is based on the following vision on the future urban traffic process:

Every car is equipped with an in-car navigation system. At departure the desired destination is entered into the system and the driver is informed on which route to take. When entering the urban area a central guidance system takes over. This system registers the desired destination and sends a route and parking advice, for the individual road user, to his navigation system. This advice is based on the current situation and the policy of the local government. If for example the air quality in the city center exceeds the limits, the road user is guided around this area. If one parking location is almost full the user is guided to another location. A road user decides either to follow or ignore the guidance. If he ignores the guidance, he chooses his (perceived) least cost route and switches his navigation system to this route. Every couple of minutes the central guidance system estimates, per origin-destination relation, the optimal split of traffic over available routes and updates the recommendations accordingly.

This vision is the basis for the guidance model. Every road user, that enters the urban area, receives a route advice (including parking location), from the central guidance system. This individual guidance can also be translated to route and parking directions at variable message signs (VMS). Especially for parking guidance this is a good option. For route guidance, VMS, can not guide to the optimal split, since only a limited number of directions can be displayed at the same time. The following four paragraphs give a complete overview of the model.

Bi-level model and optimization

The guidance model consists of two levels. On the upper level, the guidance settings are fixed; the lower level computes the route choice and traffic assignment and propagation, according to those guidance settings. The guidance settings consist of a split of the traffic, per OD pair, over the available routes. The two levels are connected in an optimization loop. In every iteration of the loop, guidance settings are fixed at the upper level. At the lower level the traffic assignment and propagation are performed and the corresponding network performance is computed.

Based on the performance of the solution in the current iteration, guidance settings for the next iteration are chosen. The performance is evaluated in relation to the objective and the constraints. If the objective is to minimize the average travel time, this measure is computed in each iteration. The traffic assignment and calculation of performance measures are performed, for different guidance settings, to approximate the optimal solution. A simulated annealing algorithm is used to choose the new guidance settings for the next iteration in the optimization loop, based on the results of the previous calculation. Chapter 4 presents the theoretical model, which describes in detail the lower level problem. Chapter 5 discusses the optimization model and simulated annealing algorithm.

User groups

The guidance model uses four user groups, that differ in two characteristics: using or ignoring guidance and using public or private parking locations. The compliance percentage (η) defines the percentage of traffic, per parking type, that uses the guidance. The parameter θ defines the percentage of traffic, per destination, that uses public parking locations.

The public parking locations are accessible for every road user. Private parking locations are for example the parkings at companies, which are only accessible for employees. Public parkings are explicitly incorporated in the model. Traffic, that parks at these locations, uses a route that includes one of the parking locations and a walking link from there to the final destination (zone centroid). Private parking locations are not explicitly incorporated. Traffic using these locations is guided to the centroid of the destination zone.

Time periods

The application uses three different time periods. A large period ($\sim$15 minutes), a medium period ($\sim$5 minutes) and a small period ($\sim$20 seconds). The demand varies over the large periods, an OD matrix is defined per period. The guidance settings are optimized per medium period and also traffic assignment (to routes) is fixed per medium time period. The traffic propagation is performed in every small period, together with the computation of the network performance.

Route choice behavior

The route choice behavior differs for traffic using and traffic ignoring guidance. The traffic that does not comply with the guidance chooses its own route, based on the perceived least costs. This behavior results in a user equilibrium (explanation in Section 3.1.5). In the guidance model, this route choice is computed at the beginning of every medium time period (5 minutes), based on the network situation at the end of the preceding period. The result is a split of traffic over the available routes for each OD-pair. This split is averaged with the split of the previous period to account for traffic already in the network.

The route splits remain constant over the complete medium period. After the computation of the route choice of traffic without guidance, the optimization loop is started to find the optimal guidance settings for the traffic that uses guidance. In this process the assignment of non-guided traffic is fixed. This means that during a medium time period, traffic without guidance does not adapt to the guided traffic. This is a reasonable assumption, since the traffic without guidance is less informed and is not able to adapt immediately to changes in the network situation. Furthermore, traffic without guidance is assumed not to switch routes, once in the urban area. Traffic with guidance uses the guidance update at the beginning of every medium time period and does switch routes if the guidance changes.

Chapter 4

Theoretical model

4.1 Introduction

This chapter explains the translation of the conceptual model of the traffic process into a theoretical model. Detailed descriptions of the traffic assignment, route choice and traffic propagation are given. This introduction starts with an overview of the theoretical model. Section 4.1.2 explains the main choices made in the development of each of the model components. The outline of the chapter is given in Section 4.1.3.

4.1.1 Overview of the theoretical model

The main purpose of the theoretical model is to translate the concept, of a traffic process with guidance, into a mathematical model, which can be implemented in a programming environment. The final application calculates, for every period of 5 minutes, the optimal split of traffic over available routes and the corresponding network situation. The model accounts for traffic that does not or can not use the guidance and for the constraints, related to the different user groups and the network capacities.

The basis for the theoretical model is a representation of the network as a directed graph. Every link in this graph is characterized by its capacity, speed limit and start and end node. At the border of the study area entrance/exit nodes are defined, which represent the origins and destinations of traffic outside the study area. The study area itself is divided into zones, which are represented by centroids, where traffic can enter and exit the network. The centroids and the entrance/exit nodes are the origins and destinations in the demand matrix, that is given as input. Figure 4.1 explains the structure of the theoretical model. The demand (dynamic OD matrix) and the network model (directed graph) are the model inputs. The demand (the number of trips per OD relation) is split into demand of guided traffic and demand of non-guided traffic. The split is calculated with the compliance percentage (a model parameter).

Three different time steps are used in the model. The demand varies per large time period ($\sim$15 minutes in peak periods, 1 hour otherwise). The first step on this level is the calculation of route choice sets for both guided and non-guided traffic. For each group and for each OD pair several routes are calculated, that are likely to be used during the coming large time period. Per OD-relation, each vehicle is assigned to one of these routes, when entering the network. Furthermore, the signal settings for the intersections (cycle and green times) are adapted to the network situation at this level. The route generation can also be performed offline. The routes are saved in a database and in every (medium or large) time period routes can be chosen from this database.

On the medium time level (∼5 minutes), route inflows for the two traffic groups are calculated. The traffic that does not comply with the guidance chooses its own route, based on the perceived least costs. This behavior results in a user equilibrium (explanation in Section 3.1.5). Route choice of non-guided traffic is computed at the beginning of every medium time period, based on the network situation at the end of the preceding period. This results in a split of traffic over the available routes for every OD-pair. This split is averaged with the split of the previous period to account for traffic already in the network. The split remains constant over the complete medium period and is updated at the beginning of the next period. After the computation of the route choice of traffic without guidance, the optimization loop is started to find the optimal guidance settings for the traffic that uses guidance. In this process the assignment of non-guided traffic is fixed. This means that during a medium time period, traffic without guidance does not adapt to the guided traffic. This is a reasonable assumption, since the traffic without guidance is less informed and is not able to adapt immediately to changes in the network situation.

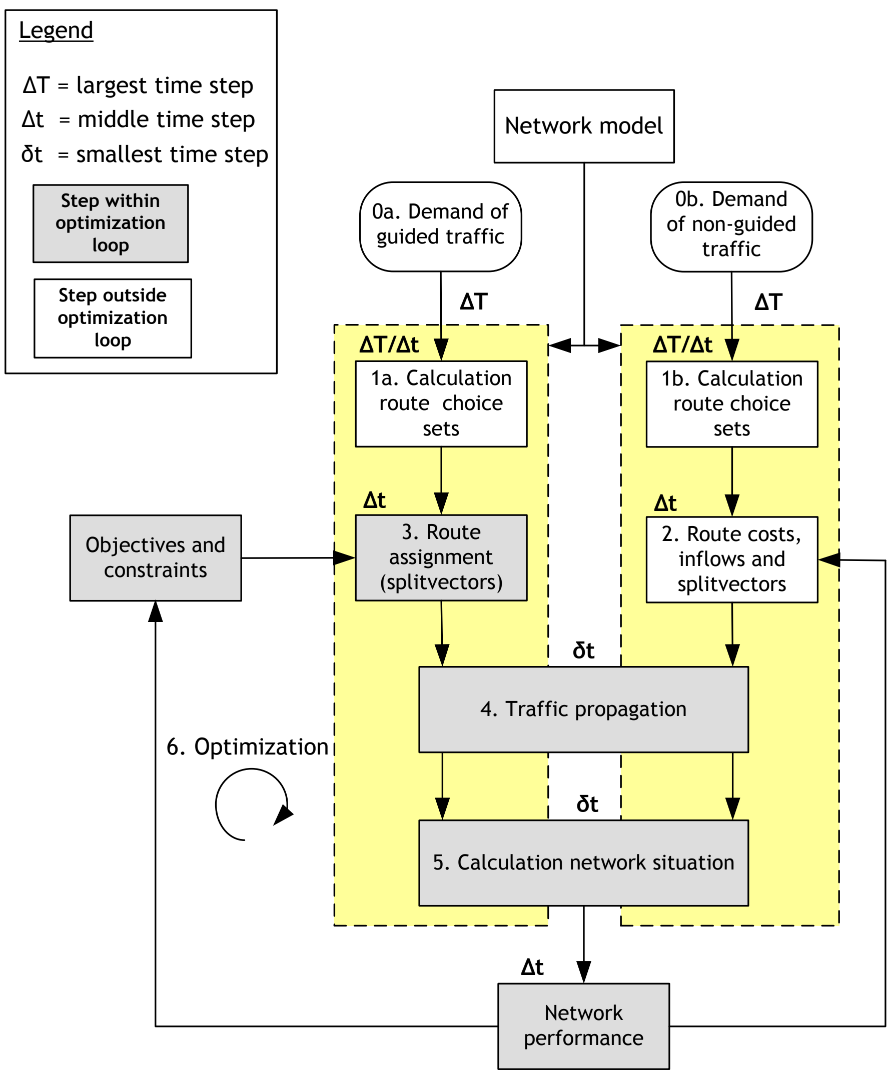


Figure 4.1: Structure of the theoretical model

On the level with the smallest time steps ($\sim$20 seconds) the traffic is propagated through the network. The link inflow, outflow, travel time and occupancy are updated. This step is summarized as calculation of the network situation. Based on the network situation in every small time step, the total network performance for each medium time period is calculated. The objective function value can be calculated from the network performance measures. A simulated annealing algorithm (mathematical search algorithm) is used to change the guidance, in every iteration of the optimization loop, and to search for an optimal solution.

The basis for the theoretical model is a macroscopic, analytic traffic model. With this model traffic is propagated through the network and flow conservation and continuation are ensured. Traffic flows are described in terms of route- and link in- and outflows (vehicles/second). The route inflows are calculated at the medium time level. The link outflows are a function of the inflow and the travel time of the link. The link inflows in turn are calculated based on outflows of preceding links. Average delays and travel times are calculated in each small time step, for every link, based on occupancy and capacity.

4.1.2 Characteristics of the model components

This section explains the main choices made in the development of the theoretical model and gives argumentation to support these choices. First the model requirements are described and next each of the main model characteristics. This section describes only those aspects, which are the basis for the model development. Other model details are explained within the sections of this chapter.

Model requirements
The guidance settings, per medium time step, are the main model output. To be able to produce this output the model should perform dynamic traffic assignment in every time step, calculate realistic network performances and compute good guidance settings. The theoretical model must give a proper translation of the aspects, defined in the conceptual model. This results in the following requirements:

- The possibility to incorporate the interests of different stakeholders as objectives and constraints and to calculate network performance in relation to these objectives and constraints.
- Correct representation of the user behavior in the route choice and assignment component.
- A realistic representation of the traffic process in the traffic propagation component.

Another important requirement for the model is accuracy. To be able to perform guidance optimization and to define the improvements in the network performance, the model must work properly. The correct functioning of the model is discussed in Chapter 7.

Analytic, macroscopic model for DTA
One of the main requirements is a fast model, to enable online implementation. The DTA is executed many times in the optimization loop of each medium period and determines for a large part the computational requirements. Therefore, the computational requirements of the DTA have to be limited. Another requirement is a flexible formulation, which easily can be adapted to

different cities and situations. Because of these two requirements the choice is made to develop an analytic, macroscopic formulation. Such a model has the least computational requirements and leads to simple and understandable formulations.

The main disadvantage of an analytic, macroscopic formulation is the loss of detail in the traffic description. Traffic is represented in average flows, with average delays. Individual vehicle/road user characteristics can not be accounted for. However, there is no need for a detailed description of user behavior, in terms of for example driving style. The most relevant aspects related to the stakeholders are the guidance and the route and parking choice. These aspects can be covered in a macroscopic formulation. The only stakeholder that is difficult to incorporate is the air quality. A macroscopic model can not give an accurate estimation of emissions, however, it is possible to use indicators to account for the air quality interests. Possible indicators are the IC ratio, total delay and average travel time. Minimization of these indicators improves the air quality.

Travel times
The DTA and the guidance optimization are based on instantaneous travel times: the travel times at departure. The road users are guided, and are assumed to choose their routes, based on the travel times at the time of their departure. Many simulation based models use predictive travel times, i.e. the travel times that will be actually experienced by road users. The use of these travel times asks for continuous simulation of future situations and is computational demanding. The use of predictive travel times can improve the assignment and the guidance, however the use of instantaneous travel times also has several advantages:

- The use of predictive travel times implies that road users know the future situation on the network at the beginning of their trip, which is not always realistic. Especially in larger cities where the network situation can vary per day, instantaneous route choice is more realistic.
- In urban networks the time spent between entering and reaching the destination is limited. A road user chooses a route when entering the urban area and will only change this choice in special circumstances. In this situation instantaneous route choice (and no route switching) is an acceptable assumption.

Furthermore, the use of instantaneous travel times reduces the computational requirements. Concluding, the use of predictive travel times does not considerably improve the model and since the use of instantaneous travel times has several important advantages, these are used.

Route switching
Non-guided traffic is assumed not to switch routes in the study area. When entering, each vehicle chooses a route and stays on this route till the destination is reached. No route switching is assumed for three reasons:

- The length of a route within the study area (city center) is often short. While traversing this route, the network situation does not change much and therefore, there is no reason to switch.
- Non-guided road users are not aware of the situation on other routes and therefore, have no incentive to leave the route they are using at the moment. They do not know if there is a better route.

- Choosing a route within a city center often corresponds to choosing one side of a ring road (or one of two main directions). Once the driver is on a side of the ring, it is not logical to switch to the other side, since this would lengthen the route a lot.

Road users using guidance have the advantage that they are informed on the actual situation at the network. If these users can improve their trip by switching to another route, an in-car navigation system leads the user to the other route. Therefore, for these road users the possibility to switch routes is incorporated in the model.

Adaptation to guidance
The routes for the guided traffic are calculated at the start of every medium time step. The assignment of the other traffic (not using guidance) is based on a user equilibrium, however including or excluding the guided traffic from this equilibrium leads to a different assignment. If the guided traffic is included as fixed traffic into the user equilibrium, the non-guided traffic can adapt instantly to the guidance. However, this is not realistic if the guidance changes every few minutes. If the routes are calculated, based on the situation in which there is no guidance, this equals the situation in which the non-guided traffic does not adapt to the guidance (during a medium period). This second situation is implemented in the guidance model. Since the guidance is updated every few minutes it is reasonable to assume that non-guided traffic does not adapt to the guidance.

Another possibility is to vary the time steps for the two user groups. The routes of non-guided traffic can be fixed for longer time periods, or the guidance can be updated more often. These variations correspond again to more or less adaption of the non-guided traffic. In the first model implementation the same time period is used for both route inflows.

Deterministic versus stochastic
The theoretical model, as described in this chapter, is a deterministic model. The road users are assumed to have perfect knowledge on the network, the routes in their choice set and the actual situation. Also the demands (OD matrix) are deterministic and do only change per large time period. The assumption that these aspects are deterministic is not realistic. However, the model is mainly required to represent the average behavior of road users correctly. Stochasticity in individual user behavior has a limited influence on this average behavior. The introduction of stochasticity is very important in microscopic models that study individual behavior, however, in macroscopic models stochasticity does not necessarily lead to a better model. Therefore, the theoretical model is deterministic.

4.1.3 Outline of the chapter

Section 4.2 introduces the network model: the main input for the implementation. Section 4.3 describes the calculation of route choice sets and route costs. Section 4.4 presents the dynamic traffic assignment (DTA) model. This section discusses the adaptations of the basic traffic model (presented in Chapter 3), that are necessary to use the formulation in the guidance model. The resulting traffic model performs the traffic propagation and the calculation of route inflows. The complete mathematical formulation of the theoretical model is given in Appendix C.

Section 4.5 presents the models, which are used to calculate travel times and delays: the most important performance measures. Section 4.6 describes the objectives and constraints, representing the stakeholder interests. Finally, Section 4.7 gives an outline of the model framework that brings together the basic dynamic traffic assignment, the guidance and the optimization. This last section is an introduction to the model implementation in Chapter 6. Chapter 5 discusses the optimization model that is used in the implementation.

4.2 The network

Figure 4.2 shows a small example network, which is used to support the description and development of the theoretical model. The network G consists of a set of nodes $n \in N$, a set of network links $a \in A$, a set of walking links $w \in W$, a set of parking locations $p \in P$, a set of zone centroids $z \in Z$ and a set of centroid connectors $c \in C$. The following characteristics are defined for the network attributes:

- N: each node n is characterized by the type of intersection (signalized, non-signalized) and by the links that are connected to the node.
- A: each link $a \in A$ is a directed arc with a tail node (where traffic enters) and a head node (where traffic exits), $a = (TL_a, HD_a)$. A road section with two directions, consists of two links. For each link a the following characteristics are given: the number of lanes n_a, the capacity c_a per lane, the length l_a and the free-flow speed V_a. Furthermore, for links ending at signalized intersections the green time for the link, the cycle time at the intersection and the departure rate during green are defined.
- Z: the centroids z are the nodes where traffic enters and exits the network. The OD matrix specifies the amount of traffic per time period from each centroid to every other centroid. The centroids z_1 to z_4 in the test network represent the centroids of the zones within the study area. The other centroids represent all destinations and origins outside the network; these are the exit/entrance points to the study area. Z is a subset of N.
- W: each walking link $w \in W$ runs from a parking location to a zone centroid. The length and walking speed are input. The walking time τ_w can be calculated from these two variables. Walking time is a static variable, not dependent on the network situation. The test network incorporates walking links from each of the parking locations to each of the centroids within the study area. In larger networks the number of walking links is limited, by choosing a maximum walking distance. W is a subset of A.
- P: for each parking location $p \in P$ the capacity of the location cap_p and the parking charge c_p are given. The locations are modeled as links and are part of the routes (see also Figure 4.5). P is a subset of A.
- C: the centroid connectors are 'virtual' roads that represent the fine mazed network within a zone. These roads are mainly used to reach the final destination or to access the main network when leaving the origin. The same characteristics are specified as for the normal network arcs. The centroids z_5 to z_{12} are directly connected to the main network. These centroids represent all origins and destinations outside the study area and are the entry to and exit points from the network. C is a subset of A.

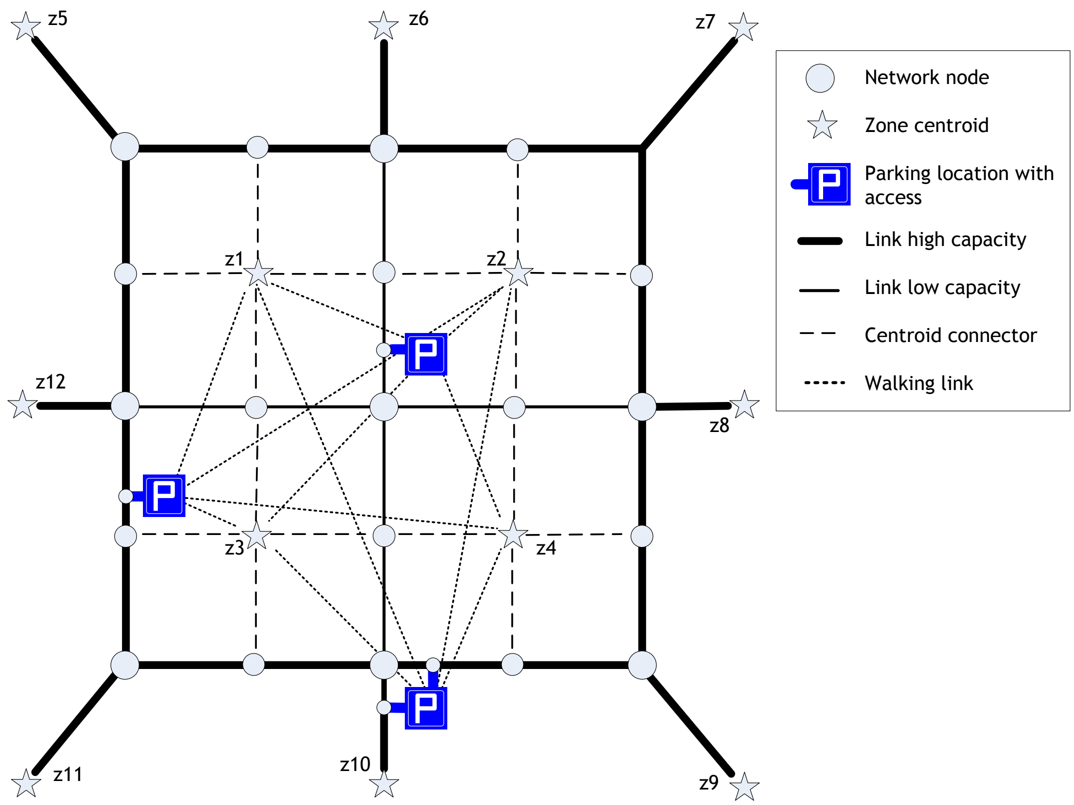


Figure 4.2: The test network

4.3 Route choice

The first step in the model is the calculation of the route choice sets for both the guided and non-guided traffic. To be able to translate the parking behavior realistically different parking options are distinguished in the routes: public and private parkings. For the road users using the public locations, parking and walking are incorporated in the route. For the users using private locations, parking is not modeled explicitly. These users are routed from the origin centroid to the destination centroid.

Two route choice sets are necessary, since traffic using public locations, uses different routes (via these locations and walking links) than traffic using private parking. Therefore, different user groups and route choice sets are defined. The user groups are discussed in Section 4.3.1. Section 4.3.2 explains the way route sets are calculated. Route choice is based on the disutility of a route. The calculation of the route disutility (the route costs) is described in Section 4.3.3.

4.3.1 User classes

Not all users in the traffic model have the same route choice possibilities, therefore four user classes are distinguished:

- Class 1: Traffic using one of the public parkings, with a route via a parking location and a walking link, not using guidance.
- Class 2: Traffic using private parking or traffic having a destination outside the study area, with a route from centroid to centroid (without parking and walking), not using guidance.
- Class 3: Traffic using one of the public parkings, with a route via a parking location and a walking link, using guidance.
- Class 4: Traffic using private parking, with a destination in the study area, with a route from centroid to centroid (without parking and walking), using guidance.

Classes 1 and 3 share the same route choice set and classes 2 and 4 share another choice set. The classes 1 and 3 consist of traffic with a destination in the study area, using public parking locations. Classes 2 and 4 combine all traffic that does not use a public parking location. This can be traffic with a destination outside the study area or traffic using private parking. These classes have routes that start and end at an origin centroid and that do not use the walking and parking links. Figure 4.3 shows the difference between the two route types.

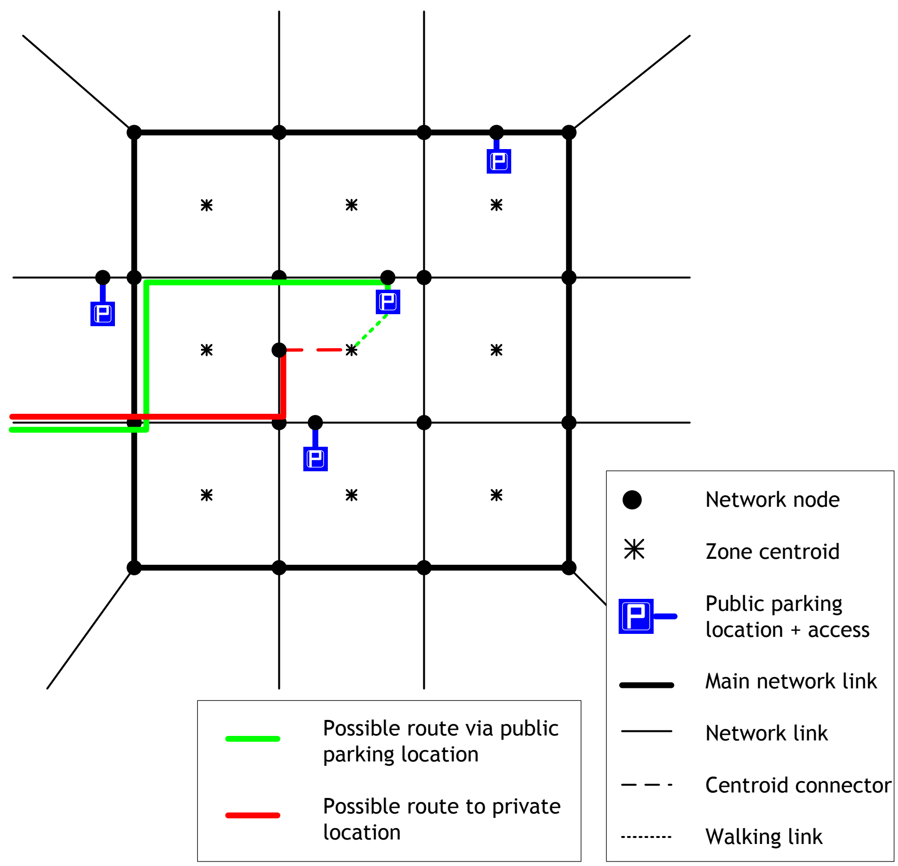


Figure 4.3: Two route types

4.3.2 Choice set generation

For each large time period, route choice sets are created. The development of the route choice sets is based on the Dijkstra algorithm for calculation of shortest paths. Furthermore, a link penalty approach is used (a k-shortest path approach). This method determines in each iteration (for each OD-pair) the shortest route. At the end of an iteration the cost of the links in the shortest route is increased, to be able to find other shortest routes in the next iterations. In the guidance model, instead of the shortest routes, the routes with the smallest disutility are calculated, based on the actual network situation. The road users choose their routes based on this disutility.

4.3.3 Route disutility

Most traffic models use the travel time as route disutility/cost. The user equilibrium is achieved if every user, departing at the same moment on the same OD relation, experiences the same travel time. In this research (according to the conceptual model) the road users are assumed to base their route choice on the following aspects:

- Congested travel time (free travel time + delay);
- Walking time from parking location to destination (τ_w);
- Parking charge per minute (c_p).

With these aspects the following route cost function is developed:

$$C_r^{od}(t) = \sum_{a \in r} \tau_a(t) + \alpha \cdot \tau_w + \beta \cdot c_p \cdot EPD_p. \tag{4.1}$$

In this function $\tau_a(t)$ is the actual, congested travel time on link a at time t (including delay), EPD_p is the average parking duration (in minutes) at location p, α is the parameter that values the walking time with respect to the in car travel time and β transforms the parking charge into units of time.

This cost function can be used for all users. For the traffic using private parking or for traffic leaving the study area, the walking time and the parking charge are equal to zero. The cost function does not include aspects related to the parking location (except for the walking time). If occupancy and searching time in parking locations are not known on forehand these do not influence the initial route choice. If information on parking occupancies is provided to the road users (and in guiding users), or if a situation is modeled with many familiar road users, the following two attributes are added to the disutility function:

- The time from arriving at the parking location till leaving this location by foot, to the destination (τ_p);
- Occupancy of the parking location (OCC_p).

This leads to the following route cost formulation:

$$C_r^{od}(t) = \sum_{a \in r} \tau_a(t) + \alpha \cdot \tau_w + \beta \cdot c_p \cdot EPD_p + \gamma \cdot \tau_p(t) + \kappa \cdot OCC_p(t). \tag{4.2}$$

The parameters γ and κ are used to value the time to park the car and leave the location and the occupancy of the location, in relation to the in car travel time.

Both disutility formulations are based on travel times and occupancy at the time the road users enter the route. The walking time and parking charge are constant over time. For small and medium sized networks the assumption of constant disutility, during the traversion of the route, is reasonable. In large networks, travel times and parking occupancy might change considerably during the traversion of the route. Therefore, for these large networks the model is less accurate.

4.4 The DTA model

Chapter 3 presents a standard VI-DTA formulation (Dynamic Traffic Assignment, with a Variational Inequality formulation). This formulation is adapted and extended to be applicable for the guidance model. The standard formulation is based on route travel times only, does not include different costs related to stakeholder interests and user classes, does not incorporate parking or walking and does not give a travel time and delay formula. These aspects are incorporated to be able to translate the conceptual model into an analytic formulation.

Section 4.3 presents the calculation of route choice sets and route costs. The travel time and delay formulation (network performance) is discussed in Section 4.5. The other necessary adaptations are directly related to the DTA formulation and are discussed in this section. The following components are adapted in the standard formulation:

- Incorporation of parking into the DTA model with a parking model (Section 4.4.1);
- Adaptation of the network representation (Section 4.4.2);
- Disaggregation of the model to the different user classes (Section 4.4.3);
- Replacement of the route travel times by the route disutilities (Section 4.4.4);
- Specification of the parameters in the disutility function (Section 4.4.5).

4.4.1 The parking model

The first part of this section discusses the main topics related to parking, that are translated from the conceptual model into a theoretical formulation. The second part presents the parking model.

Translation of parking aspects

In real life an individual can decide on a parking location in several manners:

- He decides before departure to park in a certain parking location. He drives to that location and parks there. Only if the location is full he goes to another location.
- A road user drives toward his destination and looks for a parking space close to this destination. If a place on street is free he uses this place, otherwise he goes to one of the larger parking locations.

- A road user drives toward his destination and uses parking guidance to choose a parking location.
- A road user drives to the private parking location at his work and parks there.
- ...

To be able to translate this parking behavior realistically, two user groups are distinguished: road users using public parkings and road users using private parkings. For the road users using the public locations, parking and walking are incorporated in the route. For the users using private locations, parking is not modeled explicitly. These users travel from the origin centroid to the destination centroid. The percentage of road users per parking type, is a parameter that can be varied per destination. In the city center the percentage of public parking is often high, in residential areas this percentage is close to zero.

A second important aspect is the manner parking places are included in the model. The public parkings are split into two types: the large(r) parking locations (dedicated parking areas) and the parking places that are spread along the streets. The larger locations are each separately included in the model. The other places are aggregated into a small number of parking facilities (if data on these locations is available). In a small zone these parking places are aggregated as one location, located next to the centroid. In larger zones parking aggregations are made per sub zone and are placed there. These aggregated facilities are connected with walking links to the zone centroid in the same manner as the large(r) parkings.

In a guidance system, which is effected through VMS, it is not possible to present information for all parkings at the same time. The guidance is presented on message signs, which have a limited number of lines to present information. With such a system only the large(r) parking locations can be guided-to. In the future, however, guidance will be effected through in-car navigation systems. With these systems each road user can be guided individually and all locations can be included. The guidance model focuses on the implementation through in-car navigation.

The large public parkings and the aggregated smaller locations are included in the same manner in the model. If no data on the smaller parking locations is available, the use of these places is added to the private parking group. The percentage of traffic using public and using private parking is a parameter in the model input. This percentage depends on the available amount of private parking locations and the day of the week.

Parking model formulation

Figure 4.4 presents the basis for the parking model. The parking locations are translated to parking links p. A parking link has a tail node, $TL(p)$, which is the network node from which the parking location can be accessed and a head node, $HD(p)$, which connects the parking link to the walking links (see Figure 4.5). The cars enter the parking link in the same manner as any other link. However, the cars do not traverse the complete link; the passengers do. The variable τ_p expresses the time the passengers spend at the parking location, from entering the parking link till entering the walking link. This time depends on the occupancy (searching a place) and the arrival rate (queuing at the entrance).

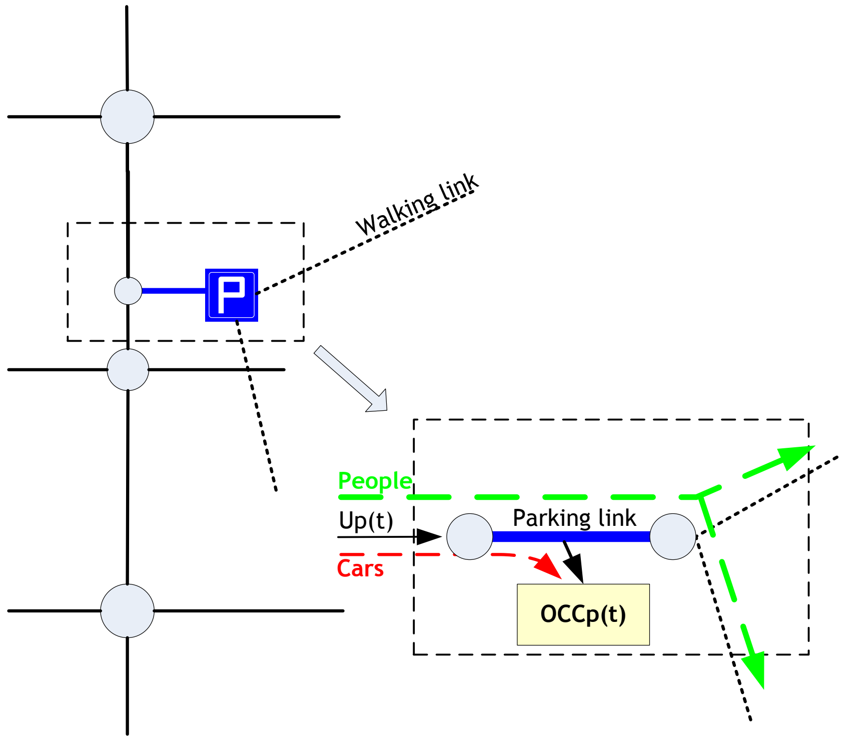


Figure 4.4: Parking model for incorporation in VI formulation

The time τ_p consists of three parts:

- A minimum time spent from entering till leaving the location;
- A factor that increases the minimum time based on the occupancy (the time spent is assumed to depend linearly on the occupancy);
- The waiting time before entering, based on the entering capacity and the arrival rate. With a general distributed arrival process, ce parallel entrances and an exponential distributed service time with mean ES_p, the waiting time can be modeled with a $G/M/ce$ queue (G for general arrival process, M for exponential service times and ce for the number of servers).

The resulting time spent in the parking link is formulated as (with a standard approximation for the delay in a G/M/ce queue (Zijm, 2003)):

$$\tau_p(t) = \tau_p^{min} \cdot (1 + OCC_p(t)) + \frac{c^2_{u_p(t)} + 1}{2} \cdot \frac{\rho^{\sqrt{2(ce_p+1)}-1}}{ce_p(1-\rho)} \cdot ES_p, \tag{4.3}$$

where τ_p^{min} is the minimum time spent in the parking link, $c^2_{u_p(t)}$ is the coefficient of variation of the arrival process, $\rho = u_p(t)ES/c$ and ES_p is the service time at the entrance (passing the barrier when first in the queue).

If the arrival process to the parking location is Poisson distributed, the formula simplifies to:

$$\tau_p(t) = \tau_p^{min} \cdot (1 + OCC_p(t)) + \frac{\rho^{\sqrt{2(ce_p+1)}-1}}{c(1-\rho)} \cdot ES_p. \tag{4.4}$$

In the model development, the following values are used for the parameters of the large(r) parking locations: ce_p is 2, ES_p is 10 seconds (1/6 minutes) and τ_p^{min} equals 2 minutes. For the aggregated parking locations there is no queuing, since these places are located along the road. For these aggregations τ_p^{min} represents the average time spent driving around the destination to find a place. ES_p equals zero, resulting in elimination of the queuing time in the formulation.

Since the passengers proceed in the network (in units of average number of passengers per car), the flow continuation is ensured. The cars are 'removed' from the network and stored in the occupancy variable for the parking location. The change in occupancy is described with:

$$\frac{OCC_p(t)}{dt} = \frac{u_p(t)}{cap_p} - \frac{e_p(t)}{cap_p}, \tag{4.5}$$

where $e_p(t)$ is the exit flow from the parking location (cars) at time t:

$$e_p(t) = u_p(t - EPD_p), \tag{4.6}$$

EPD_p is the expected parking duration for location p.

4.4.2 Adaptation of the network representation

To enable implementation, the network representation, as given in Section 4.2, is simplified. The main change is the introduction of the parking links. Furthermore, the centroids are represented as network nodes. The simplified representation is shown in Figure 4.5.

4.4.3 Disaggregation to user classes

For the disaggregation a set of user classes, $m \in M$, is introduced. Each flow variable is specified by the user class. Changes in the model structure are not necessary, since each of the user classes experiences the same travel costs along the links, that they can use. Each user class has its own route choice set and for each user group the constraints must hold. This results in the following, adapted, VI formulations (respectively route and link based):

$$\int_0^T \sum_{od} \sum_m \sum_{r \in R_m^{od}} \eta_{rm}^{od*}(t)[f_{rm}^{od}(t) - f_{rm}^{od*}(t)]dt \geq 0, \tag{4.7}$$

$$\int_0^T \sum_{od} \sum_m \sum_a \Omega_{am}^{oj*}(t)\{u_{am}^{od}[t + \pi_m^{oi*}(t)] - u_{am}^{od*}[t + \pi_m^{oi*}(t)]\}dt \geq 0. \tag{4.8}$$

4.4.4 Replacement of travel time by disutility

Two adjustments are necessary to replace travel time by disutility. In the model framework, where travel time is used, this is replaced by the travel disutility C_r^{od}. The variables π, η and Ω are specified in terms of the travel disutility instead of travel time.

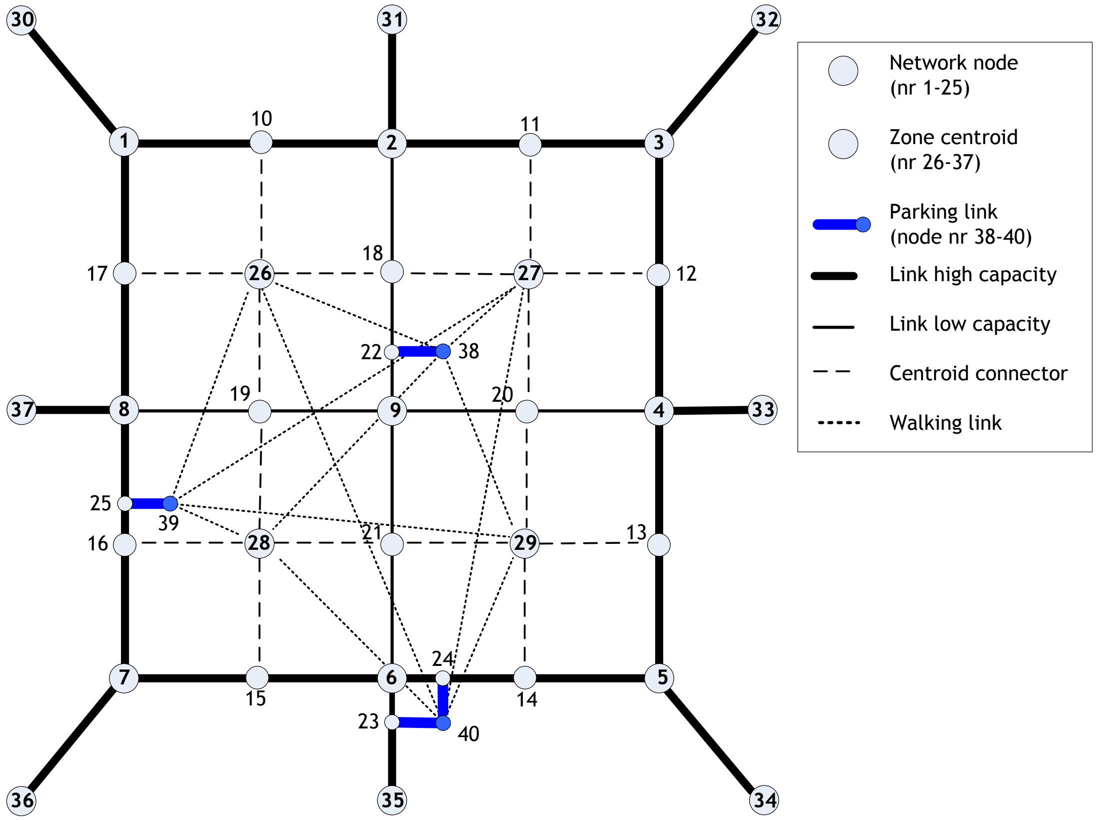


Figure 4.5: Translation of the test network for implementation

Furthermore, the following equation is added:

$$C_r^{od}(t) = \sum_{a \in r} \tau_a(t) + \alpha \cdot \tau_w + \beta \cdot c_p \cdot EPD_p. \tag{4.9}$$

This formula is explained in Section 4.3. The variable $\tau_a(t)$ is an output of each time step of the traffic propagation. The other two variables are static model inputs. The utility function can be extended by incorporating extra variables (see Section 4.3.3) or random terms.

4.4.5 Specification of the parameters

The parameters in the assignment model (especially in the parking model and in the utility function) have to be specified. This can be done based on field research or calibration of the model in comparison to another (calibrated) traffic model. For the development of the model the values are estimated based on literature and several small tests (see Section 7.3). The exact estimation of the parameter values is not within the scope of this research.

4.5 The network performance

The network performance is expressed in travel times, delays, IC ratios (intensity/capacity) and link occupancies. The link occupancies and IC ratios are direct output of the traffic propagation in every time step. Travel times and delays have to be estimated separately. The (congested) travel time estimation is one of the most crucial components in traffic models (related to accuracy). Section 3.4 gives an introduction to several methods for estimation of travel times and delays in macroscopic models. This section introduces macroscopic travel time modeling (Section 4.5.1), describes the travel time and delay estimations used in the model implementation and gives argumentation for the chosen formulations (Section 4.5.2 to Section 4.5.5).

4.5.1 Introduction to macroscopic travel time modeling

The total travel time on a link $\tau_a(t)$, experienced when entering the link at t, consists of the time to traverse the link and the delay at the end of the link. Most models for urban traffic use a fixed free flow travel time t_a for the link, which equals l_a/V_a (the length divided by the free flow speed) and a flow dependent delay at the intersection. This formulation has three important characteristics:

- The assumption of a free flow speed for traversion of the link is not completely realistic, since this speed decreases with higher flows, resulting in extra delay. However, this delay is small compared to the delay, which is experienced while queuing at the end of the link.

- This travel time model uses a point queue at the end of the link. All traffic is assumed to traverse the whole link and queue at the end, without occupying physical space. Therefore, the queue can become larger than the capacity of the link. In reality this leads to a spill back to the preceding links. This phenomenon is not covered in the model. In crowded cities spill back can result in severe blockage of the network. The resulting delay is partly neglected in the current model. However, incorporation of this phenomenon in an analytic model complicates the formulation and especially the process of a calculating a solution and is therefore not part of the (initial) formulation.

- Most formulas, used to describe the delay at the end of the link, do not account for interaction between subsequent (signalized) intersections and between the different traffic streams arriving at one intersection. Complete incorporation of these interdependencies is only possible in a microscopic formulation. However, it is possible to introduce variable cycle and signal times based on the interaction between traffic streams, arriving at the same intersection.

The formulation with a fixed free flow travel time and a delay at the end of the link is used for the signalized links. For these links the delay at the intersection determines the travel time. For non-signalized links and highway links other formulations are used. The delay and travel time formulations for each of the link types are presented in the following sections.

4.5.2 Delay formulation for signalized links

In the first model runs (with the test network), Websters formula is used to describe the delays at signalized intersections. This formula is explained in Section 3.4.1. Websters formula is one of the most used models to describe delays and is generally accepted as a good approximation (especially for isolated intersections). Furthermore, this formulation is easiest to implement in a macroscopic model.

However, Websters formula has several important disadvantages (as described in Section 3.4.1. One important disadvantage is that the formula is not applicable for loads larger than 0.8. This is problematic in the application. For heavy loads the formulation fails. Therefore, not Websters formula but the formula of Akçelik is implemented in the guidance model. This formula is explained in Section 3.4.2. Akçelik introduces an overflow queue in the delay model to represent delays when the load is larger than 1. Therefore, this formula is also applicable in situations with heavy loads. However, the formula has the same other disadvantages as Websters.

The other disadvantages of the delay formulation are intrinsic to macroscopic models. In these models traffic flow is represented per link and not per direction or turning movement and the intersection lay out is not explicitly incorporated. To improve the delay formulation it is necessary to introduce flows per direction, signal groups, green times per signal group (instead of per link) and a intersection lay out in terms of lanes per direction. Furthermore, improvements can be made with adaptive signal and green times. Improvement of the delay formulation is further discussed in Section 4.5.5.

4.5.3 Delay formulation for non-signalized links

It is difficult to develop one general delay formulation for non-signalized links, since the delay depends heavily on the link type and the intersection type at the end of the link (roundabout, (no) priority, stop line etc.). Furthermore, the centroid connectors are not always real network links, but a representation of the fine mazed network close to origins and destinations. In the first model implementation a simple travel time approximation for the group of non-signalized links is chosen. The travel time is approximated with the following formula:

$$\text{travel time } = (1 + \frac{\text{link flow}}{\text{capacity}})^2 \cdot \text{free flow travel time.} \tag{4.10}$$

The travel time increases quadratically with the link load in this formula. This relation is based on the expectation that on smaller roads traffic slows down very fast if it becomes crowded, due to narrow roads and many interactions with other traffic (also non-motorized). Furthermore, a steep function prevents the model to predict unrealistic,large traffic streams over the smaller roads. The formulation calculates the travel time as a function of the load on the link itself. In practice, delay is largely determined by other links ending at the same intersection. In the formulation it is assumed that there is a strong correlation between non-signalized links that connect to each other. The non-signalized links are the smaller roads within a neighborhood, it is assumed that within such an area all small links are loaded more or less equally. The formula does not account for the intersection type at the end of the link.

In further development of the model, the non-signalized links can be divided into roundabouts, priority and non-priority links. For these link types several travel time approximations exist. In the first model implementation, however, no difference is made between these non-signalized link types. Priority is given to development of the general model structure and the formulation for the main city roads. The non-signalized links are of less importance in the model and further detailing these link types brings along large data requirements.

4.5.4 Delay formulation for highway links

For highway links the delay is not caused by intersections. The delay is a result of decreasing speeds, due to an increase in traffic density. A well known description of the speed-density relation for highway traffic, is the fundamental relation of Greenshields. This relation is depicted in Figure 4.6. The jam density in Greenshields formulation is calculated as:

$$\text{density at capacity} = \frac{\text{capacity per lane}}{\text{speed at capacity}}, \tag{4.11}$$

$$\text{speed at capacity} = \frac{\text{free flow speed}}{2}, \tag{4.12}$$

$$\text{jam density} = 2 \cdot \text{density at capacity} = \frac{4 * \text{capacity per lane}}{\text{free flow speed}}. \tag{4.13}$$

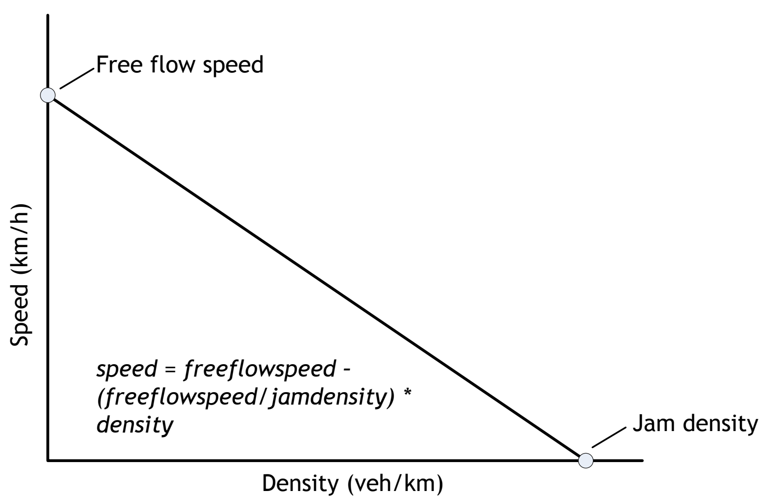


Figure 4.6: The Greenshield speed-density relation for highway sections

The Greenshields model gives a rough estimation of the highway speed. However, the model deviates from measurements at low densities and at densities close to the jam density. At low densities the model underestimates the speeds and at densities close to the jam density speeds fluctuate heavily in practice. In general, the formulation gives a good estimation of speeds. Furthermore, the data requirements for this model are limited. Therefore, this formulation is chosen as basis for the highway travel time formulation. To prevent negative travel times due to densities above jam density, the relation is flattened toward the end.

One main adaptation is necessary in the Greenshields formulation. The formulation is based on one highway section, with one density. However, in the guidance model there are several highway links that follow each other. If the travel time is only based on the density at the link itself, the traffic process is not captured realistically. If there are two links A and B that follow each other and there is a jam on link B, this will spill back to link A. The speed on link A decreases and the jam moves from link B to link A. To capture this spill back, a new formulation is developed for the guidance model. The speed on highway links is calculated based on the density of the link itself and of the next link. In the case where link B (second link) has a lower speed than link A (based on the density of the links itself), the speed of link A is reduced to the average of the speeds on link A and B. With this speed reduction the spilling back of queues is covered and the propagation from link A to B becomes smoother.

4.5.5 Improvement of the delay formulation

The delay formulation can be improved in four aspects:

1. Incorporation of general arrivals instead of Poisson arrivals;
2. Incorporation of interdependency between subsequent intersections;
3. Incorporation of signal settings per turning movement instead of per link;
4. Incorporation of adaptive cycle and green times.

The first two aspects are difficult to realize. Most macroscopic travel time formulations are based on the Poisson assumption. There are formulations for general arrivals; however, in these formulations it is still assumed that the arrivals in consecutive time periods are distributed independent and identical. Platooning of traffic can not be covered with these formulations. Real general arrival patterns can currently only be modeled with microscopic formulations. The same holds for dependency between subsequent intersections. Incorporation of this aspect asks for (optimal) linking of signal settings of several intersections over time.

Incorporation of signal times per turning movement is possible. This is done in the traffic simulation model Omnitrans (Omnitrans International, 2007). However, incorporation of this aspect brings along large data requirements. Detailed intersection lay-outs are necessary, to define conflict distances, lane capacity per lane group and crossing times. Furthermore, information on conflicting traffic streams and conflict groups is needed. Another problem is the traffic propagation. To be able to use signaling per turning direction, the traffic propagation also has to be performed per direction. If on average two or three outgoing directions per link are possible, the traffic propagation problem becomes two or three times as large. Because of the large data requirements and the large increase in problem size (and computation time) the signal times are not split out per direction. It is possible to incorporate a more detailed intersection model in follow-up research.

The last aspect, the use of adaptive cycle and green times, is incorporated in the current macroscopic formulation of the traffic process. A separate model component is developed that calculates the optimal cycle time and green times. These values are adapted every large time period, but this can also be done for smaller or larger periods. The following formulas are used to determine the optimal cycle time and the green times (Maarseveen et al, 2001). The green times are given per signal group: a (set of) direction(s) that has its own traffic light.

$$C_{opt} = \frac{1.5 \cdot T_v + 5}{1 - Y}, \tag{4.14}$$

$$G_{eff,i} = \frac{y_i}{Y} \cdot (C - T_v) \tag{4.15}$$

C_{min}	Minimal cycle time
C_{opt}	Optimal cycle time
T_v	The internal loss time of the cycle (due to switching between streams)
Y	The total load of the largest group of conflicting traffic streams
$C - T_v$	The total effective green time (cycle - loss time)
$G_{eff,i}$	Effective green time per cycle for traffic stream i
y_i	The load of signal group i (flow/capacity during green)

Appendix A gives a theoretical background, based on Polling models, for the formulas. The formulas for the optimal cycle time and the green times are specified based on loads per signal group. In the guidance model loads and green times are specified per link. However, a link often has two or three signal groups (one per turning direction). In the link based model the signal groups of one link are forced to share one green time period, while it might be optimal to let other signal groups (for example two opposing through going streams) share a green period. Therefore, the formulas are adjusted to fit with the description based on link flows. Appendix B explains these adjustments of the cycle and green time formulas.

4.6 Objectives and constraints

This section describes the incorporation of the interest trade off in the theoretical model with objectives and constraints. Section 4.6.1 describes the objectives and Section 4.6.2 the constraints.

4.6.1 Objectives

For each stakeholder, one main objective is selected to be used in the model implementation. It is possible to include other objectives, however, the following objectives are currently supported by the model implementation:

- The road user: the objective is minimization of personal disutility. This leads to a user equilibrium, where no individual user can shorten his trip by changing routes. This objective is split into a non-guided user equilibrium and a guided equilibrium in the model. In the first case the users choose a route, when entering the network, based on the situation at that moment. If during their trip the situation changes, the users in the network do not adapt. Therefore, the resulting situation differs from the intended user equilibrium. In the guided equilibrium, the road users in the network are redirected every medium period, to the UE at that moment. If the medium period is small the network situation converges to a true UE at every time instance. Both types of the UE can be chosen as objective in the guidance model. The user equilibrium, without guidance, is the basic scenario; the results for other objectives, with guidance, are compared to this basis.

- The local government: the objective for the local government is minimization of total travel time: a system optimum. The total travel time is difficult to use in the model implementation, since there is not a fixed number of vehicles that can be traced in every period. Therefore, the weighted average link travel time is used. This is the average link travel time, weighted by the number of vehicles that use each link. This measure is computed every period, based on link flows and link travel times. Minimization of the average weighted travel time leads to minimization of the total travel time.
- The parking holders: the objective for the parking holders is an optimal spread of traffic over all parking locations. This objective minimizes searching time and results in optimal use of the parking stock. In every period the differences in occupancy between the parking locations are combined in one performance measure. For this objective it is assumed that all parking locations belong to the same owner. If this is not the case the location holders that are disadvantaged by the guidance have to be compensated. It is also possible to apply this objective to groups of parking locations with different owners.
- Air quality: the objective for air quality is minimization of the average IC-ratio per link. By reducing this ratio, the congestion is minimized and the traffic flow is smoothened. This aspect is very important for the air quality. A related objective is minimization of the number of links with an IC-ratio above a critical level ($\sim$0.80). The guidance model can minimize both the average IC-ratio per link as well as the weighted average IC-ratio per user. In the second option the IC-ratio is weighted based on the number of vehicles using each link.

When using the guidance model, the objective is chosen based on a trade-off between the interests of the stakeholders. The interest that is thought to be most important is used as objective. The interests of the other stakeholders are incorporated as constraints. It is also possible to use a weighted combination of the objective functions of the stakeholders. This option can be used if several interests are equally important.

4.6.2 Constraints

This section describes the constraints, that can be used in the guidance model. For each stakeholder several constraints are currently incorporated in the model. Other constraints can be incorporated in further development.

The road user
The two main constraints of the road user are limited walking distance and limited detour of the assigned route (compared to the shortest route). The walking distance constraint is expressed as follows:

$$\tau_w \leq \tau_w^{max} \quad \forall o, d, r \in R^{od}. \tag{4.16}$$

The maximal walking distance, τ_w^{max}, can be varied per situation. In practice only those walking links, with a reasonable length, are included in the network.

The detour constraint is expressed as follows:

$$\sum_{a \in r} \tau_a(t) \leq df_{max} \cdot \min_{r \in R^{od}} \sum_{a \in r} \tau_a(t) \quad \forall o, d, \tag{4.17}$$

where df_{max} is the maximum detour factor that is allowed for routes assigned to road users by the guidance system. This parameter can be varied according to the importance of this constraint.

Air quality
The interest of the air quality stakeholder is minimization of emissions. However, the choice for a macroscopic model limits the possibilities to calculate emissions. Calculation of emission based on the outputs of the macroscopic model, results in a very rough estimation. Therefore, the choice is made not to calculate emissions, but to use air quality indicators to incorporate the air quality interests. The main objective for air quality is the minimization of the average IC-ratio. Furthermore, the following constraints related to air quality are supported by the model implementation:

- A maximum IC-ratio for several or all links, expressed as:

  $$\frac{u_a(t)}{c_a} \leq \text{ Maximum ratio.} \tag{4.18}$$

  Since a direct incorporation of this constraint can lead to infeasibilities, it is implemented by penalizing ratios larger than the maximum.

- A maximum load or maximum density for several or all links. This can be implemented in the same manner as the maximum IC-ratio.

The air quality interests can be valued more or less by changing penalty values and limits in the constraints.

Local government
The local government can have very diverse interests. However, the main interest is to guide traffic toward a system optimum, which is the local government objective. Furthermore, the government interests are often related either to air quality or to improving the situation for the parking holders or the road user. Constraints that are formulated for these stakeholders, can also be applied for the local government.

Parking location holders
The optimal spread over the parking locations is used as objective for the parking holder. In addition to this objective, one constraint is incorporated in the model. This constraint is a limit on the maximum occupancy of parking locations to prevent searching, within the parking location, and queuing at the entrance.

$$OCC_p(t) \leq \text{max. OCC} \quad \forall p. \tag{4.19}$$

4.7 Integration of the assignment and optimization

This section gives a first introduction to the design of the optimization model and the combination of this model with the traffic assignment model. Section 4.7.1 introduces the use of an optimization model. Section 4.7.2 explains the use of the different time steps.

4.7.1 Outline of the optimization model

The basis for the optimization model is shown in Figure 4.1. The optimization model consists of three different levels, according to the different time steps. On the highest level the demand input is varied and the route choice set is defined. This demand is used in the medium time periods. $\Delta T/\Delta t$ medium time periods together constitute one large time period. In each of these medium periods the guidance is determined by executing the following model components:

- Defining initial guidance settings;
- Calculation of the user equilibrium (UE) for the non-guided traffic;
- Optimization of the guidance settings, by iteratively changing the settings and calculating the resulting network performance.

The traffic propagation is described on the lowest level (smallest time step). Per time step traffic is propagated according to the route inflows. The number of possible guidance settings is very large. Therefore, an efficient optimization method is necessary to be able to find a good solution in a limited number of iterations. The optimization model is discussed in Chapter 5. The implementation of the complete model is further developed in Chapter 6.

4.7.2 Time steps

Three time steps are used in the model: the largest time step ΔT, the medium time step Δt and the smallest time step δt. These time steps are model parameters and can be varied. The value of each of the time steps is subject to several requirements. The largest time step must be small enough to capture variation in demand. Usually this period is taken between 10 and 15 minutes. The medium time step must be small enough to provide real dynamic guidance, but large enough to prevent the guidance changing to frequently. Furthermore, the largest time step must be an integer multiple of the medium time step. The medium time step is in the range of 3 to 6 minutes.

The smallest time step must be small enough to describe the traffic propagation. The time step must be smaller than the smallest link travel time. Furthermore, the medium time step must be an integer multiple of the smallest time step. The smallest time step is in the range of 10-30 seconds. Overall smaller time steps increase the computational requirements. Therefore, a trade-off between the accuracy and computational requirements is necessary. The model is tested with several time steps to find the best configuration (see Section 7.3).

Chapter 5

Optimization model

This chapter presents the optimization model that is used to determine the optimal guidance in every medium time period. Section 5.1 discusses the optimization problem. The section describes the solution representation and the solution space. A simulated annealing algorithm is used to search for the optimal solution in the solution space. An introduction to this method is given in Section 5.2, as well as argumentation for the choice to use this algorithm. Section 5.3 presents the detailed design of the algorithm in the guidance model.

5.1 The optimization problem

This section gives a mathematical expression for the optimization problem (Section 5.1.1), explains the representation of a guidance solution (Section 5.1.2) and describes the solution space (Section 5.1.3).

5.1.1 A bi-level programming problem

The optimization problem is a bi-level programming problem. On the upper level the guidance settings are fixed. The optimization algorithm changes the settings in every iteration, to search for better solutions. On the lower level the traffic assignment and propagation are performed, based on the guidance settings at the upper level. Mathematically the bi-level programming problem can be expressed as follows (with minimization of total travel time as objective):

$$\min_{\psi \in \Omega} TT(\psi, \mathbf{f}^*(\psi)) = \sum_t \sum_a \tau_a(t, \psi, \mathbf{f}^*(\psi)) u_a^*(t) \delta t. \tag{5.1}$$

The corresponding flows result from the combination of guided traffic and the UE for non-guided traffic:

$$\sum_t \sum_{od} \sum_{m_1, m_2} \sum_{r \in R_m^{od}} C_{rm}^{od^*}(t) [f_{rm}^{od}(t) - f_{rm}^{od^*}(t)] \geq 0, \tag{5.2}$$

subject to interest trade-off constraints, network flow constraints, flow continuation constraints, flow propagation constraints and definitional, non-negativity and boundary constraints,
where

$\mathbf{f}^*$ the optimal route flow pattern;
TT the total travel time;
ψ the guidance settings;
Ω the feasible set of guidance settings.

This formulation searches for those guidance settings (at the upper level), that minimize the total travel time. The total travel time can be found at the lower level as a result of the traffic assignment of both guided and non-guided traffic. For each guidance period (medium time period) this problem is solved by the optimization model.

Equation 5.1 uses minimization of the total travel time as objective. Important in the implementation is to relate the total travel time to the number of vehicles that actually move through the network. If several links are completely blocked, the outflow is limited. If only the travel time of vehicles leaving these links is accounted for, the total travel time turns out to be small. However, the travel time per vehicle is large due to the congestion. Therefore, it is better to use the average link travel time per vehicle as indicator. Minimization of total travel time can be replaced in the formulation by other objective functions.

5.1.2 Representation of a guidance solution

An instance of the guidance solution consists of a division of the traffic, per OD-pair, over the available routes. In the route generation a maximum number of routes is generated per OD-pair: *maxroutes*. The guidance per OD-pair is represented by a vector of length *maxroutes*: the split vector. Element i of the vector gives the traffic share, that is assigned to the i^{th} generated route for this OD-pair. The vector elements sum to 1 and are all larger or equal to zero. Every vector element is a multiple of the fraction $1/split$, where $split$ is the factor that determines the minimal fraction of traffic assigned to a route in use. If $split$ is set to 100, this minimum is 1% (1/100). If $split$ is set to 2, every route gets either 0, 50 or 100% of traffic assigned. The larger $split$ the larger the number of options to divide the traffic over the available routes. By choosing split small the solution space can be reduced. The parameter $split$ is called the split parameter.

The split vectors, one for each OD-pair, together form the split matrix. Every split vector is a column of the split matrix and defines the traffic split for one OD-pair. The number of rows in the resulting split matrix equals *maxroutes*, the number of columns equals the number of OD-pairs (with guidance possibility). Two split matrices are used in every iteration of the optimization model: a matrix for traffic using public parking and a matrix for traffic using private parking. For these two user groups separate route sets are generated and separate guidance settings. The split matrix for period i and user group m is denoted by $\psi_{i,m}$.

5.1.3 The solution space

The solution space depends on the number of guided OD relations, the value of *maxroutes* and the value of $split$ (the split parameter). If for example *maxroutes* equals 5 and $split$ equals 2, there are 15 possible solutions per OD-pair. The following matrix shows these 15 solutions; every column is a possible split vector:

$$\begin{bmatrix} 2/2 & 1/2 & 1/2 & 1/2 & 1/2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1/2 & 0 & 0 & 0 & 2/2 & 1/2 & 1/2 & 1/2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1/2 & 0 & 0 & 0 & 1/2 & 0 & 0 & 2/2 & 1/2 & 1/2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1/2 & 0 & 0 & 0 & 1/2 & 0 & 0 & 1/2 & 0 & 2/2 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 1/2 & 0 & 0 & 0 & 1/2 & 0 & 0 & 1/2 & 0 & 1/2 & 2/2 \end{bmatrix}$$

With *split* equal to 2, in each option traffic is either divided over two of the five routes (2 times 1/split) or all traffic is assigned to one route (2/split). The number of solutions per OD-pair is named $nr.odsol$. The number of guided OD-pairs is named $nr.odsguided$. The total number of solutions for the split matrix for one time period and one user group can now be expressed as: Number of solutions = $nr.odsol^{nr.odsguided}$

For the test network, with 32 guided OD-relations and 15 possible solutions per OD-relation, the total solution space consists of $15^{32} = 4.3144 \cdot 10^{37}$ options. This is already a very large solution space and for larger networks the solution space increases rapidly. Important to notice is that not all solutions in the solution space are feasible. In the route generation at maximum *maxroutes* are generated for every OD-pair. However, for origins and destinations that are close to each other, it is possible that less routes are generated. Therefore, in the solution generation only the feasible columns (per OD-pair) are used. Due to the infeasible solutions the real solution space is smaller, than calculated with the formula in this section. If constraints on the detour are introduced even more solutions become infeasible.

5.2 Introduction to simulated annealing

Section 3.3.2 describes several probabilistic optimization methods. Simulated annealing is chosen to be used in this research. This section introduces the simulated annealing method (Section 5.2.1 and Section 5.2.2) and explains why this algorithm is chosen for implementation (Section 5.2.3).

5.2.1 Threshold algorithm and simulated annealing

SA is part of the class of threshold algorithms, which is a subclass of local search algorithms. This subsection first introduces the threshold algorithm. Next the basic form of a SA algorithm is explained. Emile Aarts and Jan Karel Lenstra (1997) give an extended introduction. Furthermore, argumentation is given for the application of SA in this research.

The general threshold algorithm

A threshold algorithm uses the following input:

(Ω, f)	the instance of the minimization problem;
Ω	the set of feasible solutions;
$f : \Omega \rightarrow R$	the cost function, which values each solution;
$N : \Omega \rightarrow P(\Omega)$	the neighborhood function;
ψ	solution instance;
$N(\psi)$	set of neighboring solutions, $\forall \psi \in \Omega$;
k	the iteration number;
t_k	threshold value for iteration k.

The general threshold procedure can be described with the following pseudo code:

```
begin
        INITIALIZE(ψ_start)                     (select a start solution)
        ψ := ψ_start
        k := 0
repeat
        GENERATE(j from N(ψ))                   (select next solution from neighborhood)
        if f(j) − f(ψ) < t_k then ψ := j        (accept solution if difference below threshold)
        k := k + 1
until   STOP                                    (continue till stop criterion is reached)
end.
```

An initial solution (ψ_{start}) is selected and the corresponding objective value ($f(\psi_{start})$) is calculated. In the guidance model this corresponds to selection of first guidance settings at the upper level and the performance of traffic assignment, propagation and calculation of the network performance at the lower level. In the next step a new solution is selected from the neighborhood of the preceding solution and the objective value for this solution is calculated. If the difference between the objective value for the new and the old solution is below the threshold, the new solution is accepted and the next iteration starts with this solution. Otherwise, the old solution is used again in the next iteration. The threshold can differ per iteration. In general for low k the threshold is high, which leads to the acceptance of both improvements and deteriorations in the solution. If k becomes larger, the threshold is lowered. In the limit the threshold becomes zero and only improvements are accepted. In the whole optimization loop, the route choice of the non-guided traffic is fixed. This traffic does not adapt to the changing guidance settings for the guided traffic.

The general simulated annealing algorithm

Section 4.7.2 gives a short introduction to the SA algorithm. This section discusses the algorithm in more detail. The main difference between the general threshold algorithm and the SA algorithm is the criterion for acceptance of the new solution. Simulated annealing does not use a fixed threshold but a probability function. Furthermore, SA uses a temperature instead of a threshold. The temperature is lowered per level k. Per level a fixed number of iterations is used. These iterations are called transitions and the number per temperature level is indicated by the parameter $trans$. The probability for acceptance of a solution is expressed as:

$$P_{c_k}(\text{accept } j) = \begin{cases} 1 & \text{if } f(j) \leq f(\psi) \\ exp\left(\frac{f(\psi)-f(j)}{c_k}\right) & \text{if } f(j) > f(\psi) \end{cases}, \tag{5.3}$$

where

k	The temperature level;
c_k	The temperature at level k;
$P_{c_k}(j)$	The probability of accepting solution j at level k.

Every step, in which a new solution is valued and accepted or not, is called a transition (according to a transition in a Markov chain). Per temperature level k the value c_k can be lowered and a number of transitions is performed.

The cooling schedule specifies the (finite) sequence of values of the temperature c_k (via a decrement function) and a (finite) number of transitions ($trans$) at each value of the parameter. Furthermore, it specifies the initial and final value of the temperature (c_{start} and c_{end}). According to the physical process of the cooling down of steal, the cooling schedule starts at a high temperature. At a high temperature a large part of the possible new solutions is accepted, also if the new solution is not an improvement. This corresponds in the physical process to a high temperature, where the steal deforms easily, also to formations with higher energy. During the process the temperature is lowered and the probability that worse solutions are accepted decreases. Finally, when the parameter approaches zero, only improvements are accepted. At high temperatures the algorithm can proceed out of a local optimum. At lower temperatures this is not possible anymore.

In theory, if the neighborhood structure and the cooling schedule are designed carefully, if the solution space has certain characteristics and an infinite number of transitions is allowed, the SA algorithm finds the optimal solution with probability 1. In realistic applications the number of transitions must be finite and only a limited number of solutions can be evaluated. There is no guarantee that the algorithm terminates at the optimal solution. However, through careful design of the neighborhood structure and the cooling scheme the solution space can be explored efficiently. The chance to end with a bad solution can be reduced with a good detailed design of the algorithm.

5.2.2 Design aspects of the SA algorithm

A SA algorithm has four main design aspects:

- The problem representation (solution space, (mathematical) description of solutions);
- The neighborhood function (selection of solutions that belong to the neighborhood of the current solution);
- The transition mechanism (selection of the new solution from the neighborhood);
- The cooling schedule.

The representation of the guidance settings and the solution space are discussed in Section 5.1. There are no general rules for the design of the neighborhood function and the transition mechanism. The design of these aspects depends on the problem that is studied and the problem representation. These aspects are further discussed in Section 5.3. Also the cooling schedule depends on the problem, however, there exists a general classification of these schedules. Cooling schedules are divided into static and dynamic schedules. Static schedules use fixed parameters.

The following parameters are used in a basic, static cooling schedule:

c_{start}	Δf_{max} (choose the initial control parameter equal to the maximum (estimated) difference in objective values);
c_{k+1}	$c_{k+1} = \alpha \cdot c_k$ (choose α between 0.8 and 0.99);
c_{end}	Choose a fixed small value for the final temperature;
Transitions	Choose a fixed number of transitions per level.

Other static schedules are variations and extensions of this basic schedule. Dynamic schedules do not use fixed parameters, but use dynamic parameters like for example:

- The initial value for the control parameter based on a minimum acceptance probability for the first solutions;
- The number of transitions per c_k based on a minimal number of accepted transitions;
- End of the optimization if for a certain number of $c_k's$ the objective value remains constant (no improvement).

Dynamic schedules can be customized to the problem that is studied. Many variations are possible.

5.2.3 Argumentation for simulated annealing

The problem studied in this research does not have a smooth objective function and the solution space is very large (explained in Section 5.1.3). Furthermore, the evolvement of the objective function is not predictable. However, it is possible to give an indication of the expected change in objective function, based on traffic patterns. If for example there is one major bottleneck in the network and the traffic on routes using this bottleneck is reduced and spread over other routes, the expectation can be a reduction in congestion.

Based on the large solution space and unpredictable objective function values, simulated annealing (SA) and evolutionary algorithms (EA) are selected as suitable algorithms. More information on optimization algorithms is given in Section 3.3. The main difference between SA and EAs is that an evolutionary algorithm evolves more randomly than SA. EAs use a random starting population of solutions and find new solutions through cross over and mutation. The process does not use information on the evolvement of the objective function and functions randomly during cross-over and mutation.

SA proceeds in every step to a neighbor solution of the current solution and can use characteristics of the current solution to choose the next solution to evaluate. For example, if in the current situation several links are overloaded, in the new solution less traffic can be assigned to routes using these links. The algorithm searches in the neighborhood of current solutions. EAs explore a larger part of the solution space. Furthermore, with an EA a group of solutions is generated and evaluated in every iteration. In SA only one solution per iteration is studied.

If there is enough knowledge on the problem and the objective function to choose a good initial solution, it is more efficient to use SA than an EA. In this research guidance settings of a preceding period are expected to be a good start for the new period. Furthermore, it is possible to indicate the effect of certain changes in the guidance settings. Therefore, simulated annealing is implemented.

To improve the SA algorithm a database with solutions, earlier found, can be built. In every new situation solutions from this database can be chosen as starting point (based on for example loads) and SA may proceed fast to a good solution. For example, if the total load on the network is small, the best solutions will use the shortest routes only. If this knowledge is used as starting point, a good solution can be found very fast. Since, SA is better able to use relations between solutions than EA, SA is chosen to be used in this research.

The main disadvantage of SA is the larger chance (compared to EA) to get stuck in a local optimum. To prevent this happening SA can be started from different initial solutions for every guidance period. For these initial solutions, either the solutions from preceding periods, or solutions from a historical database can be used. The optimization loop is run several times per medium time period if more start solutions are used.

5.3 Detailed algorithm design

This section describes the implementation of the SA algorithm in the optimization model. In Section 5.3.1 a detailed structure is described, that can be adapted based on the problem structure and available time for computation. Section 5.3.2 shortly describes the parameters that are chosen for the case study and gives argumentation for the choices made.

5.3.1 The algorithm structure

The basis for the algorithm structure is the SA schedule as described in Section 5.2.1. Equation 5.3 is used to calculate the acceptance probability for a solution. This section describes the neighbor structure per OD-relation and the construction of a new split matrix from the current solution. The third paragraph discusses the cooling scheme and the fourth part the initialization of the algorithm. The last part introduces the implementation structure.

Neighbors per OD-pair

The guidance is represented, per OD-pair, with a split vector (Section 5.1.2). The neighborhood of a split vector consists of those split vectors that are closely related to the current split vector. Two methods to define the neighborhood are developed for the algorithm: a method based on a linear ordering of the possible split vectors and a method based on a shift of traffic from one route, to another route.

Neighborhood based on linear ordering of split vector options
In Section 5.1 the split vector configuration, based on split parameter $split$ and the maximum number of routes, is explained. Depending on these two parameters all possible split vector configurations can be constructed. These options can be ordered, as columns, in a matrix, based on the 'distance' between the options. Such a linear ordering can be used to define a neighborhood per OD-pair.

A possible ordering for the split vectors with parameters $split$ equal to 2 and $maxroutes$ equal to 5 is:

$$\begin{bmatrix} 2/2 & 1/2 & 1/2 & 1/2 & 1/2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1/2 & 0 & 0 & 0 & 2/2 & 1/2 & 1/2 & 1/2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1/2 & 0 & 0 & 0 & 1/2 & 0 & 0 & 2/2 & 1/2 & 1/2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1/2 & 0 & 0 & 0 & 1/2 & 0 & 0 & 1/2 & 0 & 2/2 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 1/2 & 0 & 0 & 0 & 1/2 & 0 & 0 & 1/2 & 0 & 1/2 & 2/2 \end{bmatrix}$$

This ordering starts with the option of all traffic on the first generated route and ends with the option with all traffic on the last generated route. These options are least related. The second column is the option where half of the traffic is assigned to the first route and the other half to the second route. This solution is closely related to the first solution. However, the complete linear ordering is arbitrary. It is not directly clear which solutions are closest to each other. A possibility to order the columns, is to calculate the average cost of the routes and order from lowest to highest cost. However, this ordering should be renewed every time period, since the route costs change.

With the linear ordering, a neighborhood can be defined by those split vectors that are within n columns to the right or the left of the current split vector. The parameter n determines the size of the neighborhood and can be chosen based on the specific problem characteristics. If n is chosen small, the new solution is close to the current solution. This is useful if the current solution is close to the optimum. If n is large the algorithm can explore a larger part of the search space. The advantage of this neighborhood definition is that the size of the neighborhood can be adapted easily. The disadvantage is the arbitrary definition of the linear ordering.

Neighborhood based on traffic shift between routes
The second method for neighborhood construction is based on shifting traffic between routes. A new split vector can be created from the current one, by reducing one of the positive elements by $1/split$ and increasing one of the other elements by $1/split$. In this case the neighborhood consists of all the vectors with a reduction of $1/split$ in one of the elements and an increase of $1/split$ in another, compared to the current solution. If $split$ is large the change from the current solution to a neighbor is small. Therefore, if $split$ is large the procedure can be repeated for several elements to find a new solution. This increases the neighborhood. The advantage of this method is that the definition of the neighborhood is completely clear and easy to adapt. The second neighborhood method (shift of traffic) is used in the case study, since the linear ordering is arbitrary.

Construction of the new split matrix

The preceding paragraph discusses the neighborhood of the split vectors per OD-pair. However, if per iteration the split for one OD-relation is changed, it is necessary to evaluate a large amount of solutions due to the small change made per solution. If the computational time is limited, it is necessary to take larger steps per iteration. Therefore, per iteration split vectors of several OD-pairs are changed. The following structure is used in the construction of the new split matrix:

1. Calculate the number of columns to change in the current split matrix with the *change* parameter; *change* is the parameter that defines the percentage of the OD-pairs for which the split vector is changed. Randomly select the columns with split vectors, that are changed.
2. Create for each of the selected split vectors a new vector from its neighborhood by removing $1/split$ from one of the positive vector elements and adding $1/split$ to one of the other elements. This neighborhood structure can be adapted as explained in the preceding paragraph.
3. Check the feasibility of the new vectors and change infeasible vectors into feasible solutions.
4. Replace the selected split vectors in the current solution by the feasible new vectors to create the new split matrix.

This procedure gives a basic structure that can easily be adapted per problem. The parameter *change* determines the size of change from the current to the new solution. If *change* is chosen small, the new solution is close to the current. If *change* is large, the new solution might be completely different. A possible adaptation is to select a fixed percentage of the total traffic flow to be changed, instead of a fixed percentage of OD relations. Since the traffic flow per OD-pair is known, this can be done by randomly selecting columns till the selected traffic flows sum to a certain number. Another possibility is to select OD-pairs with a large flow, with a larger probability. In this way the OD-relations with the largest influence on the network situation are changed more often. A third option to improve the neighbor solution, is to use information on the network situation to come to a new solution. If certain links are congested, the split can be changed for the OD-pairs that use these links. The adaptations are not implemented in this study, however, they are interesting to study in follow-up research.

Cooling scheme

The cooling scheme can largely influence the outcome of the process. If the temperature is lowered very fast, the amount of iterations in which worse solutions are accepted is small. Therefore, it is difficult to escape from local minima. If many iterations are used the computation time becomes large. A basic cooling scheme, as explained in Section 5.2.2 is used in the implementation. Without testing, it is difficult to determine the best values for the start and stop temperature and the cooling per step (parameter α). Therefore the values are chosen with the following procedure:

1. Fix the total number of transitions ($totaltrans$) that is allowed in the algorithm. This number can be calculated by dividing the allowed computational time for the transitions, by the time needed per transition.

2. Fix the number of transitions per temperature level ($trans$). The best value for this parameter can be found by testing. Compute the number of temperature levels (k) from the parameters $trans$ and $totaltrans$.

3. Fix a desired percentage of solutions to be accepted at the first temperature level. At the start of the algorithm it is desirable that almost all solutions are accepted, to be able to move away from local optima.

4. Calculate the objective value for a large number of randomly generated solutions. The number can be varied based on available computation time. Order the objective values from minimum to maximum and calculate the differences of all objective values compared to the minimum. Find the maximum objective value difference that should be accepted at the first temperature level, with the percentage that is fixed in the preceding step.

5. Choose the start temperature (c_{start}) equal to the maximum objective value difference that should be accepted.

6. Choose the end temperature (c_{end}) below the smallest difference found between objective functions. The end temperature should be such, that in the end only improvements are accepted.

7. Compute the value of the cooling parameter $alpha$ from the number of temperature levels, the start and the end temperature.

A possible alteration to this method is to fix the cooling parameter $alpha$ and the parameter $totaltrans$ and to compute the number of transitions per temperature level. Furthermore, if the computation time is no bottleneck, it is also possible to fix $alpha$ and $trans$ and compute the corresponding number of total transitions needed.

Initialization

To reduce the number of transitions needed in the algorithm, it is important to begin with a good start solution. If the network is (almost) empty at the start of the study period (morning peak, whole day) the start solution is chosen in which all traffic is assigned to the shortest route. This is a logical start, since if there is no congestion it is (near) optimal to use the shortest routes. For the evening peak, the solution at the end of the morning peak can be used as start. For the time periods following the first period, the solution of the previous time period can be used as start solution. Again this is a logical choice, since the change in the network situation between two subsequent periods is small.

At the beginning of a period in which new routes are calculated, the current solution can be infeasible. If the route choice sets do not have the same number of routes for each OD-pair, the current solution can not be used as start. With the use of a route database, the number of routes is always the same and the current solution is feasible. In the case study a route database is used. In studies where this is not the case, a new start solution should be generated together with a new route choice set.

Implementation structure

The algorithm is implemented in five separate syntaxes in Matlab. The structure is shown in Figure 5.1. The complete model implementation is shown in Figure 6.2.

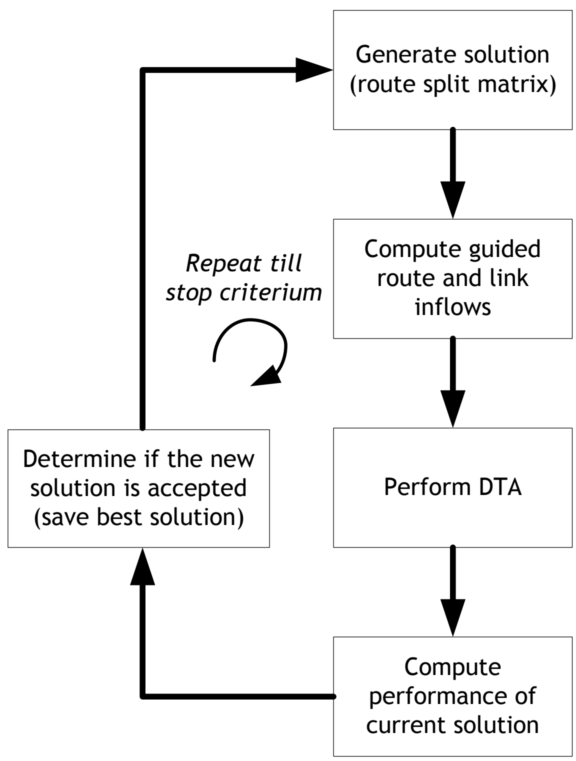


Figure 5.1: Implementation of the optimization algorithm in Matlab

5.3.2 Case study implementation

For the case study implementation of the optimization two considerations are important:

- The implementation is currently programmed in Matlab. This programming language is very good for development of a model, however slow in the implementation. Therefore, every iteration of the optimization model is expensive (in terms of time consumption). The translation of the program to another language is not within the scope of this research.
- The available time for the case study and the available computer capacity are limited within this research.

Both considerations imply that, within this research, time is the bottleneck and the implementation of the algorithm should be as efficient as possible. Within this first case study, it is not possible to implement an extended optimization algorithm. Based on this observation the following choices are made for the implementation:

- The maximum number of routes per OD-pair (*maxroutes*) is fixed at 5. This number is large enough to include all often used routes.
- The split parameter (*split*) is fixed at 2. To be able to keep the computational time limited, it is necessary to take large steps from one to the next solution. Therefore, *split* should be small. Furthermore, a small split parameter reduces the size of the solution space. The limitation to a split of traffic over two routes per OD-pair is compensated by the update of the split every couple of minutes. Due to the update the number of routes actually used is larger than 2.
- The cooling scheme (total number of transitions) is based on the time available for the model runs. The begin and end temperature are chosen based on differences in objective values. The values for the parameters are based on tests in the model calibration (see Section 7.6).

Chapter 6

Implementation

This chapter describes the implementation of the theoretical model together with the optimization algorithm. In Section 6.1 the demand input for each of the user classes is specified. Section 6.2 translates the continuous traffic model formulation, as developed in Chapter 4 to a discrete time formulation. The use of link split vectors is explained in Section 6.3. Section 6.4 discusses the solution algorithm that is used to solve DTA in every iteration to find the route inflows. Finally, Section 6.5 presents the implementation in Matlab. The Matlab syntaxes are not included in this report, but are available on CD.

6.1 Specification of user classes

In the implementation four user classes are distinguished. The network flow for each of the user classes is calculated with the compliance and parking type parameters (η and θ). The total network inflow per OD relation is given in the dynamic OD matrix (model input).

- Class 1: Traffic using one of the public parking locations, route via parking location and walking link, using no guidance. This group has the following network inflows:

$$f_1^{od}(t) = (1 - \eta_1) \cdot \theta_d \cdot f^{od}(t) \quad \forall d \in D_{in}. \tag{6.1}$$

- Class 2: Traffic using private parking or traffic having a destination outside the study area, routes from centroid to centroid without parking and walking, using no guidance. This group has the following network inflows:

$$f_2^{od}(t) = (1 - \eta_2) \cdot (1 - \theta_d) \cdot f^{od}(t) \quad \forall d \in D_{in}, \tag{6.2}$$

$$f_2^{od}(t) = f^{od}(t) \quad \forall d \in D_{out}. \tag{6.3}$$

- Class 3: Traffic using public parking, route via parking location and walking links, using guidance. This groups has the following network inflows:

$$f_3^{od}(t) = \eta_1 \cdot \theta_d \cdot f^{od}(t) \quad \forall d \in D_{in}. \tag{6.4}$$

- Class 4: Traffic using private parking, route from centroid to centroid, using guidance. This group has the following network inflows:

$$f_4^{od}(t) = \eta_2 \cdot (1 - \theta_d) \cdot f^{od}(t) \quad \forall d \in D_{in}. \tag{6.5}$$

The first two classes behave according to user equilibrium. The network inflows of these classes are input to the VI formulation and the route inflows are the output. The last two classes are guided; route inflows for these classes are calculated with the optimization model.

6.2 The discrete time model

The theoretical model describes the continuous model for DTA. The complete continuous time model is included in Appendix C. A continuous model is very difficult to solve, therefore it is necessary to translate the continuous model into a discrete time model. In the discrete time model time is split into periods of length δt, which are indexed by t. For each small interval flows and travel times are assumed to be constant. This results in the following formulation.

Network flow constraints

$$x_{arm}^{od}(t+1) = x_{arm}^{od}(t) + u_{arm}^{od}(t) \cdot \delta t - v_{arm}^{od}(t) \cdot \delta t \quad \forall a, r, m, o, d, \tag{6.6}$$

$$S_{rm}^{od}(t+1) = S_{rm}^{od}(t) + s_{rm}^{od}(t) \cdot \delta t \quad \forall r, m, o, d \neq o. \tag{6.7}$$

Flow conservation constraints
Total flow conservation at nodes:

$$\sum_a \delta_{B,a}^{n} \cdot v_{arm}^{od}(t) = \sum_a \delta_{A,a}^{n} \cdot u_{arm}^{od}(t) \quad \forall n, r, m, o, d; n \neq o, d. \tag{6.8}$$

Flow conservation per route:

$$v_{arm}^{od}(t) = u_{brm}^{od}(t) \quad \forall o, d, r, i | a = r(i), b = r(i+1). \tag{6.9}$$

Conservation at arrival:

$$\sum_{a,r} \delta_{B,a}^{d} \cdot v_{arm}^{od}(t) = s_{m}^{od}(t) \quad \forall o, d; d \neq o. \tag{6.10}$$

Flow propagation
Propagation of cars from the parking location:

$$e_p(t) = u_t(t - EPD_p/\delta t) \quad \forall p \in P. \tag{6.11}$$

Outflow-inflow relation:

$$v_{arm}^{od}(t + \tau_a(t)/\delta t) = \frac{u_{arm}^{od}(t)}{\frac{\Delta \tau_a(t)}{\Delta t \delta t} + 1} \quad \forall a, r, m, o, d. \tag{6.12}$$

For this outflow-inflow relation $\tau_a(t)$ is the average travel time over period t and this time must be expressed as a multiple integer of δt:

$$\bar{\tau}_a(t) = i \cdot \delta t \quad \text{if } (i - 0.5) \cdot \delta t \leq \tau_a(t) < (i + 0.5) \cdot \delta t. \tag{6.13}$$

To prevent large deviations the travel time must be larger than δt: $\tau_a(t) > \delta t$. In the implementation the travel time is assumed to be constant in a small time period, reducing the inflow-outflow relation to:

$$v_{arm}^{od}(t + \tau_a(t)/\delta t) = u_{arm}^{od}(t) \quad \forall a, r, m, o, d. \tag{6.14}$$

Appendix D presents in more detail the travel time estimation and the relation between link in- and outflow.

Definitional, non-negativity and boundary constraints

$$\sum_{odrm} u_{arm}^{od}(t) = u_a(t), \quad \forall a, \tag{6.15}$$

$$\sum_{odrm} v_{ar}^{odm}(t) = v_a(t), \quad \forall a, \tag{6.16}$$

$$\sum_{odrm} x_{arm}^{od}(t) = x_a(t), \quad \forall a, \tag{6.17}$$

$$x_{arm}^{od}(t), \quad u_{arm}^{od}(t), \quad v_{arm}^{od}(t), \quad s_{rm}^{od}(t), \quad S_{rm}^{od}(t) \geq 0 \quad \forall a, r, m, o, d, \tag{6.18}$$

$$S_{rm}^{od}(0), \quad x_{arm}^{od}(0) = 0 \quad \forall a, r, m, o, d. \tag{6.19}$$

Link and route costs
See Section 4.5 for the travel time formulas for signalized, non-signalized and highway links. The parking formulas are given in Section 4.4.1. Route cost (disutility) is calculated with:

$$C_r^{od}(t) = \sum_{a \in r} \tau_a(t) + \alpha \cdot \tau_w + \beta \cdot c_p \cdot EPD_p + \gamma \cdot \tau_p(t) + \kappa \cdot OCC_p(t). \tag{6.20}$$

Variational inequality
Constraints:

$$C_{rm}^{od^*}(t) - \pi_m^{od^*}(t) \geq 0 \quad \forall r, o, d, m_1, m_2, \tag{6.21}$$

$$f_{rm}^{od^*}(t)[C_{rm}^{od^*}(t) - \pi_m^{od^*}(t)] = 0 \quad \forall r, o, d, m_1, m_2, \tag{6.22}$$

$$f_r^{od^*}(t) \geq 0 \quad \forall r, o, d, m. \tag{6.23}$$

Variational inequality:

$$\sum_{t=1}^{T} \sum_{od} \sum_{m_1, m_2} \sum_{r \in R_m^{od}} C_{rm}^{od^*}(t)[f_{rm}^{od}(t) - f_{rm}^{od^*}(t)] \geq 0. \tag{6.24}$$

6.3 Traffic propagation with split-vectors

The optimization is based on assignment of routes to vehicles. However, for the traffic propagation the route assignment is translated into link-split vectors. The translation of route percentages (per OD pair) to split vectors at the end of links (per OD pair) is shown in Figure 6.1. Every link has a split vector per OD pair. The split vector for a link a has a size equal to the number of outgoing links from this link. The vector defines for each outgoing link the percentage of traffic (per OD-pair) that uses that link as next link. If the set of routes for OD pair od using link a is defined as R_a^{od} the split value for link b (coming from a) can be calculated as:

$$\gamma_{ab}^{od} = \frac{\sum_{r \in R_a^{od} \cup R_b^{od}} f_{ar}^{od}(t)}{\sum_{r \in R_a^{od}} f_{ar}^{od}(t)}. \tag{6.25}$$

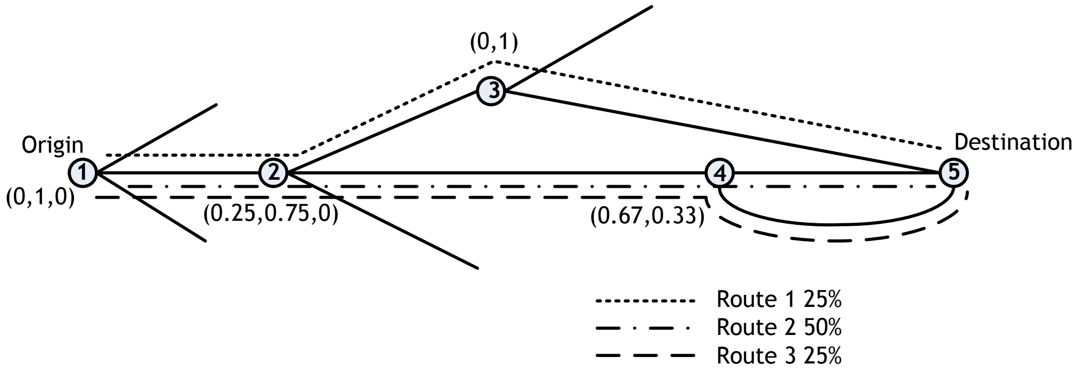


Figure 6.1: Translation of routes into link-split vectors

6.4 Calculation of route inflows

This section describes the solution of the discrete DTA problem that is derived in Section 6.2. The solution of the problem results in the route inflows, according to a user equilibrium (UE). Non-guided traffic is assumed not to adapt to the guided traffic. Therefore, this traffic behaves according to UE, as if there is no guided traffic. The non-guided route inflows can be calculated by multiplying the percentage of non-guided traffic, per OD-relation, with the equilibrium flow. The solution for the DTA is based on two important assumptions:

- Route choice is based on instantaneous route costs at the moment the road user enters the study area;
- When a route is chosen, the road user stays on this route, there is no route switching.

The discrete time DTA is formulated with a VI as follows:

$$\sum_{t=1}^{T} \sum_{od} \sum_{m_1,m_2} \sum_{r \in R_m^{od}} C_{rm}^{od^*}(t)[f_{rm}^{od}(t) - f_{rm}^{od^*}(t)] \geq 0. \tag{6.26}$$

However, since the route choice for traffic entering in a discrete time period only depends on the situation at the beginning of that period, there is no interaction between the periods (except for the propagation and conservation constraints). Therefore, for each period k the following problem can be solved:

$$\sum_{od} \sum_{m_1,m_2} \sum_{r \in R_m^{od}} C_{rmt}^{od^*}[f_{rmt}^{od} - f_{rmt}^{od^*}t] \geq 0. \tag{6.27}$$

Based on the solution for period t the route costs at the beginning of the next period $C_{rm(t+1)}^{od}$ can be found and the problem can be solved for this period. This problem per period is a static user equilibrium. The route costs are assumed to be fixed and traffic (per OD relation) is divided over the routes in such a way that every user experiences equal and minimum travel time.

For the solution of this subproblem two simple algorithms are available: the method of successive averages (MSA) and the Frank-Wolfe (or convex combination) algorithm. The following steps are the basis for both algorithms:

1. Initialize the current link costs (resulting from the previous time period) and initialize all new route inflows $f_a = 0$, set $n = 0$.
2. Compute for each OD-pair and each user group the costs of the routes in the route choice set and find the route with minimal cost for each (o, d, m)-combination, set $n = n + 1$.
3. Assign all traffic per (o, d, m)-combination to the minimum cost route to obtain a set of auxiliary route flows fa^{od}_{rmt} and compute the corresponding auxiliary link flows fa_a .
4. Calculate the current link flows as ($0 \leq \psi \leq 1$):
$$f^n_a = (1 - \psi) f^{n-1}_a + \psi f a_a. \tag{6.28}$$
5. Compare the flows f^n_a and f^{n-1}_a. If a convergence criterion is reached (small change between flows in two consecutive steps), stop. Otherwise proceed to step 2.

The MSA algorithm uses $\psi = 1/n$, this choice leads to a solution that converges to the user equilibrium (Ortúzar, 2002), however not very efficiently. The Frank-Wolfe (FW) algorithm estimates optimal values for ψ in order to speed up the convergence. The FW algorithm converges faster, however, also more cost evaluations are necessary per iteration. For the first model implementation the MSA algorithm is used. The calculation of non-guided route inflows is not part of the optimization loop and therefore the computation time is less important.

6.5 The Matlab structure

Figure 6.2 gives an overview of the implementation in Matlab. The implementation is split up into separate syntaxes (Matlab executables) for each model component. These syntaxes interact via the variables. Every small rectangular box in the figure represents a syntax. 'Model complete' can be run to execute all syntaxes at once. This syntax runs the programs with numbers 1 to 10. First the input data (link data, node data and od data) is loaded and second the model is initiated. The model initiation is split into 6 syntaxes that initiate one of the components (parameters, network, etcetera). With the third syntax a loop starts that repeats for every large time period, in which the demand changes. The first step in this loop (syntax 3) is adaptation of the signal settings (for signalized intersections) to the actual network situation. The second step in the loop (syntax 4) is the creation of route choice sets.

Next the medium time loop is entered which is ran several times during every large time step. If a route database is available, the creation of route choice sets can also be performed every medium time step. In the medium loop first the route inflows of non-guided traffic, according to UE, are calculated and expressed into split vectors (5 and 6). These inflows (and split vectors) are combined with the inflows of guided traffic (syntax 7) and together form the input for the dynamic traffic assignment (DTA). The DTA consists of the third loop, of small time periods, which runs several times every medium time period.

For every small time period three syntaxes are repeated: computation of link occupancies, computation of link costs (and travel times) and the traffic propagation (computation of link in- and outflows). In syntax 9 the network performance for the medium time period (according to the objective) is calculated.

The last component within the medium time period loop is the optimization algorithm, which determines the guided route inflows. This optimization algorithm introduces a fourth loop into the model. For every solution that the algorithm examines, the syntaxes 7 to 9 have to be executed (including the small time period loop of DTA). Since the number of possible solutions is very large the optimization algorithm needs to examine a large number of solutions. Therefore, this loop is run many times during every medium time period. To be able to perform the optimization it is very important that the syntaxes 7, 9 and especially 8 (the small period loop) are fast.

The Matlab structure as presented in Figure 6.2 is based on the assumption that non-guided traffic does not adapt to guided traffic during a medium time period (several minutes). Therefore, the route inflows and split vectors of non-guided traffic are not part of the optimization loop. If non-guided traffic adapts to guided traffic these syntaxes have to be taken into the optimization loop and have to be computed once for every solution.

The structure can be used to study different time periods. For the morning peak and the Saturday an empty network is the starting point. This is reasonable since early in the morning the network will be almost empty. For the afternoon peak, the end of the morning peak (10:00) can be used as starting situation or a static UE assignment of the average demand in the first hour of the afternoon peak.

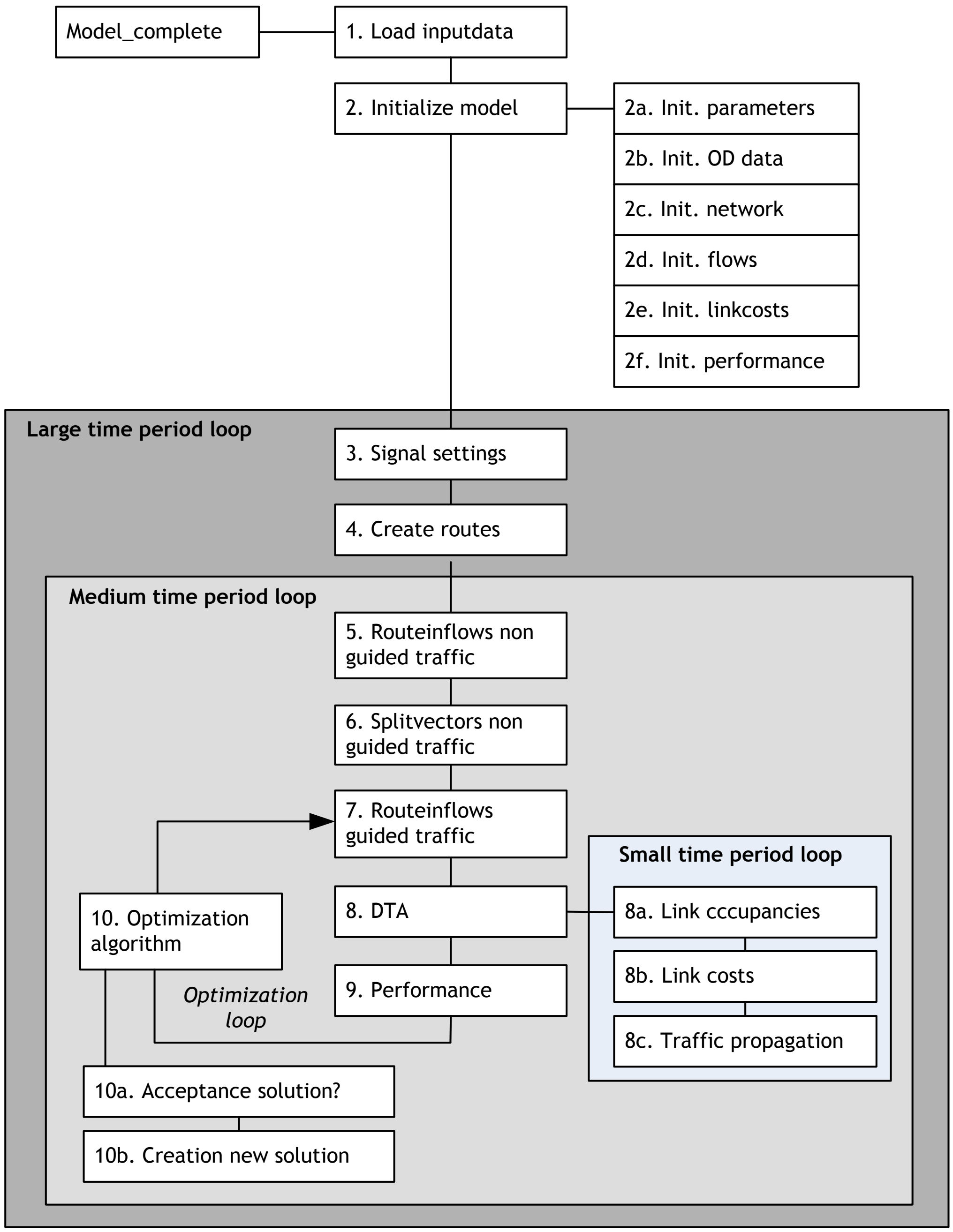


Figure 6.2: Structure of the model implementation in Matlab

Part III

Model testing

Chapter 7

Model verification and calibration

Before applying the model, it is verified and calibrated. Section 7.1 introduces the verification and calibration and gives an outline for the chapter.

7.1 Introduction

Section 7.1.1 introduces the concepts of verification, calibration and validation. Section 7.1.2 explains how the verification and calibration are applied to the guidance model. Section 7.1.3 presents the outline for the remaining part of the chapter.

7.1.1 Definition of verification, calibration and validation

Verification is described as 'the act of reviewing, inspecting and testing of a system, to establish that the system meets the specification requirements' (Wikipedia, 2008). In short, verification of a model can be described as checking if the model works as it is intended to do.

Calibration refers to the process of determining the relation between the output of a measuring instrument and the value of the input, compared to a measurement standard. Calibration often includes the process of adjusting parameters to find the output that agrees with the value of the applied standard. For a traffic model this corresponds to comparing the output to measurements or other model results and adapting the parameters to fit the measurements/results.

Usually, the verification and calibration of a model are followed by the validation. In the validation the calibrated model is tested on one or more cases, which are not used in the calibration. The validation is used to confirm that the model consistently delivers good results, independent of the case.

7.1.2 Verification and calibration in this research

In this study the amount of available data is limited. The verification and calibration are adjusted to this data availability. Validation is not possible since only one data set is available, which is used in the calibration. The city of Rotterdam, The Netherlands, is used as case study. The study area and input data are described in Section 8.1. Measurements of traffic flows are not available, therefore an existing traffic simulation model is used in the verification and calibration: the RBV (regional Dutch traffic simulation model) for the region of Rotterdam.

Traffic assignments (link loads) of the RBV are available for every 15 minutes in the morning and evening peak and every hour on Saturday and Sunday. The RBV does not include parking or guidance and is therefore only used to calibrate the basis of the guidance model. Due to the limited data availability and the large computational requirements of the guidance model, it is not possible to perform a complete calibration. Therefore, the verification and calibration are mainly used to test and improve the functioning of the model and the plausibility of the results. Several model parameters are estimated in the calibration, others are chosen based on literature. The RBV focuses on the regional roads, instead of the urban roads. Since the accuracy for the urban roads is insecure, an extended calibration, leading to results that fit the RBV completely, is not performed. The model is calibrated to find reasonable results and an overall fit to the RBV. A thorough calibration and validation are necessary in follow-up research.

With the verification the functioning of the model is studied. Every component is tested and the results are compared to expectations. This is done both during model development, as well as with tests described in this chapter. During the verification the components that do not function correctly or suboptimal are adapted. The verification is split into three parts: verification of the basic traffic assignment (without guidance), verification of the parking component and verification of the guidance component.

Also the calibration is split into three parts. The most extensive calibration is performed for the basic traffic model. The assignment (without parking and guidance) is compared to the assignment in the RBV. Parameters and settings of the guidance model are adjusted to fit the output to the RBV results. Calibration of the parking component is very limited, since almost no data is available. For the guidance component the calibration is used to choose the parameters of the optimization algorithm. However, since the model is computational demanding only a first rough calibration is possible.

7.1.3 Outline of the chapter

Section 7.2 describes the verification of the traffic assignment model (without parking and guidance). In this section the functioning of the flow assignment, the route generation, the route choice and the traffic propagation are tested and improved. Section 7.3 presents the calibration of the traffic assignment. Section 7.4 discusses the verification and calibration of the parking component. Section 7.5 presents the verification of the guidance component and Section 7.6 describes the calibration of this component. The Rotterdam network, which is used in the case study, is used in the verification and calibration as well. Chapter 8 gives a description of the network.

7.2 Verification of the traffic assignment

The verification of the traffic model is split into tests related to the link flows, the route generation, the route choice and the traffic propagation. For the tests an assignment to the Rotterdam network is used, without parking and guidance. The traffic behaves according to a user equilibrium and travels from centroid to centroid.

7.2.1 Verification of the link flows

The link flows are studied in four model runs. In each run adaptations are made in the model description to verify and improve the link flow calculation. In the runs a dynamic assignment for the morning peak is performed, without parking and guidance. For each link, the average flow per period of 15 minutes is calculated. The requirements for the link flows are:

- Non-negative flows: flows should always be positive.
- No large flow fluctuations between consecutive periods of 15 minutes: the model should not predict large fluctuations in average link inflows between consecutive periods.

The non-negativity is checked throughout the model development and the tests. The model guarantees positive flows. The flow fluctuations are verified by plotting the average flow (per large time period) per link. For each link type several representative links of the Rotterdam network are used. The results of the four runs are depicted, per link type, in the figures in Appendix E. The flows are given for periods in the morning peak, ranging from 6:00-6:15 (period 1) to 9:45-10:00 (period 16). The model adaptations and results per run are described in this section.

Run 1: No model adaptations
The results for this run are given in the first figure for each link type in Appendix E. These figures show that there are large fluctuations in the average link inflows, between consecutive periods. These fluctuations are not realistic. There are two main causes for the flow fluctuations, related to the route choice and route generation components.

The route choice is based on the route and link costs in one preceding small time period. However, the link costs and the in- and outflows can fluctuate considerably, due to the fixed travel time assumption (explanation in Appendix D). Per small period, travel time is fixed and the inflow of one period is assigned to one outflow period. If the travel time changes between periods this results in fluctuation in the in- and outflows. In reality the fluctuation is smoothened, because the travel time changes gradually over the periods. Since the route inflows for a complete medium time period are determined based on one small time period, the route inflows fluctuate.

The route generation is performed at the start of every large time period, resulting in two to five routes per OD pair. If the number of generated routes is small it can happen, for example, that in period 1 two generated routes are completely overloaded, in period 2 the same happens for two other routes and in period 3 the two first routes are used again. This leads to large flow fluctuations. Furthermore, the route generation is based on the route costs in the preceding small time period, which can fluctuate heavily, as explained in the preceding paragraph.

Run 2: Use of average link costs and a larger route choice set
In the second run two adaptations in the model formulation are introduced, to reduce unrealistic flow fluctuations. The first adaptation is the use of average link costs in the route choice, traffic propagation and route generation component. The link costs are averaged over a set of preceding small periods. With this adaptation the fluctuations, due to the fixed travel time assumption, are compensated. This leads to more realistic route choice and generation.

The second adaptation is the use of a route database. A database is created, with all routes that are generated in previous simulations. At the start of every time period, for each route the cost is computed. The five least cost routes, per OD pair, are used as route choice set. With this adaptation, there are always five routes for every OD pair. Furthermore, the use of a route database reduces the computational time, since route generation can be performed off line.

The results of model runs 1 and 2 can be compared with the figures in Appendix E. The comparison shows that the flow fluctuations are largely reduced, especially for the highway links. The routes in the choice set do fluctuate less, due to the larger choice set and the use of average costs. In an additional test the number of routes per OD-pair is increased to 10. This increase does not significantly change the flow assignment. This implies that for most OD relations the model can be restricted to the five least cost routes, since only these routes are used.

Run 3: More frequent route set calculation
In the first and second run the route choice set is calculated every 15 minutes. However, during 15 minutes the network situation can change considerably. This can lead to large differences in the route choice sets of consecutive periods and therefore, also to flow fluctuations. In the third run the route choice set is calculated every medium period. More frequent adaptation of the route choice set can reduce the changes in the set per period. The results of this run show a reduction in flow fluctuation.

Run 4: Actuated cycle and green times
With the improvements in the second and third run the flow fluctuations on the highway and non-signalized links are reduced to an acceptable level. The fluctuations on the signalized links are still large. The model uses fixed signal settings (green and cycle times) at these links, however, in practice these are often adapted to the actual demand. If cycle and green times are adapted to the actual flow, there is better flow through at intersections, resulting in less flow fluctuations. Therefore, in the third run adaptive signal settings are introduced.

The modeling of adaptive signal settings is explained in Section 4.5.5. The results are depicted in the fourth figure for each of the link classes in Appendix E. The route costs vary less over consecutive time periods if the signal settings are adapted to the actual situation. This results in less route change over the periods and less flow fluctuations. Still, there is a considerable amount of fluctuation at the signalized links, however, also in practice the flow on these links fluctuates most. Furthermore, detailed information on road user behavior is necessary to be able to explain the fluctuations further.

7.2.2 Verification of the route generation

In the route generation, those routes have to be found, that are most likely to be used. To verify the functioning of this component, the generation is studied for two OD-relations. In a first model run the routes generated during an hour (four large time periods) are saved. In a second run the cost of a crucial link is increased. The routes of both runs are visualized to check if the route generation adapts correctly to the changing link costs.

The results are shown in Figure 7.1. The first OD relation runs from origin 30 to destination 3. There is one main route for this OD relation, using the highway. The route generation is as expected, since this route is most logical and far faster than other possible routes. In the second run for one of the highway links the travel time is increased heavily. Figure 7.1 shows that different routes are generated, which avoid the use of this link. The route over the highway is still a possibility, but it is not the main route anymore. The second OD relation runs from origin 51 to destination 41. Again, there is one main route with several important alternatives. The main route uses the shortest path. For one of the links on this path (and the centroid connectors surrounding this link) the cost is increased. Again a set of alternatives is generated. The test with these two OD relations, together with checks for other OD relations, shows that the route generation algorithm functions correctly.

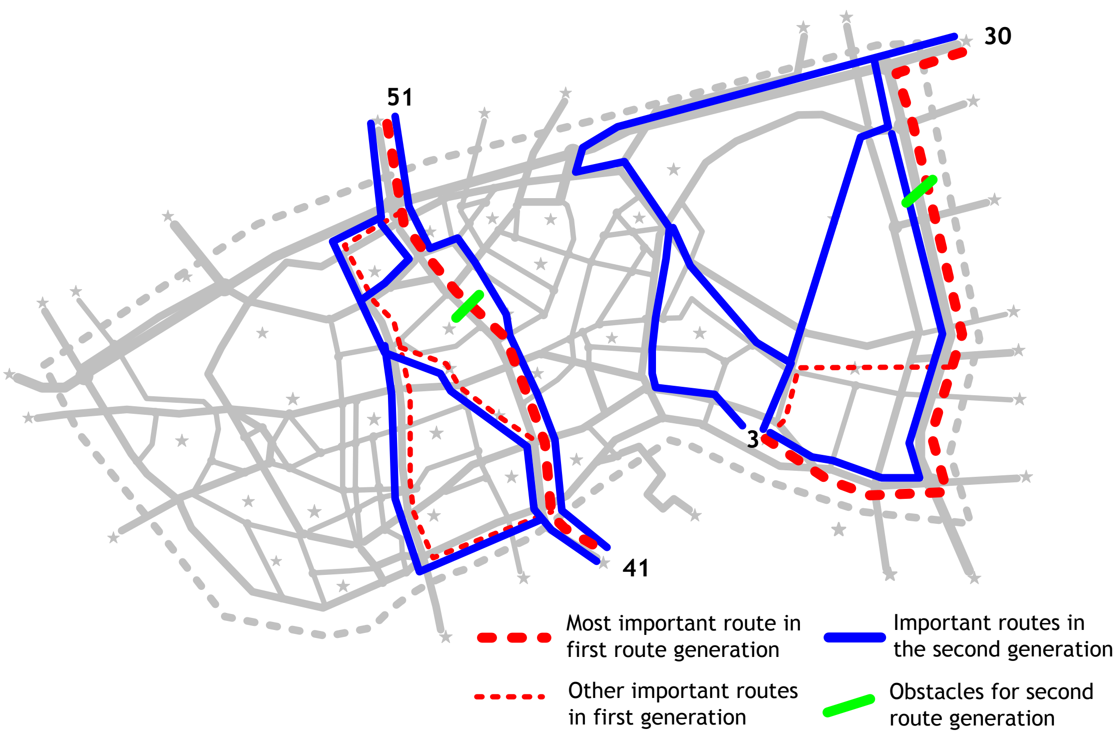


Figure 7.1: Verification of the route generation for two OD relations

7.2.3 Verification of the route choice

The route inflows are estimated with a successive averaging algorithm. This algorithm results in an assignment according to a user equilibrium: the costs of the routes in use are equal and minimal (Section 3.1.5). At the start of every medium period the route inflows are calculated. In the test the route inflows and route costs are checked to examine the functioning of the algorithm.

A part of the output:

```
od =  3021
routecost =
    5.6998    6.1974    5.9328    6.0545    7.1171
routeinflows =
    0.0077         0    0.0000         0         0

od =  3024
routecost =
   13.3836   13.8812   16.9744   13.6166   17.4719
routeinflows =
  1.0e-003 *
    0.3128         0         0    0.0015         0
```

This example presents the output for two OD relations: the OD number, a vector with route costs for five routes and a vector with inflows for the same routes. The flow is assigned to the routes with the least costs. The costs of the routes in use are not exactly equal, but the difference is small and most flow is assigned to the minimum cost route. The difference depends on the convergence criterion. If the criterion is very strict, the differences approach zero, but the computation time increases. Therefore, small differences in route costs are allowed. The results for other OD relations are in line with the results shown above. The results show that the route choice algorithm functions correctly.

7.2.4 Verification of the traffic propagation

Concerning the traffic propagation, there are many aspects to test. In basic tests travel times, flows and occupancies are checked. These have to be non-negative and within certain limits. Furthermore, three aspects are studied: flow conservation, the relation between flows/occupancies and travel times and the link occupancy.

Flow conservation
The flow has to be propagated through the network without loss. All traffic that entered the network, should at every time instance either have arrived at the destination or still be in the network. In a test run the arrivals, vehicles in the network and vehicles that entered the network are counted, in every time step. The sum of the first two, must equal the third number at every time instance. This is the case in the implementation, therefore flow conservation is guaranteed.

The relation between flows/occupancies and travel times
If the flow/occupancy at a link increases, in general travel time increases too. It is tested if the guidance model predicts this relation correctly. Figures of the tests are included in Appendix F. Figure F.1 shows the relation between occupancies and travel time on two representative highway links. The travel times increase with occupancy, as expected. Furthermore, in the first graph the travel time stabilizes for very high occupancies. This is a result of the travel time formulation, in which a fixed low speed is assumed for densities around the jam density.

Figure F.2 presents the relation between flows and travel times on two representative non-signalized links. The travel time increases with the flow. The discontinuities in the graph are caused by rounding off of travel times. For the signalized links, the relation between flows and travel times is less obvious. The link travel time depends on the signal settings and on the inflow of previous periods. For these links the travel times are checked on non-negativity and erratic samples. The tests show that the travel time calculation functions correctly.

Link occupancies
The link occupancy is expressed as the number of vehicles at a link. In reality a maximum number of vehicles fits in a link. If the link is full, traffic is spilled back to preceding links. This phenomenon is not accounted for in the macroscopic, analytic formulation for traffic propagation. However, it is studied if the guidance model predicts realistic link occupancies. In a test run the link occupancies are compared to the maximum link occupancy. For approximately 30 links (of in total 897) the model computes unrealistically high occupancies. Several of the high occupancies are a result of errors in the link data. For these links the data is adapted. Other high occupancies can be found on the links entering and exiting the network. These links are included with a small link length and the demand input concentrates on these links. Furthermore, high occupancies are found on highway entrances and exits. These are short links, which are modeled as normal non-signalized links. However, the capacity of these links is larger than of other non-signalized links. In follow-up research a separate travel time function for this link type can be introduced.

The remaining part of the high occupancies is caused by the simple traffic propagation formulation, that does not account for spill back. In the calibration (Section 7.3.2) several model settings are changed to improve the model performance. These changes also reduce the number of links with unrealistic occupancies. In the calibrated model there is still a small number of links for which the occupancy is too high. However, this has a limited impact on the complete model and can not be prevented in a macroscopic formulation. The topic of spill back is further discussed in Chapter 9.

7.3 Calibration of the traffic assignment

This section describes the calibration of the dynamic traffic assignment model, without parking and guidance. This DTA model is the basis for the guidance model. The traffic assignment is compared to output of the RBV for the Rotterdam case study area. For a complete model calibration a large amount of data (and time) is necessary. Within this study, the main purpose is to test the model and not to give exact predictions for the case study. Therefore, the calibration is limited to several main aspects. The purpose of the calibration is to choose the settings, with which the model results are closest to the traffic process in practice. Section 7.3.1 presents the comparison of the first model results to the RBV traffic assignment. Section 7.3.2 discusses the calibration of several model components, to fit the guidance model results to those of the RBV. Finally, in Section 7.3.3 the calibrated model is compared to the RBV.

7.3.1 First comparison of the assignments

The results of the comparison, between the guidance model assignment and the RBV assignment, are presented in the figures in Appendix G. For periods 1 (6:00-6:15), 8 (7:45-8:00) and 15 (9:30-9:45) the flow assignment of the guidance model and of the RBV model are given, as well as the link speeds. The results of the guidance model are presented in Manifold (GIS environment), those of the RBV in Omnitrans (traffic simulation environment). The RBV figures show the flows and speeds for each direction on a different side of the link. It is not possible to do the same in Manifold. The flows of two directions are printed on top of each other, resulting in an invisible flow for one direction. The flow tables are used in the comparison to check these flows.

In general, the guidance model gives a plausible assignment, with the largest flows on the most logical routes. Overall the two assignments show large similarities. However, there are also several dissimilarities. These differences are studied in the calibration. The RBV is a calibrated model, but the model is developed to study the regional network and not an urban network. Therefore, the assignment within the urban area, might be less accurate. Furthermore, it is not exactly known how the RBV model is calibrated and which assumptions are used (for example on actual guidance and road works). However, the RBV gives a general idea of the actual traffic situation and is the best comparison available. There are four main differences between the two assignments and the two speed patterns.

Larger inflows
There are larger in- and outflows to the network in the guidance model, than in the RBV; especially to and from the centroids 35, 43, 51 and 54. These flows are direct input from the OD matrix and therefore, the difference is not caused by the functioning of the model. There are two possible causes for this difference. Either, the RBV model underestimates the inflow to the network at these points, or the OD matrix for the study area is not estimated correctly. The estimation of the study area OD matrices is described in Section 8.2.2. The matrices are calculated with a static AON assignment. Such an assignment overestimates, in general, the flow on the shorter routes through an urban area, in comparison to the highway routes around such an area. Therefore, it is probable that the difference in the inflows is caused by the OD matrix estimation. In the calibration, the OD matrix is adapted.

More use of city routes
The guidance model predicts a larger use of several city routes, than the RBV model. Especially for the route from zone 50 to the south (the second main north-south connection, seen from the east of the study area) and for the east-west route from zone 31 to zone 45 (through the middle of the study area). There are several possible causes:

- The travel times for the highways are overestimated and/or those for the urban roads are underestimated, resulting in more road users choosing routes through the urban area;
- The routes through the urban area have larger flows, due to the larger inflows of the guidance model (compared to the RBV);
- The RBV underestimates the use of routes through the urban area, since the model is calibrated for the regional network.

The influence of the first two aspects is studied in the calibration by adaptation of the link cost formulation for highways, by calibration of signal settings and by adaption of the OD matrix (see also previous paragraph).

Different queue formation on highway links
In period 1 the guidance model and RBV show the same speeds and same flow pattern for the highway links. In later periods the flows and speeds differ, especially around 'Kleinpolderplein', the highway intersection connected to zone 50. There are two main causes:

- The guidance model uses a simple formulation to estimate the highway speeds, which does not fully account for the interaction between consecutive links. Therefore, the formation and spill back of queues is not correct. In the calibration the interaction between the highway links is adapted.
- The capacities around 'Kleinpolderplein' are not estimated correctly in the preparation of the link data. These capacities are changed in the calibration.

Lower speeds (on highway links)
The guidance model predicts lower speeds on the highway links than the RBV model. This difference is strongly connected to the three aspects, which are discussed above. In the calibration the highway formulation and the inflows are adapted to improve the speed prediction.

7.3.2 Model calibration

In the calibration changes in the main model settings and parameters are studied to improve the model results. Not all parameters are studied, since not enough accurate data is available for a detailed calibration. The calibration is used to remove illogicalities and errors from the model and to fit the results to expectations. However, the calibration is not used to manipulate the results to exactly fit the RBV results, since these are also only model results.

Section 7.3.1 describes the main discrepancies between the results of the basic traffic model, developed in this study, and the results of the RBV. The calibration focuses on these discrepancies and the main model settings. Six components are studied: the study periods, the length of time steps, the route generation frequency, the OD input, the highway formulation and the signal settings. This section describes the choices and changes made for these components.

Study periods
Data is available for three study periods: the morning peak, the evening peak and the Saturday. The morning and evening peak are best suited to calibrate the basic traffic model in congested situations. The morning peak period is used for this purpose; the model can start with an empty network in this period, where the evening peak needs a calibrated start situation. On Saturdays, the amount of public parking is maximal, therefore, the parking model can best be studied and calibrated with this period. The parking calibration is further discussed in Section 7.5.

Length of time steps
During the model development the length of the time steps is varied. The following time steps are used in the final model implementation:

- Small time step: 20 seconds. The smallest time step should not be larger than the minimum free flow link travel time. This is necessary to be able to give a correct representation of the traffic propagation. On the other hand the time step should be as large as possible to speed up the computation. In the free flow situation there is a couple of links with a travel time smaller than 20 seconds. However, this is only the case in an almost empty network. The travel time for these links is rounded up to 20 seconds, to be able to propagate the traffic. This leads to a small increase in travel time, however, this has little influence on the total traffic process. On average the link travel times are considerably larger than 20 seconds.
- Medium time step: 5 minutes. This time step determines the frequency of computation of the guidance settings. More frequent computation is not desirable due to the large computational requirements. Furthermore, if the guidance is updated more frequent, the changing recommendations could confuse the road user. The time step is not larger, to be able to give real dynamic guidance and to react to the actual network situation.
- Large time step: 15 minutes. The OD demand is given per 15 minutes, therefore, the large time step is fixed at this length.

Route generation frequency
The route generation frequency is discussed in Section 7.2.1. During the verification and model improvement the frequency of route generation is changed from once per large period to once per medium period. If the route generation is performed once per large period, there are large changes in the route choice set from one period to the next. This leads to non realistic fluctuations in the traffic streams. Therefore, the route generation is fixed at once per medium period. It is not desirable to perform the route generation more frequent, since this increases the computational requirements.

OD input
The first model validation shows that the demand from and to the zones 35, 43, 51 and 54 is strongly overestimated (about 200%). This demand is reduced during calibration to fit the RBV results. The reduction is realized by multiplying the OD-demand from and to the four zones by 0.5.

Highway formulation
The formulation for highway speeds is adapted to create a more realistic description of the flows on these links. The following components are calibrated:

- The jam density formulation: Section 4.5.4 explains the formula that is used to compute the jam density for the highway links. During calibration the use of higher jam densities is studied. This results in unrealistically high flows on the highway links. Therefore, the original jam density formulation is used in the calibrated model.

- Density computation: the density is based on the link occupancy in one small time period. To prevent large fluctuations, the density in the calibrated model is computed based on the occupancies in four small time periods.

- Speed: the speed on the highway links depends heavily on the speed of proceeding sections. If the next section is jammed, the speed on the current section drops too. This dependency is introduced in the calibrated model, by computing the speed on a highway link as an average of the speed on the link itself (based on the density) and the proceeding section(s). Several formulations are tested during calibration.

Signal settings
The signal settings are computed every large time period. The parameters are tested in several calibration runs. The following values are used in the calibrated model:

- The maximum cycle: 180 seconds;

- The minimum cycle: 40 seconds;

- The minimum green per direction: 5 seconds;

- The maximum share of the cycle for one direction: 80%;

- The parameters used in the computation of total effective green time and total cycle time: these parameters are explained in Appendix B. The green factors 1 to 3 are fixed at 1.1, 1.3 and 1.5. The cycle factors 1 to 3 are fixed at 0.9, 0.8 and 0.7.

7.3.3 Comparison of the calibrated assignments

Appendix H presents the comparison of the calibrated assignment to the RBV results. The comparison, in relation to the results before calibration, leads to the following conclusions:

- The differences between highway flows and speeds of both models are reduced. The queue formation is still not completely correct in the guidance model. However, the differences are acceptable, especially since the model focuses on the urban area.

- There are less illogical flows and speeds than before calibration, several errors are removed from the link data.

- The inflows of the calibrated model correspond better to the inflows of the RBV than before calibration. However, still for several origins and destinations the in- and outflow is larger. It is decided not to adapt the OD matrix further, since this does not change the model functioning.

- The city routes in the calibrated model are still used more than the city routes in the RBV results. This is caused, for a large part, by the high inflows to the study area. Furthermore, it is possible that the RBV underestimates the use of city routes.

Overall there are large similarities between flows and speeds of the RBV assignment and the calibrated model results. Since the RBV focuses on regional roads and not on the urban roads, it is decided not to calibrate further. It is not known if the assignment of the RBV for the urban area is more accurate than the assignment of the calibrated model. The verification and limited calibration have resulted in a basic traffic model that gives logical results and functions as it is supposed to do. Further calibration is not necessary for the purposes of this research and not possible with the data available.

7.4 Verification and calibration of the parking component

In the parking verification the logical functioning of the parking model is studied. The parking model is verified without guidance, to test the basic functioning. There are two main aspects that are tested in this verification:

- The logical assignment of parkings to road users in relation to destination, walking time and parking charge. This part is verified by studying the parkings assigned to the road users per destination. The tests show that the parking assignment is logical.
- The occupancy of parkings. Parkings should not be occupied for more than 100%. Therefore, during verification the parking disutility is increased heavily if the parking is almost full. This is necessary to prevent the model simulating more than 100% occupancy.

Calibration of the parking model is difficult, since very limited data is available. For three parkings occupancy data for Saturdays and Thursdays is available. The Saturday is used in the calibration and model occupancies, without guidance, are compared to this data. Furthermore, the occupancies and locations are compared to logical expectations. The parking model is calibrated in two aspects: the vector θ with the percentage of public parking per destination and the utility parameters α, β, γ and κ.

Several calibration runs are performed to find the settings that result in a realistic parking process for the Saturday. It is not possible to find occupancies that have a good match with the few data available. To be able to model a realistic parking behavior the parameters and the average parking duration have to be varied per location and per time period. However, no data is available to calibrate these parameters. Therefore, fixed values are chosen for the case study. This means that the parking behavior can not be modeled realistically. Due to this limitation the case study focuses on route guidance. The parking component is only used in a few parts of the case study. The differences between parking with and without guidance are studied.
The calibration results in the following parameter values:

- α is 3 (walking time is valued 3 times as heavy as driving time), β is 1 (1 Euro parking charge is valued the same as 1 minute extra driving time, this means that the charge is of little importance in the parking choice), γ is 1 (queuing and searching at the parking location is valued equal to driving time) and κ is 5 (the occupancy of the parking location is valued heavily).
- The value of κ is multiplied by 50, if the parking location becomes occupied heavily, to prevent extra cars if the location is almost full. This is necessary since the model does not

support switching to another location if the current location is full at arrival. If the guidance is updated frequently, the guided traffic is automatically guided away from full locations, however, if guidance is updated less often it can happen that traffic is guided to a full location.

- The percentage of public parking (for the Saturday) is fixed at 3% for zones 26, 27 and 29, at 20% for zones 7, 10-14, 20, 22 and 23, at 50% for zone 19, at 70% for zones 9 and 17, at 90% for zones 8 and 18, at 95% for zone 15 and at 100% for zone 16.
- The average parking duration is fixed at two hours for all locations.

The values chosen for α and γ correspond to values used in other studies (Axhausen, Polak, 1991; Bifulco, 1993), where the walking time is valued two or three times as heavy as driving time. The searching and queuing time is, in most studies, valued approximately equal to driving time. The values for β and κ can not be compared easily to other studies. The value of time (β) differs per location and travel motive and changes over the years. The occupancy (κ) is excluded in most parking choice studies.

Figure 7.2 shows the resulting average occupancies of the parking locations on a Saturday between 14:00 and 15:00, without guidance. The occupancies are within a logical range. However, 'Schouwburgplein' is too empty in comparison to the available data.

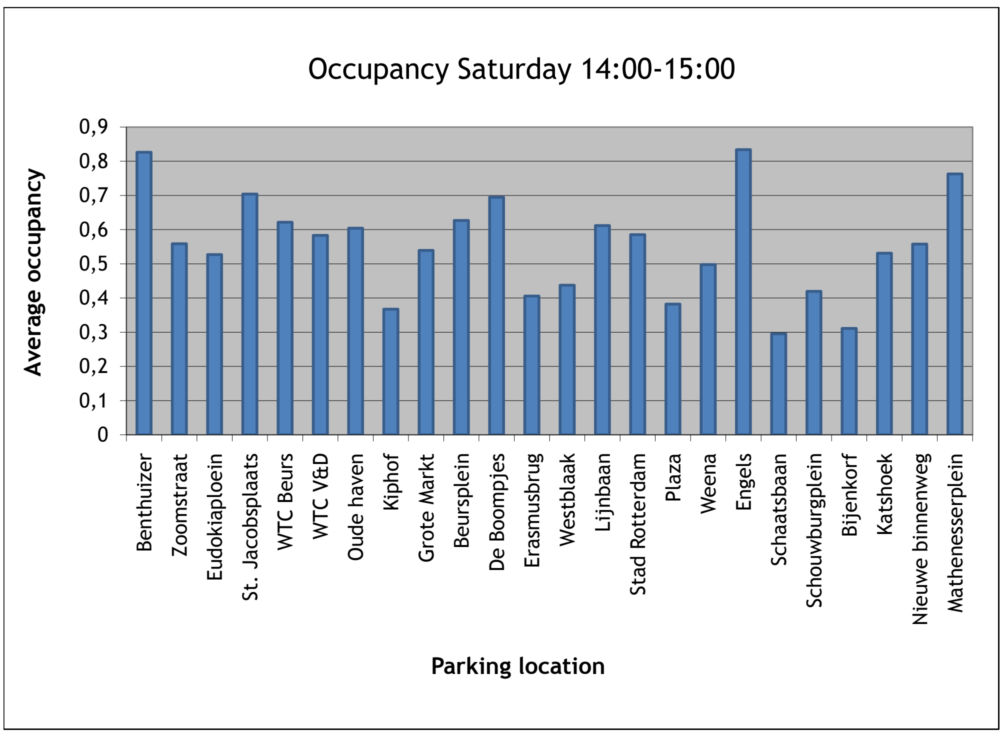


Figure 7.2: Average occupancies of parking locations on the Saturday afternoon, predicted by the model without guidance

7.5 Verification of the guidance component

The verification checks the logical functioning of the guidance. The three main aspects in this verification are the result of different objective functions, comparison between guidance and no guidance and the route assignment.

Results with different objective functions
Test runs are performed with different objectives. The results show that lower values are found for the aspect that is minimized in a run, compared to the values for that aspect with another objective. Table 7.1 shows results for the minimum weighted average travel time found with the guidance model, for four periods from 7:00 to 7:20 in the morning peak. Runs are performed with three objectives: minimization of weighted average link travel time, minimization of average IC ratio per link and minimization of the number of links with a high IC ratio. Minimization of the weighted average link travel times results in smaller travel times than runs with other objectives, except for one result in the period that start at 7:10. Table 7.2 shows similar results for minimization of the average IC ratio.

Start of time period	Minimization avg tt	Minimization IC avg	Minimization IC large
7:00	1.8222	1.9254	1.9089
7:05	1.8328	2.0975	2.1709
7:10	2.1401	1.9924	2.4376
7:15	2.1395	2.1875	2.3251

Table 7.1: Comparison minimum average travel times with different optimization objectives

Start of time period	Minimization IC avg	Minimization tt avg	Minimization IC large
7:00	0.23425	0.25719	0.27009
7:05	0.24016	0.26947	0.26346
7:10	0.2582	0.28845	0.26388
7:15	0.27405	0.30542	0.29621

Table 7.2: Comparison minimum average IC ratios with different optimization objectives

Comparison guidance, no guidance
A second important aspect in the verification is the result of guidance. Figure 7.3 shows the average weighted link travel times with a UE and those with guidance, based on minimization of the travel times, and a compliance percentage of 50%. For the medium periods 1 to 15 (06:00 to 07:15 am) 50 iterations of the optimization algorithm are used and for the periods 16 to 20 (07:15 to 07:40 am) 200 iterations. With this small number of iterations the link travel times with guidance are on average 2% below those with a UE. For several medium periods the figure shows a considerable improvement. For other periods the guidance does not improve the situation. This is the result of the small number of iterations. If the algorithm starts with a bad solution, there is a large chance that no better solution is found. Similar improvements for the average IC ratio are presented in Figure 7.4 and Figure 7.5. The relatively small improvements are caused by the limited number of iterations in the optimization algorithm. Furthermore, only a small part of the traffic can be guided: the traffic from zones outside the study area to zones in the area.

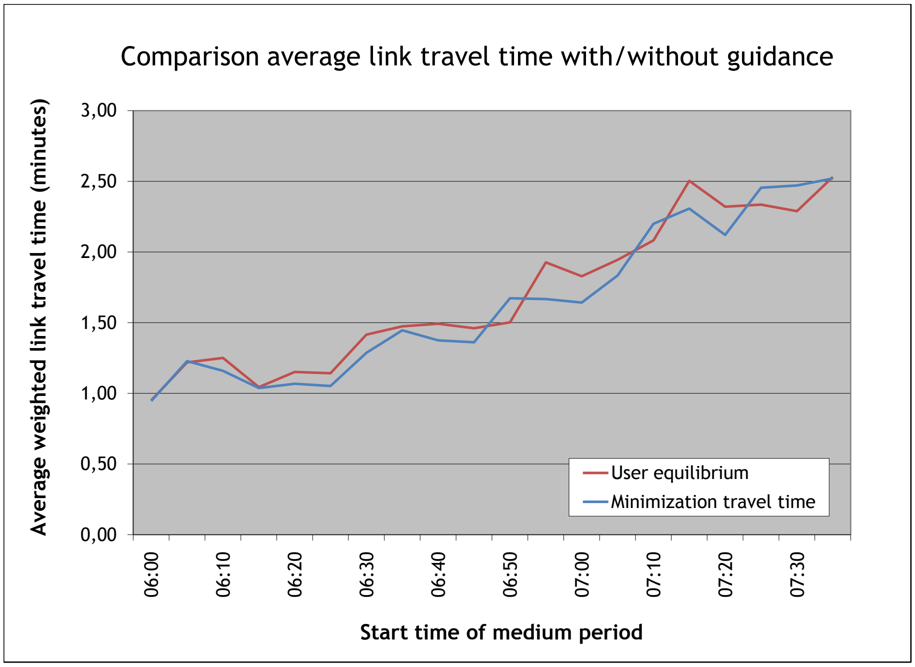


Figure 7.3: Comparison of travel times in a UE without guidance and with guidance based on minimization of the weighted average link travel time

Verification of route assignment

The route assignment is studied in two manners: with the route split matrices and with the assignments of guided and non-guided traffic. The split matrices show a change over time. For the first periods almost all guided traffic is assigned to the shortest routes (first generated). In later periods the traffic is more and more assigned to other routes, with larger detours. This is a logical pattern. During the first periods the network is almost empty and assigning guided traffic to the shortest routes is optimal. In later periods the shortest routes get congested. To reduce average travel times and IC ratios the guided traffic is assigned to other routes, to spread the traffic over the network. The detour of the assigned routes is studied in the scenario analysis (Section 8.3).

Appendix I shows the assignments of guided and non-guided traffic, from 7:45 to 8:00 in the morning, with minimization of the average IC ratio per link. Two interesting aspects are highlighted in the assignments. The first aspect (number 1 in the figures) shows two links that are heavily overloaded by non-guided traffic. The amount of guided traffic on these links is limited. With this assignment the guidance reduces the total congestion. The second aspect (number 2 in the figures) shows two parallel north-south routes, with several east-west connections. The guided traffic is assigned in a different manner than the non-guided traffic, to reduce average IC ratios. Overall, it is not easy to see the differences in route assignment, since the figures present the aggregated assignment. However, the study of split matrices and the assignments together show a logical functioning of the route assignment.

7.6 Calibration of the guidance component

Calibration of the guidance component with measurements or other model results is not possible, since these are not available. Therefore, the calibration is used to select parameter values for the SA algorithm, which result in optimal functioning, within the computational limitations. Due to the implementation in Matlab it is not possible to use a large number of iterations in the optimization. Only a very small number of iterations can be used, compared to what is desirable. Therefore, thorough calibration of the parameters is difficult.

This section results in first estimations of the parameters and presents the methods for the calibration. However, for further application of the model the calibration should be performed again with a largely extended optimization. Six aspects are studied in the calibration: start and end temperatures, the number of iterations of the SA algorithm, the split factor, the number of temperature levels in the cooling scheme, the generation of neighbor solutions and the selection of start solutions.

Start and end temperature
In a SA algorithm the start temperature should be chosen such that almost every new solution is accepted. Therefore, the start temperature is close to the maximum difference between objective values of two solutions. The end temperature should be such that only improvements are accepted. Therefore, the end temperature is smaller than the minimum difference between objective values. For each of the objectives, for the periods in the first two hours of the morning peak, 100-200 iterations of the SA algorithm are run. The objective values of these runs are recorded and the minimum and maximum differences are calculated. The results and the chosen start and end temperatures are listed in Table 7.3. The start temperature for the travel time minimization is chosen considerably lower than the maximum difference between objectives. Except for the maximum difference, all other differences are smaller than this start temperature. The start and end temperature for the weighted IC ratio (per vehicle leaving a link) are chosen equal the temperature for the average link IC ratio.

	Max. diff.	Min. diff.	Start temp.	End temp.
Average weighted travel time (min)	0.6249	0.00444	0.3	0.004
Average IC ratio per link	0.0443	0.000788	0.04	0.0005
Difference parking occupancies	0.07585	0.00346	0.1	0.003

Table 7.3: Calibration results for start and end temperatures SA

Number of iterations of SA algorithm
Tests are run with 100, 200 and 500 iterations per medium time period. Compared to the UE assignment, without guidance, the runs with only 100 iterations do not perform well. For many periods the UE assignment results in lower average travel times and IC ratios, than the values found for these aspects with optimization. This result is caused by the very small number of iterations. If the algorithm starts in a bad solution, there is a large chance that within 100 iterations no good solution is found. Furthermore, the algorithm easily gets stuck in a local minimum due to the decreasing temperature after a small number of iterations.

With 200 or 500 iterations per medium time period the optimization results in improvement in comparison to the UE values (see Figure 7.3). The runs with 500 iterations give, on average, better results than those with 200 iterations, however, the difference is small. It is not possible to perform extended test runs with more than 200 iterations per period. With more iterations a complete run for the morning peak lasts longer than a week on the available computers.

For runs with 200 or 500 iterations the same problem exists as for 100 iterations. The number is very small and the algorithm can easily get stuck in a local minimum, or it does not reach a good solution within the limited number of iterations. To find good results with a larger probability, thousands of iterations are necessary. Often 10.000 to 100.000 iterations are used in simulated annealing algorithms. The small difference between the runs with 200 and 500 iterations is caused by the fact that both numbers are very small compared to what is necessary. Within 200 iterations, on average 5-10 improvements are found in the solution. This number is too small to come close to an optimal solution.

The choice is made to use 200 iterations per period. With this number the results show improvement, compared to no guidance. However, also with this number of iterations the optimization lasts for more than a week for a morning peak period of four hours. Therefore, only 50 iterations are used for the first 5 quarters (6:00 to 7:15) and the period is shortened till three hours (6:00 to 9:00). With these settings the computation time is shortened to 4 or 5 days.

To find good guidance settings, for every guidance period, 200 iterations is not enough. It is possible to find rather good settings for some periods with this number, but probably much more improvement can be reached with a larger number of iterations. Since extended optimization is not possible in this calibration and in the case study, the results only give an indication of the effect of the guidance. Furthermore, due to the small number of iterations, there is large variation in the results. For one period a quite good solution can be found and for the next a very bad solution. The same holds for runs with different values for the parameters. A large part of the difference is caused by the variation in the results. Therefore, it is difficult to conclude on the effect of changes in parameters.

In follow up research the optimization has to be extended to at least 10.000 iterations per guidance period. Furthermore, restarts of the algorithm and the use of a solution database can be introduced to improve the functioning.

The size of the split factor

The guidance model is tested with a split over at maximum 2 routes and 4 routes, per OD-pair and per period. It is expected that a split factor of 4 will enable better results, since this factor increases the possibilities for spreading the traffic over the network. However, due to the small number of iterations in the optimization it is not possible to conclude on the best size of the split factor. It is chosen to use a split factor 2 in the case study, to reduce the size of the solution space for this first implementation.

Number of temperature levels in cooling scheme
Three temperature level settings are tested: 5 levels, 10 levels and 20 levels (with a total of 200 iterations). The results are depicted in Figure 7.4. The figure presents the average IC ratio per medium period in the situation without guidance (UE) and with guidance optimization and 5, 10 and 20 temperature levels. The use of various numbers of temperature levels does not result in large differences. Each of the numbers performs best for several medium periods. The small differences are probably caused by the limited number of iterations, as explained in the preceding part of this section. The variation in the results is larger, than the difference caused by the parameter value. In the case study 20 temperature levels (of 10 iterations each) are used.

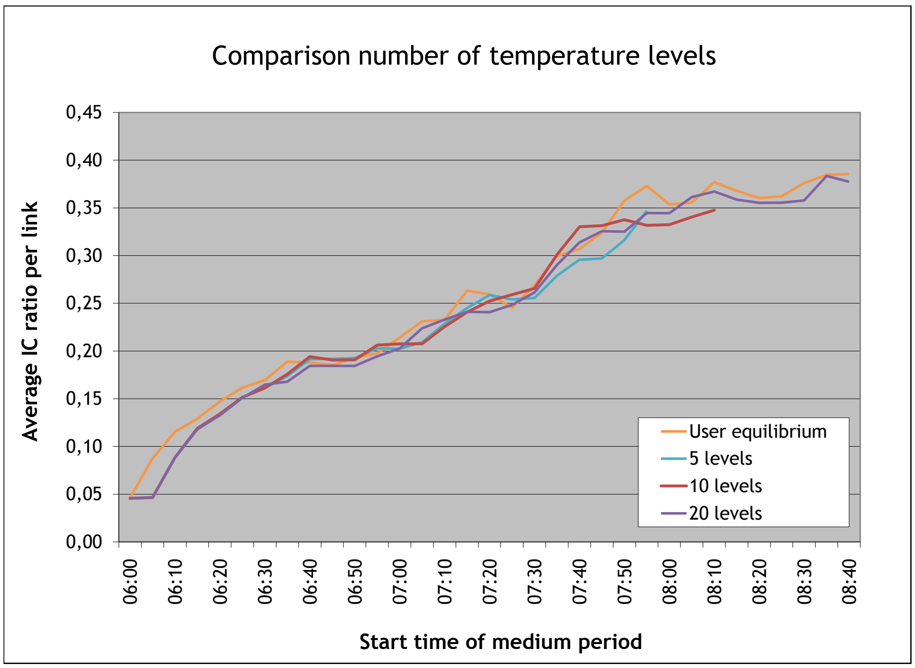


Figure 7.4: Minimization of the average IC ratio per link, with different numbers of temperature levels in the SA algorithm

Generation of neighbor solutions
Three options for the neighbor generation are studied: replacement of 10% of the current solution, 25% and 35%. The results are shown in Figure 7.5. The figure presents the average IC ratio per medium period in the situation without guidance (UE) and with guidance optimization and 10%, 25% and 35% change of the solution per iteration. The differences between the runs are again small. However, overall the run with 10% change per iteration performs slightly better, than the other runs. Therefore, in the case study 10% change is used to generate a neighbor solution from the current solution.

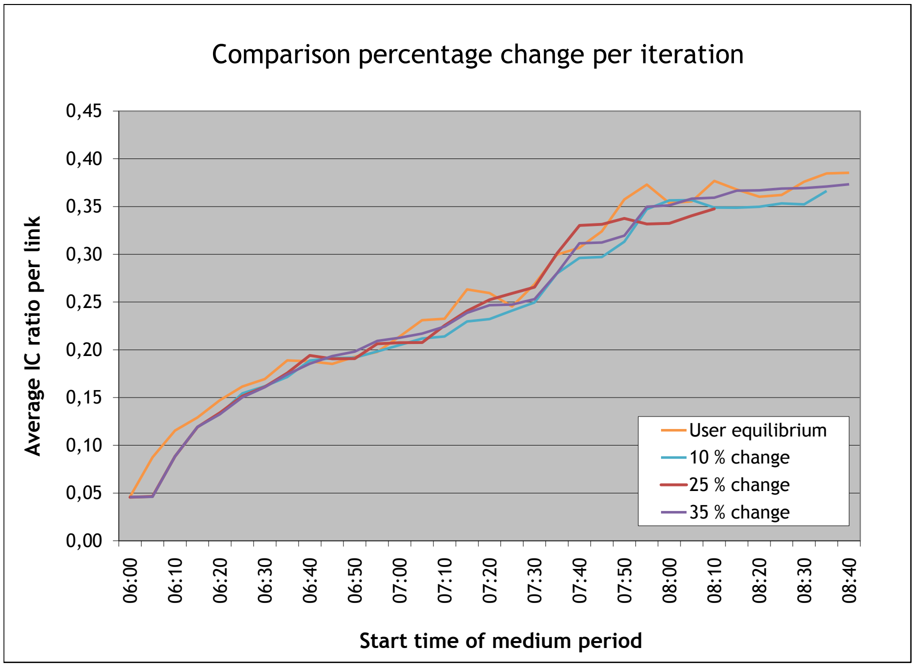


Figure 7.5: Minimization of the average IC ratio per link, with different percentages of change from the current solution to a neighbor solution

Selection of start solutions

Two options for the start solution are tested: the best solution of the preceding period and a random solution. It is expected that the solution of the preceding period is the best start, since the changes in the traffic situation, between consecutive periods, are small. The tests do not show a clear difference between the start solution options. Due to the small number of iterations, for many periods the algorithm does not find a good solution. Therefore, the use of this solution as start for the next period is not better than the use of a random solution. Although, there is no clear difference, the solution of the previous period, is implemented as start solution. It is expected that this option gives the best results, when the optimization is extended.

Chapter 8

Case study

The Dutch city of Rotterdam is used as a case study to test the guidance model. Section 8.1 introduces the study area. In Section 8.2 the input data is described and the data preparation is explained. Section 8.3 introduces the scenarios that are studied. The results of the analysis are given in Section 8.4. The chapter concludes on the model results in Section 8.5.

8.1 Case description

Rotterdam is the second largest city of the Netherlands, with 584046 inhabitants (Wikipedia, January 2008). The city is located, on the coast, in the south-west of the country. Rotterdam has the third largest harbor in the world. The central part of the city is used in this case study. The study area is bordered by the national highways A20 and A16 and the river Maas. The study area is translated into a network of zones, links and nodes for application of the model. The city and the translated study area (with the zone numbers) are shown in Figure 8.1. The study area is delineated with a black line in the top figure and presented as graph in the bottom figure.

8.2 Data input

Section 8.2.1 lists the data sources that are used in the case study. Section 8.2.2 describes the preparation of the data as input to the model.

8.2.1 Data sources

The data for the case study is provided by Witteveen+Bos and by the municipality of Rotterdam. The following data sources are used:

- The Rotterdam network: the network nodes, links and traffic signals are described in text files (from the RBV traffic model). A network representation is given in the traffic simulation model Omnitrans.
- OD matrices: matrices (for the complete city) are available for the morning peak (6:00 till 10:00), afternoon peak (15:00-19:00), a Saturday and Sunday (00:00-24:00) and for the night. The matrices are disaggregated per 15 minutes for the peak periods and per hour for the complete days. The matrices of the morning peak and the Saturday are used. The matrices are given in text files.
- Parking facilities: information on the parking facilities is provided by the municipality of Rotterdam, for a large part at the website of the city (February, 2008). The parking facilities are characterized by location, capacity and charges.

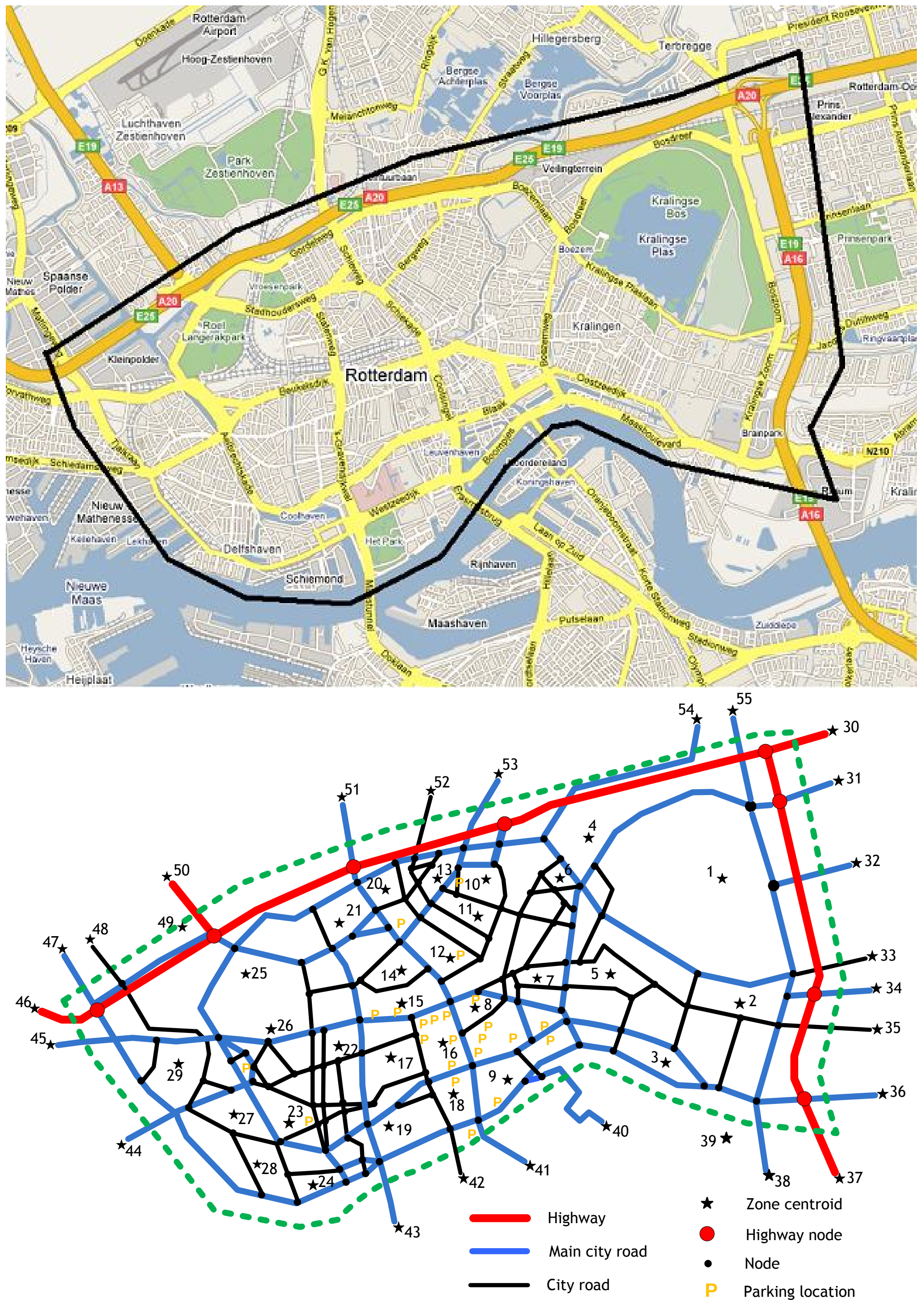


Figure 8.1: The case study area in the city of Rotterdam

The study area is extracted from the Omnitrans network. The encoding of the links and nodes in this network differs from the encoding in the text files with characteristics. Therefore, the links are selected in the Omnitrans network, converted to the RBV encoding and matched with their characteristics.

8.2.2 Data preparation

Four steps are used in the data preparation: selection and conversion of the encoding of network elements, calculation of the OD matrices for the study area, introduction of connectors, parking and walking links and visualization in a GIS environment.

Selection and conversion of encoding of the network
The links and nodes of the study area are selected in the Omnitrans network with a cordon. Each of the objects is matched to the corresponding object in the RBV encoding. The objects are listed in a link table and a node table. To simplify the network, links not ending at an intersection are merged with subsequent links. The signal settings, for signalized links, are added by matching the signal code with the signal data. Finally, all data is checked and links connecting the study area to the boundary zones are added.

Calculation of the OD matrices
The available OD matrices include all zones in the Rotterdam city area. However, for the case study a matrix is needed that specifies the OD relations between the zones within the study area and the entrance and exit points. The cordon matrix function of Omnitrans is used to create the necessary matrices. First a cordon is drawn in the network. Next, a short script is written, with which an assignment is performed. The relations that use the study area are selected and assigned to the available zones within the study area and to newly created zones at the boundary of the cordon.

Introduction of connectors, walking and parking links
The connectors, walking and parking links are not available in the Omnitrans network. These are added manually to the data. Each zone centroid is connected to several close by intersections. The parking exits are included as nodes and parking links are introduced to connect these nodes to the network. Extra nodes are introduced, where the parking links connect to the network. Finally, walking links from every parking location to the surrounding zone centroids are added. Only those walking links, with a reasonable length, are introduced.

Visualization in a GIS environment
For visualization of case study results, the network is imported in a GIS environment (Manifold). The coordinates (Dutch system) of the nodes are available in the input data. In the node table the nodes are listed with their coordinates and this table is introduced into Manifold as a drawing. Also the link table is imported in Manifold and the links are visualized by matching the tail and head node with corresponding coordinates. The link drawing uses a table with link attributes, that can be changed easily. With colors and bandwidths the link attributes are visualized. In Figure 8.2 the GIS representation of the Rotterdam network is given. The two links for a road section with two directions are printed on top of each other. In the figure several links are blue with a black line. These road sections end at a signalized intersection on one side and a non-signalized intersection on the other side.

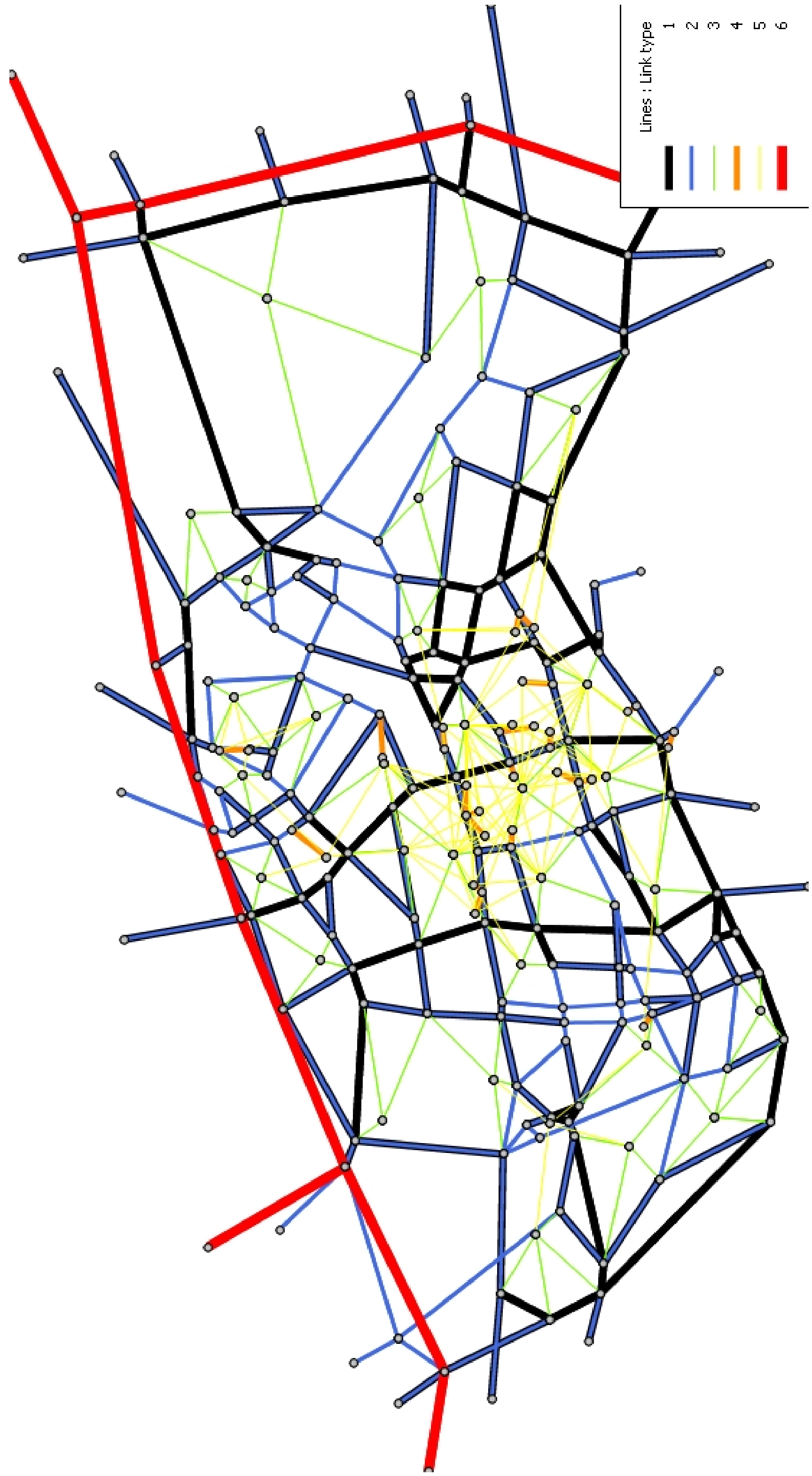


Figure 8.2: Representation of the network in a GIS environment. Link types: 1 signalized link, 2 non-signalized link, 3 connector, 4 parking link, 5 walking link, 6 highway link.

8.3 The scenario analysis

The scenario analysis is used to study the possibilities of the guidance model. Due to the limited optimization the case study can not be used to conclude on the possible improvements that can be reached with guidance. However, the case study introduces the opportunities with the guidance model and gives an indication of the effects of guidance. Section 8.3.1 introduces the possible model applications. Section 8.3.2 describes the scenarios, which are studied.

8.3.1 Possible model applications

The opportunities of the guidance model are large. A future application is the online generation of guidance. However, for analysis the model can already be applied to various types of problems. The analysis applications are categorized into the following groups:

- Application as dynamic traffic model: the basis for the guidance model is a simple dynamic traffic assignment model. This model is verified and calibrated and gives good results (see Section 7.2). The model can be used for every problem related to dynamic traffic assignment and includes parking. Examples are studying the effect of network or city expansion, adjustments in the parking stock or the effect of traffic management measures. The advantage of the guidance model is that it is completely stand alone. The model is developed in Matlab, however, can be translated to a stand alone executable.
- Effects of guidance: the model can be used to study the effect of guidance on the performance of the traffic process. The performance can be studied in relation to several objectives and in various situations. For example, the effect of guidance with light, medium or heavy traffic or the situation with a large peak in the demand for one specific location.
- Effects of stakeholder objectives and constraints: the model can be used to calculate the optimal guidance settings from the viewpoint of the stakeholders. If this is done for one stakeholder, the effects for the other stakeholders can be studied. Furthermore, the effect of constraints can be analyzed in the same manner.
- Effects of user behavior, related to guidance: in this category the impact of user compliance is the main aspect. The compliance is a parameter in the model and is expected to determine for a large part the effect of the guidance. Furthermore, the impact of the percentage public and private parking is a possible study aspect.
- Effects of user behavior, related to utility: the model can be used to study the influence of the valuation of aspects in the utility function. An example is to study the effect of more or less reluctance to walk on the parking behavior.
- Influence of model parameters: the model uses many parameters both in the traffic assignment and in the optimization model. The effects of changes in these parameters can be studied. This is mainly an aspect of verification and calibration.

The list shows that there are many possibilities for scenario analysis. The next section describes the analyses that are performed within this study.

8.3.2 Description of the scenarios

The guidance model is applied to five sets of scenarios. For each of the sets choices are made for the study period and objective. It is not possible to study different periods and different objectives for every scenario set, due to the large computational requirements. In most runs the minimization of the average IC ratio per link is used as objective, since it is expected that this air quality objective results in the largest changes in the traffic process, compared to the user equilibrium. Furthermore, in most runs parking is excluded, because of the very limited calibration of the parking component.

The scenarios are chosen to give an overview of the possibilities of the guidance model and to test the functioning in several fields. The results are presented in Section 8.4. The remaining part of this section gives a description of each of the scenario sets.

Guidance optimization per stakeholder
Section 4.6.1 describes the main objective for each of the stakeholders. In each scenario the guidance is optimized for one of the stakeholders. The following runs are used:

1. Morning peak without guidance: this run results in the UE, the objective of the road user. The resulting network situation, without guidance, is not a real UE, since the users choose their route when entering the network. If the route costs change during the trip, the road user does not switch routes. Therefore, in addition to the UE without guidance, three runs are performed where users are guided toward the UE at that moment.

2. Morning peak with minimization of the average weighted link travel time: this run corresponds to the objective of the local government. The average weighted link travel time, is the average link travel time, weighted by the number of users that use each link.

3. Morning peak with minimization of the average IC ratio: this run corresponds to the objective of air quality. In addition to the minimization of the average IC ratio per link, also the weighted IC ratio, per user leaving a link, is minimized.

4. Saturday without guidance and including parking: this run results in the UE including parking, the basic situation without guidance.

5. Saturday with minimization of the difference in occupancies of the parking locations: this run corresponds to the objective of the parking holders.

In the first three (sets of) runs public parking is not included, since not enough data is available to calibrate parking in the morning peak. The results of these three runs are compared to study the effect of the road user, local government and air quality objectives. The last two runs are for the Saturday with parking. These runs are compared to study the influence of the parking objective. The number of runs for the Saturday is limited, due to the very large computation time.

Detour constraints
The detour constraints are studied in combination with two objectives: minimization of average weighted link travel time and minimization of average IC ratio per link. The runs are performed for the morning peak (6:00-9:00), without public parking. For both objectives scenarios are studied

with maximum detours of 1.1, 1.25, 1.5, 2 and 5 times the shortest route. By using a maximum detour factor the solution space is reduced. On one hand this can result in a larger probability to find good solutions, on the other hand good solutions might not be feasible, due to detour limitations. With this scenario set the influence of the detour factor is studied.

Compliance percentages
The compliance is varied from no compliance (UE) to 100% compliance for the guided relations. The following compliance percentages are used: 10%, 25%, 50%, 75%, 90% and 100%. The effect of guidance is studied in relation to the compliance percentage.

Demand variation
The total OD demand is varied from light to heavy demand, to simulate situations varying from a very quiet morning peak to a very busy peak period. This analysis uses scenarios with 50%, 75%, 100%, 125% and 150% of the OD matrix as input. For each of the demands a run with guidance (minimization average IC ratio per link) and a run without guidance (UE) is performed. The effect of guidance is studied in relation to the demand. Furthermore, the average detours for guided traffic are studied with variable demand.

Large event
A large demand peak, for one location, during a short time interval is simulated. The differences between guidance and no guidance for this situation are studied. The demand for the central shopping area (zone 16) is increased 20 times for the (departure) period from 7:30-8:00. Public parking is included in the analysis and two objectives are studied: minimization of average IC ratio per link and minimization of parking occupancy difference.

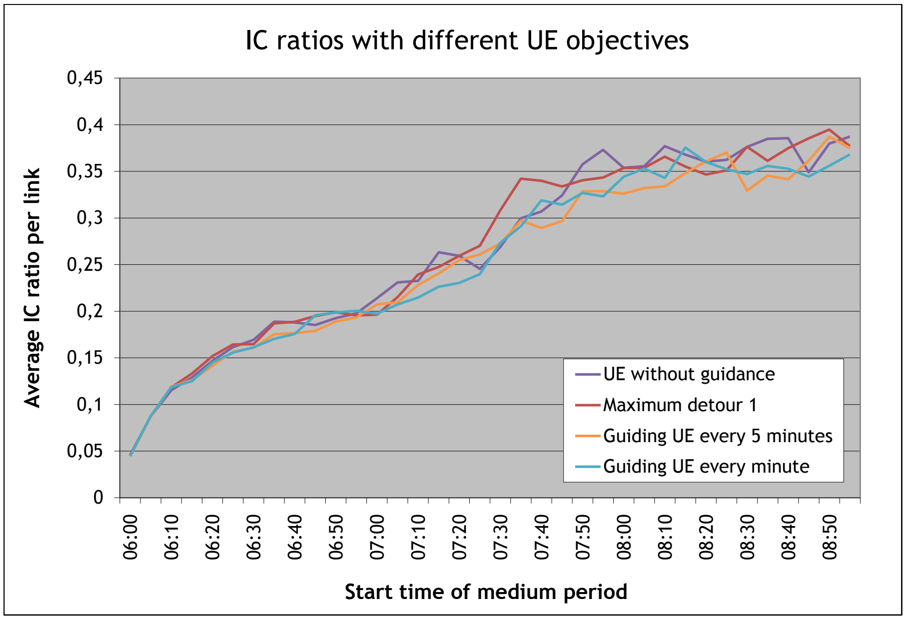
8.4 Results of the scenario analysis

8.4.1 Optimization per stakeholder

In this scenario, guidance is optimized for each stakeholder in a separate run. First the optimization objectives for the road user and for air quality are discussed. Next, the results of optimization for the local government, air quality and the parking holders are presented and compared.

Road user and air quality objectives

The road user objective
The objective of the road user is minimization of personal disutility, resulting in a UE. However, the UE without guidance is not a true UE. The road users choose their route, when entering the network. If the network situation changes during their trip, they do not switch routes, since they are not aware of the changing situation. Therefore, the real UE is not reached. With guidance the road users can be redirected toward the UE. This road user objective is implemented in two manners in the guidance model: redirection to the UE and guidance to the shortest route. Four runs are performed to compare the different implementations of the road user objective: UE without guidance, UE with guidance per 5 minutes, UE with guidance per minute and guidance to the shortest routes per 5 minutes (max detour 1). The results of these runs are presented in Figure 8.3.



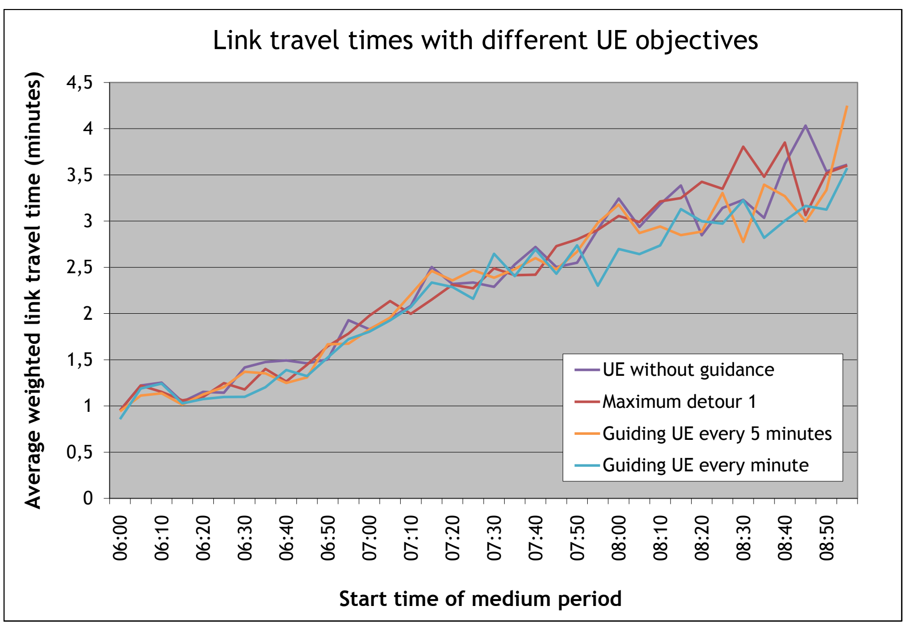


Figure 8.3: Comparison of average IC ratios per link and average weighted link travel times, with four road user objectives

The top part of Figure 8.3 shows the comparison of the average weighted link travel times for the four runs. The bottom part shows this comparison for the average IC ratios per link. The differences between the four objectives are small. However, overall the redirection to UE results in the lowest travel times and IC ratios. Especially, if the redirection is performed frequently the traffic situation is optimized. Guidance to the shortest route results in higher travel times and IC ratios, since all guided traffic is directed to one route during a guidance period. This results in high loads and congestion on several routes. This is what happens if all road users use an individual navigation system, which recommends the shortest route. The UE without redirection has the same problem. If the network situation changes, the road users in the network do not adapt, therefore the users travel by suboptimal routes. This can result in congestion and increasing link travel times and IC ratios.

This analysis shows the advantage of a central guidance system, which accounts for traffic dynamics, compared to individual navigation systems. Both for the road user, as well as for the other stakeholders, the situation improves if the road user is redirected toward UE instead of to the shortest route. In the remaining part of the scenario analysis the UE without guidance is used in every comparison. This equilibrium represents the basic situation without guidance.

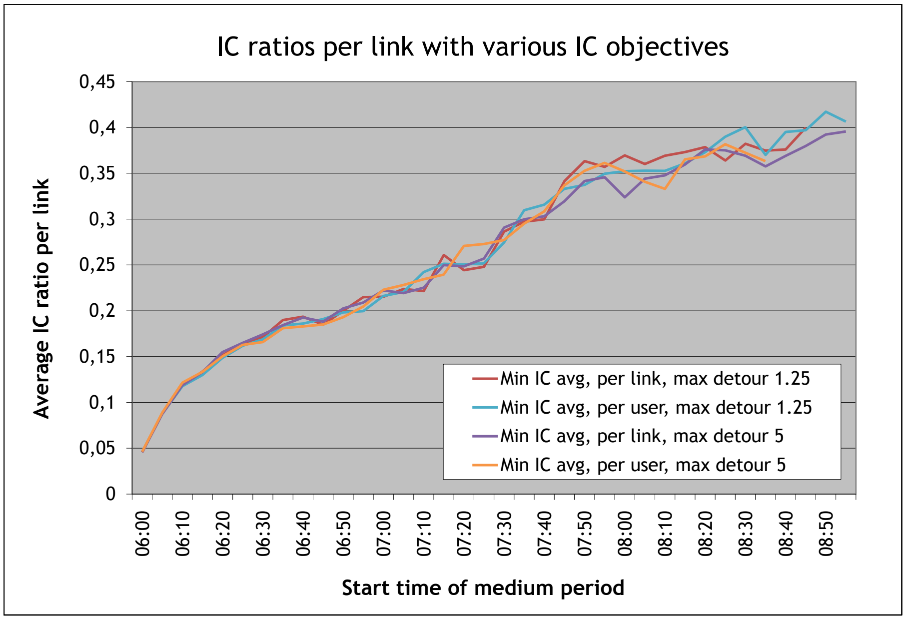
The air quality objective

The air quality interests are implemented with two objectives in the guidance model: minimization of the average IC ratio per link and minimization of the average IC ratio per user leaving a link. It is expected that minimization of the ratio per link results in the lowest ratios per link and that minimization per user results in the lowest ratios per user. However, since both objectives are closely related the differences between the optimization results will be small.

Results of test runs with the two objectives are presented in Figure 8.4. The figures show a large difference between the average IC ratio per user (on average 0.7) and per link (on average 0.3). This is a logical result. If the IC ratio is weighted per user leaving a link, the links with high IC ratios are weighted heavy. Furthermore, the figures show little difference in the two measures with the different objectives. The results seem to support the expectation, that minimization of one of the two measures also gives the best results for this measure. However, the differences are too small to conclude. Extended optimization is necessary to study this aspect.

The (bottom) figure for the average IC ratio per user shows the largest differences. With minimization of the ratio per link, the ratio per user fluctuates heavily. The minimization per user results in smoother results. This can be caused by the fact that heavy loaded links are only accounted for once with minimization per link. Therefore, several high link IC ratios do not influence the average ratio per link a lot, however, these can lead to a large increase in the average ratio per user.

In the remaining part of the scenario analysis the average IC ratio per link is used in the tests; for further applications both objectives are implemented in the model.



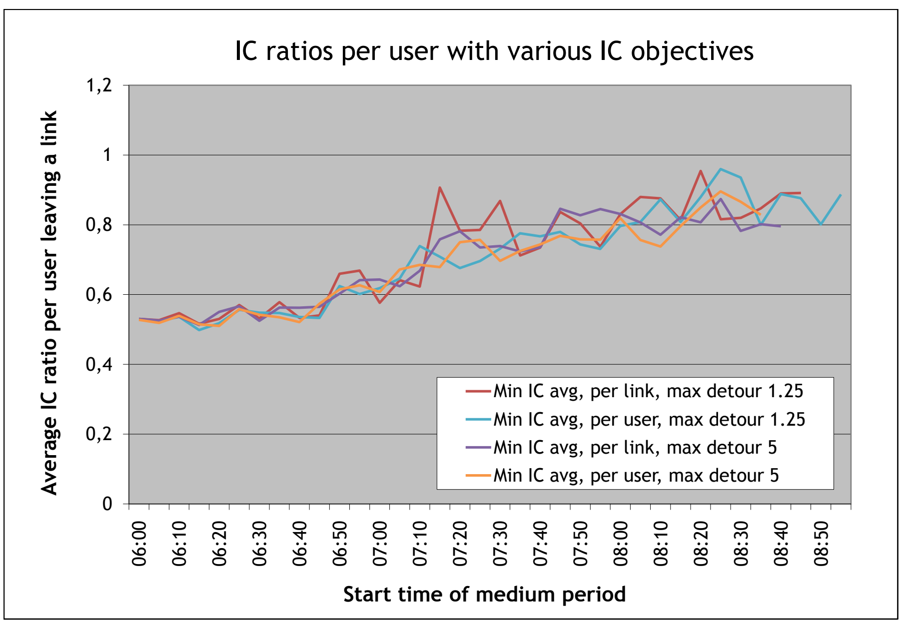


Figure 8.4: Comparison of results with minimization of the average IC ratio per link and minimization of the average IC ratio weighted per road user leaving a link

Comparison optimization per stakeholder

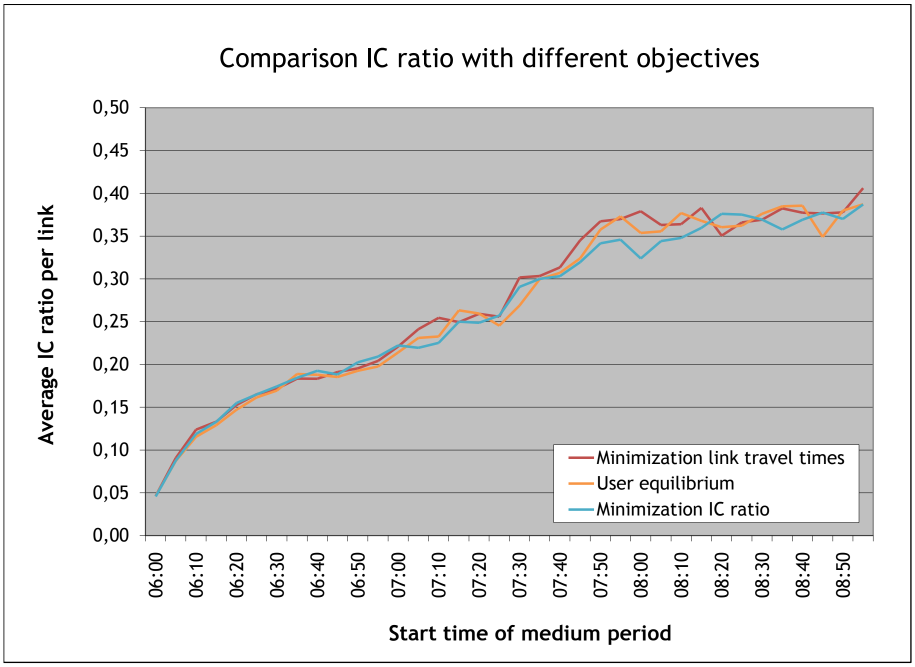
Travel times and IC ratios with different objectives
The average weighted link travel times and the average IC ratios per link are compared in three runs with different objectives: the UE without guidance, minimization of the average IC ratio per link and minimization of the average weighted link travel time. The results are depicted in Figure 8.5. Minimization of the IC ratio or travel times results in a reduction in these measures, compared to the UE. However, the average reduction is small. For several medium periods large improvements are found, for other periods the guidance does not results in a reduction in the objective value.

The variable results are mainly caused by the very small number of optimization iterations. With 200 iterations the probability to find the good solutions out of a set of more than 15^{700} is limited. If a bad starting solution is used, the chance to find a good solution is small. This can influence the results for several consecutive periods. Furthermore, the algorithm can easily end in a local optimum, since the temperature is lowered fast with a small number of iterations.

The fact that the guidance does result in improvements, with the limitations described above, indicates that larger improvements are possible. With a more extended optimization, it is expected that the size of the improvements found for several periods in these results, is (at least) possible for all periods. That means that improvements of 10% or more (in link travel times or IC ratios) are within reach. However, extended optimization and calibration are necessary to conclude on the improvements.

There is no large difference between minimization of link travel times (per vehicle) or IC ratios (per link). Both objectives result in travel times and IC ratios in the same range. This is a logical result since there is a strong connection between IC ratio per link and average weighted link travel times. The difference is that with minimization of travel times it might be optimal to load several short links heavily, instead of using longer links. When minimizing the average IC ratio, traffic is spread equally over links, and longer routes are assigned. Due to the limited number of iterations in the optimization, the difference between the two objectives is small.

Detours with different objectives
Figure 8.6 shows the detours for the guided traffic, with minimization of the average weighted link travel time and minimization of the average link IC ratio as objectives. The detour is expressed as a multiple of the length of the shortest route at the start of the guidance period. A part of the non-guided traffic will use this shortest route, resulting in an increase of the travel time on this route. Therefore, the actual experienced detour can be smaller than the detours in Figure 8.6. However, the difference is not large, since the route travel times are updated every five minutes. The average detour, per guided user, is around 20% for both objectives. In Section 8.4.2 the effect of detour constraints is discussed.



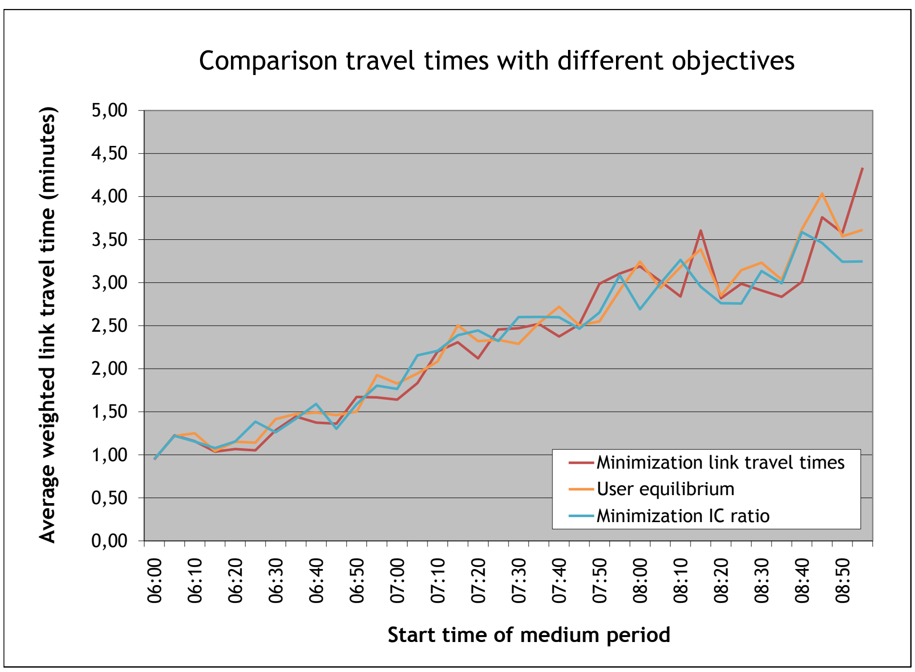


Figure 8.5: Comparison of the average IC ratio per link and the average weighted link travel times, with different guidance objectives

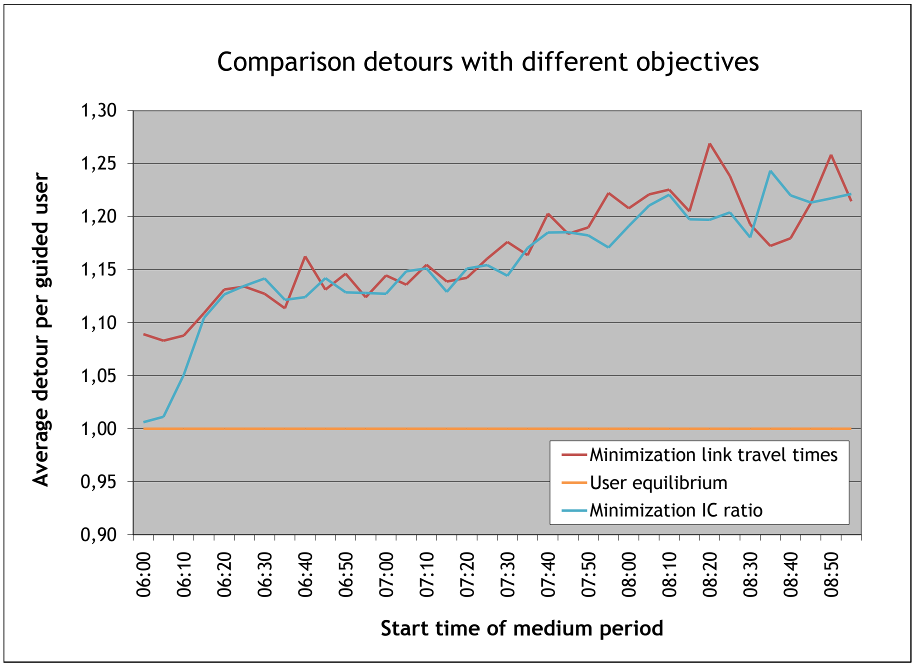
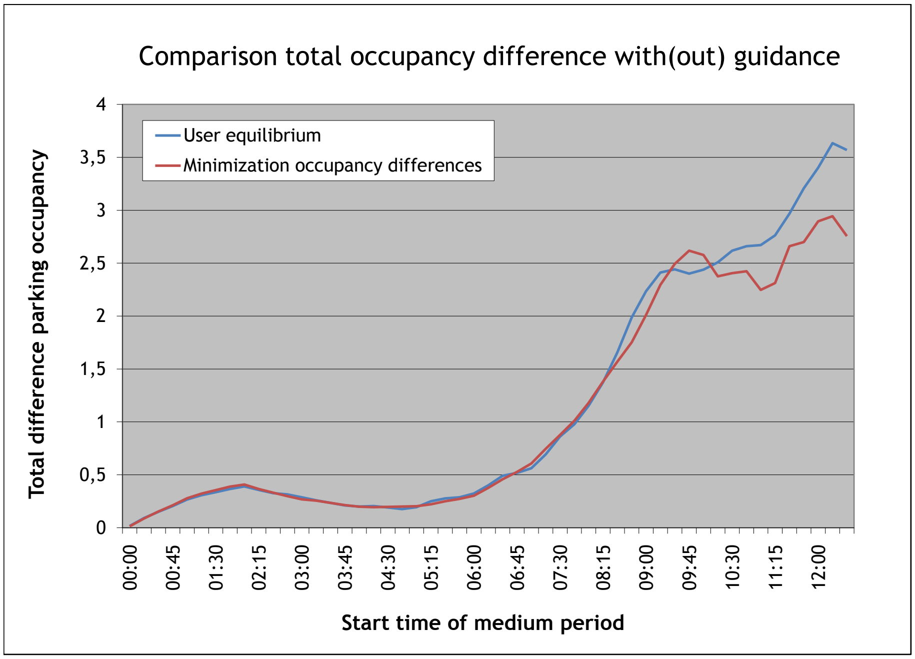


Figure 8.6: Comparison of average detours per guided user with different guidance objectives

Parking occupancies with and without optimization
The parking objective is studied for the Saturday. Two runs are performed: one without guidance (UE) and one with guidance, based on minimization of the difference between parking occupancies. The results are shown in Figure 8.7.

The optimization is run till 13:00 to avoid the long computation time for a whole day. Furthermore, the results till 9:00 in the morning are not used in the analysis, since the actual amount of parking is limited during the night and early morning. The top part of Figure 8.7 shows a clear difference between the results for the user equilibrium and for the minimization of occupancy differences. With guidance the traffic is spread more equally over the parking locations. The total difference in occupancies is reduced by approximately 25% around noon.

The bottom part of Figure 8.7 shows the average occupancy per parking location between 12:00 and 13:00 with and without guidance. Traffic is guided away from the locations with very high occupation, toward locations with ample space (like 'Schouwburgplein'). The figure shows logical changes in the occupations and indicates that large improvements are possible with the parking guidance. The detours for the guided traffic are around 10%.



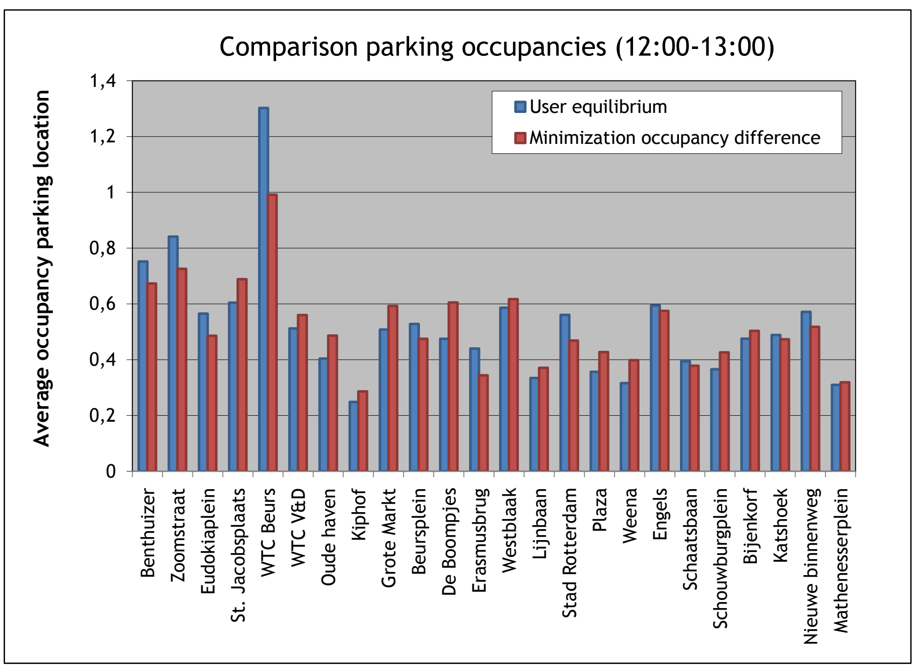


Figure 8.7: Comparison of average parking occupancy differences (top) and average parking occupancies (bottom) on Saturday with/without guidance

8.4.2 Detour constraints

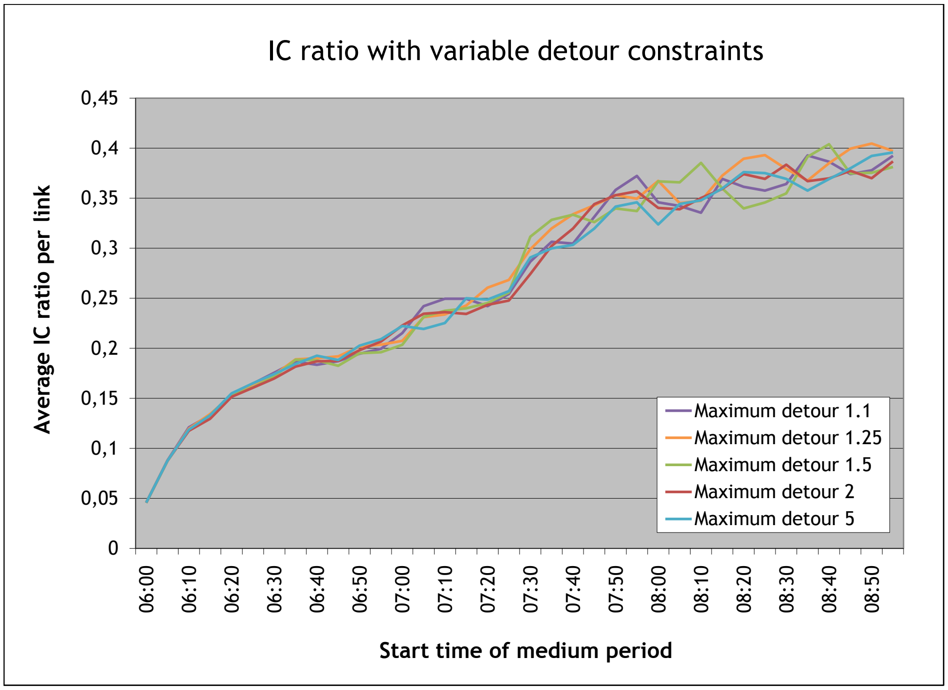
The effects of detour constraints are studied for two objectives: minimization of the average IC ratio per link and minimization of the average weighted link travel time. Figure 8.8 presents the results of guidance, based on minimization of the IC ratio per link, with variable detour constraints. The constraints vary from a maximum detour of 10% (1.1) to 500% (5). It is expected that the best results are found with the least strict detour constraints.

The results, in the top part of the figure, show a small difference in IC ratios between optimization with the various detour constraints. With the most strict constraints the IC ratio is on average 3% higher, than with the least strict constraint. The difference is smaller than expected. One explanation is the use of the route choice set. This set consists of the routes that are most likely to be used, which means that most routes have only a small detour compared to the shortest route. The detours are already constrained by the choice set.

The other explanation is the limited optimization. For the least strict detour constraints, the solution space is the largest. There is a large chance that the algorithm ends in a local optimum or does not find a good solution within 200 iterations. If the number of iterations is large the algorithm should always find the best solutions with the least strict constraints, since with stricter constraints the solution space is simply a subset of the space with the least strict constraints.

The bottom part of Figure 8.8 shows that the average detours do differ with the varying constraints. The stricter the constraint, the lower the average detour. This means that with looser constraints, longer routes are assigned. It is expected that with an extended optimization significantly larger improvements are found without detour constraints than with strict constraints. However, an interesting conclusion from the results is that improvements are possible, without forcing the use of routes with a large detour. With a maximum detour of 10%, considerable reductions in the average IC ratio are possible.

Figure 8.9 shows the results for minimization of the average weighted link travel time, with detour constraints. These figures show similar results as those for minimization of the average IC ratio per link.



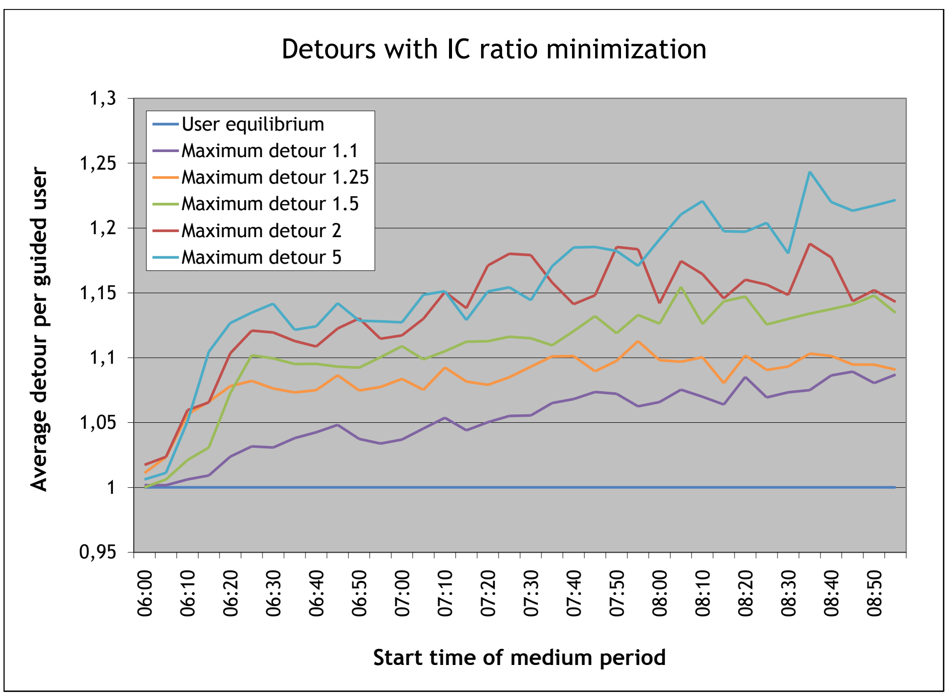
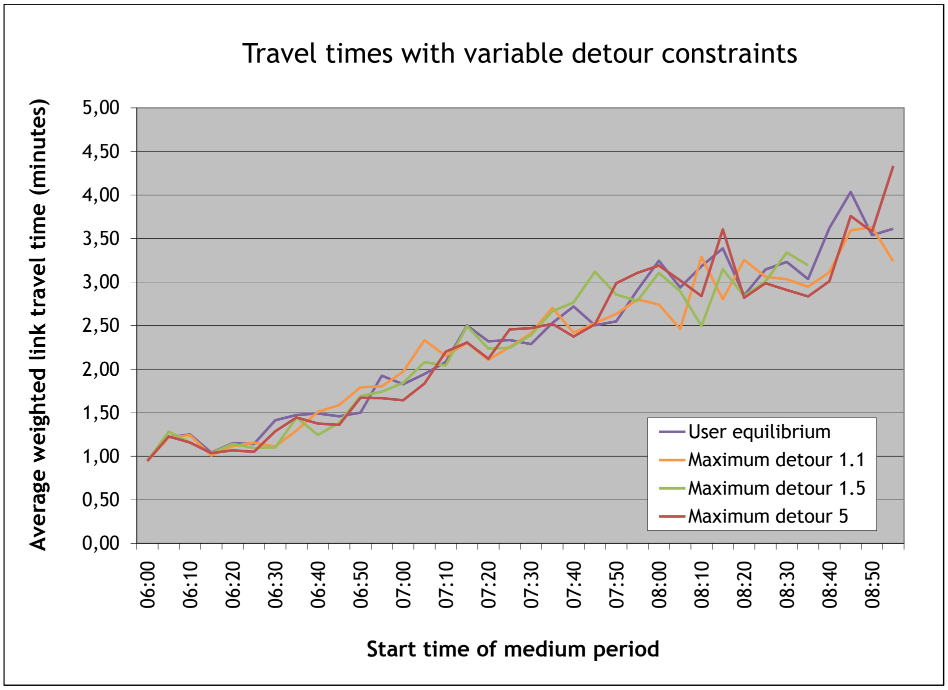


Figure 8.8: Comparison of average IC ratios per link (top) and average detours per guided user (bottom), with variable detour constraints and minimization of the average IC ratio per link as objective



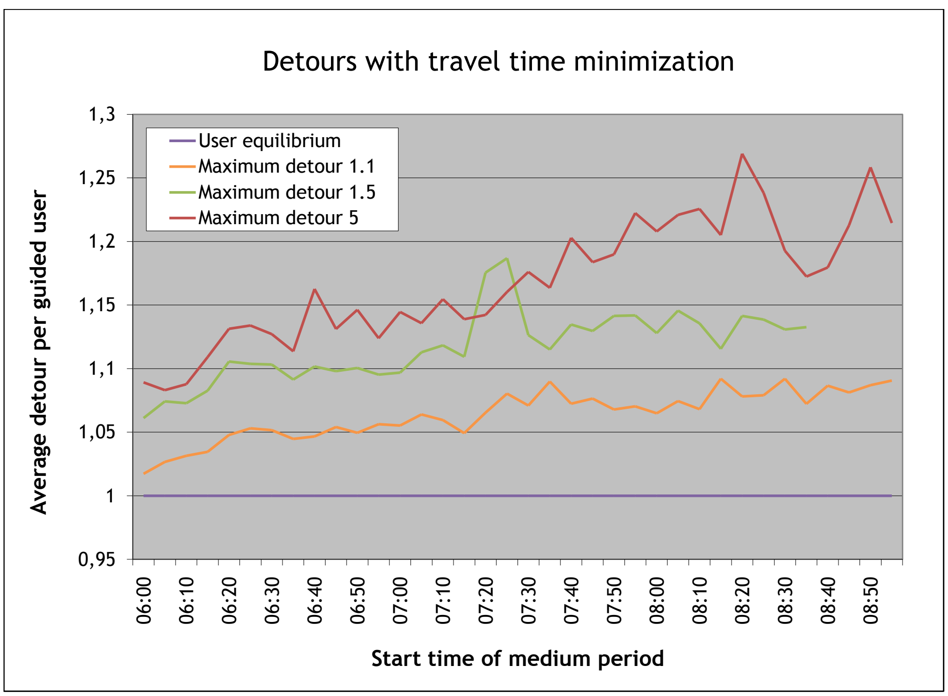


Figure 8.9: Comparison of the average weighted (aw) link travel times (top) and average detours per guided user (bottom), with various detour constraints and minimization of the aw link travel times as objective

8.4.3 Compliance percentages

The effect of the compliance percentage is studied in six runs with a compliance of 10%, 25%, 50%, 75%, 90% and 100%. It is expected that the best results are found for a compliance of 50 or 75%. No considerable improvements are expected for larger compliance rates, since also with guidance a part of the traffic will be guided over the routes that are used in the UE. For compliance rates below 50% the improvements will decrease, since a large part of the traffic chooses its own route, resulting in a suboptimal spread of traffic over the network, that can not completely be compensated by the guided traffic.

The differences between the scenario runs, with variable compliance percentages, are marginal (Figure 8.10). There is no compliance percentage that gives consequently better results than the other percentages. The absence of difference is caused by the too limited number of iterations in the algorithm. Therefore, with these results it is not possible to conclude on the influence of the compliance percentage. A more extended optimization and better calibration of the model are necessary. The results indicate that also with low compliance rates rather good solutions are possible, however, more research is necessary to conclude on this.

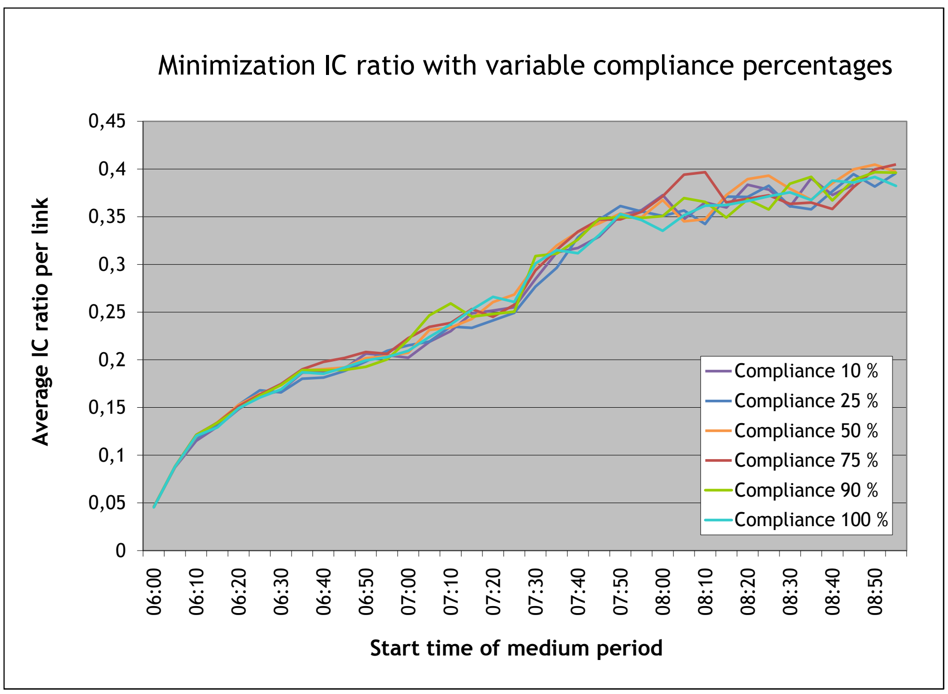


Figure 8.10: Comparison of average IC ratios per link, with variable compliance percentages

Figure 8.11 shows the average detours with variable compliance percentages. On average the detours are similar for all scenarios, however, the higher compliance percentages, result in a larger variation in detours. Per period only two routes can be assigned to the traffic. The larger the volume of this traffic, the larger the probability that the optimal routes change between consecutive periods. This can lead to variation in detours.

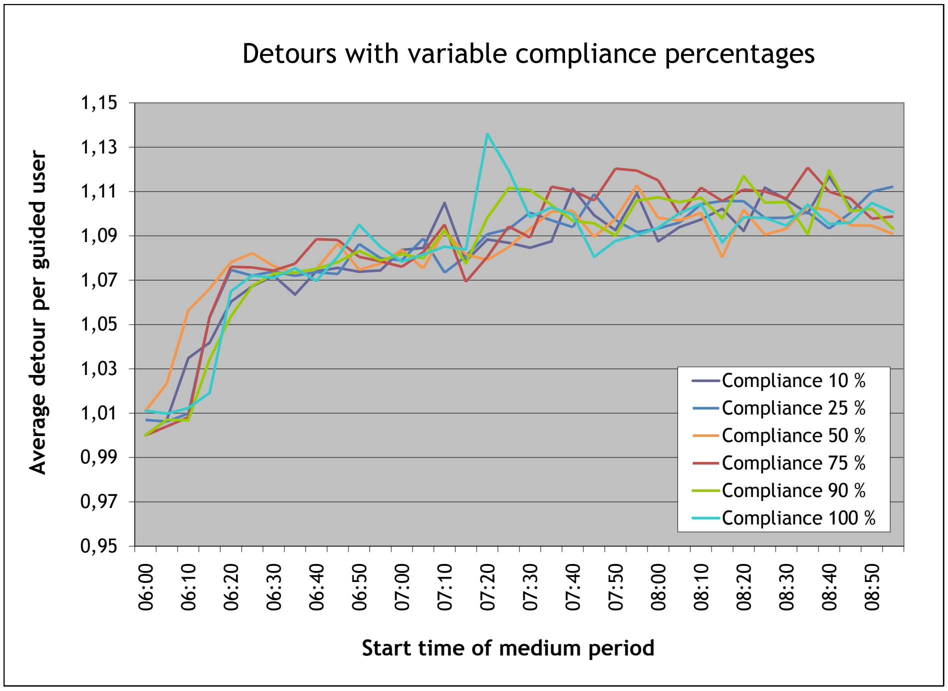
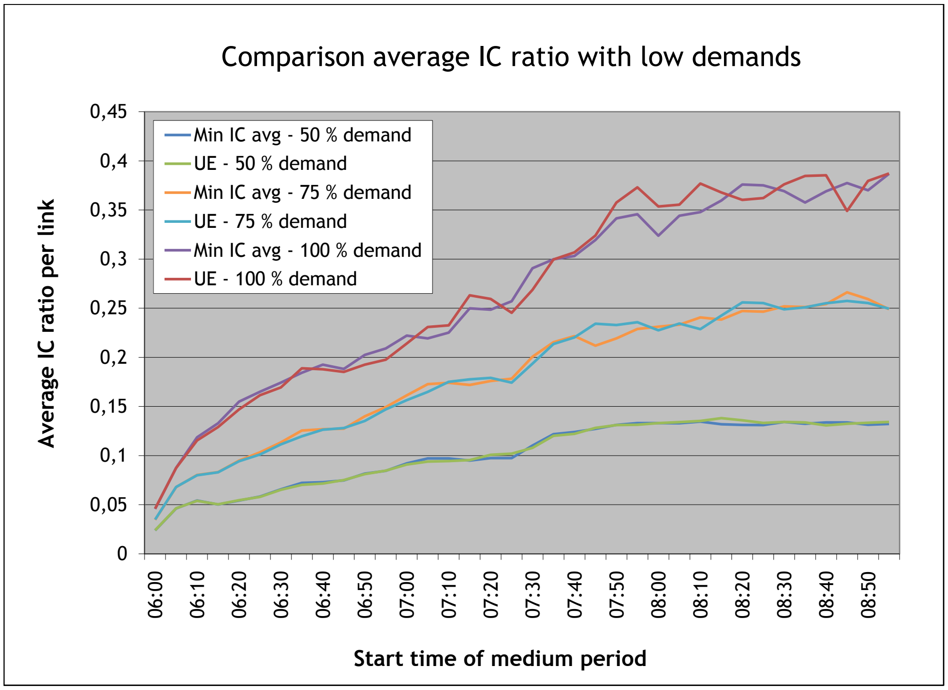


Figure 8.11: Comparison of detours, per guided user, with variable compliance percentages

8.4.4 Demand variation

For the study of the effect of guidance, with different demand sizes, the OD matrix is varied from 50% to 150% of a normal morning peak. The top part of Figure 8.12 shows the average IC ratio per link, per medium period for a demand of 50%, 75% and 100% of a normal morning peak. The figure shows results for the UE (no guidance) and for guidance with minimization of the average IC ratio per link. For a demand of 50% the guidance has no effect at all. The results with and without guidance are almost completely the same. For a demand of 75% a small improvement in the IC ratios for several medium periods is found. For a demand of 100% larger reductions in the IC ratios are possible. However, for several periods the optimization also performs worse.

With very low demands there is no congestion and it is optimal to use the shortest routes, therefore, there is no difference between the UE and the situation with guidance. The optimization algorithm can easily find the optimal solution, since the start solution assigns the shortest routes to the users. When the demand increases it is optimal to assign other routes than the shortest to the road users. Therefore, with larger demands the guidance leads to improvements. However, in this case the start solution is not optimal and probably not even close to optimal. The optimization algorithm does not always find a good solution within 200 iterations. For several periods the algorithm ends with a worse solution than the UE due to the limited number of iterations. However, other periods show that improvements are possible.



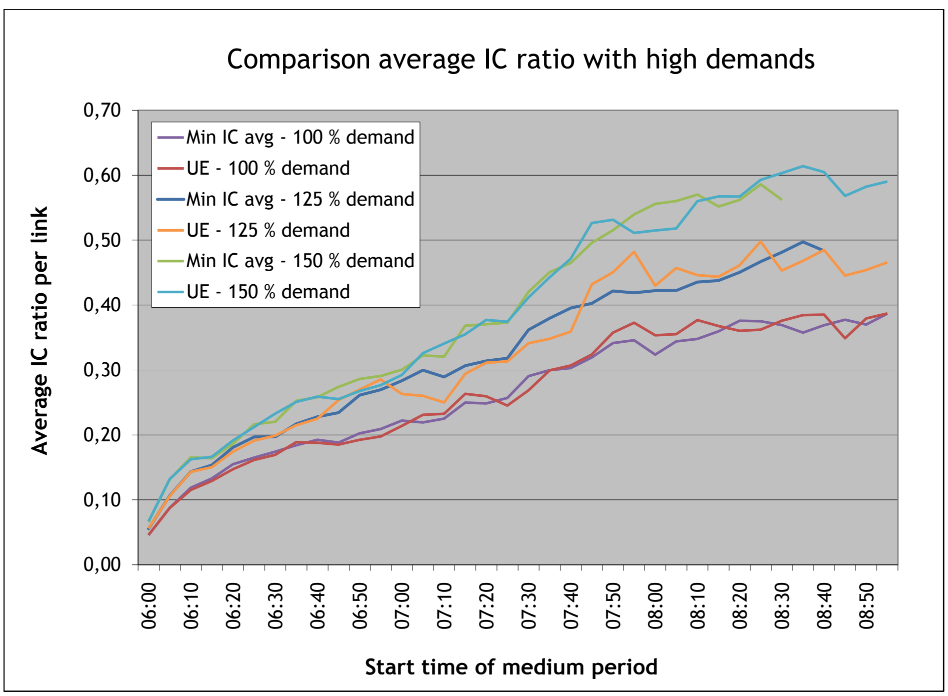


Figure 8.12: Comparison of the average IC ratio per link, with and without guidance, for demands below average (top) and above average (bottom)

The bottom part of Figure 8.12 shows similar results for demands of 125% and 150% of a normal morning peak. With a demand of 125% there are large differences between guidance and no guidance. With a demand of 150% the effect of guidance (both positive and negative) reduces. With very high demands, all roads in use are heavily loaded and spreading traffic does not improve the situation. Most effect of the guidance is found for loads between 75% and 125% of a normal morning peak.

Figure 8.13 presents the average detours, for the guided traffic, with varying demands. The larger the demand, the larger the detour of guided routes. With low demands it is optimal for traffic to use the shortest routes, since the network is not congested. With high demands it is optimal to guide the traffic away from the most crowded routes, resulting in larger detours.

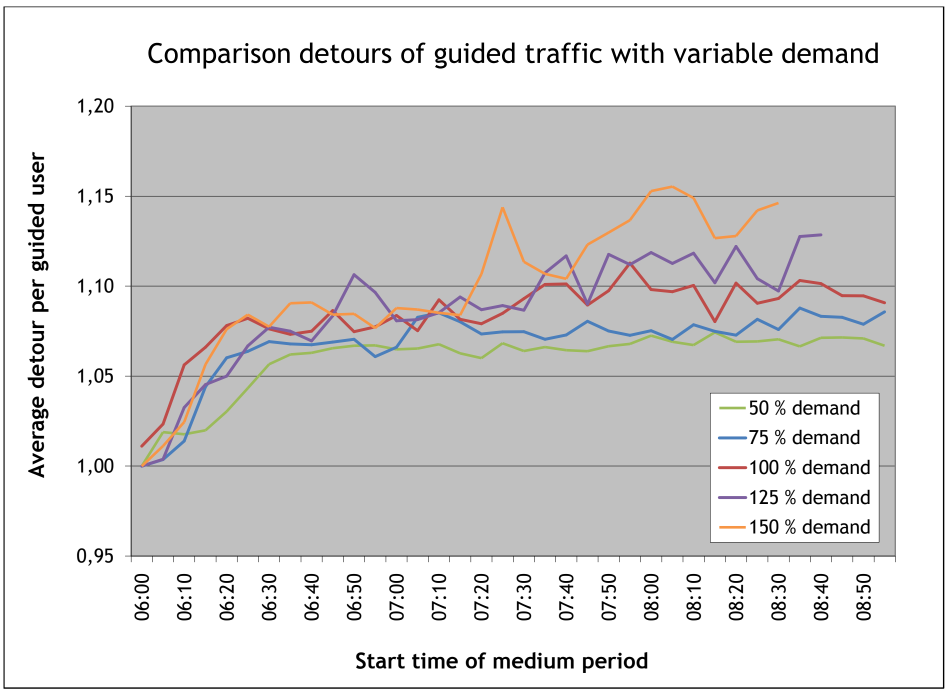


Figure 8.13: Comparison of detours of guided traffic with variable demand levels

8.4.5 Large event

The demand for the central city center zone (zone 16) is multiplied 20 times, for the period from 7:30 to 8:00 in the morning, to simulate a large demand peak. The situation without guidance, with guidance based on minimization of parking occupancy differences and with guidance based on minimization of the average IC ratio per link are compared for this situation. The scenario includes public parking. In this scenario, the amount of public parking for zone 16 is 90% and for surrounding zones 10%. Furthermore, 80% of the public parkers uses guidance and 50% of the private parkers.

Minimization of the average IC ratio has very small influence on the traffic situation, since the demand peak is too concentrated to have a large influence on the average IC ratio in the whole network. Therefore, only the parking results are included and these show large improvements. Shortly after the start of the demand peak the difference in parking occupancies increases largely for the UE situation. With guidance this increase is suppressed. This is illustrated in Figure 8.14. Figure 8.15 shows the average parking occupancies between 8:15 and 8:30: just after arrival of the demand peak. With guidance traffic is rerouted from the highly occupied locations ('WTC Beurs', 'Bijenkorf' and 'Stad Rotterdam') to large locations with low occupancies ('Schouwburgplein' and 'Westblaak'). The results show that route and parking guidance can help to spread traffic arriving to events.

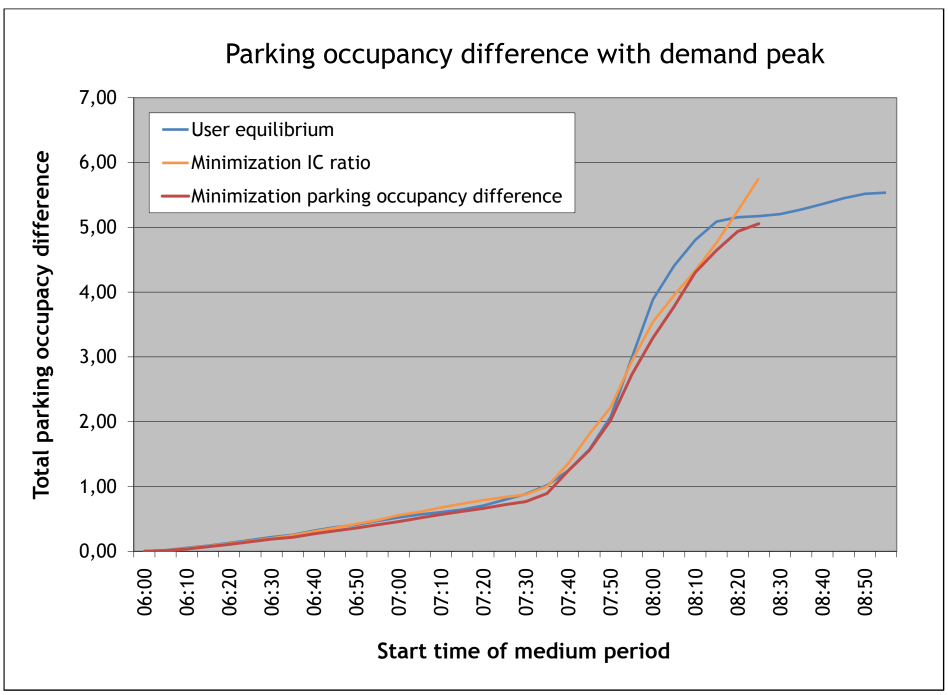


Figure 8.14: Parking occupancy difference with and without guidance, with a demand peak, for zone 16, from 7:30 to 8:00

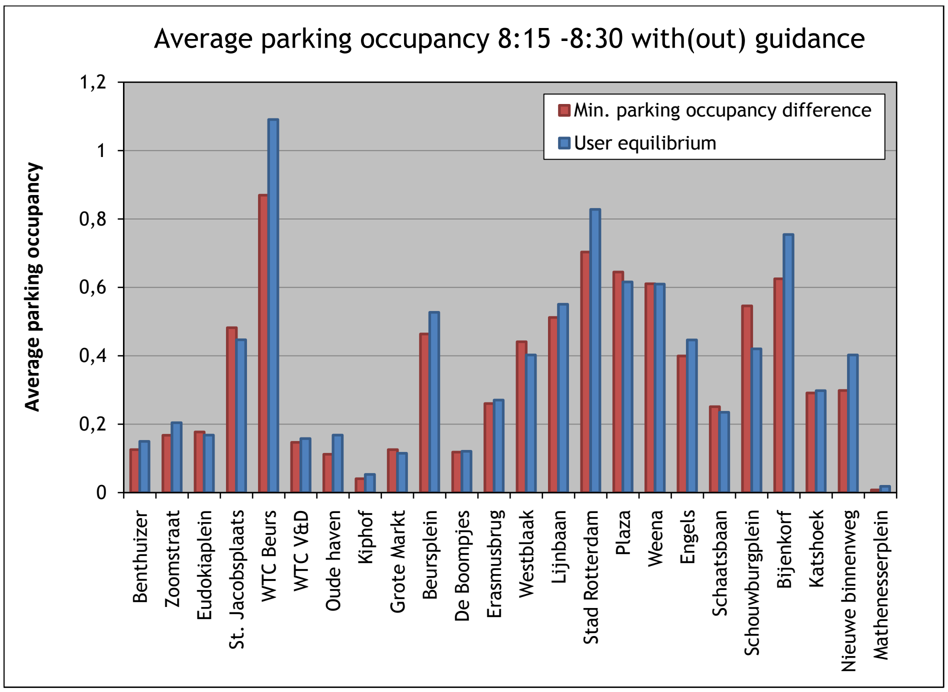


Figure 8.15: Average parking occupancies, with and without guidance, with a demand peak, for zone 16, from 7:30 to 8:00

8.5 Conclusions of the case study

The results of the case study can be evaluated in two manners:

- The guidance results in very small improvements in the average IC ratios and average link travel times. The guidance does not consequently improve the traffic process compared to the user equilibrium. The only objective where the guidance does have a large effect is the minimization of differences between parking occupancies. For this objective, the guidance results in a clear improvement, with logical changes in parking occupancies.
- The case study shows that the guidance can make a large difference compared to the user equilibrium for all objectives. The guidance can both improve and worsen the traffic process. Due to the limited number of iterations used in the case study, improvements are not always found. However, the results show that the improvements are possible and with extended optimization the guidance will perform better.

All results together support the second evaluation. With a very limited optimization the scenarios show considerable improvements. These improvements are not found in all runs and for all periods. However, the most probable explanation for worse solutions is a bad starting point and a too limited number of iterations in the optimization. Overall, logical results are found concerning the influence of the size of the demand, detours with varying demand or constraints and the influence of parking guidance.

Especially, with parking guidance the model shows that large improvements are possible. The guidance prevents searching traffic by guiding traffic away from locations with a large occupancy. The case study results show that parking guidance can make a large difference.

The case study shows several promising results. It is expected that with guidance improvements of at least 10% in network performance are possible. However, further research is necessary to conclude on this. Adaptations have to be made in follow up study and for application in practice. The model must be translated to a faster programming language, a thorough calibration is necessary and the optimization must be extended. Recommendations for follow up are given in Chapter 10.

The case study gives a first indication of the possibilities of the guidance model and the effects of guidance. The results show a logical functioning of the guidance model. The case study is promising on the possibilities of the model, but follow up research is necessary to be able to come to solid conclusions.

Part IV

Discussion and follow-up

Chapter 9

Discussion

This chapter gives a review of the study results. Section 9.1 discusses the final guidance model in relation to the study goals. The model weaknesses are explained in Section 9.2 and the model strengths in Section 9.3. Finally, Section 9.4 discusses the impact of the guidance.

9.1 The final product

The final product of this study is a very flexible, guidance optimization model. The current implementation can generate guidance related to four objectives: user equilibrium, minimization of the average weighted link travel time, minimization of average IC ratio (weighted per link or per road user) and minimization of the difference in parking occupancies. Furthermore, the model facilitates constraints related to the maximum IC ratio, maximum parking occupancy, maximum walking distance and maximum detour. Other objectives and constraints can be added to the model if necessary.

The guidance is expressed as a split of the traffic over available routes, per OD relation and per medium time period. For application in practice, this split is translated to individual, in-car guidance. Translation to guidance on VMS is also possible, especially for parking guidance this is a good option. For route guidance this is more complicated, because of the large number of destinations and different routes. The model is generic in the sense that it can be implemented without adaptation to every city, study period and for every combination of constraints and objectives. For each case, only the input data and the model parameters have to be changed.

The model gives a clear structure for guidance generation, which can be adapted and improved in further research. When the current model is translated to a faster programming language, it is suited for analysis of the traffic process with or without guidance. Possible applications are the study of impact of guidance in different traffic scenarios and with different user behavior, analysis of the influence of traffic management measures and network adaptations and analysis of the results of different guidance objectives and constraints. The model is not yet suited for implementation in an urban area to generate online guidance. However, the model provides a solid basis for this future application.

The objective of this study is formulated as:
Development of a generic model for the optimization of dynamic route and parking guidance, based on a trade-off between interests of specific stakeholders.

The characteristics of the final product fit very well to this objective. The final guidance model is generic, generates dynamic route and parking guidance and facilitates the interest trade-off with several objectives and constraints. For two aspects, the final model does not completely meet the study objective: for the air quality stakeholder and the parking guidance.

The air quality stakeholder
In the conceptual model, air quality is defined as an important stakeholder, with the objective of emission minimization. With a macroscopic, analytic model formulation it is not possible to calculate accurate emission estimations. Therefore, the air quality interests are translated into air quality indicators and the importance of this aspect seems to be small in the current guidance model. However, if the model is implemented online in an urban environment, air quality measurements can be used as constraints in the guidance generation. In this manner also the air quality can be fully accounted for.

Parking guidance
In the current model, route guidance is emphasized more than parking guidance. The first reason is that more road users can be reached with route guidance, also those users that have access to private parking. The second reason is the limited parking data availability. In the case study only the large public parking locations are included and calibration is not possible. This results in less emphasis on parking and more on route guidance. However, the model structure allows for inclusion of all public parking locations (also on street). The current model provides the structure for advanced parking guidance, which can be implemented in future applications.

9.2 Weaknesses of the guidance model

The weaknesses of the guidance model are related to the computational requirements, the traffic propagation, the travel time formulas and the parking model.

Computational requirements
The current model is implemented in Matlab. This environment is very well suited for model development and testing, however, it is slow. Therefore, in Matlab it is not possible to use extended optimization schemes. To be able to calibrate the model thoroughly and to apply it for analysis and online guidance generation, translation to a fast language is necessary. Furthermore, efficiency improvements in the programming code are needed to improve the computation speed.

In the case study, a limited number of iterations is used in the optimization algorithm. With this limited optimization the algorithm is not able to find good solutions for every period and every scenario. Therefore, it is not possible to conclude on the effect of guidance. With the chosen model settings, one model run takes at least 4 days at the computers available at Witteveen+Bos. With a fast computer the same run can currently be performed in less than 1 day. For calibration and online implementation this should at least be reduced to one hour (for a complete morning peak).

Traffic propagation
A simple traffic propagation formulation is chosen to be able to use a macroscopic, analytic model for DTA. The consequence of the simple formulation is on one hand a simple and relatively fast model, but on the other hand a less realistic traffic propagation. The current formulation does not ensure FIFO (first in first out), due to the fixed travel time assumption, and does not simulate spill back. This is not realistic. To ensure FIFO, the traffic propagation should account for the change in travel time from the start of a period to the end. However, to do so the travel time at the end of a period has to be predicted and the inflow of a period can not be assigned to one outflow period. This leads to complicated constraints and results in problems with the flow continuation.

The simple formulation does not give a realistic propagation per small time period. Therefore, link costs, traffic propagation and route choice are based on average in- and outflows of several preceding small periods. With this adaptation, the model ensures flow conservation and continuation and results in a realistic traffic propagation. The spill back is not accounted for. Spillback occurs when a link is completely occupied and traffic can not enter from the previous link. To account for spillback, traffic should be held back in the propagation if the preceding link is full. This is not possible with a simple analytic formulation.

Travel time formulas
The model uses separate travel time formulas for signalized, non-signalized and highway links. To fit the analytic, macroscopic DTA, simple formulations are chosen with limited data requirements. The travel time formulations give rough estimations and can be improved by incorporation of several aspects: interdependency between links and signals, actuated signal settings, influence of other traffic modes than the private car and detailed signal lay out. Most of these improvements are not possible in a simple macroscopic formulation and data is required, that is not available in this study. A very detailed travel time estimation is not necessary in a macroscopic model, however, with more data several aspects can be improved in follow up research.

Parking model
The parking model is less developed than the other model components, due to data limitations. Therefore, the parking model has several shortcomings:

- The same average parking duration is used for all parkings and for all periods. In further development the parking duration should be varied per period and per parking(type). This is possible if data is available. Another option is to use measurements of arrivals and departures at parkings, in an online model implementation.
- The percentage public parking is currently varied per destination, but not per period. However, during shopping times the percentage will be larger than in other periods. In further development the public parking parameter should be varied per period. Again data is necessary to be able to estimate the parameters.
- The parking utility parameters are guessed with limited data. Further calibration is necessary to give a good estimation.

The limitations of the parking model can be solved either by calibration or by implementing the model online and using measurements at parkings.

9.3 Strengths of the guidance model

The strengths of the model are related to its flexibility, the new model type and the clear structure.

- New development: The model developed in this research is new, compared to existing models, in two aspects: inclusion of parking in the route choice and calculation of optimal guidance for both route and parking choice with varying objectives. Currently the interest for the development of guidance models and for inclusion of parking guidance in navigation systems is raising. Therefore, this research responds to the actual questions in society.

- Generic model: The model is completely generic. It can be applied to every city and for every study period, if the right input data is available. Only the values for the parameters have to be changed per case.
- Component structure: The model is built up out of components. This results in a very clear structure, that can easily be adapted. The model is no black box.
- Macroscopic and analytic: The macroscopic and analytic formulation gives the basis for a fast application. This formulation is less computational demanding than a traffic simulation model.
- Stand alone: The model is currently programmed in Matlab, however, it can be translated to stand alone executables. The model does not depend on a certain computer program.
- Applications: There is a large number of possible applications for the guidance model. The model can be used as a standard, dynamic traffic assignment model, but also to generate guidance. Furthermore, the influence and possibilities of guidance in various situation can be studied.
- Good basis for further development: Finally, the model is a very good basis for further development. The model is kept simple in this first development. Therefore, the model is transparent and the functioning can be studied. Due to the clear structure it is possible to develop the model further in follow up research.

9.4 Guidance impact

The main study objective is to develop a model to optimize guidance. However, such a model is only useful if the guidance leads to improvements in the network situation. The case study gives a first indication of the effect of guidance and the first results are promising. The case study shows that significant improvements are possible for all objectives. Especially, the parking guidance leads to logical and considerable improvements in the spread over parking locations.

Based on the case study, it is expected that at least an improvement of 10% in the network performance is possible with an extended guidance optimization. Furthermore, the parking guidance can reduce searching traffic largely and can lead to a much better spread of traffic over the parking locations. On the other hand, the case study shows that a faster model, thorough calibration and additional tests are necessary, before further application. The optimization algorithm has to be extended to produce reliable results with the model. And the computation speed has to be improved to enable good analysis and online implementation. However, the case study convinces that the guidance model has large possibilities and gives a start for further development.

Chapter 10

Follow up

This chapter gives recommendations for further development of the guidance model in Section 10.1. The recommendations present the most important requirements and possibilities for further development of the guidance model. It is recommended to start with these aspects and prepare the model for online implementation. The possibilities for future application are discussed in Section 10.2.

10.1 Recommendations for further development

In the chapters on verification, calibration and the case study several necessary and possible improvements of the model are indicated. Two necessary improvements are an increase in the computation speed and a thorough calibration. Furthermore, several extensions are possible. This section gives recommendations on these three improvements.

10.1.1 Increase in computation speed

It is recommended to start follow up research by translating the Matlab model to a fast programming language. Furthermore, the efficiency of the programming should be improved. A faster model is a requirement for calibration and further development. Currently a fast computer can run the model for a complete morning peak within 20 hours (with the settings chosen in this research). This time should be reduced to less than an hour with a more extended optimization.

10.1.2 Thorough calibration

Thorough calibration is necessary for all parameters and settings in the model. However the calibration is most important for three aspects: the optimization algorithm, the parking model and the signal setting parameters. When thorough calibration is finished, the model can be validated by testing it for several cities. The optimization algorithm should guarantee good guidance settings for every period, to be able to use the guidance model in practice. Therefore, the following parameters have to be studied:

- The total number of iterations in the optimization: in the case study 200 iterations per time step are used, which is not enough. The expectation is that at least 10.000 iterations per time step are necessary to ensure good solutions for every time period.
- The cooling scheme: the main aspects to calibrate in this scheme are the number of temperature levels and the cooling per level. This determines the probability to proceed from or end in a local optimum.

- The formulation of neighbor solutions: the percentage of change per iteration and the split factor have to be calibrated. It is expected that the best change percentage is between 10 and 20% of the current solution. The most logical value for the splitfactor is larger or equal to the maximum number of routes. With these values traffic can be spread over all routes. However, this leads to a very large solution space and a smaller probability to find optimal solutions. It is expected that the algorithm performs optimal with a splitfactor of 3 or 4.

- The use of restarts, solution information or a solution database: these three options to improve the functioning of the optimization algorithm should be studied. By using restarts the probability of ending in a local optimum can be reduced. Both random restarts and restarts from a solution database can be studied. A database with solutions from preceding simulations can be used to choose start solutions. Finally, the use of information in the generation of neighbor solutions should be studied. With information, a neighbor solution, that guides traffic away from the most congested links or routes, can be chosen.

Also thorough calibration of the parking model is very important, since the incorporation of parking in the model is one of its important strengths. For the parking component the percentage of public and private parking and the parking duration have to be varied and calibrated per time period and per destination. Furthermore, the parameters that value walking time and parking charge in comparison to the driving time have to be calibrated.

The signal settings are the third aspect for calibration. Within the urban environment a correct representation of delays at intersections is very important. Therefore, the functioning of adaptive signals should be modeled correctly. The parameters for the signal settings can be calibrated with measurements at intersections and with a microsimulation model.

10.1.3 Model extensions

The most important model improvements are the increase in computation speed and the calibration. However if these requirements are fulfilled, many extensions are possible. It is recommended to start with extensions to improve the intersection formulation and to include other modes, than the private car, in the model.

By introducing a more detailed intersection description, the delay estimation can be improved. A first extension is the introduction of more intersection types, such as priority intersections, round abouts and highway entrances and exits. A second improvement is a more detailed description of the intersection lay out, with the number of lanes, length/width per lane and lanes per direction. As third extension separate signal groups per direction should be introduced to improve the description of delays at intersections. These three improvements are possible within the current model structure, however, bring along extra data and computational requirements.

A second interesting extension for the guidance model is the inclusion of other modes. Currently the model only includes private cars. In further development other transport modes like public transport and cycling can be included. For this extension it is necessary to add a mode choice component to the model and to introduce separate user groups, travel time formulas and flow variables per mode. It is especially interesting to include public transport (PT) as a separate user group. With guidance, priority can be given to PT.

10.2 Future application of the guidance model

Two main applications can be distinguished for the guidance model: the model as analysis tool and as online guidance model. In the current version, when translated to a fast program, the model can be applied for analysis; the intended future application is online guidance. The possibilities as analysis tool are discussed in Section 8.3.1.

The online implementation is based on individual in car navigation. Every individual road user receives a route advice when entering the network, according to the split over routes per OD-pair. The complete traffic process can be guided and traffic can be spread over the network per OD-pair. It is also possible to translate the guidance to directions at VMS. This is a good option for the parking guidance, however, less for route guidance. With VMS it is not possible to guide many routes and destinations at the same time. Therefore, the guidance looses the possibility to guide the complete traffic process. The traffic streams can only be directed at crucial locations with VMS; the effect of the guidance is reduced.

The guidance model can be implemented in several manners, varying from a very basic implementation to a real advanced system. In the most basic scenario an OD matrix is used as input and this matrix is adapted to traffic measurements. Furthermore, measurements are used to adapt link costs, computed by the model, to actual link costs. In the same manner severe congestion or blockage of links is fed back to the model.

In the most advanced implementation the guidance model uses complete online information. The actual network inflow, destination per car, the parking occupancy and link in- and outflows are input to the model and are used in the optimization algorithm. The model output is an individual route advice per vehicle (percentage per route). Every car sends its destination to the central system before entering the study area and the system sends the advice to the individual via his/her navigation system. For example, GSM can be used for the data exchange.

Although, the advanced implementation sounds futuristic, it can be realized within several years. Data exchange between cars and infrastructure elements is already possible and a lot of information on link flows is available through counting loops. Furthermore, arrivals and departures at parkings can be registered easily. The main challenge is to bring all information together in one central system. This system has to process the data fast and integrate the information in the guidance model. Furthermore, the guidance model should be improved according to the recommendations in Section 10.1.

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Part V

Appendices

Appendix A

Polling models and signal settings

This appendix gives mathematical background for the calculation of the signal settings. The cycle times and green times are calculated with formulas from traffic theory. These formulas are closely related to the theory for Polling systems. The first section introduces the traffic theory formulas. The second section presents the theory on Polling models in comparison to the traffic theory. The third section gives a short discussion and conclusion.

Traffic theory

Based on traffic theory (Maarseveen et al., 2001) the following formulas can be used to calculate the cycle time at signalized intersections:

$$C_{min} = \frac{T_v}{1 - Y} \tag{A.1}$$

$$C_{opt} = \frac{1.5 \cdot T_v + 5}{1 - Y} \tag{A.2}$$

C_{min}	Minimal cycle time
C_{opt}	Optimal cycle time
T_v	The internal loss time of the cycle (due to switching between streams)
Y	The total load of the largest group of conflicting traffic streams

The effective green times are calculated based on the relative load per traffic stream:

$$G_{eff,i} = \frac{y_i}{Y} \cdot (C - T_v) \tag{A.3}$$

$C - T_v$	The total effective green time (cycle - loss time)
$G_{eff,i}$	Effective green time per cycle for traffic stream i
y_i	The load of traffic stream i

Exhaustive Polling model

A polling system is a multi-queue single-server system in which the server visits the queues in some order to process requests pending at the queues (Mei, Winands, 2006). A Polling system can serve according to an exhaustive or a gated policy. In an exhaustive policy the server stays at one station till there are no customers left. In the gated policy, the server only serves those customers that where at the station, when the server arrived. The mean cycle time for a Polling system is computed with:

$$E[C] = \frac{E[S]}{1-\rho} \tag{A.4}$$

$E[S]$	Expected total set-up (or switch-over) time in a cycle
$E[S_i]$	Expected set-up time (loss time) for station i
ρ	Total occupancy rate of the server (total system load)
ρ_i	Occupancy rate of station i (load)

Equation A.1 and Equation A.4 are very similar. The total loss time in the traffic cycle corresponds to the total set-up time in the Polling model. In a Polling system the server is working (effectively) a fraction ρ_i of the time on queue i (Mei, Winands, 2006). Equation A.3 expresses the fraction of time in the traffic cycle that stream i can be served (has an effective green light), as a fraction of the total effective service time ($C - T_v$). The fraction is determined by the ratio of the load of the traffic stream compared to the total load. For the Polling system the total effective service time per cycle is:

$$E[C_{eff}] = E[C] - E[S] = \frac{E[S]}{1-\rho} - \frac{E[S] \cdot (1-\rho)}{1-\rho} = \frac{\rho \cdot E[S]}{1-\rho}$$

If this formula is used in Equation 4.15, the following result is found:

$$E[C_{eff,i}] = \frac{\rho_i}{\rho} \cdot \frac{\rho \cdot E[S]}{1-\rho} = \frac{\rho_i \cdot E[S]}{1-\rho} = \rho_i E[C]$$

This effective working time for station i, based on the traffic theory formulation, is exactly the same as in the Polling model. The green time formula for traffic signals distributes the effective service time in the same manner as a Polling system.

Discussion and conclusion

The preceding sections show that the traffic theory for signal settings is closely related to the theory for Polling systems. This does not mean that a traffic signal works exactly the same as a Polling system. The average visit time to a station in the Polling system equals the fixed green time at a traffic signal. However, in the Polling system the visit times to each of the stations are variable. An actuated traffic signal, where a direction gets green as long as there is traffic, works in the same manner as exhaustive Polling. An actuated traffic signal with maximum green times per direction functions in the same manner as gated Polling.

Furthermore, the average Polling cycle equals the minimum cycle time for the signal settings. However, the minimum cycle time is not often used at traffic signals. Each of the directions should get a minimum green time to enable traffic to drive off safely. The sum of the minimum green times and the loss times easily exceeds the minimum cycle time. Therefore, Equation A.2 is used to calculate the cycle time.

Appendix B

Adjustments intersection model

Equation A.2 and Equation A.3 are used in the model component, that calculates the cycle time and green times per link in every large time period. These equations define green times per signal group. A signal group is a direction or a set of directions that shares one traffic light. In the model implementation green times are given per link, therefore one signal group per link is assumed. This means that the right/left turning and straight going traffic, of one link, has green at the same time and all directions of the other links have to wait. However, in reality there is often a separate signal group for the left turns and the right turns. If the green time is divided per link, the signal groups of the link are forced to share a green period, which is often not optimal. If for example two opposing straight ahead going streams are very large, these streams should share a green period in the optimal signal settings.

Figure B.1 gives an example of signal settings with green per link and green per signal group. In this example there are two large straight ahead going streams, that do not conflict (streams 5 and 11). The signal setting diagram in the top of the figure shows the situation with optimal settings. The streams 5 and 11 share a green period, all loads are below 85% and the cycle time is 52 seconds. The diagram at the bottom shows the signal settings, when green times are divided per link, with the same loads on each of the directions. This results in a cycle time of 275 seconds (which is too large to use in practice) and two directions with load larger than 90%. This is an extreme example, however, it shows which problems can occur if green time is given per link. On the other hand, if the flows on one link, for the right turn, the left turn and the straight ahead direction are all of the same size, it could be optimal to divide the green times per link.

In the example in Figure B.1 the link with directions 3, 4 and 5 and the link with directions 10, 11 and 12 can share the same green period for a large part. This is possible, since the right and left turning flows are small. These flows can be dealt with first and both straight ahead going streams can share the remaining green period. This is much more efficient than first having a large green period for one link and then a large green period for the other link. However, in the model implementation the green times have to be specified per link. To prevent the prediction of large intersection delays in the model, in situations as described in the example, the calculation of cycle times and green times is adjusted to the intersection situation. Extra green time is assigned if green per link leads to suboptimal solutions. Three categories of intersection loads and adjustments are distinguished:

- Category 1: In this category the flows per direction are within a small range. There is no large difference between the largest flows and the smallest flows. The right, left and straight directions are loaded to the same extent. It is not far from optimal to split the total effective green over the links. The conflict load (Y) can be calculated as the sum of each of the link loads. The effective green time is multiplied with the parameter $greenfactor1$, to find the amount of green time to be assigned. The parameter is in the range of 1.0 to 1.2.

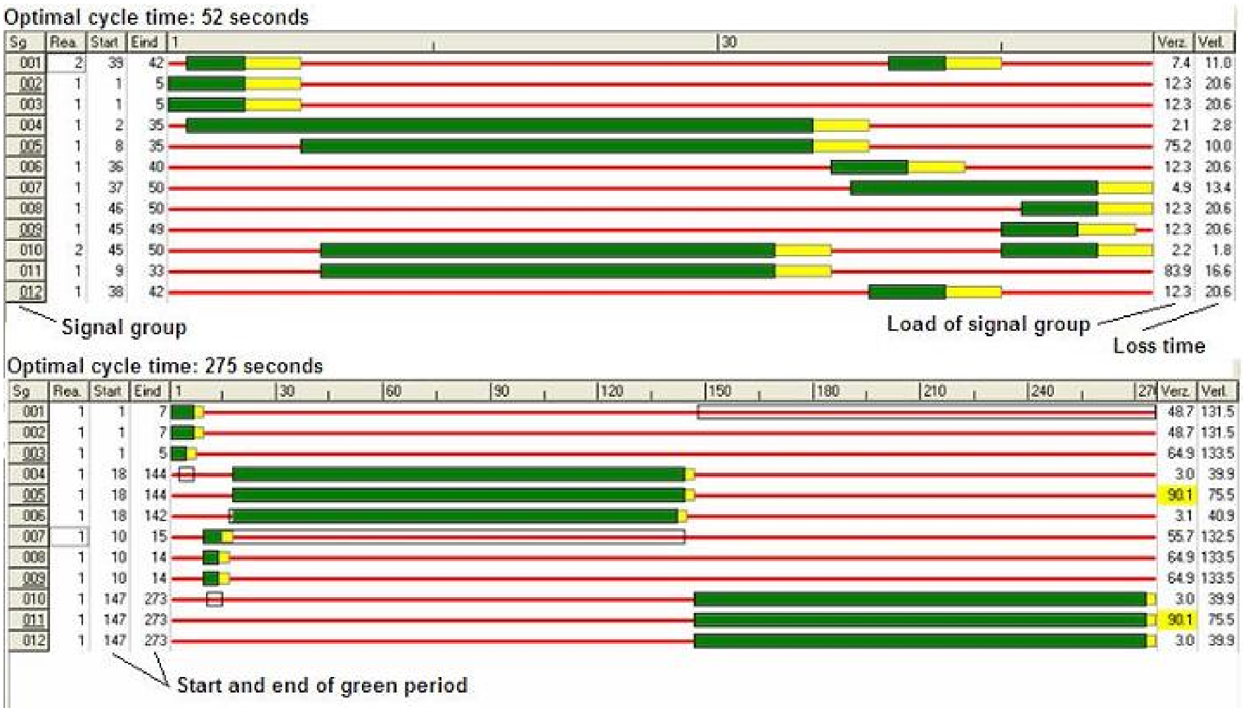


Figure B.1: Example with signal timings per link or per signal groups

- Category 2: In this category there are two large flows (compared to the other flows), not starting at the same link, that do not conflict. In the optimal situation these flows share a green period. To compensate for the suboptimal solution with green times per link, extra green time is assigned to the links. More than 100% of the effective green time is assigned to account for the possibility that the two large flows both use the same green period. In the conflict load (Y) the smallest of the two dominant flows is excluded, since this flow is served in the same time as the other dominant flow. The model implementation multiplies the effective green time with the parameter $greenfactor2$, to find the amount of green time that is assigned. The parameter is in the range of 1.2 to 1.5. The value is based on the study of different signal settings in Cocon and on model calibration.
- Category 3: This category uses the same explanation as category 2 (see preceding point). However, now there are two or more couples of large, dominating flows. In the conflict load, of each couple, the smallest flow is excluded and the parameter $greenfactor3$ is used to calculate the amount of green time to assign. The parameter is in the range of 1.5 to 1.8.

For all three categories the conflict load Y overestimates the actual conflict load, since only the largest non-conflicting loads are subtracted. Therefore, the parameters $cyclefactor_i$ (ranging from 0.7 to 1.0) are used to correct the computed cycle time.

Appendix C

Continuous model for DTA

This appendix lists the complete model formulation for continuous dynamic traffic assignment.

Network flow constraints

$$\frac{dx_{arm}^{od}}{dt} = u_{arm}^{od}(t) - v_{arm}^{od}(t) \quad \forall a, r, m, o, d. \tag{C.1}$$

$$\frac{dS_{rm}^{od}(t)}{dt} = s_{rm}^{od}(t) \quad \forall r, m, o, d \neq o. \tag{C.2}$$

Flow conservation constraints
Total flow conservation at nodes:

$$\sum_a \delta_{B,a}^n \cdot v_{arm}^{od}(t) = \sum_a \delta_{A,a}^n \cdot u_{arm}^{od}(t) \quad \forall n, r, m, o, d; n \neq o, d. \tag{C.3}$$

Flow conservation per route:

$$v_{arm}^{od}(t) = u_{brm}^{od}(t) \quad \forall o, d, r, i | a = r(i), b = r(i+1). \tag{C.4}$$

Conservation at arrival:

$$\sum_{a,r} \delta_{B,a}^d \cdot v_{arm}^{od}(t) = s_m^{od}(t) \quad \forall o, d; d \neq o. \tag{C.5}$$

Flow propagation
Outflow-inflow relation:

$$v_{arm}^{od}(t + \tau_a(t)) = \frac{u_{arm}^{od}(t)}{\frac{d\tau_a(t)}{dt} + 1} \quad \forall a, r, m, o, d. \tag{C.6}$$

Propagation from parking location for cars:

$$e_p(t) = u_p(t - EPD_p) \quad \forall p \in P. \tag{C.7}$$

Definitional, non-negativity and boundary constraints

$$\sum_{odrm} u_{arm}^{od}(t) = u_a(t) \quad \forall a. \tag{C.8}$$

$$\sum_{odrm} v_{ar}^{odm}(t) = v_a(t) \quad \forall a. \tag{C.9}$$

$$\sum_{odrm} x_{arm}^{od}(t) = x_a(t) \quad \forall a. \tag{C.10}$$

$$x_{arm}^{od}(t), \quad u_{arm}^{od}(t), \quad v_{arm}^{od}(t), \quad s_{rm}^{od}(t), \quad S_{rm}^{od}(t) \geq 0 \quad \forall a, r, m, o, d. \tag{C.11}$$

$$S_{rm}^{od}(0), \quad x_{arm}^{od}(0) = 0 \quad \forall a, r, m, o, d. \tag{C.12}$$

Link and route costs
The travel time formulas for signalized, non-signalized and highway links are given in Section 4.5. The parking formulas are given in Section 4.4.1. Route cost is calculated with:

$$C_{rm}^{od}(t) = \sum_a \delta_r^a \cdot \tau_a(t) + \sum_w \delta_r^w \cdot \alpha \cdot \tau_w + \beta \cdot c_p \cdot EPD_p \quad \forall r, m, o, d. \tag{C.13}$$

Variational inequality
Constraints:

$$C_{rm}^{od^*}(t) - \pi_m^{od^*}(t) \geq 0 \quad \forall r, o, d, m_1, m_2, \tag{C.14}$$

$$f_{rm}^{od^*}(t)[C_{rm}^{od^*}(t) - \pi_m^{od^*}(t)] = 0 \quad \forall r, o, d, m_1, m_2, \tag{C.15}$$

$$f_r^{od^*}(t) \geq 0 \quad \forall r, o, d, m. \tag{C.16}$$

Variational inequality:

$$\int_{T_i}^{T_{i+1}} \sum_{od} \sum_{m_1, m_2} \sum_{r \in R_m^{od}} C_{rm}^{od^*}(t)[f_{rm}^{od}(t) - f_{rm}^{od^*}(t)]dt \geq 0. \tag{C.17}$$

The variational inequality is specified per guidance period. Each of these periods has length Δt (the medium time period). For this period the guidance is optimized with the user equilibrium as sub-problem.

Appendix D

Travel time estimation

This appendix discusses the travel time estimation and the implementation of the inflow-outflow relation in the model. The theoretical model uses the following outflow-inflow relation:

$$v^{od}_{arm}(t + \tau_a(t)/\delta t) = \frac{u^{od}_{arm}(t)}{\frac{\Delta\tau_a(t)}{\Delta t\delta t} + 1} \quad \forall a, r, m, o, d. \tag{D.1}$$

The equation incorporates the average travel time of the current time period, however, this asks for a prediction of this average travel time at the start of the period. There are two possibilities for this prediction. Either use the travel time at the beginning of the period as estimation for the average during the period, or use the travel time change during the previous period to predict the change during the current period. Both options are shown in Figure D.1.

Different notations for travel time are necessary in the travel time prediction:

- $\tau_a(t)$: the travel time calculated at the beginning of period t based on the travel time and delay formula. This travel time is only a help variable in the discretized model.
- $\bar{\tau}_a(t)$: the estimated travel time at the end of period t. This travel time is used to calculate the estimation for the average travel time in the period.
- $\tau_a^{\bar{avg}}(t)$: the estimated average travel time for period t. This travel time is used in the traffic propagation.

If the travel time is estimated based on the change in the previous period, the following equations are used:

$$\bar{\tau}_a(t) = \bar{\tau}_a(t-1) + (\tau_a(t) - \tau_a(t-1)). \tag{D.2}$$

The estimated average travel time for period t can be found with:

$$\bar{\tau}_a{}^{avg}(t) = \bar{\tau}_a(t) + \frac{1}{2}(\tau_a(t) - \tau_a(t-1)). \tag{D.3}$$

And if the travel time is estimated based on the time at the beginning of the period:

$$\bar{\tau}_a{}^{avg}(t) = \tau_a(t). \tag{D.4}$$

The formulation based on the change in the previous period can result in negative travel times if the travel time dropped a lot during the previous period. Furthermore, flow conservation is difficult to guarantee. This formulation can only be used if the time steps are chosen very small. Therefore, the travel time is assumed to be constant during a small time period.

The following equation for the estimated outflow rate during period $t + \bar{\tau}_a{}^{avg}(t)/\delta t$ can be found:

$$v^{od}_{arm}(t + \frac{\bar{\tau}_a{}^{avg}(t)}{\delta t}) = u^{od}_{arm}(t) / \left(\frac{\bar{\tau}_a{}^{avg}(t + \bar{\tau}_a{}^{avg}(t)/\delta t) - \bar{\tau}_a{}^{avg}(t)}{\bar{\tau}_a{}^{avg}(t)} + 1 \right) \quad \forall a, r, m, o, d. \quad \text{(D.5)}$$

This equation is not completely correct, since two outflows can fall together if for example:

$$k + \bar{\tau}_a{}^{avg}(t)/\delta t == (t + 1) + \bar{\tau}_a{}^{avg}(t + 1)/\delta t.$$

Or the FIFO constraints can be harmed if:

$$t + \bar{\tau}_a{}^{avg}(t)/\delta t < (t + 1) + \bar{\tau}_a{}^{avg}(t + 1)/\delta t.$$

In this last case the inflow of interval $t + 1$ leaves the link earlier than the inflow of interval t. These two problems can be solved by summing all outflows that fall together and adding also outflows that would harm FIFO. This can be done with the following equation:

$$v_a(t + \frac{\bar{\tau}_a{}^{avg}(t)}{\delta t}) = \sum_{i=t}^{t+\bar{\tau}_a{}^{avg}(t)/\delta t} v_a(i + \frac{\bar{\tau}_a{}^{avg}(i)}{\delta t}) \quad \forall i | i + \frac{\bar{\tau}_a{}^{avg}(i)}{\delta t} \leq t + \frac{\bar{\tau}_a{}^{avg}(t)}{\delta t}. \quad \text{(D.6)}$$

This equation should be used for values of t for which the following holds:

$$t + \frac{\bar{\tau}_a{}^{avg}(t)}{\delta t} > i + \frac{\bar{\tau}_a{}^{avg}(i)}{\delta t} \quad \forall i < t.$$

For the other values of t the outflow falls together with the inflow of other periods and is accounted for with the summing equation.

The outflow equations developed in the preceding paragraph have one problem. Due to the approximations for the travel times the flow conservation is not guaranteed. If the time steps are taken very small the problems are limited, however if the time steps and travel time differences are larger, flow continuation is harmed. A simple solution to this problem is to assume constant travel time per time period, resulting in the following outflow:

$$v^{od}_{arm}(t + \frac{\bar{\tau}_a{}^{avg}(t)}{\delta t}) = u^{od}_{arm}(t). \quad \text{(D.7)}$$

This equation assigns each period-inflow to one outflow period (again flows assigned to the same period are summed) and guarantees the flow continuation. This equation does not account for travel time changes during the traversion of a link, however, on average this equation results in proper traffic propagation.

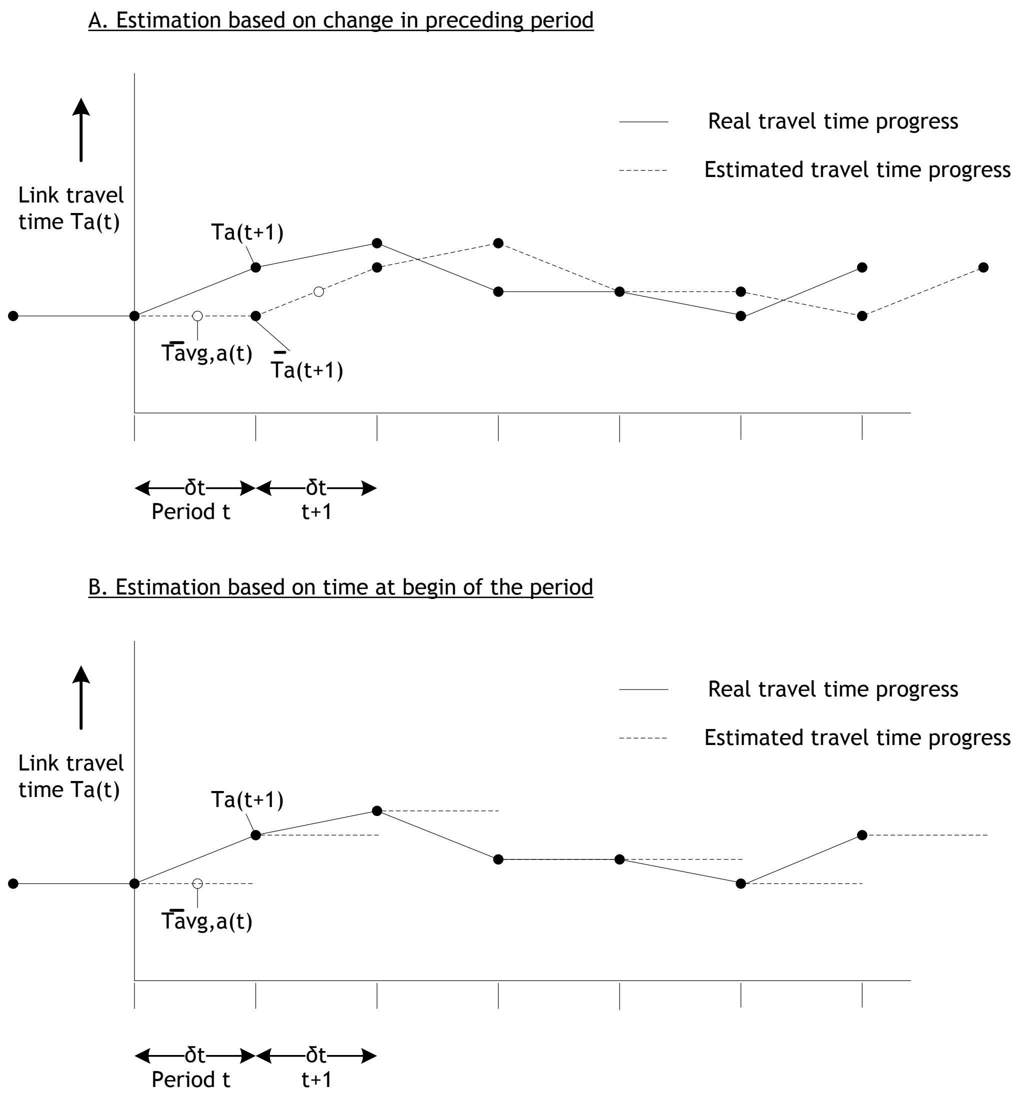


Figure D.1: Two options for the travel time estimation

Appendix E

Figures verification flow fluctuation

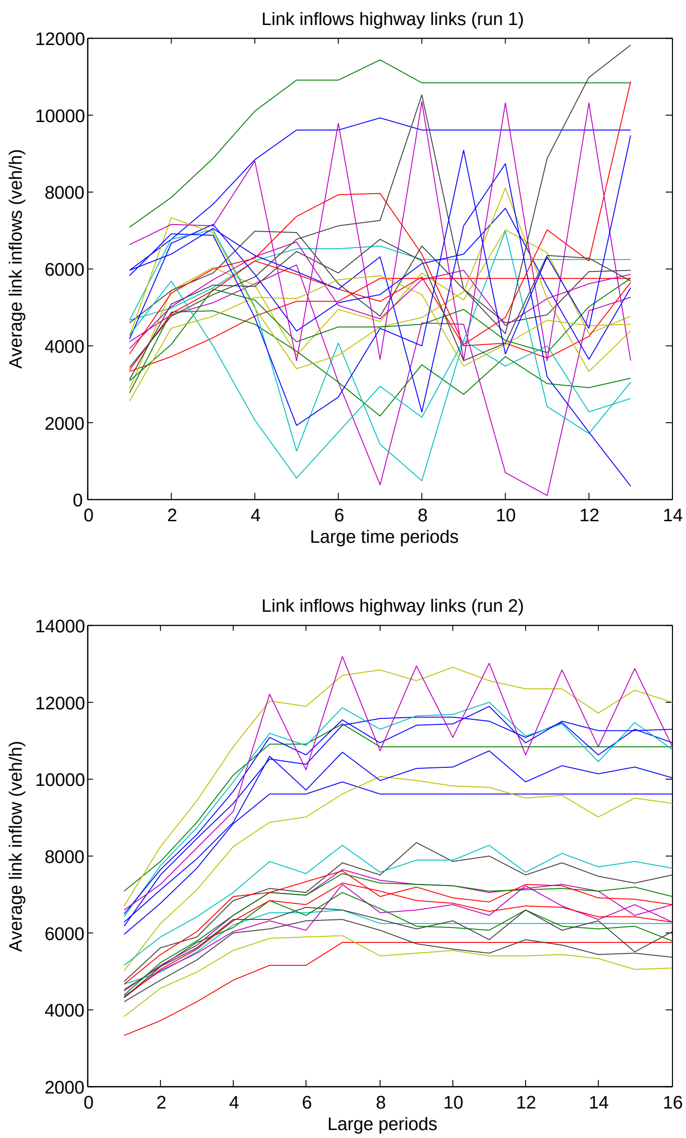
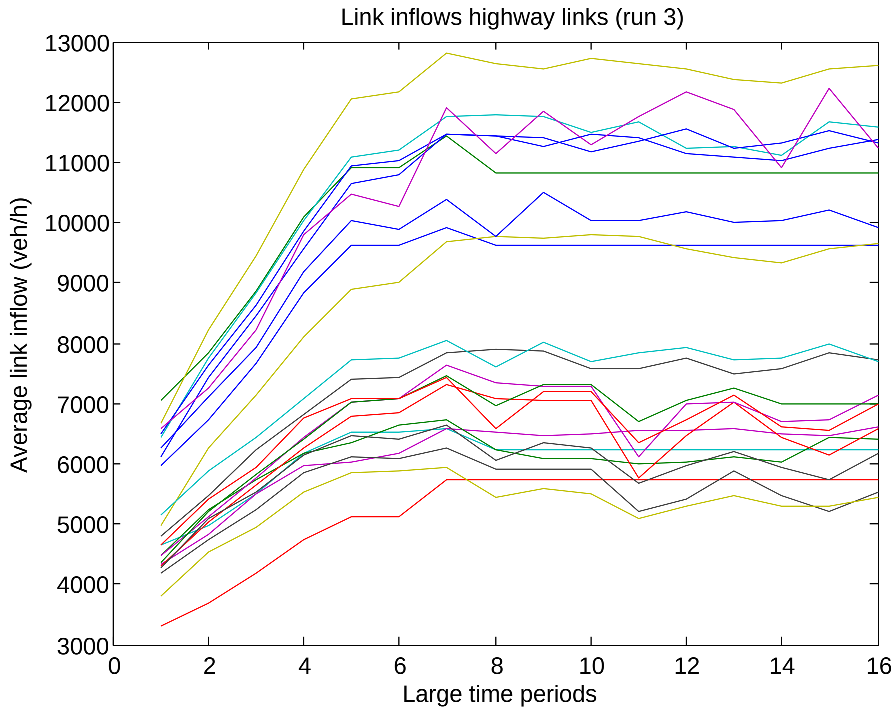


Figure E.1: Average highway link inflows for runs 1 and 2



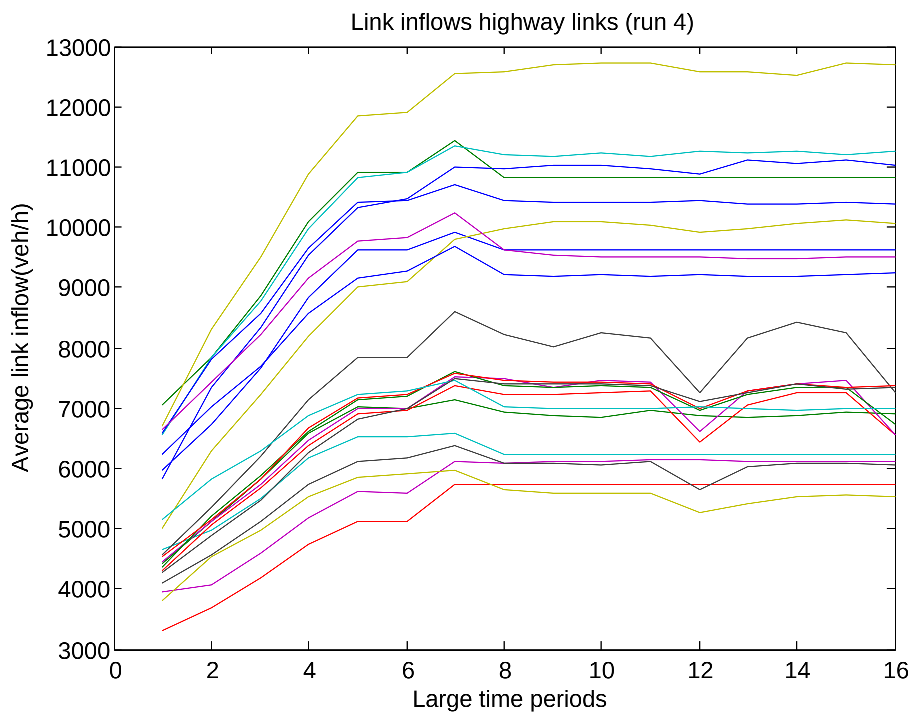
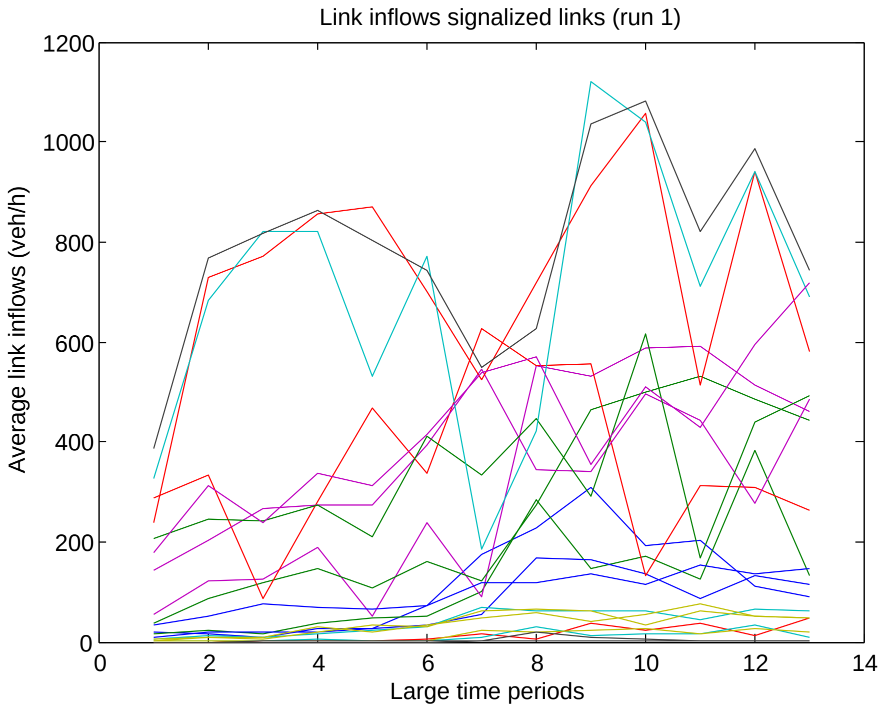


Figure E.2: Average highway link inflows for runs 3 and 4



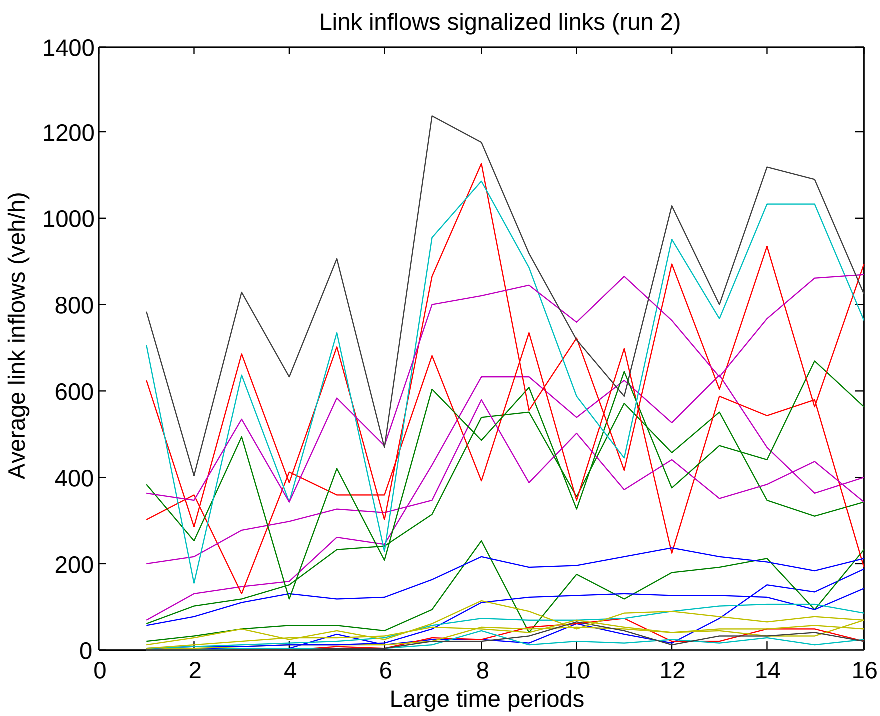
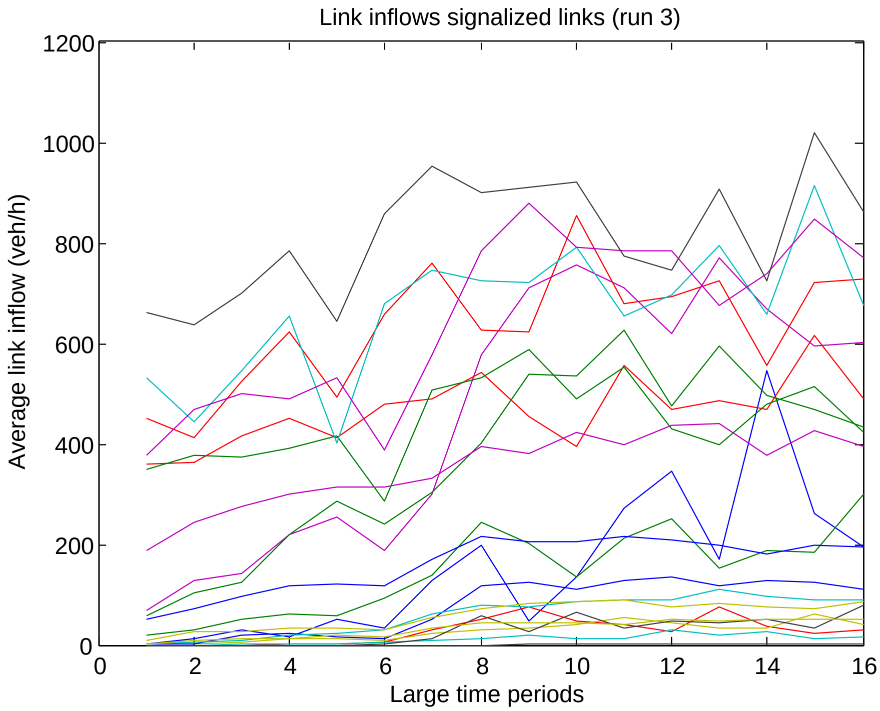


Figure E.3: Average signalized link inflows for runs 1 and 2



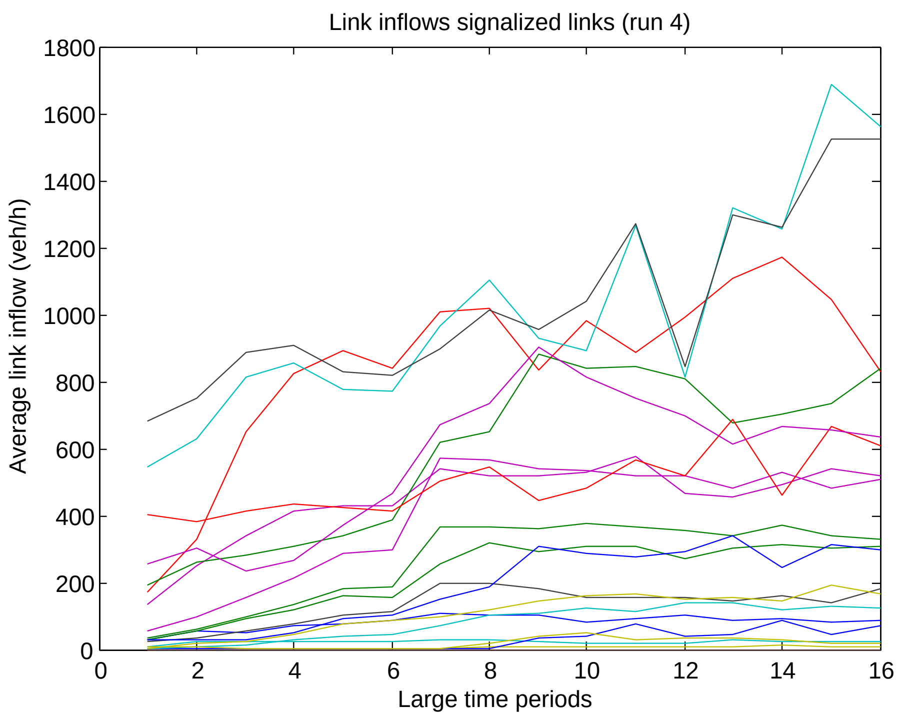
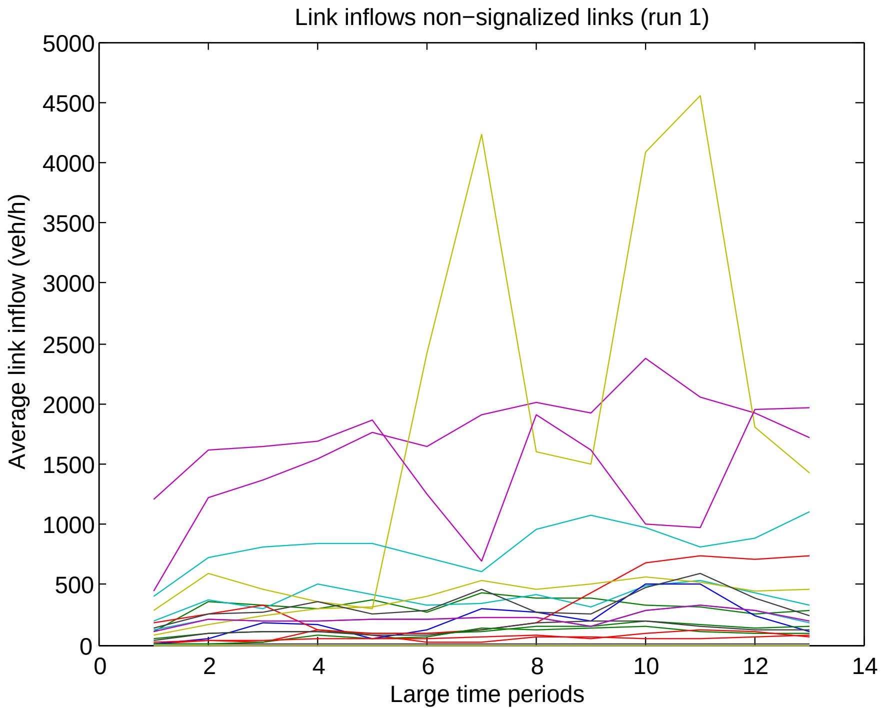


Figure E.4: Average signalized link inflows for runs 3 and 4



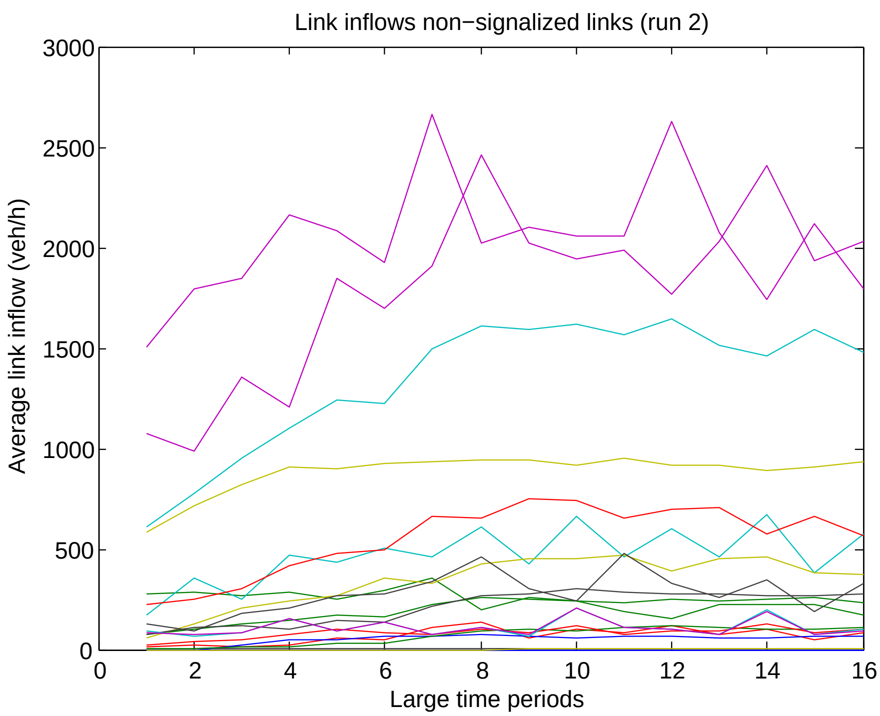
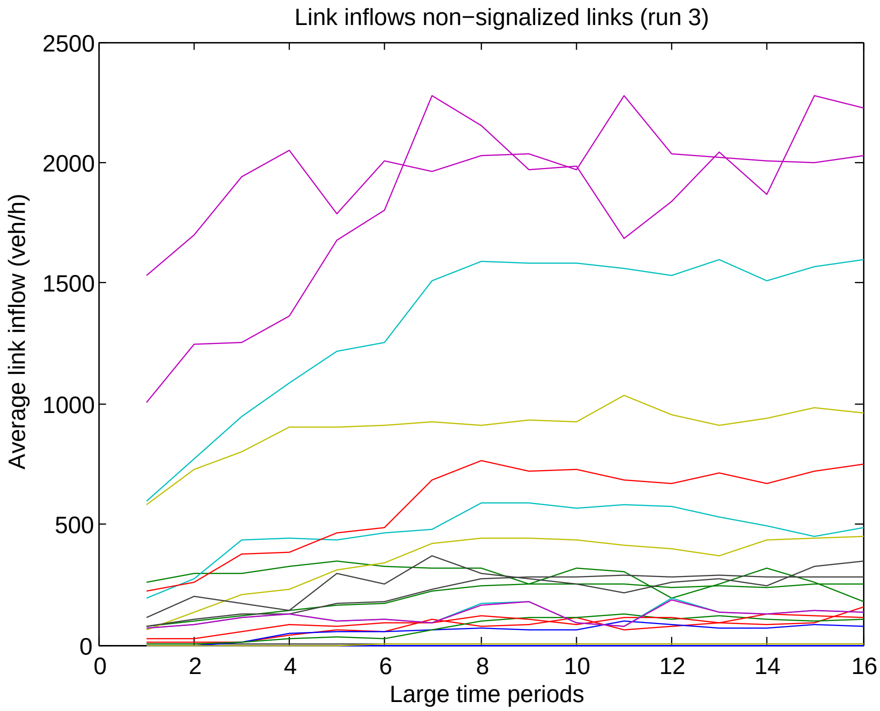


Figure E.5: Average non-signalized link inflows for runs 1 and 2



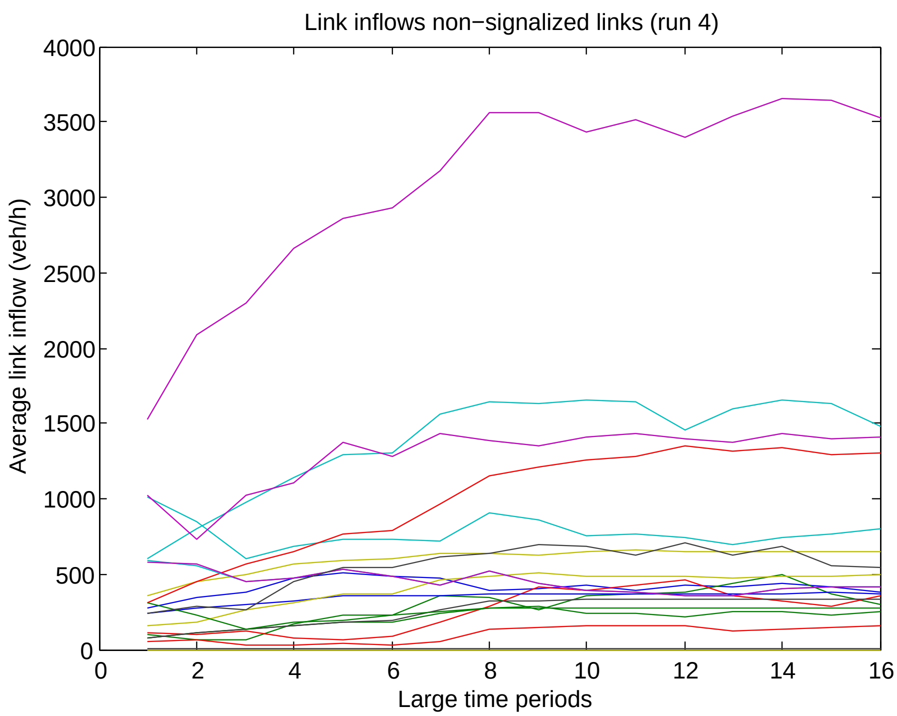


Figure E.6: Average non-signalized link inflows for runs 3 and 4

Appendix F

Figures verification traffic propagation

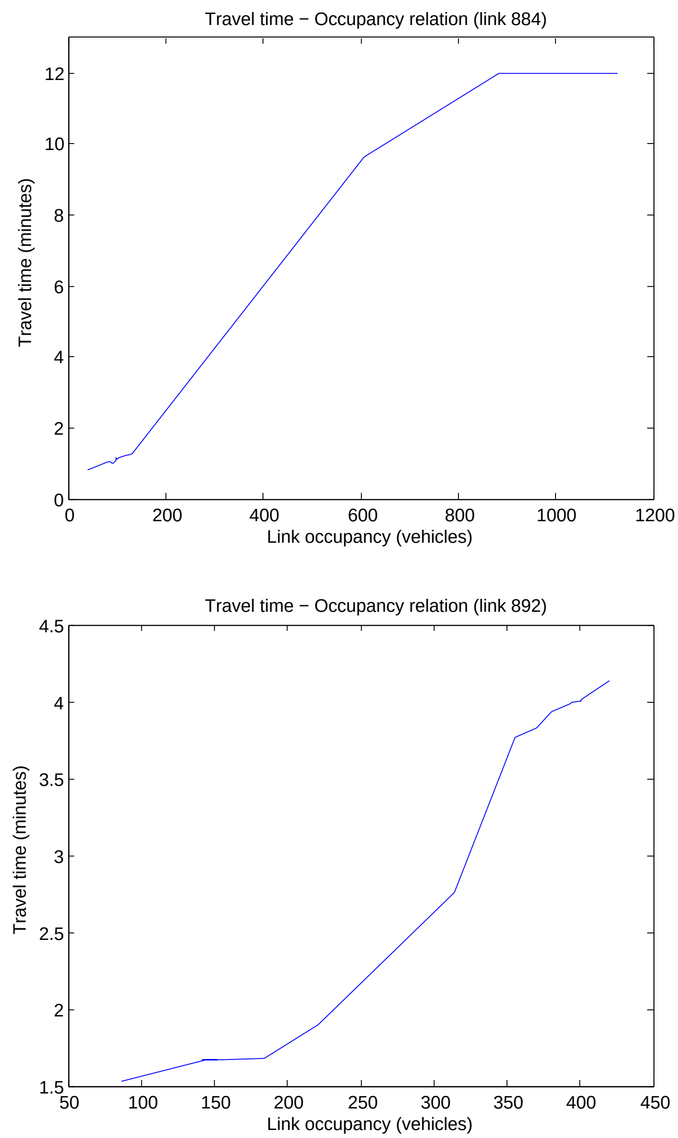
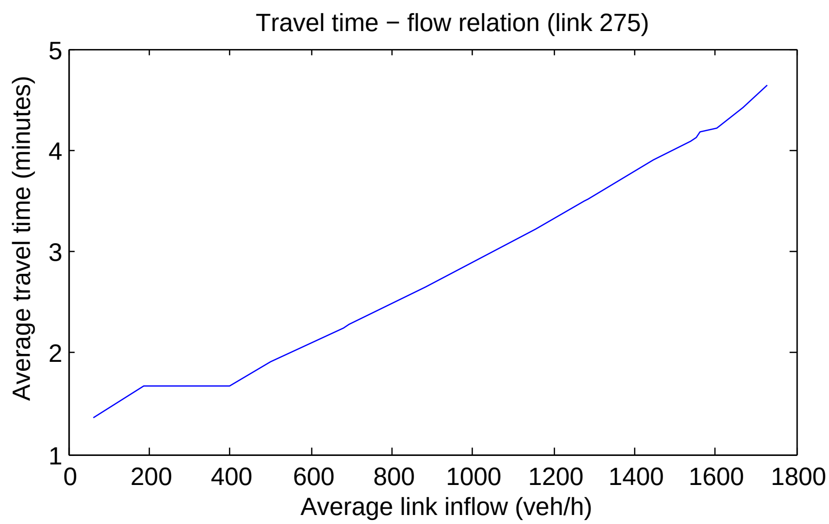


Figure F.1: Travel time occupancy relation at highway links



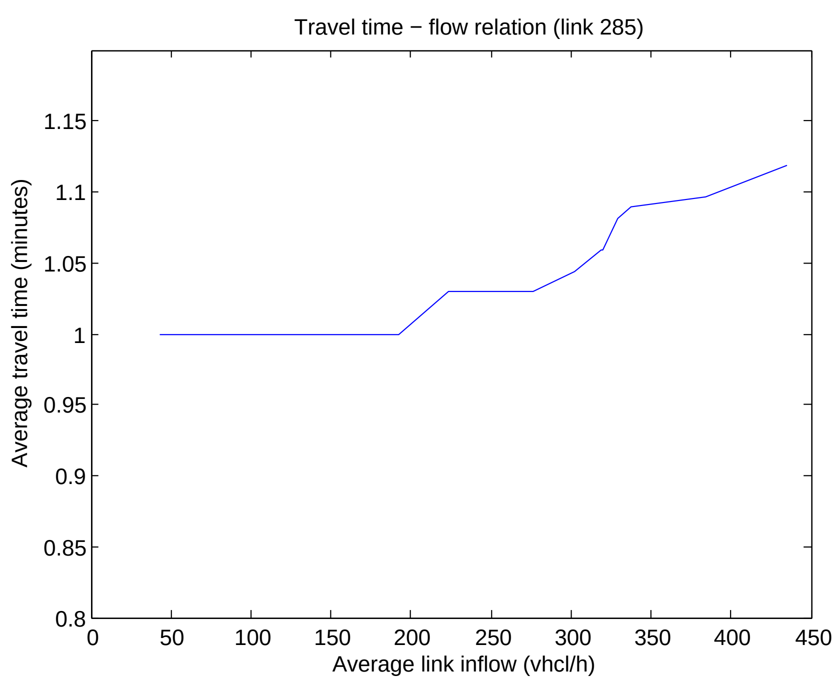


Figure F.2: Travel time flow relation at non-signalized links

Appendix G

Comparison assignments of guidance model and RBV

This appendix presents the figures that are used in the first comparison in the model calibration. The legend in Figure G.1 is used in all figures. Furthermore, bandwidths are scaled to the link loads.

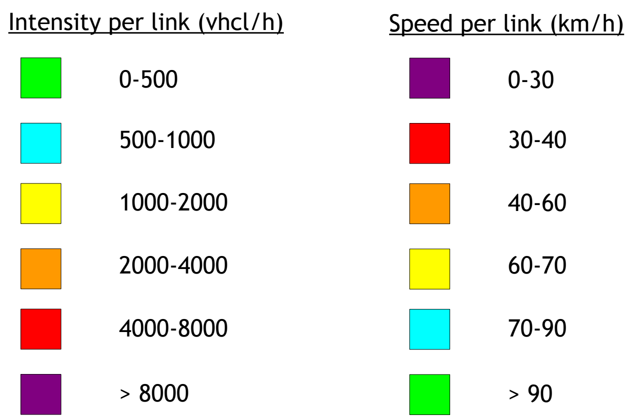


Figure G.1: Legend for the calibration figures

Figure G.2: Comparison of link flows period 1 (top: RBV, bottom: guidance model)

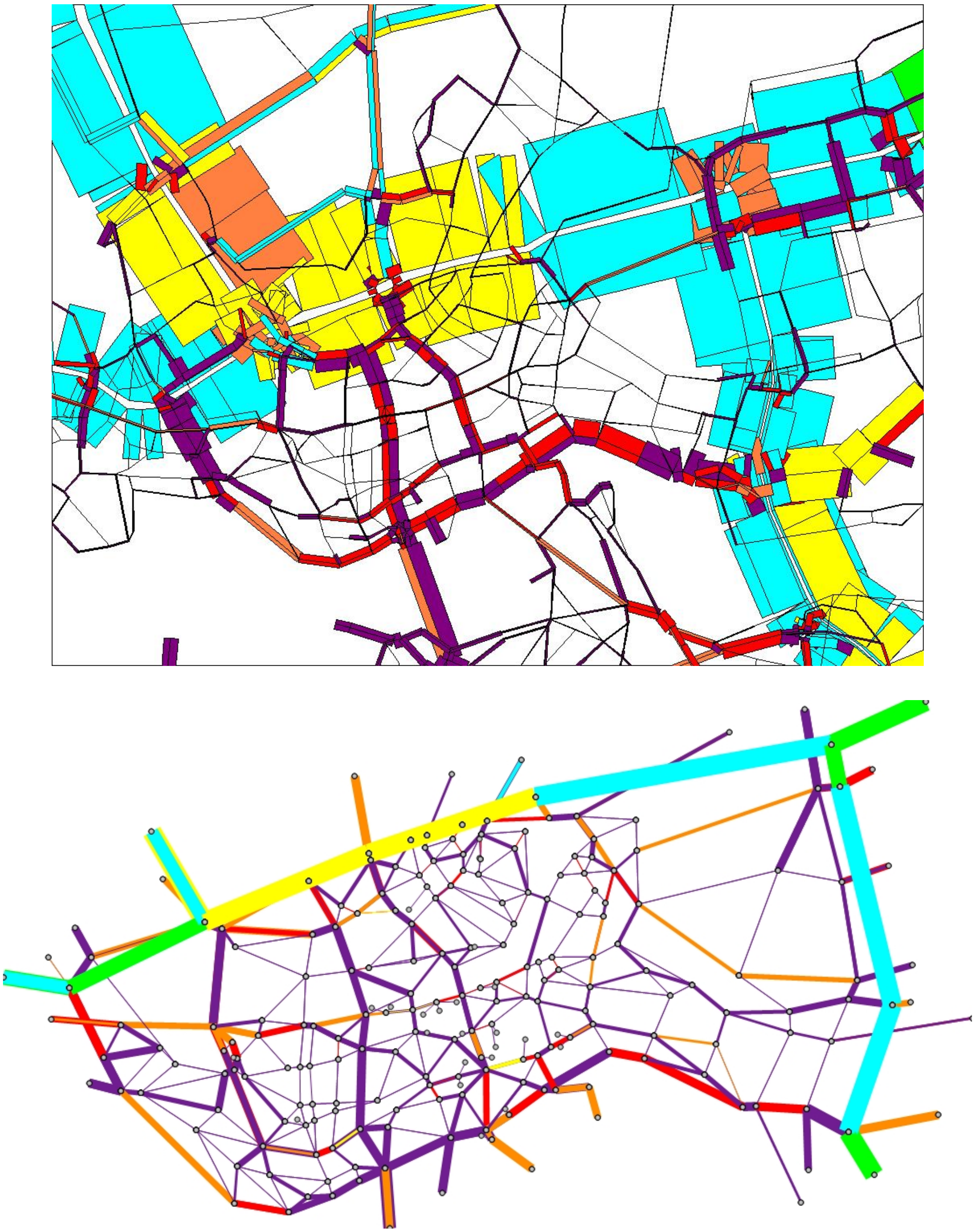


Figure G.3: Comparison of link speeds period 1 (top: RBV, bottom: guidance model)

Figure G.4: Comparison of link flows period 8 (top: RBV, bottom: guidance model)

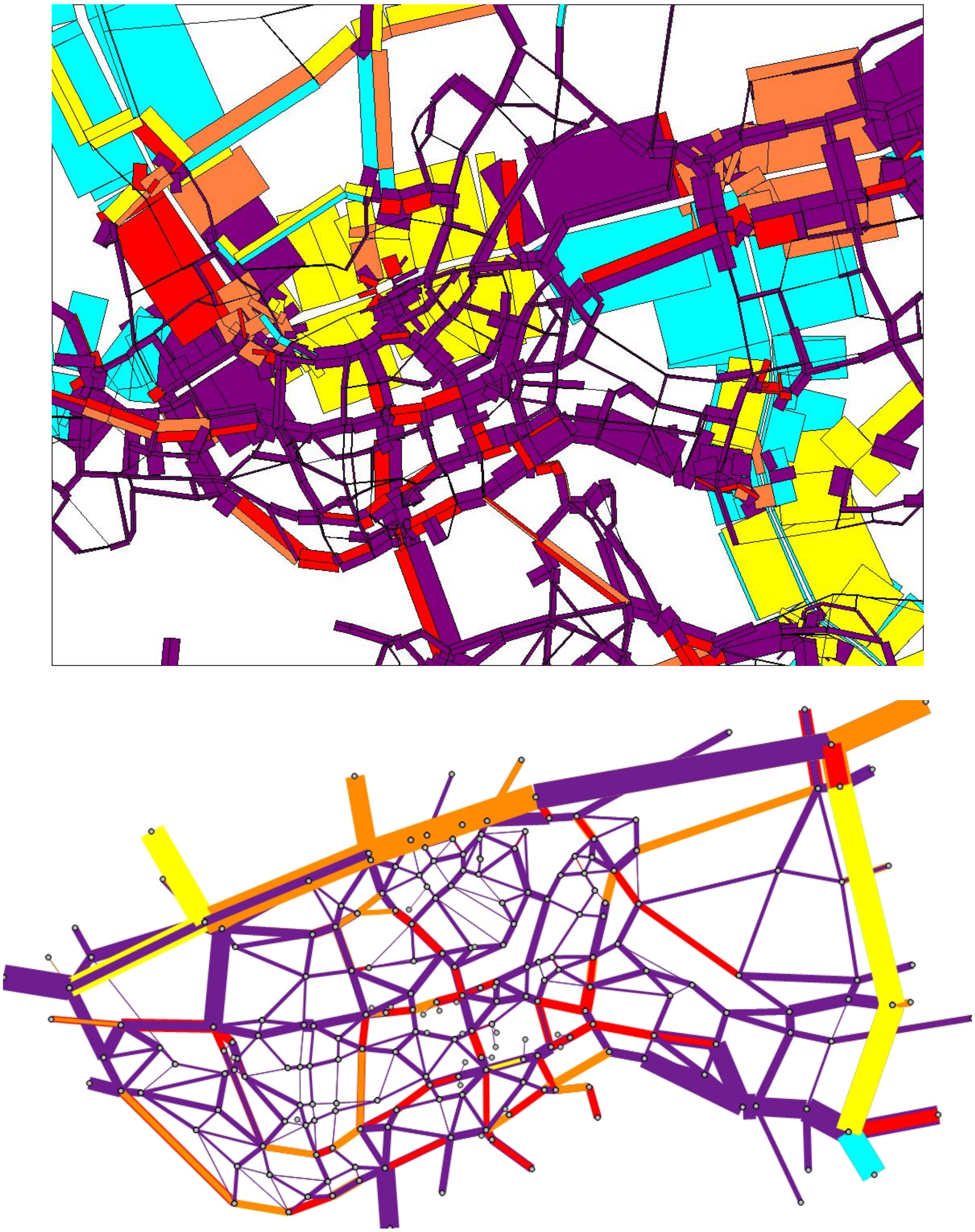


Figure G.5: Comparison of link speeds period 8 (top: RBV, bottom: guidance model)

Figure G.6: Comparison of link flows period 15 (top: RBV, bottom: guidance model)

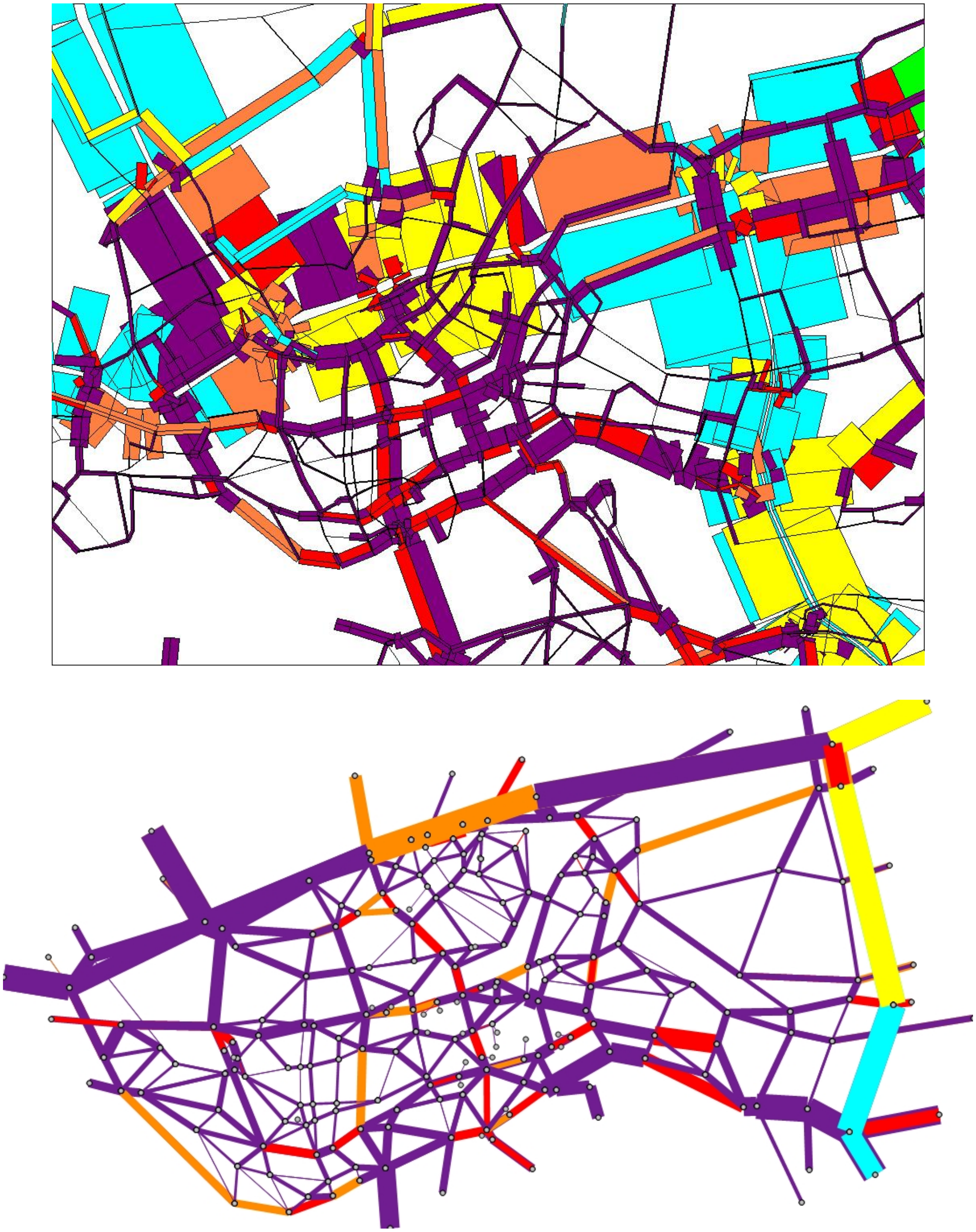


Figure G.7: Comparison of link speeds period 15 (top: RBV, bottom: guidance model)

Appendix H

Comparison of assignments after calibration

This appendix presents the figures that are used in the second comparison in the model calibration. The legend in Figure H.1 is used in all figures. Furthermore, bandwidths are scaled to the link loads.

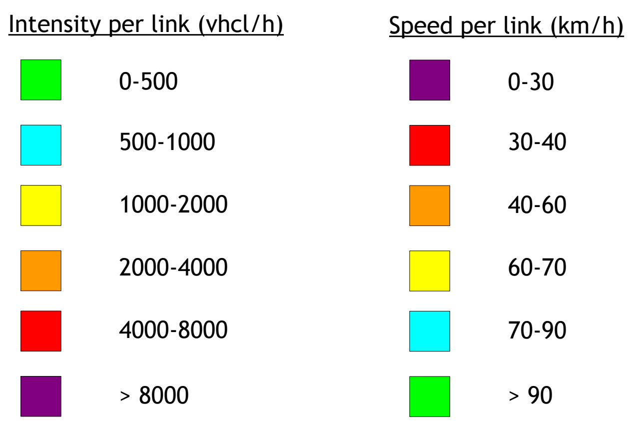


Figure H.1: Legend for the calibration figures

Figure H.2: Comparison of calibrated link flows period 1 (top: RBV, bottom: guidance model)

Figure H.3: Comparison of calibrated link speeds period 1 (top: RBV, bottom: guidance model)

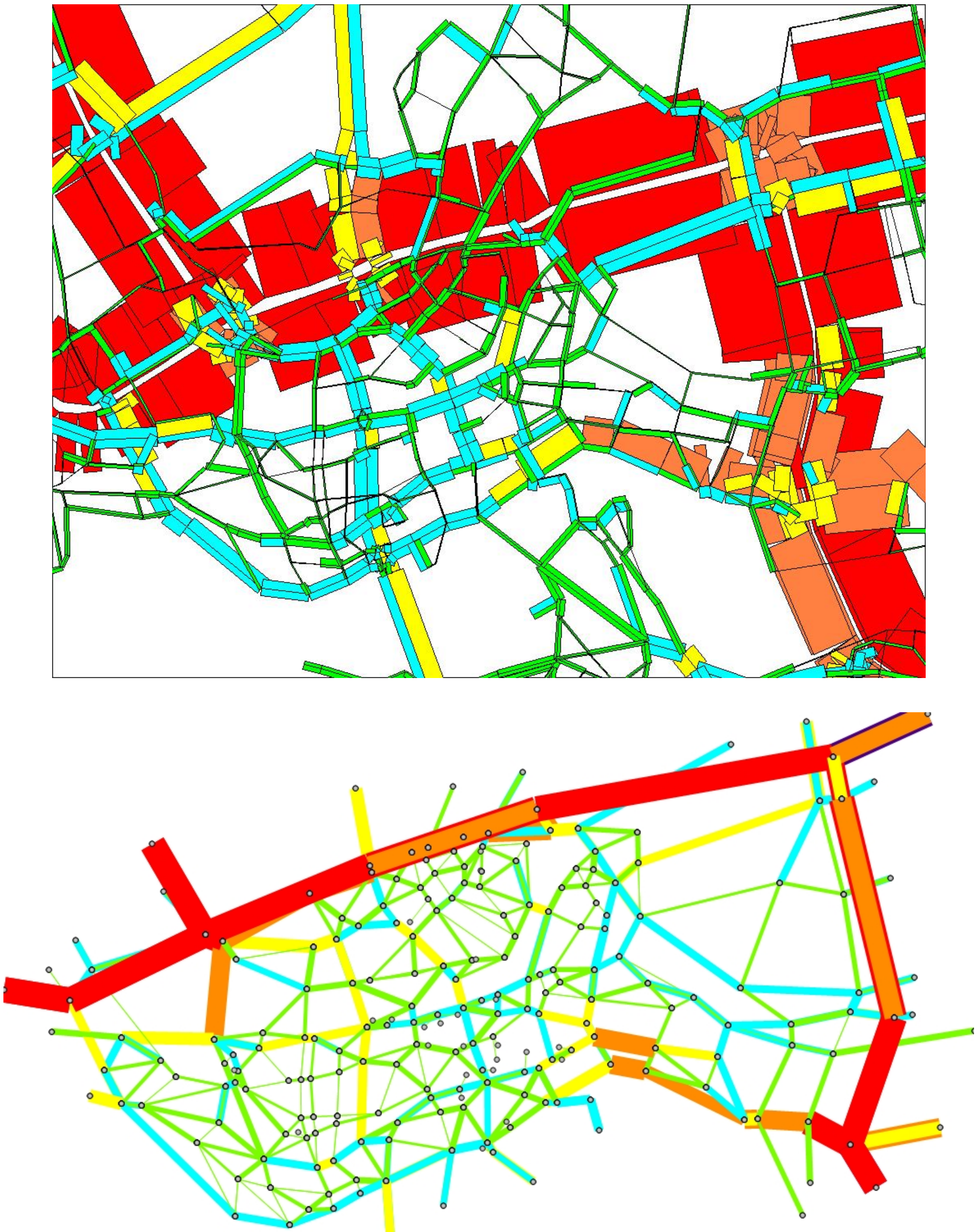


Figure H.4: Comparison of calibrated link flows period 8 (top: RBV, bottom: guidance model)

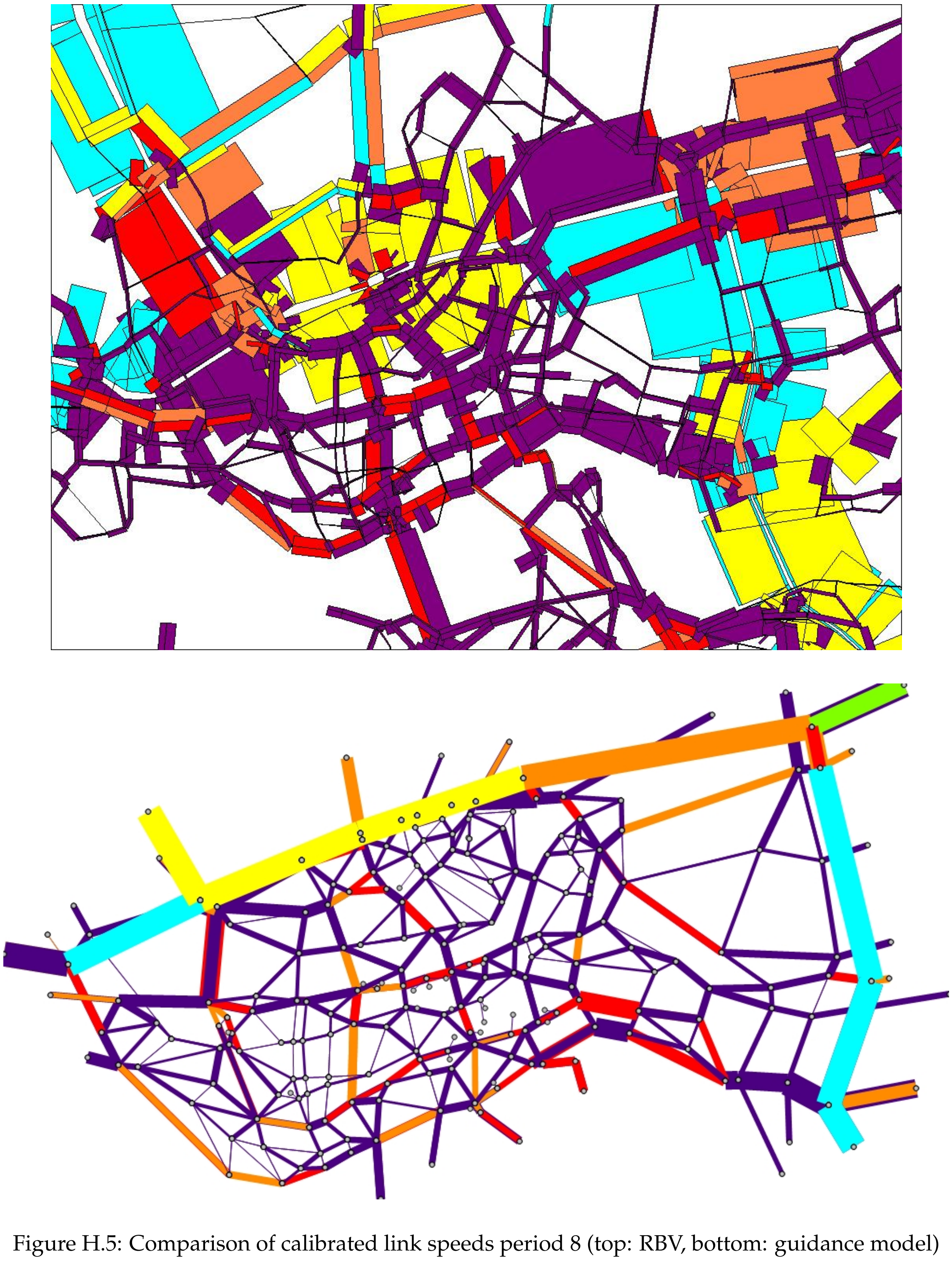


Figure H.5: Comparison of calibrated link speeds period 8 (top: RBV, bottom: guidance model)

Figure H.6: Comparison of calibrated link flows period 15 (top: RBV, bottom: guidance model)

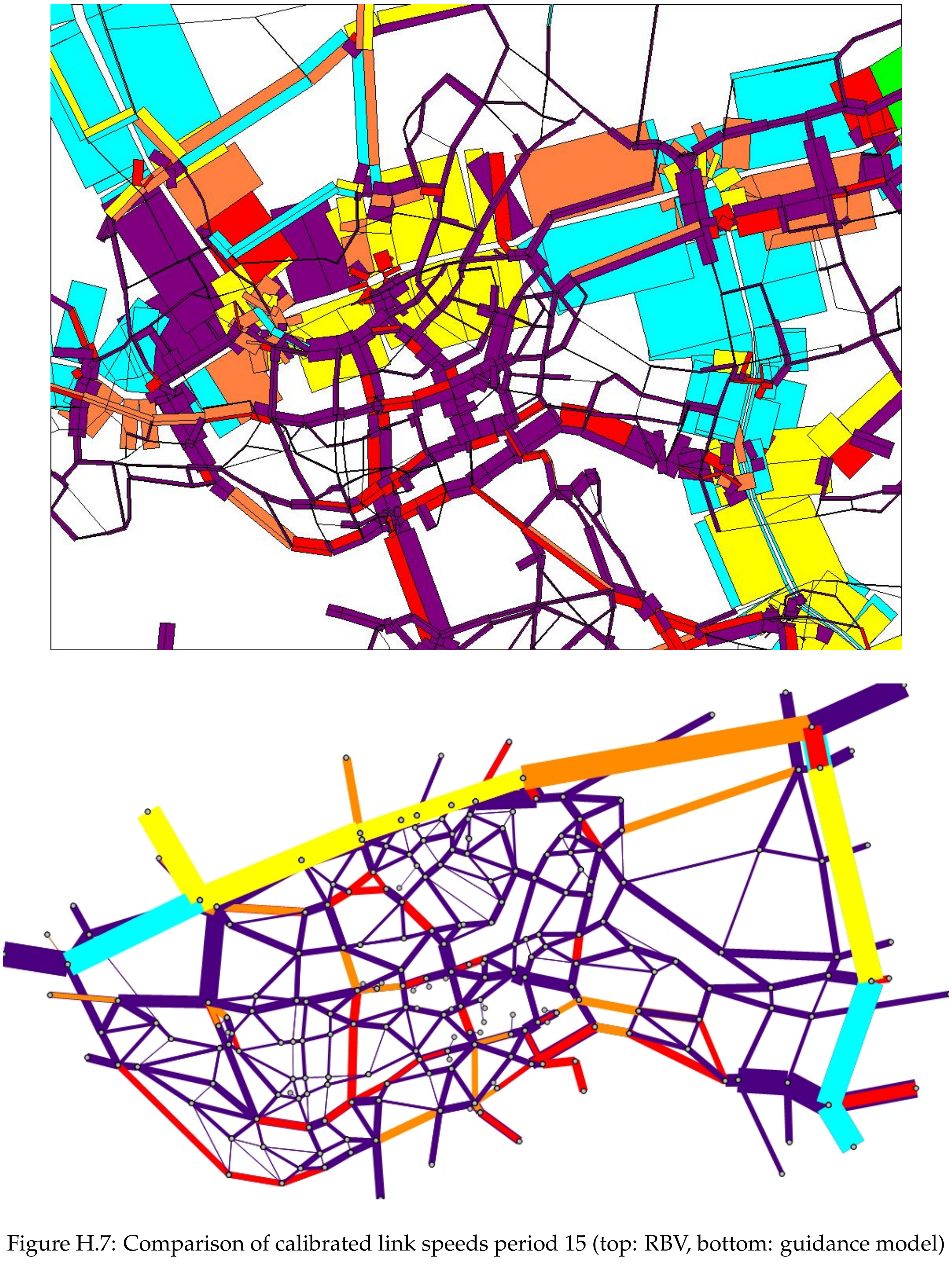


Figure H.7: Comparison of calibrated link speeds period 15 (top: RBV, bottom: guidance model)

Appendix I

Comparison guided and non-guided traffic flows

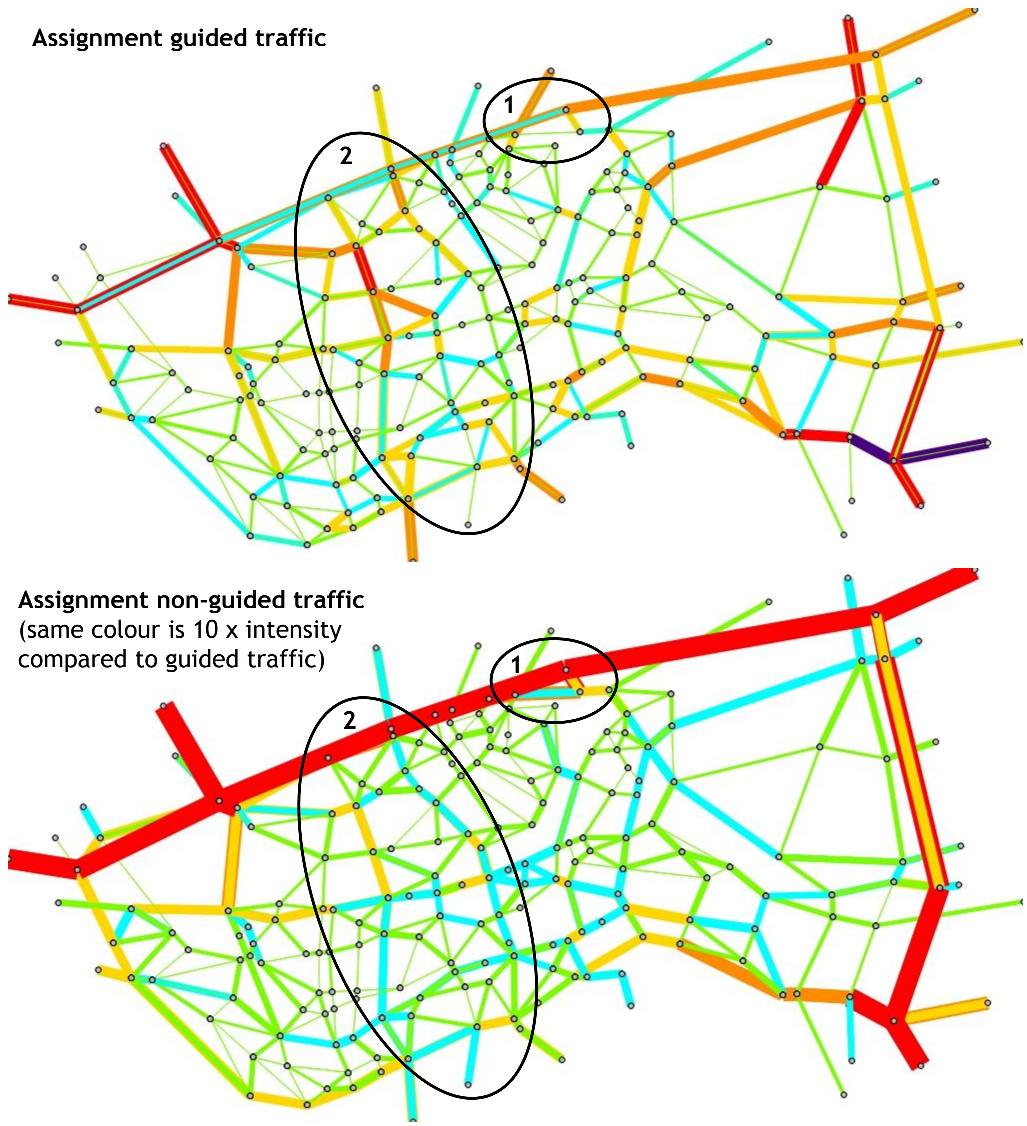


Figure I.1: Comparison of the assignment of guided and non-guided traffic, legend in Figure G.1 (with intensities/10 for guided traffic)