–Cause And Effect–

An Agent-Based Approach to Simulate Strategic Level Driver Behavior

vorgelegt von

Diplom Informatiker
Marco Lützenberger

von der Fakultät IV — Elektrotechnik und Informatik
der Technischen Universität Berlin
zur Erlangung des akademischen Grades

Doktor der Ingenieurwissenschaften
— Dr.-Ing. —

genehmigte Dissertation

—Promotionsausschuss—

Vorsitzender:	Prof. Dr. Gühmann	(TU Berlin)
Berichter :	Prof. Dr. Dr. h.c. Albayrak	(TU Berlin)
Berichter :	Prof. dr. ir. Yasar	(Universiteit Hasselt)
Berichter :	Prof. Dr. Galland	(UT Belfort-Montbéliard)

Tag der wissenschaftlichen Aussprache: 19. Februar 2015

Berlin 2015
D 83

There is no certainty in sciences where one of the mathematical sciences cannot be applied, or which are not in relation with these mathematics.

— Leonardo da Vinci

Abstract

Contemporary traffic simulation systems are able to reproduce traffic situations in a highly realistic fashion. Most of these systems capture the physics of relevant elements and use these models to reproduce traffic scenes of selected roads, cities, and even entire countries. All too often, these models neglect human factors, yet, is it not that human beings significantly determine the outcome of traffic situations?

The aim of this thesis is twofold. The first objective is to determine to what extend current traffic simulations are able to reproduce human behavior in traffic situations. For this purpose, psychological behavior conceptualizations are analyzed and compared to the expressiveness of those models that are currently implemented in computer-aided traffic simulation frameworks. The comparison reveals that there are in fact deficiencies—especially in the representation of one particular form of behavior, namely strategic level driver behavior. This particular form of behavior, however, has a serious impact on traffic situations and is therefore of great importance for traffic simulation systems, respectively. Identified deficiencies mainly concern the representation and implementation of those factors that, following human factors psychology, significantly affect strategic level driver behavior.

The second objective of this work is to correct this misalignment and to present a simulation model which reproduces strategic level driver behavior in compliance with psychological findings. This work substantiates the thesis that such a simulation model can be realized by means of *agent-technology* and the *service* metaphor.

Zusammenfassung

Aktuelle Verkehrssimulationssysteme sind in der Lage Verkehrssituationen nahezu realitätsgetreu abzubilden. Die meisten dieser Systeme bilden die Physik der zu simulierenden Elemente ab und reproduzieren auf Grundlage dieser Modelle das Verkehrsgeschehen von Straßen, Städten, ja sogar von ganzen Ländern. Gerne wird in diesen Modellen jedoch der *Faktor Mensch* vernachlässigt—dabei trägt Letzterer durch sein Verhalten entschieden zu der Entwicklung von Verkehrssituationen bei.

Das erste Ziel dieser Arbeit ist es einen Überblick darüber zu schaffen, bis zu welchem Grad aktuelle Verkehrssimulationssysteme in der Lage sind menschliches Verhalten zu reproduzieren. Zu diesem Zweck werden psychologische Modelle für menschliches Fahr- und Verkehrsverhalten analysiert und deren Ausdrucksstärke mit jenen Modellen verglichen, die derzeit in computergestützten Verkehrssimulationssystemen umgesetzt sind. Diese Analyse zeigt auf, dass es insbesondere auf der Ebene des strategischen Verkehrsverhaltens Defizite in aktuellen Implementierungen gibt. Strategisches Verkehrsverhalten hat jedoch einen gravierenden Einfluss auf das Verkehrsgeschehen und somit auch eine signifikante Bedeutung für Simulationssysteme. Die identifizierten Defizite beziehen sich in erster Linie auf die Repräsentation und die Umsetzung von Faktoren, welche aus Sicht von Psychologen für strategisches Verkehrsverhalten signifikant sind.

Das zweite Ziel dieser Arbeit ist es diesen Missstand zu korrigieren und ein Simulationsmodell vorzustellen welches strategisches Verkehrsverhalten im Einklang mit psychologischen Erkenntnissen reproduziert. Diese Arbeit belegt die These, dass ein solches Simulationsmodell mit den Mitteln der *Agententechnologie* sowie der *Dienst*-Metapher umgesetzt werden kann.

Acknowledgments

Only one name appears on the cover of this thesis, but a great many people have been indirectly involved in its production...

First of all I would like to thank Dr Benjamin Hirsch, who sparked my enthusiasm for science and logic.

Likewise, I would like to thank all my colleagues at the DAI-Labor and those at the competence center ACT in particular. Axel, Baschi, Micha, Nils, Jan, Thomas, Tobi, thanks for your support, suggestions, and criticism.

Special thanks to Prof. Dr. Dr. h.c. Sahin Albayrak for inspiring me, for giving me the opportunity to create this work, and for supporting me to complete it.

Most importantly, I would like to thank Elisabeth, for her love and support and my parents for absolutely everything.

Contents

List of Figures

List of Tables

Part I

Introduction

1. Introduction

Despite the fact that major companies start to present prototypes of autonomous cars, our everyday traffic situation is still determined by vehicles that require a real driver. Without a human driver most contemporary vehicles would not turn, not accelerate, not break—not even start.

To provide some figures: In Germany, at an average day, 281 million trips are done (Federal Ministry of Transport, Building and Urban Development, 2010, p. 24). Out of these, roughly 9% are done by means of public transportation, 10% are done with a bicycle, 24% are done on foot, and 58% are done with a vehicle, which is controlled by a human being (Federal Ministry of Transport, Building and Urban Development, 2010, p. 25). These figures substantiate that our everyday traffic scene is significantly determined by vehicles that are controlled by a real driver and by the decisions and the behavior of these drivers, respectively.

In order to control, to maintain, and to improve traffic and transport systems one particular tool has gained increased attention over the last years, namely computer-aided traffic simulation. Given the importance of human behavior for the outcome of traffic situations, the question arises in how far human behavior is actually reflected in these imitations of real traffic. In fact, most state-of-the-art solutions account for human factors. Krajzewicz (2010), for instance, presents an approach which integrates the imperfection of human beings to maintain a desired velocity. Kuwahara et al. (2010) present a lane change mechanism that accounts for the driver's preferences. Bellemans et al. (2010) and Raney and Nagel (2004) incorporate the abil-

ity of drivers to change their departure times and to adapt their routes to unforeseen incidents.

The question that still remains is in how far these models are able to reflect reality. Human behavior is complex, volatile, and highly individual. One model may perfectly fit for one particular situation, though, the same model may completely fail for others.

The aim of this thesis is twofold. First, it is my intention to clarify in how far current approaches are able to reflect the characteristics of human behavior in a computer-aided traffic simulation. In order to do so, I analyze psychological driver behavior conceptualizations and determine to what extend psychological models are implemented in contemporary traffic simulation frameworks. It is my aim to reveal the frontiers of simulating human behavior in traffic environments.

The second objective of this thesis is to move these borders and to present an improved model which implements psychological findings and thus better copes with reality. I motivate and clarify this improvement below.

1.1 Motivation

In order to assess in how far contemporary traffic simulation frameworks account for human factors, one has to understand the nature and the dependencies of human behavior in general, and human driver behavior in particular. There is no field of research with more experience in analyzing, explaining and formalizing human behavior than human factors psychology. Our current understanding of human driver behavior begins with the work of Michon (1985). Michon (1985) argues that human driver behavior is less a monolithic construct but rather a hierarchically ordered structure of three loosely coupled levels of behavior, namely the strategic level behavior on top, the tactical level behavior in the middle, and the control level behavior at the bottom of the hierarchy. Michon (1985) argues that with an increasing behavioral level, the decision-making process becomes more and more detached from the driving task, such that on control level, drivers reason about controlling the speed or following the road, while on strategic level, drivers generally plan the trip and determine trip goals and routes.

A more detailed look into commonly accepted and well-established driver behavior conceptualizations (e.g., van der Molen and Bötticher, 1988;

Hale et al., 1990; Summala, 1996; Hatakka et al., 1997; Krajzewicz and Wagner, 2002; Bekiaris et al., 2003; Anderson et al., 2004; Keskinen et al., 2004; Engström and Hollnagel, 2007, to name but a few) shows that human driver behavior was and still is conceptualized in compliance with the mechanism that was proposed by Michon (1985).

Furthermore, these approaches show that human driver is affected by no less than four factors. First, decisions on one particular level of behavior can be affected by the outcome of behavioral levels that are directly connected. Secondly, decisions on each level of behavior are always affected by the driver's personality. Thirdly, the outcome of each level of behavior is determined by the driver's experience and knowledge. Finally, decision-making is always affected by external factors, which can be further devided into alternative options, such as public transport, and environmental factors, such as weather conditions.

A look into state-of-the-art traffic simulation models (e.g., Illenberger et al., 2007; Fellendorf and Vortisch, 2010; Krajzewicz, 2010; Kuwahara et al., 2010; Sykes, 2010) shows that contemporary implementations indeed reflect facets of human driver behavior. However, the focus of most frameworks is on tactical level behavior. Control level behavior is not supported at all, while strategic level behavior is represented, although not as comprehensively as tactical level behavior. The lack of control level behavior is easily explained with the area of application in which most frameworks are used. Most analyzed frameworks were developed in order to examine traffic flows on street, highway, or city level. Human control level behavior has only little impact on this granularity. Nevertheless, the focus of this work is different. While the tactical level is already comprehensively covered by contemporary works, there are several aspects of strategic level behavior that are described by psychologists but not implemented in contemporary traffic simulation models.

One aspect that is not adequately covered is that strategic level decision making of human drivers is always affected by the driver's awareness for alternative options and environmental factors. There are only few frameworks which account for this connection, yet the way in which the implementations are done does not comply with psychological findings. While psychologists provide a rather generic definition for alternative options and environmen-

tal factors, available traffic simulation frameworks exclusively account for concrete forms of these two concepts and generally neglect a generic representation. The bottom-line is that the flexibility and the expressiveness of psychological models is not reflected by simulation-based approaches.

A second difference between psychological models and simulation-based implementations is the representation of knowledge. Most simulation-based approaches are based on the assumption that drivers make optimal decisions. The effects of sub-optimal decisions—e.g., as a result of incomplete or erroneous knowledge—are not conceptualized. On the large scale this approach fits its purpose, but with an increasing level of detail the approach becomes inaccurate.

In this thesis, I argue that there is indeed a discrepancy between strategic level driver behavior as it is described by psychologists and the implementation of strategic level driver behavior as it is implemented in contemporary traffic simulation frameworks. This thesis aims to correct this misalignment and to present a simulation model which formalizes strategic level driver behavior in compliance with psychological findings. In particular, it is my intention to present a simulation model which conceptualizes human strategic level driver behavior as a result of the driver's personality and generic factors that evolve from the driver's environment. Contrary to available approaches, this simulation model accounts for incomplete knowledge of drivers and for sub-optimal decisions of drivers in traffic environments. I clarify this objective below.

1.2 Problem Statement

Despite the fact that strategic level driver behavior is reflected in contemporary traffic simulations, available approaches do not comply with requirements and connections that are defined by psychologists. Current works fall short in at least three aspects:

1. The assumption that drivers aim to optimize their efficiency applies to large-scale analysis but looses precision with increasing level of detail. Sub-optimal decisions, which result from incomplete knowledge, are currently not reflected.

2. Alternative options are limited to public transportation. A more generic concept, which accounts for other means of travel or other forms of transportation is missing.

3. Environmental factors are represented in a predefined fashion and occur globally. A generic representation, as described by psychological works, with distinct occurrences, is not possible.

While it is the first objective of this thesis to reveal the current frontiers in simulating human driver behavior and to substantiate the above-presented problem statement, the second objective of this thesis is the development of a simulation model which addresses these problems and improves the representation of human driver behavior as it is described by psychologists in computer-aided traffic simulation frameworks. I argue that such simulation model can be realized by means of *agent-technology* and the *service* metaphor. In this work I substantiate this thesis.

1.3 Outline

This thesis comprises six parts. In Part I, I introduce the reader to the topic of this work. I provide this introduction in Chapter 1.

In Part II, I explain human driver behavior from a psychological point of view. This part comprises two chapters.

In Chapter 2, I consider the questions:

- What is human driver behavior?
- What is strategic level driver behavior?

To answer these questions, I provide an introduction to the field of human factors research in driver psychology and explain how our current understanding of human driver behavior evolved.

In Chapter 3, I consider the question:

- What are the factors that determine the outcome of human strategic level decision-making in traffic environments?

I approach this question by analyzing commonly accepted and well-established driver behavior conceptualizations. Based on this analysis, I identify factors that determine the outcome of human driver behavior.

In Part III, I introduce the reader to the concept of computer-aided traffic simulation and analyze state-of-the-art approaches. The aim of this part is to determine to what extend contemporary works are able to reproduce human driver behavior. This part comprises two chapters.

In Chapter 4, I consider the question:

- What are the fundamental models of a computer-aided traffic simulation?

In order to understand the question, I introduce fundamental concepts of traffic simulation frameworks. I use this introduction in order to explain the particulars of state-of-the-art approaches.

These particulars are presented in Chapter 5, where I consider the questions:

- Is human strategic level driver behavior a factor for the outcome of contemporary traffic simulations?
- What is an appropriate approach to simulate strategic level driver behavior?
- Where are the frontiers in simulating human strategic level driver behavior?

I approach these questions by analyzing contemporary traffic simulation frameworks with particular emphasis on their capability to reflect human behavior as it is described by psychologists.

After discussing the current state-of-the-art in simulating human driver behavior, I proceed with Part IV, in which I present the concept and the development of my simulation model. Development was done in five consecutive phases—each phase is described within a separate chapter.

In Chapter 6, I answer the question:

- Are there available implementations that can be used for the development of a simulation model for strategic level driver behavior?

I answer that by presenting preliminary work, namely a framework that was developed for the simulation of electric vehicles. The simulation of electric vehicles requires models for human strategic level driver behavior, e.g., to arrange trips with respect to the battery's energy level, or to schedule charging processes. Simplified strategic level decision-making processes were already implemented within this framework, which is why I selected this simulation framework as foundation for the implementation of the model which I present in this work.

In Chapter 7, I consider the question:

- Are there established concepts that can be used to facilitate the development of a simulation model for human strategic level driver behavior?

I approach this question by presenting those concepts that I selected for the development of my simulation model. In total I used three concepts, which I present in this chapter. First, I present the agent metaphor after Wooldridge and Jennings (1995), which I used for the conceptualization of human drivers. Secondly, I present the *belief-desire-intention*, or *BDI* paradigm after Rao and Georgeff (1995), which I used for the specification of agent behavior. Finally, I present the service metaphor after MacKenzie et al. (2006), which I used for the conceptualization of external factors. After introducing these concepts on a general level, I substantiate the connection between the concepts and this work. Finally, I discuss the steps that are required to integrate the agent-based driver model and the service-oriented environment.

In Chapter 8, I consider the question:

- Is it generally possible to produce human strategic level driver behavior by using a BDI-based driver behavior conceptualization and a service-based infrastructure representation?

I try to answer that by presenting a prototypical implementation, which is based on the previously described concepts. I use this prototype to demonstrate the general applicability of the approach. The prototype implements a model for the driver and a model for alternative options, yet, support for environmental factors was not included. The model for the driver and the model alternative options are also presented in this chapter.

In Chapter 9, I consider the question:

- Is it possible to use the BDI-based approach and the service paradigm to implement a simulation model for strategic level driver behavior which accounts for the entire spectrum of external disturbances, namely environmental factors and alternative options?

To answer this, I explain how support for environmental factors can be added to the existing prototype.

In Chapter 10, I consider the question:

- Is it possible to develop a simulation model for strategic level driver behavior which complies with psychological findings and accounts for all factors that psychological literature deems to be relevant for the outcome of human strategic level decision-making in traffic environments?

I approach this question by presenting the revised and final simulation model in a uniform representation.

After presenting the development phases, I continue by presenting the evaluation of my approach in Part V. The simulation model was evaluated within three comprehensive research projects—each project application is presented within a separate chapter.

In Chapter 11, I present evaluation results from a research project in which the simulation model was used to determine the efficiency of an automated route and parking assistance system for drivers of electric vehicles. The purpose of the evaluation was to compare the efficiency of automated planning to the capabilities of intuitive planning as it is done human beings. The BDI-based simulation model was used to mimic intuitive planning.

In Chapter 12, I present evaluation results from a research project in which the simulation model was used to determine the efficiency of an automated charging assistance system for drivers of electric vehicles. The objective of the evaluation was to compare the performance of anticipatory charging to intuitive charging as it is done by humans. The simulation model was used to produce the drivers' behavior for intuitive charging.

In Chapter 13, I present evaluation results from a research project which was mainly based on the project that I presented in Chapter 12. In this project, the above-mentioned charging assistance system was improved. The evaluation procedure was similar to the one described in Chapter 12, though, considerably more complex, as different infrastructural configurations as well as different driver profiles were analyzed.

In Part VI, I conclude this thesis. This part comprises one chapter (see Chapter 14) in which I summarize and discuss the results of this work, mention further applications and outline future improvements.

1.4 Conventions used in this Thesis

This work complies with the style guidelines, proposed by the *Publication Manual of the American Psychological Association* (American Psychological Association, 2010).

Part II

Driver Psychology

The aim of this part is twofold. First, it is my intention to introduce the reader to the domain of driver psychology and to emphasize how our current understanding of human driver behavior evolved. Secondly, it is my intention to deepen the knowledge of human driver behavior and to identify factors that determine its outcome.

This part is based on the publications Lützenberger and Albayrak (2013), Lützenberger (2014), and Lützenberger and Albayrak (2014).

The conference paper Lützenberger and Albayrak (2014) won the best paper award at the 46th Summer Computer Simulation Conference 2014.

2. A History

Research in human driver behavior has a long history. It is commonly agreed (Vaa, 2001; Carsten, 2007), that the work of Gibson and Crooks (1938) can be considered as the first serious work in the domain of driver behavior research. In the subsequent years, there have been many developments that culminated in the 1960s, however, in the 1970s, the community somehow lost some of its momentum (Michon, 1985). This development was surprising, especially in view of the "cognitive revolution" that had 'swept the superordinate domain of human factors psychology back then (Michon, 1985). Despite the fact that there have been many approaches and ideas, the community of driver research somehow failed to present a model that became commonly accepted. Developments were somehow isolated—lacking an overarching connection.

The community responded in the year 1984 when the organizing committee of the annual *General Motors Symposium* asked John A. Michon, a luminary of psychological driver research, to identify reasons for the lacking progress.

In order to do so, Michon used one of his earlier works (Michon, 1976), where he identified roles in which a human being systematically interacts with the traffic and transport system. Michon used this description as a pattern in order to assess the capabilities of existing approaches and to identify the particular roles that these approaches account for.

Michon (1985) concluded that none of the examined approaches was able to account for his understanding of human driver behavior. To counter

this problem, Michon (1985) proposed a novel, a seminal approach. This approach was the first work in which different levels of driver behavior—including strategic level driver behavior—were used to explain a driver's actions. Michon's work (Michon, 1985) can be understood as the beginning of our current understanding of human driver behavior.

In this chapter, I illuminate the emergence of this work for two reasons. First, most driver behavior conceptualizations that are currently used are based on Michon's work (Michon, 1985). Thus, in order to present the particulars of contemporary conceptualizations, a fundamental understanding for this work is helpful. Secondly, Michon (1985) presented the first approach that distinguished between different levels of behavior. In doing so, the nature of driver behavior was clarified and the levels of behavior were explained in detail. This very description is commonly accepted, thus, I use it to introduce human driver behavior in general; and strategic level driver behavior in particular.

The purpose of this chapter is two answer the following questions:

- What is human driver behavior?
- What is strategic level driver behavior?

In order to answer these questions, I present the role model that was used by Michon in order to assess the capabilities of available driver behavior conceptualizations and briefly summarize his survey in Section 2.1. Subsequently, in Section 2.2, I present Michon's driver conceptualization in more detail. I conclude the chapter in Section 2.3.

2.1 An Informal Description

Back in the year 1985, John A. Michon was confronted with a difficult problem. It was his challenge to identify reasons for the lack of progress in the erstwhile so successful domain of human factors research in driver psychology.

In order to do so, Michon used one of his earlier works (Michon, 1976). In this work, Michon identified the roles in which human traffic participants occur in traffic and transport systems. It was his objective to analyze

the capabilities of available driver behavior conceptualizations to account for these roles and to identify discrepancies as well as to point out future research directions.

Michon (1976, also Michon, 1985) argued that human mobility is always surrounded by a social as well a technological environment and that any form of behavior in this environment can be considered as interaction between the human being and their environment. Michon (1976) distinguished between four *behavioral levels* of interaction between a human being and the transport and traffic system, in which the former respectively occurs in a different role and with different intentions. Following Michon (1976), a human being may either occur as:

1. an active road user,
2. as a transportation consumer,
3. as an active social being, or
4. as a psycho-biological organism.

The four roles in which human beings may occur in traffic environments are illustrated in Table 2.1.

The central message of Michon's role model is that human behavior in traffic environments serves not only one but several purposes and goals simultaneously. Human beings do not act in one but in many different roles at the same time. On the one end, humans may occur as psycho-biological organisms, trying to satisfy basic needs. On the other end, humans occur as active road users, attempting to control their vehicle. Furthermore, Michon (1976) argued that there has to be some form of interaction between the different levels. Behavior on the lower levels can be influenced by high-level behavior and vice versa. Michon (1976) described this connection as well as the arrangement of the identified levels of behavior as a "nested hierarchy".

Based on this conclusion, Michon (1985) analyzed available behavior conceptualizations in order to determine to what extend these approaches comply with his rather informal understanding of human driver behavior. Due to the large amount of available approaches, Michon (1985) proposed a classification system for driver behavior models and argued that the models

Table 2.1: Behavioral levels relative to the hierarchical structure of problem solving tasks in traffic and transportation environments (adapted from Michon, 1985, Figure 1, p. 488, after Michon, 1976).

	Behavioral Level			
	I	II	III	IV
Human Quality as a Problem Solver	Road user	Transportation Consumer	Social Agent	Psycho-biological organism
Problem to be solved	Vehicle Control	Trip making	Activity pattern (Communication)	Satisfaction of basic needs
Task environment	Road	Road network (Topographical structure)	Socio-economic structure	Nature (environment)
Task aids	Vehicles, signs, etc.	Transport mode	Transport system	"Culture", Technology

from one category of this classification system respectively behave similar. Michon (1985) analyzed only well-established approaches from each category.

The proposed classification system comprises two dimensions. On the first dimension, Michon (1985) distinguishes between *behavioural models* and *psychological models*. While the former category comprises "input-output-oriented" models, the latter implies some internal state of the driver. On the second dimension, Michon (1985) distinguishes between *functional models* and *taxonomic models*. Taxonomic models can be considered as inventories of facts as well as relations between those. Relations, which hold between these facts, are those of sets, such as super and subordination, identity, sequential relations, as well as measures on sets, such as proportions, likelihood or generalized distance. Contrary to the rather static expressiveness of taxonomic models, functional models always define a dynamic interaction between their constituting components. The two-dimensional driver behavior classification system after Michon (1985) is illustrated in Table 2.2.

Table 2.2: Michon's two-dimensional classification system for driver behavior conceputualizations (adapted from Michon, 1985, Figure 3., p. 490).

	Taxonomic	Functional
Behavioral (Input-Output)	Task Analyses	Mechanistic Models Adaptive Control Models
Psychological (Internal State)	Trait Models	Motivational Models

Based on the proposed dimensions, Michon (1985) identified five categories of driver behavior conceptualizations, namely *task analysis models*, *trait models*, *mechanistic models*, *adaptive control models* and *motivational models*. For the sake of completeness, I briefly describe the particulars of these categories below.

Task analysis refers to the mental decomposition of the driving task into tasks and subtasks (Michon, 1985). Task analysis models consist of

three different types of descriptions. First, facts about the driving tasks, the so-called *task requirements*, are defined. Secondly, behavioral requirements, the so-called *performance objectives* are specified. Finally, the ability requirements (or *enabling objectives*) which are required to perform the conceptualized task, are described.

Trait models are based on the *trait theory*, which deals with the analysis of the human personality (Kassin, 2003). As the name suggests, the trait theory particularly focuses on the human measurement process of traits. These are either defined as habitual patterns of human behavior, as human thoughts, or as human emotions.

Mechanistic models are based on the idea, that it is possible to capture the dynamics of complex systems by understanding the constituting parts of such systems as well as the connection between these atomic elements (Michon, 1985). Therefore, mechanistic models are grounded on the strict assumption that platoons of vehicles behave as an incompressible fluid.

Adaptive control models describe how drivers adapt their behavior to the dynamics of either the surrounding environment or the controlled vehicle (Peters and Nilsson, 2007). Michon (1985) further distinguished between *servo-control models* and *information flow control models*.

Servo-control models are based on the assumption that drivers intend to minimize the difference between a reference state (e.g., a target state) and the current state (Engström and Hollnagel, 2007). These models are commonly used to explain lateral and longitudinal vehicle control in constrained situations. Servo-control models do not account for high-level aspects, such as decision-making, planning, or motivational aspects of the drivers.

Information flow control models explain cognition as a sequence of logically separated computational steps that may include perception, decision, and response selection (Engström and Hollnagel, 2007). Considering the phases in isolation allows to assign limited capacities to the different action stages and thus to account for limitations in the attention and the performance of human beings.

Motivational models describe the driving task as a dynamic regulation of risk (Engström and Hollnagel, 2007). Motivational models are frequently used to capture the adaptation process of drivers to varying driving conditions. To this end, utilities and trade-offs are used to describe why drivers prefer one decision to another (Carsten, 2007). Belonging to the category of psychological models, motivational models also define attitudes and controlling factors. This is done by means of internal states and subjective risk.

Michon (1985) analyzed well-established approaches from each category and argued that none of them was able to account for his understanding of driver behavior. His main criticism was that examined approaches were focused on one particular role of human behavior in traffic environments. Other roles and connections between the different roles were generally neglected.

In more detail, Michon (1985) criticized taxonomic models to neglect dynamic relations between their individual elements. He criticized mechanistic models for having too much focus on the physics of vehicles and neglecting the behavior of the driver. Michon's hopes were on functional models rather than on taxonomic ones. It was his opinion, that the structural composition and the dynamic interaction between constituting model components as well as the comprehensive description of internal states could be used to capture the dynamics of human driver behavior. Yet, Michon (1985) also identified several problems of functional models. In the case of servo-control models, he identified shortcomings in the perception mechanism. Examined approaches were not able to account for tasks that were beyond following the road. He criticized information flow control models to not account for behavioral aspects of the conceptualized drivers. Finally, he criticized motivational models to fail in providing details about cognitive procedures and learning. Michon (1985) identified the intentional character of motivational models as their main problem. To be exact, Michon (1985) argued that motivational models put a focus on the results of cognitive functions, namely beliefs, emotions and intentions, rather than on the cognitive functions themselves.

Finally, Michon (1985) argued that all examined models were either bottom-up approaches, neglecting higher-level aspects of the driving task

(e.g., drivers as transportation consumer or social agents, see also Table 2.1) or—in the case of top down approaches—fail to specify the structure of the internal models which drivers must hold in their mind.

Michon (1985) concluded that controlling the vehicle is only one of the tasks a driver has to accomplish in traffic environments and that a more comprehensive consideration of driving is required because many traffic-related problems do not originate from the driving process per se.

Michon (1985) also stated that a more comprehensive consideration can not be captured in a monolithically structured model (the formerly prevailing design). Following Michon (1985), monolithically structured models are not able to express the dynamics of human driver behavior and thus fail to account for the different roles in which humans beings occur in traffic and transport environments.

To counter this problem, Michon (1985) proposed an entirely new design, namely a hierarchically ordered assembly. His *Hierarchical Control Model* (Michon, 1985), combines all promising aspects and neglects all misleading components of those models that Michon analyzed. In the following, I present the Hierarchical Control Model in more detail.

2.2 The Hierarchical Control Model

Michon (1985) identified several minor problems of available driver behavior models. To start with, examined approaches defined no interaction between their constituting components. Furthermore, internal states of drivers were mostly ignored. Finally, perception "as a concept", as well as cognitive procedures were neglected. However, the most significant problem that Michon (1985) identified was the monolithic assembly of available driver behavior conceptualizations.

Monolithically structured models were in conflict with Michon's understanding of human driver behavior, which is role-dependent and thus evolves from different behavior levels simultaneously. The outcome of each level is determined by different factors, such as intentions, preferences, personality, or education, to name but a few.

To counter the deficiency of available approaches and to account for different roles in which humans occur in traffic environments, Michon (1985)

proposed an approach in which three different levels of driver behavior are arranged in a hierarchically ordered assembly. Michon (1985) distinguished between *strategic level* driver behavior, *tactical* or *maneuvering level* driver behavior, and *operational level* or *control level* driver behavior, and described these levels as follows:

Strategic level driver behavior refers to the general planning stage of a trip. This stage includes the determination of trip goals, the route and the modal choice as well as a cost-risk evaluation. Furthermore, the behavior of drivers on this level is affected by general considerations about transport and mobility. Finally, concomitant factors such as aesthetic satisfaction and comfort are able to determine the outcome of this behavior level.

Tactical level or maneuvering level driver behavior refers to the ability of drivers to negotiate the directly prevailing circumstances. Maneuvers that are performed at this stage are largely constrained by the exigencies of the traffic situation, though, they have to meet the criteria that derive from the goals that were specified at the strategic level. Nevertheless, there are also cases where these goals may be adapted to fit the outcome of certain maneuvers. Examples for maneuvers that are performed at this stage are obstacle avoidance, gap acceptance, turning, and overtaking.

Operational level or control level driver behavior refers to fundamental car controlling processes such as controlling speed, following the road, and keeping the vehicle on the road. Most of the driver behavior conceptualizations that were analyzed by Michon (1985) were focused on this particular level of behavior, neglecting higher levels completely.

Based on his analysis, Michon (1985) concluded that it is necessary to define a connection between the relevant model components in order to capture the dynamics of human driver behavior. To this effect, Michon (1985) proposed an interaction between the three levels of behavior. The interaction was used to accounts for the fact that maneuvers that originate from a certain level of behavior have to meet the criteria from the upper levels and—at the same time—allow the outcome of lower levels to change these criteria.

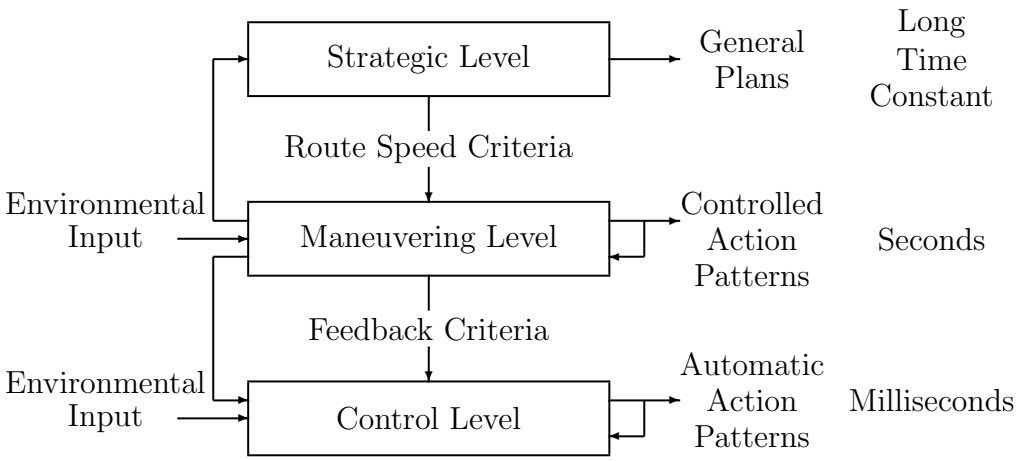

Figure 2.1: The *Hierarchical Control Model* of the road user task. The three levels of driver behavior (strategic level, tactical level, and operational level) are loosely coupled. Internal and external outputs are illustrated as well (adapted from Michon, 1985, Figure 2, p. 489).

The Hierarchical Control Model after Michon (1985) is illustrated in Figure 2.1.

The Hierarchical Control Model was the first approach that explained human driver behavior as an interplay of different levels of driver behavior—each one with different goals and objectives. It was also the first time that higher-level aspects, e.g., aspects which are not entirely related to the driving process, were used as input parameter for human decision-making in traffic environments.

The model became commonly accepted and can be considered as the beginning of our current understanding of human driver behavior (Keskinen et al., 2004). The hierarchical assembly of Michon's seminal model determines the landscape of contemporary driver behavior conceptualizations up until today.

2.3 Conclusion

The aim of this chapter was twofold. First, it was my intention to introduce human driver behavior from a psychological point of view. My objective was to explain how driver behavior can be conceptualized and to answer the question: "What is human driver behavior?"

Our current understanding of human driver behavior began with the work of Michon (1985), who identified several problems of formerly available

approaches. To counter these problems, Michon (1985) proposed his own approach which became widely accepted and helped the entire community of human factors research in driver behavior to gain new momentum.

Following Michon (1985), human driver behavior can be represented as a hierarchically ordered structure of loosely coupled behavioral levels, on which drivers attempt to solve problems. The higher the level, the more "detached" are problems that drivers attempt to solve. On the lowest level, for instance, drivers deal with fundamental car controlling processes, such as controlling speed, following the road, and keeping the vehicle on the road. On the highest level, drivers reason about the general planning of a trip and solve problems that are not entirely related to the driving task. The result of the problem solving process is an action that the driver executes. This action may solve the level-specific problem of the driver, however, it may also cause problems on adjacent levels of behavior, such that the mutual dependencies of all behavior levels can be described as nested hierarchy. Nevertheless, on each level, the drivers' decision-making process is affected by their personality, their perception, their knowledge (as a consequence to learning processes), as well as by their cognitive abilities.

The second objective of this chapter was to introduce high-level driver behavior from a psychological perspective and to answer the question: "What is strategic level driver behavior?"

Following Michon (1985), strategic level driver behavior refers to the general planning stage of a trip. This stage includes the determination of trip goals, the route and the modal choice as well as a cost-risk evaluation. The behavior of drivers on this level is affected by general considerations about transport and mobility. Finally, concomitant factors such as aesthetic satisfaction and comfort are able to determine the outcome of this behavior level.

Despite the great success of the Hierarchical Control Model, several aspects were not reflected—this was not without a reason. Michon never intended to present a complete model for human driver behavior. Rather, it was his objective to open new lines of thoughts and to help the stagnating community to gain momentum, again. To this end, the Hierarchical Control Model provides a shape, yet failed to provide details about the decision-making on the different levels.

Michon (1985) knew that his model required revisions, thus, he already motivated two potential refinements that were needed to enhance the Hierarchical Control Model to a more comprehensive representation of human driver behavior. First, Michon (1985) argued that concepts of perception and cognition are required. Michon already accounted for these concepts, though, used rather simple representation, e.g., connected relevant model elements to the driver's environment. Secondly, Michon (1985) argued that it is necessary to comprehensively specify the levels of behavior and to account for internal states of the drivers.

Michon's work became widely accepted and his guidelines were consistently implemented. Most later works used the Hierarchical Control Model as a foundation.

After this general introduction into the fundamentals of psychological driver behavior conceptualizations, I continue this work by presenting psychological models that are currently used to explain human driver behavior.

3. A Driver's Mind

In the previous chapter, I emphasized the importance of strategic level decisions for the outcome human driver behavior. In this chapter, I go into detail and clarify the nature of strategic level driver behavior.

The aim of this chapter is twofold. First, it is my intention to adapt the description of strategic level driver behavior from the previous chapter to its representation in currently used, and well-established driver behavior conceptualizations. Secondly, it is my objective to identify factors that determine the outcome of strategic level decision-making processes of human beings in traffic environments.

The purpose of this chapter is to answer the following question:

- What are the factors that determine the outcome of human strategic level decision-making in traffic environments?

To answer this question, I analyze driver conceptualizations that are currently being used in order to explain human driver behavior.

To provide some structure to this chapter, I distinguish between three categories. I present approaches that roughly maintain the hierarchy of the Hierarchical Control Model under the umbrella of *classical hierarchical structures* in Section 3.1. Broadly stated, classical hierarchical structures refine individual behavior phases or provide more detailed descriptions of involved processes. In Section 3.2, I present *multi-dimension hierarchies*.

Contrary to classical hierarchical structures, multi-dimension hierarchies extend the one-dimensional structure of the Hierarchical Control Model by further dimensions and thus account for more advanced concepts such as different levels of experience and automatism. Finally, in Section 3.3, I present *cognitive approaches*. Cognitive approaches combine hierarchically ordered structures with cognitive processing. I conclude this chapter in Section 3.4.

3.1 Classical Hierarchical Structures

Most works which are presented under the umbrella of classical hierarchical structures directly extend the Hierarchical Control Model. Approaches that fall into this category implement the guidelines that were proposed by Michon (1985) and either provide more detailed specifications for all model components or extend the behavioral hierarchy by further levels.

3.1.1 Hierarchical Risk Model for Traffic Participants

The first classical hierarchical structure that I introduce was presented by van der Molen and Bötticher (1988, also Bötticher and van der Molen, 1988). The *Hierarchical Risk Model for Traffic Participants* comprises three levels of behavior, namely the *strategical level*, the *tactical level* and the *operational level*. van der Molen and Bötticher (1988) specify the three levels in compliance with Michon (1985), such that the levels are arranged in a hierarchically ordered model structure. Long-term decisions on the strategical level affect those on the tactical level and mid-term decisions on the tactical level affect short-term decisions on the operational level. Following Michon's guidelines (Michon, 1985), van der Molen and Bötticher (1988) define a dynamic connection between the levels of behavior. Interaction between the strategical level and the tactical level is done by so called *Strategic Plans*. Interaction between the tactical level and the operational level is done by so called *Manoeuvring Plans*.

The Hierarchical Risk Model for Traffic Participants provides valuable information about the nature of strategic level driver behavior. Van der Molen and Bötticher (1988) follow Michon's definition (Michon, 1985) and argue that on this particular level, drivers perform tasks like route planning, mode choice, assessment of desired cruise speed, or estimation of travel time.

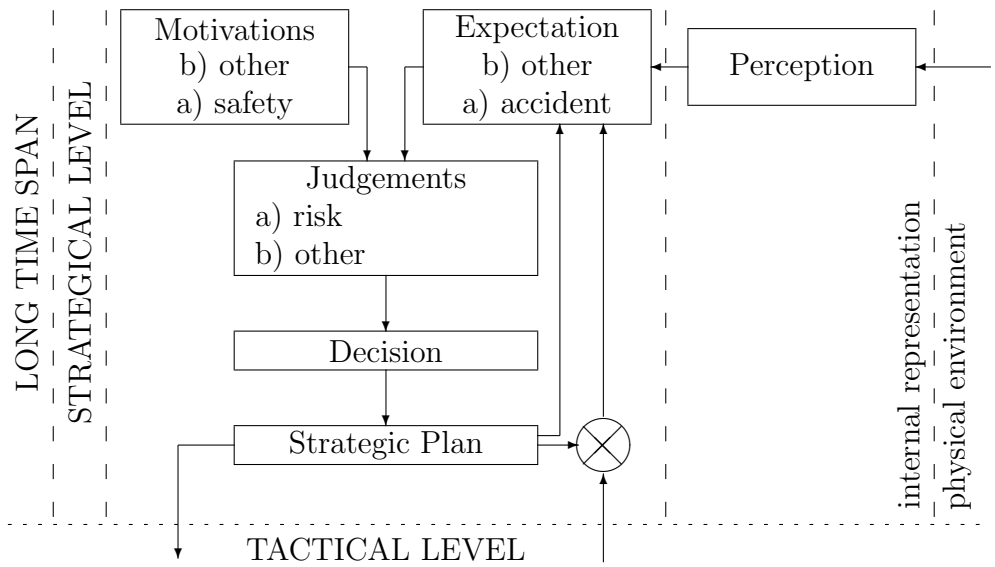

Figure 3.1: The upper part of the *Hierarchical Risk Model for Traffic Participants*. The illustration shows the internal structure of the strategical level behavior. Connections to the tactical level are illustrated as well (adapted from van der Molen and Bötticher, 1988, Figure 1, p. 539).

Despite the resemblance, the Hierarchical Risk Model for Traffic Participants considerably extends the Hierarchical Control Model by more detailed specifications for all levels of behavior. In more detail, van der Molen and Bötticher (1988) integrate behavior alternatives and subjective probabilities such as utility aspects. Van der Molen and Bötticher (1988) argue that these aspects are required to account for the personality of the driver. Furthermore, van der Molen and Bötticher (1988) account for perceptual, judgmental and decision processes of traffic participants on all levels of behavior. The most significant extension, however, is the additional connection between the driver's strategic level behavior their environment. Michon (1985) used no such connection, yet, argued that strategic level behavior is surrounded by a *physical environment* that "consists of possible routes, traffic modes, etc." (p. 539). A selected part of the Hierarchical Risk Model for Traffic Participants after van der Molen and Bötticher (1988) is illustrated in Figure 3.1.

3.1.2 Keskinen's Hierarchical Levels of Behaviour

The *Hierarchical Levels of Behaviour* were presented by Keskinen et al. (2004, also Keskinen, 1996). The approach has a strong resemblance to

the Hierarchical Control Model. Contrary to van der Molen and Bötticher (1988), Keskinen et al. (2004) do not refine the levels of behavior, but extend Michon's hierarchy by an additional level. Keskinen et al. (2004) argue that it is necessary to add this further level due to a correlation between accidents and the life-style of involved drivers. Keskinen et al. (2004) substantiate this correlation by means of accident analyses.

In total, Keskinen et al. (2004) define four levels of behavior. On the lowermost level, the *vehicle manoeuvring* level, drivers account for the controlling of speed, the vehicle's direction, and the vehicle's position. This level complies with Michon's control level. At the next higher level, the *mastering traffic situation* level, drivers adapt to the demands of the present traffic situation. This level complies with Michon's maneuvering level. At the *goals and context of driving* level, drivers reason about their purpose, their environment, their social context, and their company. This level is similar to Michon's strategic level, though, Michon (1985) does not account for a connection between the driver's strategic level behavior and their environment. Keskinen et al. (2004), however, define such connection and thus emphasize the importance of the environment as a factor for the outcome of strategic level decisions of drivers. Finally, Keskinen et al. (2004) identify factors that are able to affect a driver's decisions and that are even more "detached" from the driving task than those strategic level factors that Michon (1985) mentions. As a consequence, Keskinen et al. (2004) add a fourth level of driver behavior, namely the *goals for life and skills for living* level and argue that such additional level is able to cover the area of personality and motives, and expresses behaviors that are "less congruent with the norms of the society" (p. 18). As an example for actions that evolve from this level of behavior Keskinen et al. (2004) refer to young male drivers, which often suffer from a lack of control of their driving behavior and thus frequently cause violations against traffic regulations. The Hierarchical Levels of Behaviour model after Keskinen et al. (2004) is illustrated in Figure 3.2.

The Hierarchical Levels of Behaviour help to better understand the nature of strategic level behavior. Two aspects are particularly interesting. First, Keskinen et al. (2004) explicitly argue that strategic level decision-making is connected to the driver's environment. Such connection was proposed by van der Molen and Bötticher (1988) as well. The joint consideration of such connection substantiates its importance. Secondly, Keskinen

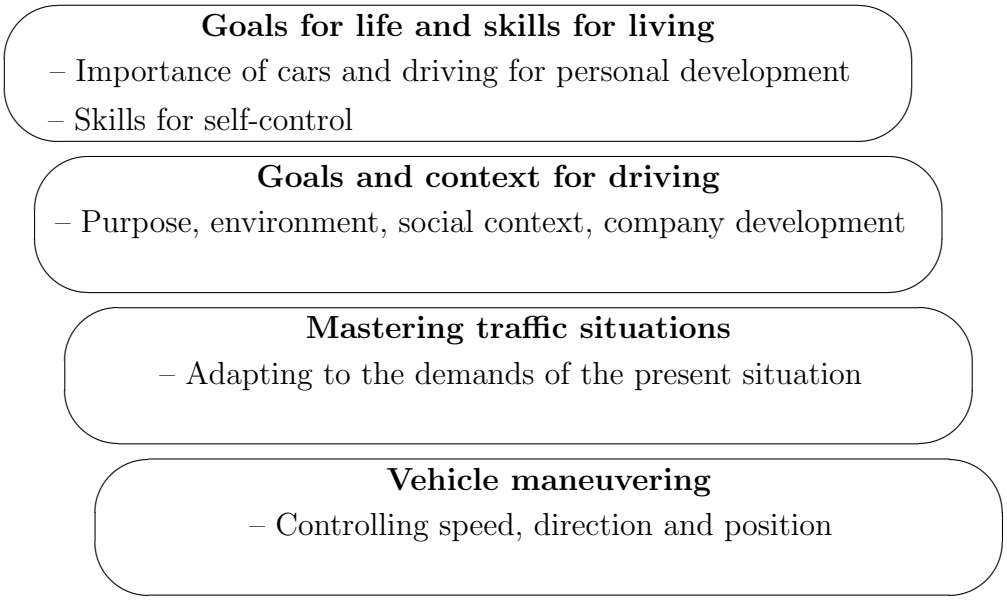

Figure 3.2: The *Hierarchical Levels of Behaviour* (adapted from Keskinen et al., 2004, Figure 5, p. 18).

et al. (2004) argue that strategic level driver behavior is not only affected by the driver's perception but also by superordinate factors such as the driver's personality, which includes their motives, their lifestyle or their gender. Van der Molen and Bötticher (1988) came to the same conclusion and argued that it is possible to generally account for this factor by means of "utility aspects".

While van der Molen and Bötticher (1988) account for these utility aspects directly within the driver's strategic behavior level, Keskinen (1996) use an additional level and connect the output of this level to the driver's strategic level behavior. Either way, I conclude that utility aspects reflect the driver's personality and affect their strategic level behavior. The heterogeneous implementation shows that the effect of utility aspects can either be modeled as a separate level of behavior or as a part of the driver's strategic behavior level.

The practical applicability of the Hierarchical Levels of Behaviour was demonstrated within the European project *GADGET* (Christ, 2000, see also Section 3.2.4). Within the GADGET project, the Hierarchical Levels of Behaviour approach was used to explain the behavior of drivers that are aware of alternative transport modes (Panou et al., 2007).

3.1.3 Discussion

The analysis of the above-presented approaches emphasizes several important factors that have to be considered for the engineering of strategic level driver behavior.

To start with, both approaches implement the structure that was proposed by Michon (1985) and arrange the different levels of behavior in a nested hierarchy. Decisions on one particular level of behavior affect goals on adjacent levels, e.g., subordinate or superior levels. The temporal scope of actions that evolve from a given level of behavior increases with the level of the hierarchy, such that decisions on the upper levels are long-term decisions while decisions on the lower levels are short-term decisions.

Both approaches arrange strategic level behavior at the upper end of the hierarchy. While van der Molen and Bötticher (1988) consider strategic level behavior as the uppermost form of human driver behavior, Keskinen et al. (2004) introduce an additional layer in order to account for the personality and the motives of the drivers. The impact of the driver's personality, however, is also reflected by the model that was presented by van der Molen and Bötticher (1988), only that this factor is distributed among several (sub-)modules (e.g., motivations, expectation, judgements, etc.) and directly integrated into the driver's strategic behavior level. Both approaches summarized factors that determine the driver's personality as "utility aspects".

What is also apparent is that both approaches define a connection between the driver's strategic level behavior and their environment. van der Molen and Bötticher (1988) describe this environment as possible routes and traffic modes. Keskinen (1996) refer to this environment as the driver's perception. The Hierarchical Control Model lacks such dependency and only connects the driver's control and tactical level decisions to their perception. I already elaborated on the reason for this deficiency. The Hierarchical Control Model was never intended to serve as a comprehensive conceptualization of human driver behavior, but rather a cause for thought. Michon's intention was to emphasize strategic level driver behavior as factor for tactical level driver behavior. It was his intention to explain the outcome of maneuver and control level processes with the decisions that evolved from the strategic level and not the other way around. To this end, strategic

level decisions such as the identification of trip goals, the route choice, or cost-risk analyses were done before the journey and not refined afterwards.

Van der Molen and Bötticher (1988) and Keskinen et al. (2004), however, intended to explain high level driver behavior (e.g., the behavior of drivers that are aware of alternative modes of transport). For this reason, van der Molen and Bötticher (1988) and Keskinen (1996) put particular emphasis on a valid representation of strategic level decision-making. This form of behavior becomes most important if one wants to explain situations in which the humans occur as traffic participants rather than as drivers.

As a matter of fact, there were only few attempts to explain driver behavior by means of classical hierarchical structures. The main reason for this is the ability of human beings to perform many tasks at the same time. One-dimensional structures are not able to reflect this parallelism. Psychologists countered this limitation by developing multi-dimensional driver behavior conceptualizations. In the following, I present the most relevant works that fall into this category.

3.2 Multi-Dimension Hierarchies

The fundamental concept of multi-dimension hierarchies is that drivers deal with many tasks and solve many problems simultaneously. Most works that I present under the umbrella of multi-dimension hierarchies implement the behavioral hierarchy that was proposed by Michon (1985) and extend its one-dimensional structure by further dimensions in order to account for varying levels of experience, knowledge, or emotions. While there were only few classical hierarchical structures, there was considerably more effort to conceptualize human driver behavior as a multi-dimensional hierarchy, or as a matrix. I present the most significant works from this category below.

3.2.1 The Matrix of Tasks

The first work that falls into this category was presented by Hale et al. (1990). Hale et al. (1990) combine the principles of the Hierarchical Control Model with the work of Rasmussen (1986), who conceptualizes expertise and automatisms for common human behavior.

Following Rasmussen (1986), human operative behavior is a combination of *knowldege-based*, *rule-based*, and *skill-based* performance. While

knowledge-based performance can be considered as conscious problem solving, rule-based performance refers to the application of learned rules and skill-based performance refers to automated skills that require no cognitive processing.

Hale et al. (1990) uses Rasmussen's conceptualization for the development of a driver behavior model which accounts for concepts of expertise and the driver's familiarity with the situation. For this purpose, Rasmussen's levels of performance are mapped to the domain of driver behavior. Hale et al. (1990) defines this mapping as follow:

Knowledge-based behavior is applied when the driver is either located in difficult environmental conditions or in an unfamiliar traffic. Furthermore, knowledge-based behavior is applied in case the driver's skills are not fully developed.

Rule-based behavior refers to the standard interaction with other road users. It is also applied when automatic routines are transferred to a new system (e.g., driving an unfamiliar car type).

Skill-based behavior is applied in all familiar traffic situations. As opposed to the other phases, this kind of behavior requires no cognitive processing.

In addition to Rasmussen's concepts of expertise and the driver's familiarity with the situation, Hale et al. (1990) uses Michon's Hierarchical Control Model as a foundation. Each level of behavior is extended by Rasmussen's taxonomy of operative performance in order to distinguish between different levels of expertise and familiarity. The *Matrix of Tasks* (Hale et al., 1990) is illustrated in Table 3.1.

The Matrix of Tasks was the first approach that was able to explain effects of different levels of experience on all levels of behavior. Tasks of skilled drivers for instance are located on the diagonal that runs from the upper left to the lower right matrix cells in the table. Cells aside this diagonal either reflect differences in the driver's experience or differences in the driver's familiarity with the situation. Tasks of novice drivers, for instance, are clustered in the upper right corner.

Table 3.1: The *Matrix of Tasks*. A combination of Rasmussen's three levels of human operative performance and Michon's Hierarchical Control Model (adapted from Hale et al., 1990, Figure 1, p. 1383).

	Planning	Maneuver	Control
Knowledge	Navigating in strange town	Controlling a skid on icy roads	Learner on first lesson
Rule	Choice between familiar routes	Passing other cars	Driving an unfamiliar car
Skill	Home/work travel	Negotiating familiar junctions	Road holding round corners

The Matrix of Tasks became commonly accepted and was discussed (Ranney, 1994) as a foundation for a comprehensive driver behavior conceptualization. There were several reasons for this success. To start with, the model was able to explain the effects of experience and familiarity throughout the entire hierarchy of driver behavior levels—including the strategic, the maneuvering, and the control level behavior. Where Michon (1985) classifies the shifting of gears as regular control level behavior, Hale et al. (1990) additionally distinguish between inexperienced drivers, which apply knowledge-based control level behavior and experienced drivers, which may accomplish the same task with skill-based control level behavior. Such distinction is also done on the strategic level behavior—which is more relevant for my own work. Consider navigation as a strategic level behavior capability, which is processed on different stages of expertise. Where Michon (1985) describes navigation as a regular strategic level action, Hale et al. (1990) distinguish between novice drivers, which apply knowledge-based strategic level behavior and experienced drivers, which use skill-based strategic level actions to navigate through familiar environments. The second reason for the popularity of the Matrix of Tasks is the model's support for motivational factors on all levels of behavior. Motivational factors, or more generally "utility aspects", were also reflected by classical hierarchical structures. Hale et al. (1990) argue that the purpose and the importance of a trip may

influence drivers throughout their journey and cause changes in their behavior. Finally, Hale et al. (1990) substantiate the necessity to account for a connection between the driver's strategic level behavior and their environment. Hale et al. (1990) argue that situations, which are encountered "en route", may trigger short-term goals that motivate tactical problem solving and affect the drivers' strategic level intentions. As an example for such connection, Hale et al. (1990) refer to a situation in which a driver, who has selected a route and a departure time which ensures a leisurely and uneventful drive, is motivated to speed up by the presence of extreme slow traffic ahead.

3.2.2 The Drivers Task Cube

Contrary to the Matrix of Tasks, Summala (1996) uses three dimensions to classify a driver's tasks. In the first dimension, a functional hierarchy distinguishes between vehicle choice, trip decisions, navigation, guidance, and vehicle control. In the second dimension, a functional taxonomy distinguishes between enclosed capabilities such as lane keeping, headway control, obstacle avoidance, crossing management, or passing and other maneuvers. In the third dimension, three psychological processing levels are defined, namely decision-making or supervisory monitoring, attention control, and perceptual motor control. The *Drivers Task Cube* (Summala, 1996) is illustrated in Figure 3.3.

Instead of a solid model, the Drivers Task Cube can be considered a description, or a list of important variables (Keskinen et al., 2004).

The model was significantly refined, shortly after it was published. I present this refinement below.

3.2.3 The Multiple Sieve Model

Summala (1997) emphasizes the importance of motivational factors for human driver behavior and argues that the first version of the Drivers Task Cube, failed to explain such concepts. As a consequence, Summala (1997) extends the initial version of the model to take motivational factors as well as emotions of drivers into account. The second incarnation of the Drivers Task Cube, namely the *Multiple Sieve Model* or the *Filter Model of Risky Behaviour and Road Accidents* is illustrated in Figure 3.4.

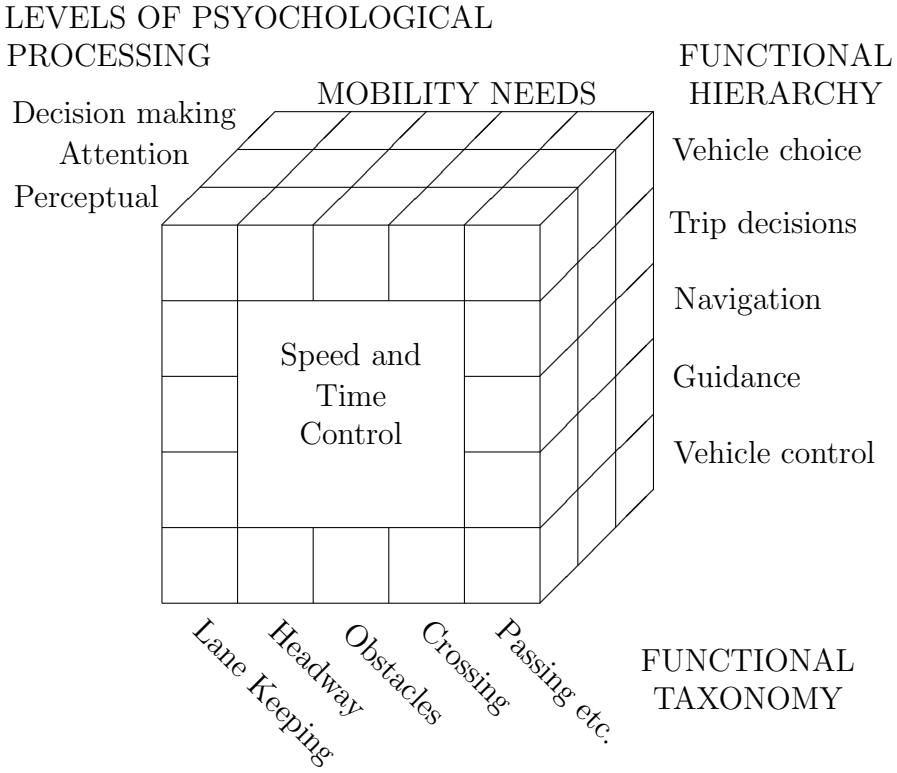

Figure 3.3: The *Drivers Task Cube* (adapted from Summala, 1996, Figure 2, p. 109).

Like the Drivers Task Cube, the Multiple Sieve Model can not be considered as a solid driver conceptualization but rather as a list of variables that affect a driver's behavior (Keskinen et al., 2004). Nevertheless, it is my intention to investigate the nature of strategic level behavior and to identify factors that determine the outcome of strategic level decision-making processes in traffic environments, thus, the work provides important information for my own work.

Once again I can argue that a driver's strategic level behavior is affected by their personality, that is, their motivation, their emotional state, and their need for mobility. All above-presented approaches summarize these factors as utility aspects.

Finally, Summala (1997) defines a connection between the driver's strategic level processing and their environment. Summala (1997) refers to this connection as *supervisory monitoring*.

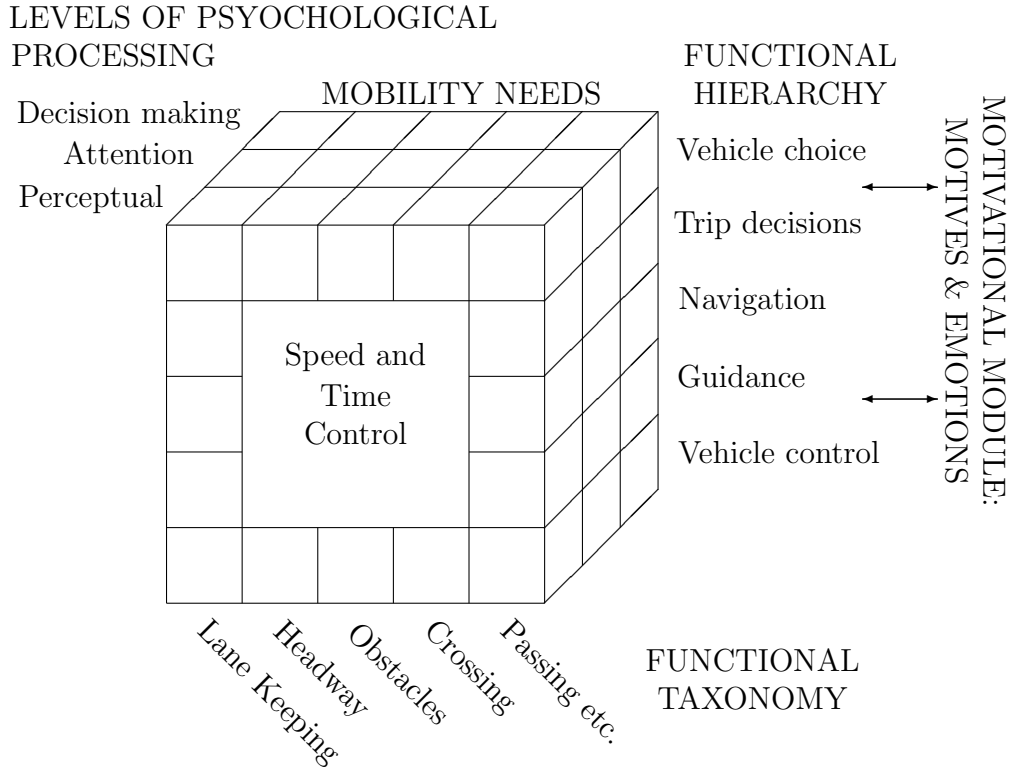

Figure 3.4: The *Multisieve Model* (adapted from Summala, 1997)

3.2.4 The GADGET Matrix

The *GADGET Matrix* was presented by Hatakka et al. (1997). Similar to the above-presented multi-dimension hierarchies, the *GADGET-Matrix* is based on Michon's Hierarchical Control Model. To be more precisely, Hatakka et al. (1997) use an extension of Michon's work, namely the Hierarchical Levels of Behaviour (Keskinen et al., 2004, see also Section 3.1.2) in order to distinguish between the following four levels of driver behavior:

Goals for life and skills for living: This level comprises behavioral factors that evolve from the background of the driver. Examples for these factors are the driver's lifestyle, social background, gender, or age.

Driving goals and context: This level comprises the strategic planning of a trip. Things like "where", "when", and "with whom someone is driving" are considered, here.

Mastery of traffic situations: This level complies with Michon's maneuvering level and can be considered as regular driving in a given context.

Vehicle maneuvering: This level complies with Michon's control level, such that the driver's attention is mainly on the vehicle.

In compliance with the guidelines that were proposed by Michon (1985), Hatakka et al. (1997) define a connection between the upper levels of behavior and the lower levels of behavior, such that decisions that evolve from the upper level are able to affect decisions on the lower levels and vice versa.

Moreover, Hatakka et al. (1997) extend the behavioral hierarchy by a second dimension. This additional dimension is used to conceptualize factors that have the impact to affect human driver behavior. In this dimension, Hatakka et al. (1997) distinguish between knowledge and skills, risk-increasing factors, and self-assessment. These factors are defined as follows:

Knowledge and skills are routines and information that are required for driving under regular conditions.

Risk-increasing factors are traffic or life related factors, which are associated with a higher risk.

Self-assessment indicates how good a driver is able to reflect their own driving skills and motivations.

Table 3.2 illustrates the part of the GADGET-Matrix, which describes the strategic level decision-making process as well as factors that affect this very process.

Hatakka et al. (1997) show that strategic level decision-making is affected by many factors. These factors include attributes of the driver, such as motives, personal values, preferences, or risk acceptance. Above-presented approaches summarized these factors as "the driver's personality" or "utility aspects".

Furthermore, a driver's environment (or their awareness for the environment) may affect their decisions. As an example, Hatakka et al. (1997) refer to the driver's awareness for alternative transport modes or the type of the driving environment, e.g., rural or urban.

Table 3.2: Selected parts of the *GADGET-Matrix*. There is a strong connection between the driver's strategic level behavior (goals for life and skills for living level and driving goals and context level) and their goals (adapted from Hatakka et al., 1997).

Hierarchical Levels of Behavior	Knowledge & skills	Risk-increasing factors	Self-assessment
Goals for life & skills for living	*Awareness About:* –Relation between tendencies skills –lifestyle/life situation –peer group norms –motives, personal values	*Risk tendencies like:* –acceptance of risks –high level of sensation seeking –complying to social pressure –use of alcohol & drugs	*Self Assessment:* –impulse control –risky tendencies –dangerous motives –risky habits
Driving goals and context	*Awareness about:* –effects of journey goals –planning & choosing routes –effects of social pressure	*Risks associated with:* –physical condition –purpose of driving –driving environment –social context & company	*Awareness of:* –planning skills –typical driving goals –alternative transport modes
Mastery of Traffic situation	*Knowledge about:* –traffic regulations –traffic signs –anticipation –communication –safety margins	*Risks associated with:* –wrong expectations –vulnerable road users –violations –information overload –unusual conditions –inexperience	*Awareness of:* –maneuvering skills –subjective risk level –subjective safety margins

Finally, Hatakka et al. (1997) argue that physical factors, such as the use of alcohol and drugs, or the driver's physical condition, e.g., their fitness or arousal, but also environmental conditions, such as heavy rain or snow, may affect a driver's strategic level decisions. Physical factors were generally neglected by previously presented approaches.

3.2.5 The DRIVABILITY Model

The *DRIVABILITY Model* was presented by Bekiaris et al. (2003). As a matter of fact, the DRIVABILITY Model is difficult to classify, as it neither complies with the assembly of a classical hierarchical structure, nor with the architecture of a multi-dimension hierarchy. Yet, the approach describes how several simultaneous factors can affect a driver's decision-making process, thus, I decided to present the DRIVABILITY Model under the umbrella of multi-dimension hierarchies.

The fundamental idea of the DRIVABILITY Model is that driver behavior evolves over time and as a result to several permanent and temporary contributors (Bekiaris et al., 2003). Bekiaris et al. (2003) define these contributors as follows:

Individual resources can be physical, social, psychological and mental conditions of the conceptualized driver.

Knowledge and skills are concepts that describe the driver's training, experience, and their knowledge. The reason for this is that basic education may influence a driver's motivation and their behavior. This contributor also comprises the driver's self-awareness.

Environmental factors summarize the effects of the driver's environment on their decisions. In addition to the status of their vehicle, environmental factors may also comprise traffic hazards, the weather condition, or the general traffic situation.

Workload & risk awareness are the two common denominators between the driver's resources and their environmental status. The driver's risk awareness is also influenced by their risk perception, their level of attention, and by on-board support systems.

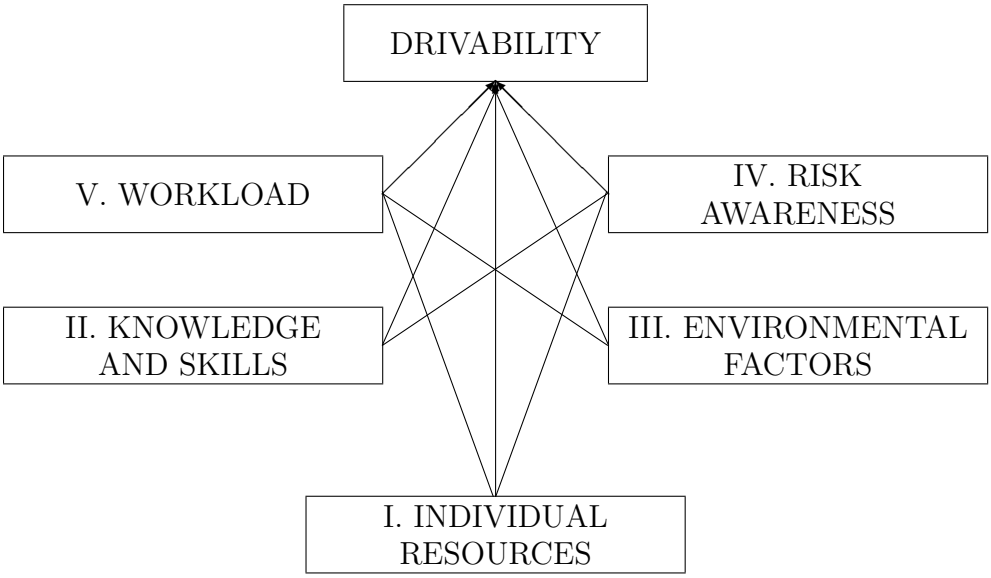

Figure 3.5: Contributors to the driver's behavior (adapted from Bekiaris et al., 2003, Figure 2, p. 155).

Figure 3.5 illustrates the mutual dependencies between the presented contributors and their effect on the driving process.

The DRIVABILITY Model conceptualizes the driving process as the outcome of five distinct input channels. Most importantly, a driver's decisions are affected by their awareness for the surrounding environment. These factors include traffic conditions, weather conditions, the visibility level, or traffic hazards. Furthermore, a driver's strategic level decisions can be affected by factors that most of the above-presented approaches summarize as the driver's personality (e.g., individual resources, the driver's attitude, their motivation, or their preferences). Another factor that was used to explain the outcome of human strategic level driver is the driver's knowledge and their skills. Finally, Bekiaris et al. (2003) conceptualize the driver's current utilization. This was done in order to have an instrument that allows to adjust the amount of information that the driver actually perceives.

The DRIVABILITY Model is one of the few approaches that neglects support for different levels of behavior. The reason for this limitation is the model's area of application. The purpose of the model is to explain the effects of the above-presented contributors on the driver's strategic level behavior—and the strategic level behavior, exclusively. This very focus, makes the DRIVABILITY Model particularly interesting if one wants to

learn more about strategic level driver behavior. It is important to mention that—from a psychological point of view—strategic level behavior can be considered in isolation, that is, without considering the impact of other levels.

3.2.6 The Adaptive Control of Thought-Rational

The *Adaptive Control of Thought-Rational*, or *ACT-R* (Salvucci et al., 2001), combines cognitive, perceptual, and motor dimension and focuses on highway driving with moderate traffic. As in the case of DRIVABILITY model, it is difficult to find a proper category for the ACT-R. Due to the striking resemblance to the DRIVABILITY model, I decided to present both approaches as multi-dimension hierarchy.

In fact, the ACT-R is a combination of two constituting models, namely the *ACT-R Architecture* (Anderson et al., 2004) and the *ACT-R Driver model* (Salvucci et al., 2001).

The ACT-R Architecture explains how the decision-making process of the driver is accomplished. Contrary to the above-presented approaches, the ACT-R Architecture explains human driver decisions by means of a physical perspective. The model complies with the brain structures and information processing steps of human beings. Anderson et al. (2004) identifies functional modules that affect a driver's decisions and defines a mapping between those and the responsible brain components. Following Anderson et al. (2004), the decision-making process is influenced by the output of four distinct information-processing modules, namely the *intentional module*, the *declarative module*, the *visual module*, and the *manual module*. The former two modules can be considered as attitudes of the driver without any connection to external factors, the latter two modules are directly connected to the driver's environment, the so called *external world*. Visual perception is processed by the visual module and may affect the drivers' decisions. Contrary, drivers execute actions by using their manual module. These actions may affect the external world. The ACT-R Architecture is illustrated in Figure 3.6.

The second model that is used by the ACT-R is the ACT-R Driver model (Salvucci et al., 2001). The ACT-R Driver model describes the driving process as a result of three parallel tasks, namely to control, to monitor, and to decide.

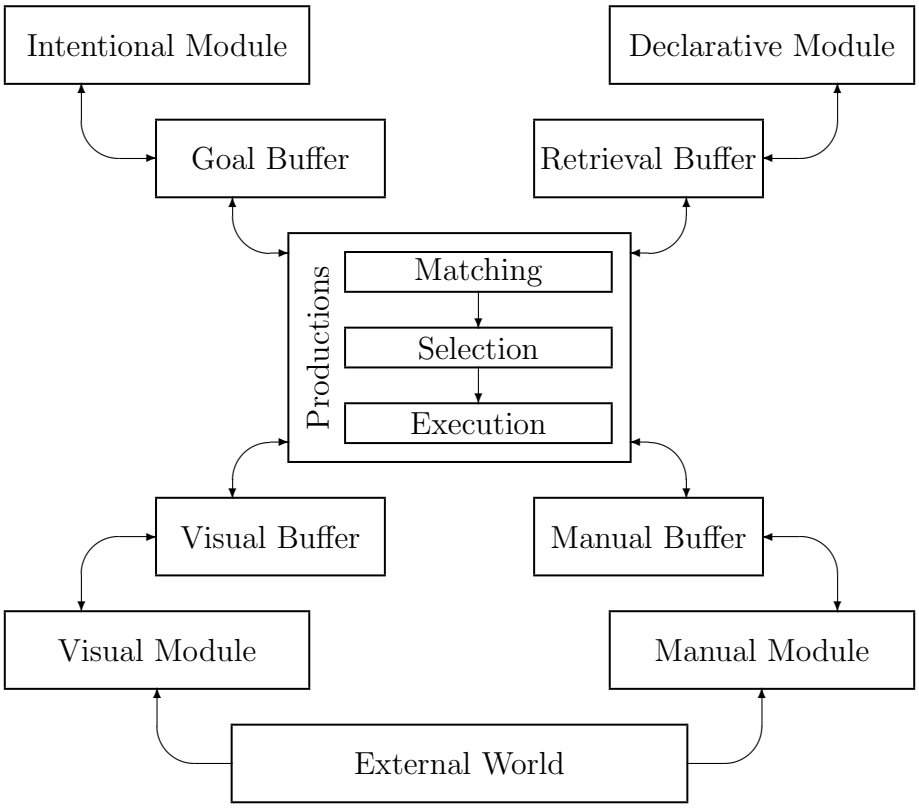

Figure 3.6: The *ACT-R Architecture* (adapted from Anderson et al., 2004, Figure 1, p. 1037).

The ACT-R puts no emphasis on one particular level of driver behavior but generically conceptualizes decision-making processes that evolve from the awareness for different input channels on any level of driver behavior. Following Anderson et al. (2004), these distractions may evolve from the driver's personal attitudes as well as from the environment (external factors).

The ACT-R is one of the few models that defines a connection from the driver's actions to their environment.[1] Anderson et al. (2004) argues that a driver's actions always affect their environment.

3.2.7 Discussion

Contrary to classical hierarchical structures, there was considerably more effort to conceptualize human driver behavior by means of multi-dimensional model structures.

[1]Most other approaches account only for the opposite direction.

Although the Hierarchical Control Model fit purposes, psychologists recognized that hierarchically ordered models generally failed to account for driver-specific factors with varying impact on the decision-making process. To this end, the "vertical" shape of the Hierarchical Control Model was extended by one or more "horizontal" dimension. Horizontal extensions were frequently designed as hierarchies themselves, thus, the resulting models had the shape of matrices or cubes.

To start with, Hale et al. (1990) extend the Hierarchical Control Model with an additional dimension in order to account for concepts of familiarity and expertise on each level of driver behavior. A similar concept is used by Summala (1996, also Summala, 1997), who distinguishes between three psychological processing levels. Furthermore, Hatakka et al. (1997) argue that a driver's behavior is affected by knowledge and skills and account for such dependency in their model. Bekiaris et al. (2003) identify a similar dependency and design their DRIVABILITY model to allow knowledge and skills to affect a driver's decisions.

Another factor, which is supported by most of the above-presented approaches, is the driver's personality. The importance of the driver's personality is substantiated by Summala (1997), who extends his previously published model (Summala, 1996) with concepts of emotions and motives. A similar approach was presented by Hatakka et al. (1997), who introduce an entirely new level of behavior, namely the "goals for life and skills for living" level. Based on the discussion of classical hierarchical structures (see Section 3.1.3), these concepts can be summarized as utility aspects. Utility aspects affect drivers on each level of behavior, yet, van der Molen and Bötticher (1988) and Keskinen et al. (2004) substantiate that it is not necessary to use a multi-dimensional structure to account for utility aspects. A one-dimensional assembly is able to reflect this capability as well.

Finally, the analysis of multi-dimension hierarchies showed that a driver's strategic level decisions are subject to their perception of the surrounding environment. Michon (1985) already accounted for such connection, but only on the lower levels of behavior. Most above-presented works, however, connect a driver's perception to their strategic level decision-making process. The DRIVABILITY model (Bekiaris et al., 2003), for instance, defines a dependency between the strategic level decisions of drivers and en-

vironmental factors, such as traffic hazards, certain traffic conditions (e.g., congestion or slow moving traffic), weather conditions, road conditions, or the visibility level. Anderson et al. (2004) use a similar design and connect the driver's perception to their decision-making modules. Finally, the ACT-R architecture defines a feedback mechanism, such that a driver's actions are also able to affect their environment.

Above, I analyzed the most popular models that can be classified as multi-dimensional driver behavior models. In the following, I present the most relevant cognitive approaches.

3.3 Cognitive Approaches

Michon (1985) argued that cognitive approaches are the most promising model category for the development of a comprehensive driver behavior conceptualization. This very conclusion caused increased efforts to further cognitive models. In the following, I present the most important approaches that fall into this category.

3.3.1 The ACME-Driver Model

The *A Common Mental Environment-Driver Model*, or *ACME-Driver Model*, was presented by Krajzewicz and Wagner (2002).

The model is based on a psychological paradigm, which was presented by Atkinson and Shiffring (1968). Atkinson and Shiffring (1968) distinguish between three different types of memory, namely the *sensoric input register*, the *short-term memory* and the *long-term memory*. The main difference between the memory types is the period of time that collected information remains available.

Krajzewicz and Wagner (2002), combine the approach of Atkinson and Shiffring (1968) with the work of Tulving (1972). Tulving (1972) distinguishes between three types of long-term memories. First, the *episodic memory* stores information about single situations from the human's life, secondly, the *semantic memory* is used to save common or logically expressible rules like rules of algebra. Finally, the *procedural memory* contains non-verbalizable information about movements. Both, the sensoric input register and the long-term memory are considered for the cognitive

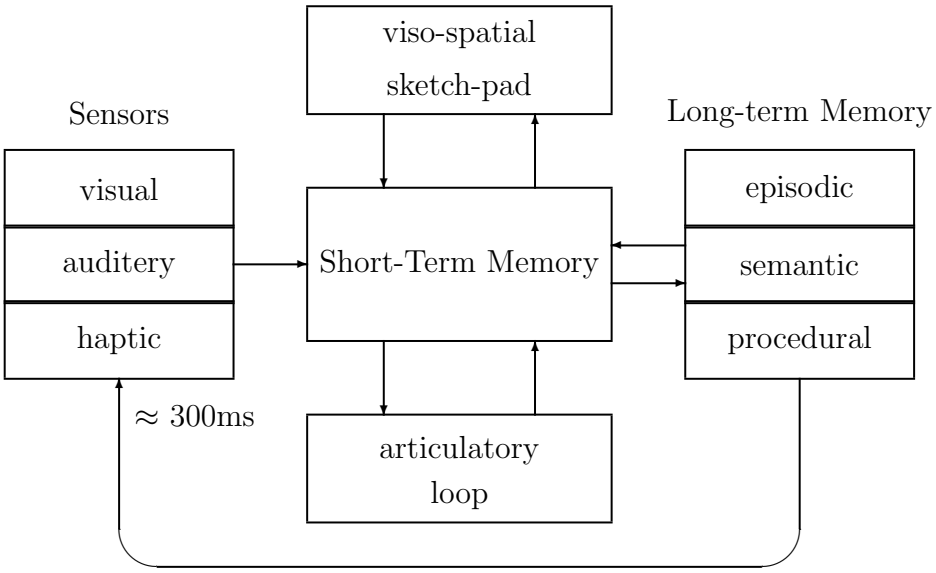

Figure 3.7: The *ACME-Driver Model* (adapted from Krajzewicz and Wagner, 2002, Figure 3, p. 690).

computation, which is ultimately done within the short-term memory of the conceptualized driver. The ACME-Driver Model is illustrated in Figure 3.7.

The ACME-Driver Model does not account for different levels of behavior, yet, Krajzewicz and Wagner (2002) explicitly argue that the model was never intended to cover the entire spectrum of human driver behavior but to focus on particular aspects, only. These aspects are not limited to one particular level of behavior but comprise different levels, such that tactical level maneuvers (e.g., lane-changing or obstacle avoidance) as well as strategic level capabilities (e.g., route finding) can be explained. The approach substantiates that—although most works conceptualize human driver behavior as a hierarchy—it is also possible to use a simplified approach if one wants to focus on analyzing the effects of particular components of human driver behavior, e.g., tactical or strategic level behavior in isolation. A similar approach was used for the implementation of the DRIVABILITY Model.

Finally, the ACME-Driver Model defines connections between the short-term memory and the long-term memory and between the short-term memory and the sensoric input register. These connections emphasize the importance of external factors (stored within the short-term memory) and the driver's personality (in the form of preferred strategies, which are stored within the long-term memory) for the outcome of a driver's decisions.

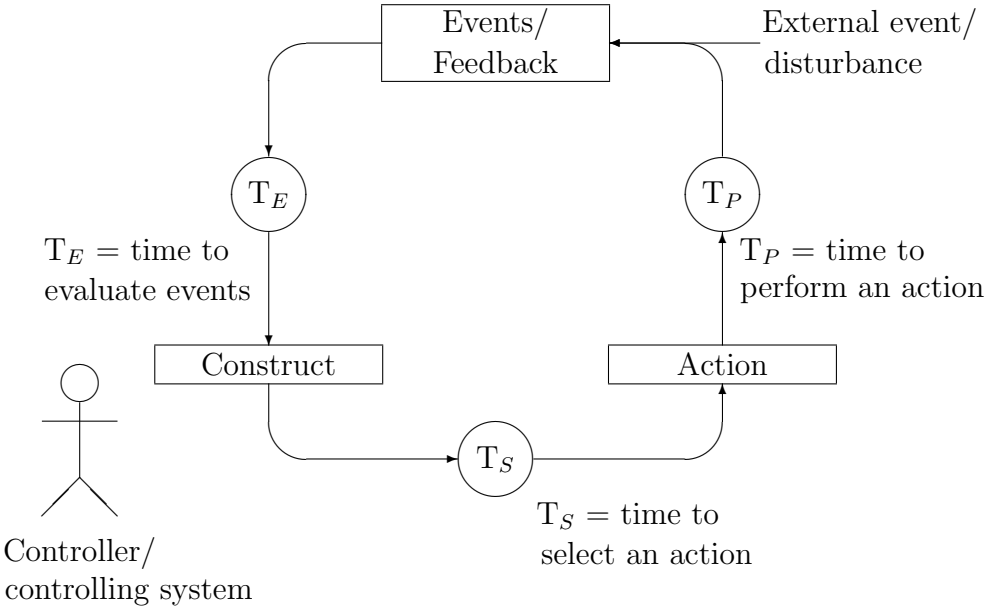

Figure 3.8: The *Contextual Control Model* (adapted from Engström and Hollnagel, 2007, Figure 4.1, p. 69).

3.3.2 The Contextual Control Model

The *Contextual Control Model*, or *COCOM*, was presented by Hollnagel (1993). The COCOM is based on the *perceptual cycle*, which was presented by Neisser (1976).

In compliance with the work of Neisser (1976), Hollnagel (1993) designed the COCOM to conceptualize the driver, as well as the controlled vehicle, as a *joint cognitive system*. The central concept of the COCOM is the *construct-action-event cycle* (the construct-action-event cycle is illustrated in Figure 3.8), which explains how a controller selects their actions based on their knowledge or their assumptions about the situation in which the action takes place. The construct-action-event cycle also conceptualizes the consequences of the selected actions on the controlled system, that is, the selected actions generate new events, which are (in combination with external disturbances) perceived by the controller again.

The COCOM approach provides a set of configuration options, e.g., to specify the time that is available for decision-making processes.

Although the approach was developed long after Michon (1985) presented his guidelines, Hollnagel (1993) neglects a representation of different levels of behavior. Nevertheless, the limitations of the COCOM were recog-

nized (Hollnagel and Woods, 2005, also Engström and Hollnagel, 2007) and the model was refined. I present this refinement below.

3.3.3 The Extended Control Model

The *Extended Control Model*, or *ECOM* (Engström and Hollnagel, 2007, after Hollnagel and Woods, 2005) extends the COCOM by support for different levels of driver behavior. In order to do so, Engström and Hollnagel (2007) combine the COCOM approach with a hierarchically ordered behavior structure. Engström and Hollnagel (2007) argue that this extension allows to capture the dynamic aspects of driving and to explain simultaneous relations between control processes of different levels of driver behavior.

In more detail, Engström and Hollnagel (2007) distinguish between four levels of driver behavior, namely the *tracking*, the *regulating*, the *monitoring* and the *targeting*. On targeting level, the driver sets general goals for the driving task. These goals constitute the input for the next level, namely the monitoring level. On monitoring level, the driver attempts to control the state of the joint vehicle-driver system relative to the driver's environment. Among others, the monitoring level comprises tasks like monitoring properties of the traffic environment (e.g., speed limits) or the location and the condition of the vehicle. On regulating level, the driver deals with conscious processes, such as keeping desired safety margins to other traffic elements. Finally, on tracking level, the driver performs momentary and automated corrections to external disturbances, such as wind gusts. The ECOM after Engström and Hollnagel (2007) is illustrated in Figure 3.9.

The analysis of the COCOM and the ECOM emphasizes two aspects. First, the focus on one particular level of behavior works if one wants to analyze this level in isolation (as done by the COCOM). More comprehensive considerations, however, require support for the entire behavioral hierarchy (as done by the ECOM). Secondly, both models emphasize the importance of the driver's perception for their strategic level decisions. Due to the lack of support for "higher-level" behavior, the COCOM defines such connection only for tactical level behavior. The ECOM, however, implements this dependency for all levels of behavior. Strategic level actions can be found on targeting and on monitoring level. Decisions that evolve from these levels are always affected by the driver's perception.

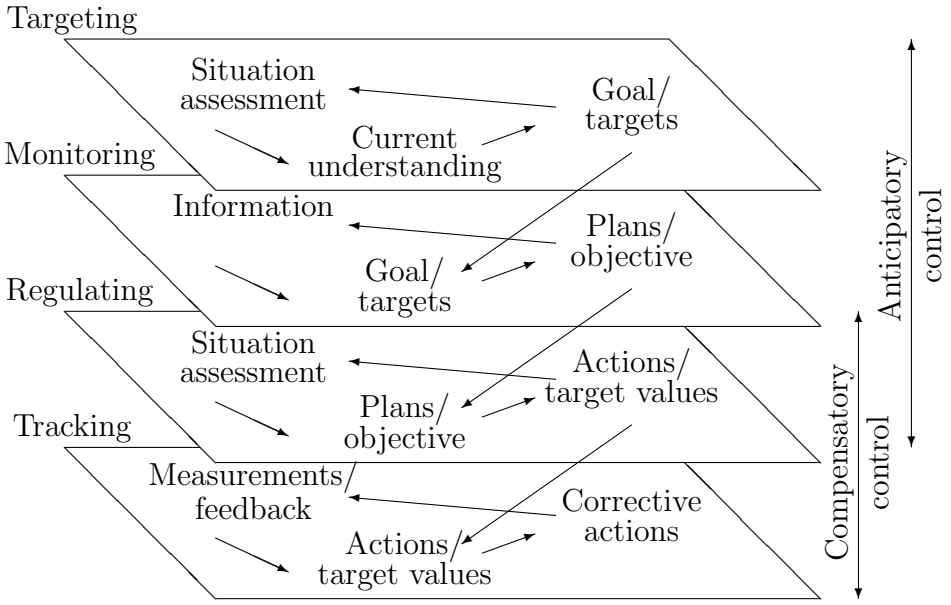

Figure 3.9: The *Extended Control Model* (adapted from Engström and Hollnagel, 2007, Figure 4.2, p. 71).

It is important to mention, that decisions that evolve from the targeting level are additionally affected by the driver's goals—elements of their personality.

3.3.4 Discussion

The analysis of cognitive approaches showed that all examined works conceptualize human driver behavior in a similar fashion. Furthermore, the examined approaches identified similar factors that affect a driver's behavior.

First, all examined approaches connect the driver's behavior to their environment. Krajzewicz and Wagner (2002), for instance, implement this connection with a set of sensors that include visual, auditory and haptic inputs. The driver's perception is stored in the short-term memory and is thus considered for decision-making processes. Hollnagel (1993) define a similar mechanism inasmuch as "external events" or "disturbances" are combined with other events and feedback and constitute the input for a joint cognitive system, which consists of of the driver and their vehicle. Hollnagel (1993) also define a connection between the driver's actions and their environment, such that the former is able to affect the latter and vice versa. Engström and Hollnagel (2007) use the same mechanism, only that

on each level of behavior a separate reasoning cycle is used to compute the decisions that respectively affect the lower levels of behavior.

The second factor that most approaches conceptualize is the driver's level of experience. Krajzewicz and Wagner (2002) use two models to reflect these experiences, namely the short-term memory and the long-term memory. Hollnagel (1993) also account for experiences. His model describes how a controller selects their actions based on knowledge and assumptions about the situation in which the action takes place. A similar concept is used by Engström and Hollnagel (2007), only that experiences affect the driver's action selection on all levels of behavior.

It is surprising that most of the examined approaches neglect the consideration of different levels of behavior. From the above-presented works, only Engström and Hollnagel (2007) distinguish between different levels. Nevertheless, the reason for this deficiency is not the general denial of the concept, but rather the focus, or the objective of the approaches. Krajzewicz and Wagner (2002) design their model to serve a particular purpose, namely to reproduce tactical level behavior in a traffic simulation. The impact of strategic level decisions on tactical level behavior is not designed as a behavioral hierarchy, but rather as a one-dimensional factor that determines the outcome of a driver's tactical level decisions. Krajzewicz and Wagner (2002) explicitly argue that their representation is simplified and geared towards the purpose. The approach demonstrates that it is possible to conceptualize human driver behavior in an abbreviated, a simplified form, if one wants to focus on analyzing the effects of particular components of human driver behavior, e.g., tactical or strategic level behavior in isolation. Hollnagel (1993) neglects the consideration of behavior levels for similar reasons. Hollnagel (1993) argues that the COCOM was intended to explain the behavior of drivers that act under the influence of stress. Thus, the original focus was on tactical level decisions, however, Hollnagel (1993) recognized that the model failed to explain certain situations in which a more holistic consideration is required. This very finding ultimately led to the development of the ECOM.

3.4 Conclusion

The aim of this chapter was twofold. First, it was my intention to adapt the description strategic level driver behavior that I have presented in the

previous chapter to the form in which it is currently used in well-established driver behavior conceptualizations. Secondly, it was my objective to answer the question: "What are the factors that determine the outcome of human strategic level decision making in traffic environments?"

In order to address both issues, I analyzed psychological driver behavior conceptualizations that are currently used to explain human driver behavior. I conclude this survey as follows:

3.4.1 Strategic Level Driver Behavior

In the previous chapter, I argued that the first approach that ever distinguished between different levels of driver behavior was presented by Michon (1985). Michon (1985) describes strategic level driver behavior as general planning stage of a trip and argues that this stage includes the determination of trip goals, the route and the modal choice as well as a cost-risk evaluation. Following Michon (1985), strategic level driver behavior is affected by general considerations about transport and mobility. Concomitant factors, such as aesthetic satisfaction and comfort are also able to determine the outcome of this behavior level. Furthermore, Michon (1985) argues that the time which is required to complete plans that evolve from this particular level of behavior exceeds the seconds range.

The analysis of well-established behavior conceptualizations showed that neither the definition of strategic level driver behavior, nor its impact on the outcome of human driver behavior in traffic environments has changed. Most of the above-presented works account for strategic level behavior (cf. van der Molen and Bötticher, 1988; Keskinen et al., 2004; Hale et al., 1990; Summala, 1996, 1997; Hatakka et al., 1997; Engström and Hollnagel, 2007) or explicitly argue why such consideration is neglected (cf. Bekiaris et al., 2003; Salvucci et al., 2001; Krajzewicz and Wagner, 2002; Hollnagel, 1993).

Based on my analysis I conclude that Michon's definition (Michon, 1985) for strategic level driver behavior is still commonly accepted. I use the same (though slightly simplified) definition for my work and define strategic level driver behavior as follows:

Definition 3.1 *Strategic level driver behavior is the level of human traffic behavior on which action plans are generated that are not entirely related*

to the driving task per se and that cannot be completed within a matter of seconds (adapted from Michon, 1985).

Despite the fact that I use a temporal component to identify strategic level driver behavior, the above-presented definition still complies with the definition that was provided by Michon (1985). I decided to use a definition which is grounded on time-based approach as it makes it easier to identify strategic level behavior—especially in a computer-aided traffic simulation.

Definition 3.1 states that the outcome of strategic level behavior are action plans. Most of the above-presented approaches (cf. Michon, 1985; Keskinen et al., 2004; Hale et al., 1990; Hatakka et al., 1997; Engström and Hollnagel, 2007) demonstrate that the purpose of these action plans is to accomplish a driver's strategic level goals, e.g., to reach a desired target location or to not run out of fuel. Based on this observation I conclude that, on strategic level, psychological driver behavior models conceptualize drivers as goal directed systems. Michon (1985) explicitly substantiates this thesis and characterizes strategic level behavior as "goal directed" or "intentional behavior". In more particular, Michon (1985) argued that a driver's behavior is geared towards accomplishing their goals and that this knowledge can be used to predict a driver's behavior. Systems that comply with this very characteristic were investigated by Dennett (1989), who refers to these systems as: *intentional systems*. The particular characteristic to follow a goal until it is reached is referred to as the *single-minded* principle (Cohen and Levesque, 1990).

For my own work, this characterization is highly important. Later, I show that there are several mechanisms that can be used to "capture" behavior within a formal and computer-interpretable specification (see Chapter 7). The better the system is specified, the easier it is to find paradigms that can be used for its development. As a matter of fact, there are well-established approaches (e.g., the belief-desire-intention programming model (Rao and Georgeff, 1995)) that can be used to capture intentional systems in a computer-interpretable form. I present these mechanisms later in this work and conclude that psychological works characterize a driver's nature as follows:

Conclusion 3.1 *A driver's strategic level behavior is goal directed. The driver is compelled to accomplish these goals. To this end, a driver complies*

with the determining characteristics of an intentional system as described by Dennett (1989). Furthermore, the behavior of drivers complies with the single-minded principle (Cohen and Levesque, 1990), that is, drivers follow a goal until it is reached or cannot be reached anymore.

While most of the above-presented works conceptualize human strategic level driver behavior in compliance with Conclusion 3.1, there is much more discussion about the factors that significantly determine the outcome of strategic level decision making processes in traffic environments.

In the following, I compile a list of those factors that most of the analyzed approaches consider as relevant for the outcome of strategic level driver behavior.

3.4.2 Factors

The analysis of contemporary driver behavior conceptualizations showed that there are several factors that affect a driver's strategic level decision-making processes. Based on the above-presented analysis, I argue that there are at least four categories of factors, namely:

1. other levels of behavior,
2. external factors,
3. the driver's personality, and
4. experience and knowledge.

In the following, I present these factors in more detail and respectively mention approaches that implement these concepts.

Other Levels of Behavior

To start with, most works conceptualize human driver behavior as a structure of hierarchically ordered levels.

The higher the level of behavior is anchored in the hierarchy, the more detached are the driver's tasks from the driving process. While each level of behavior is connected to factors of disturbance, the levels are also mutually

connected, such that the outcome of a given level may affect those levels that are directly connected to this particular level.

In the case of the strategic level behavior, decision-making is mostly affected by the tactical level behavior. Some approaches (cf. Keskinen et al., 2004; Hatakka et al., 1997; Engström and Hollnagel, 2007) use four levels of behavior and connect the strategic level behavior to a superior level which accounts for lifestyle aspects of the driver's personality. Other approaches (cf. van der Molen and Bötticher, 1988; Hale et al., 1990; Summala, 1996, 1997; Bekiaris et al., 2003; Hollnagel, 1993) demonstrate that it is possible to account for these high-level aspects by other mechanisms (e.g., integrated modules, simplified input channels, etc.), or neglect these factors entirely, if the purpose of the model is to examine the effects of one particular level of behavior in isolation (cf. Salvucci et al., 2001; Krajzewicz and Wagner, 2002). Based on this finding, I conclude:

Conclusion 3.2 *The outcome of tactical level decisions is able to affect a driver's strategic level behavior and vice versa. Furthermore, strategic level driver behavior can be affected by the outcome superior levels of behavior. Behavioral levels that have an impact on a driver's strategic level decisions can be either represented in full, included in a simplified fashion, or can be neglected if one wants to focus on analyzing the effects of strategic level behavior in isolation.*

External Factors

While Michon (1985) refrained from connecting a driver's strategic level behavior to their environment, later works (cf. van der Molen and Bötticher, 1988; Bekiaris et al., 2003; Engström and Hollnagel, 2007; Hale et al., 1990; Hollnagel, 1993; Keskinen et al., 2004; Krajzewicz and Wagner, 2002; Salvucci, 2006) emphasize the importance of such connection. These models conceptualize drivers to constantly perceive their environment and to adapt their strategic level behavior to changes that occur in this environment. The above-presented analysis showed that there are two categories of external factors that are able to affect a driver's strategic level decisions.

To start with, there are those factors that can be classified as alternative transport option. Belonging to the upper levels of driver behavior, strategic

level behavior is significantly detached from solving problems that are related to the driving task. As an example, strategic level driver behavior can also include the consideration of mode choice based on the the awareness for other means of transportation. Several works (cf. van der Molen and Bötticher, 1988; Keskinen et al., 2004; Hale et al., 1990; Hatakka et al., 1997) conceptualize the driver's awareness for alternative means of transportation. Whenever new options are perceived, drivers assess their capability to make use these alternatives. Furthermore, following Michon (1985), strategic level planning comprises a cost-risk evaluation, thus, drivers determine their expected benefit in adapting their currently pursued strategy. As drivers are intentional systems, behavioral adaptations serve the purpose to support drivers to achieve their goals. Henceforth, I refer to this first category of external factors as: *alternative options*.

The second category of factors that evolve from the driver's environment and distract their strategic level decisions can be described as natural distractions. Contrary to the first category, the drivers have no option but to accept the effects of factors from this category. Most works that conceptualize this factor (cf. Hale et al., 1990; Summala, 1996, 1997; Bekiaris et al., 2003; Salvucci et al., 2001; Krajzewicz and Wagner, 2002; Hollnagel, 1993; Engström and Hollnagel, 2007) use weather conditions (e.g., heavy rain or wind guts) as examples for environmental factors. The analyzed models provide rather heterogeneous conceptualizations for natural distractions, though, all provided concepts can be summarized as a certain condition which resides at a certain location and affects the driver psychologically. Hatakka et al. (1997) additionally account for the fact that these conditions also have a physical effect on the driver and their vehicle. Henceforth, I refer to this second category of factors as: *environmental factors*. Based on this discussion, I conclude:

Conclusion 3.3 *Strategic level decision-making processes can be affected by the driver's continuous awareness for their surrounding environment—their perception. Factors that evolve from the driver's environment and do have the capability to affect strategic level decisions are either alternative options or environmental factors.*

Internal Factors

The third category of factors that affect the strategic level decisions of human drivers evolve directly from the drivers themselves. Henceforth, I refer to this source of distraction as the driver's *personality* or *internal factors*.

Most analyzed approaches (cf. van der Molen and Bötticher, 1988; Keskinen et al., 2004; Hale et al., 1990; Summala, 1997; Hatakka et al., 1997; Bekiaris et al., 2003; Salvucci et al., 2001; Krajzewicz and Wagner, 2002; Hollnagel, 1993; Engström and Hollnagel, 2007) use internal factors to conceptualize strategic level behavior of human drivers. The representation is rather divers, such that a driver's attitude, their motivation, their preferences, their lifestyle, their gender, and/or their emotional state is reflected.

Van der Molen and Bötticher (1988, also Keskinen, 1996) argue that internal factors can be represented in an abbreviated form, such that a utility function reflects the personality of drivers. This utility function is used to assess in how far the driver is satisfied with potential decisions. The idea is that the utility function is used to determine the quality of generated action plans. The quality reflects the driver's level of agreement with the proposed action plan, such that high values indicate broad consensus, while a lower values indicate discrepancies. Given a carefully configured utility function, the utility-based approach can be used to comprehensively express elements of the driver's personality, such as the driver's attitude, their motivation, their preferences, their lifestyle, their gender, and/or their emotional state. Based on this discussion, I conclude:

Conclusion 3.4 *A driver's strategic level decisions are affected by internal factors. Internal factors can be described as the driver's attitude, their motivation, their preferences, their lifestyle, their gender, and/or their emotional state—their entire personality. Internal factors can be expressed as utility aspects, such that a utility function assesses in how far the driver is satisfied with their decisions. High quality values indicate broad consensus, while low quality values indicate discrepancies.*

Experience and Knowledge

The fourth category of factors that affect the strategic level decisions of drivers is the driver's experience and their knowledge. Hale et al. (1990)

presented the first approach that accounted for these concepts. The impact of this category of distraction is commonly accepted, such that most analyzed approaches (cf. Hatakka et al., 1997; Bekiaris et al., 2003; Salvucci et al., 2001; Krajzewicz and Wagner, 2002; Hollnagel, 1993; Engström and Hollnagel, 2007) account for experience and knowledge concepts.

Experience is also an innate part of the driver, thus, following Conclusion 3.4, it is possible to reflect this factor in an abbreviated form by means of a utility function. Abbreviated representations were done, e.g., by Salvucci et al. (2001) and Krajzewicz and Wagner (2002). Based on these findings, I conclude:

Conclusion 3.5 *Strategic level driver behavior is affected by the driver's experience and knowledge. Experience can be conceptualized by means of the utility function, which reflects the driver's personality.*

To sum up, the objective of this chapter was to answer the question: "What are the factors that determine the outcome of human strategic level decision-making in traffic environments?"

Based on the analysis of well-established driver behavior conceptualizations, I conclude that strategic level driver behavior is affected by no less than four distinct factors. First, the outcome of other levels of behavior can affect a driver's strategic level decisions. This impact can be neglected if one wants to focus on analyzing the effects of strategic level behavior in isolation. Secondly, strategic level driver behavior can be affected by the driver's awareness for their surrounding environment. Factors that evolve from the driver's environment are either alternative options or environmental factors. Thirdly, a driver's strategic level decisions are affected by internal factors that represent the driver's personality. Internal factors can be expressed as utility function, which assesses in how far the driver is satisfied with their potential decisions. Finally, strategic level driver behavior is affected by the driver's experience and knowledge. Experience—as a part of the driver's personality— can also be reflected by means of a utility function.

So far, I presented a strategic level driver behavior from a psychological perspective. In the following part, I put particular emphasis on computer-aided traffic simulation frameworks. It is my intention to introduce fundamental concepts and to identify in how far contemporary traffic simulation

frameworks are able to reproduce the psychological understanding of human strategic level driver behavior.

Part III

Driver Simulation

The objective of this part is to identify in how far contemporary traffic simulation frameworks are able to reproduce the psychological understanding of human strategic level driver behavior. In order to do so, I introduce the reader to the fundamentals of computer-aided traffic simulation. Subsequently, I present contemporary traffic simulation frameworks with particular emphasis on their capability to reproduce strategic level driver behavior.

4. Fundamentals

Contemporary traffic simulation frameworks have reached a high level of sophistication. Affordable high-end hardware has fostered the development of simulation software with an ever increasing level of detail. One reason for the high level of sophistication is the long history of research in traffic simulation. The first successful attempt was described by Gerlough (1955), who used a computer system to simulate a small number of vehicles on a selected freeway section.

Besides the fact that contemporary approaches feature a high level of detail, the basic operation principle has changed only slightly over the years. The applied models, however, became more accurate. Following Lieberman and Rathi (2005, also Barceló, 2010a), a traffic simulation is nothing more than a set of mathematical models that describe how a traffic system works, behaves, and evolves over time.

Lieberman and Rathi (2005) argues that respectively one model from at least three different model categories is required to constitute something which we better know as *traffic simulation*. The first model category describes how and when the simulated entities change their state. Following Balci (1988), this category can be referred to as *time flow mechanism* or *time flow model*. Secondly, there has to be a model that conceptualizes the traffic which is simulated. This category is commonly referred to as *traffic flow model*, or simply *traffic model*. Finally, there has to be a model that describes the variables and the interaction between the simulated entities. This category is referred to as *variable model*.

The purpose of this chapter is to present these three model categories in more detail and thus aims to answer the question:

- What are the fundamental models of a computer-aided traffic simulation?

In order to do so, I present time flow mechanisms in Section 4.1, traffic models in Section 4.2, and variable models in Section 4.3. I discuss the three categories in the light of this work and conclude this chapter in Section 4.4.

4.1 The Time Flow Mechanism

Following Lieberman and Rathi (2005), most traffic simulation frameworks describe traffic systems as a dynamical system where "time is always the basic independent variable" (p. 10–5). The time flow model describes how and when simulated elements change their state during the simulation. Lieberman and Rathi (2005) distinguish between two categories of time models, namely *continuous models* and *discrete models*.

4.1.1 Continuous Models

Continuous models describe how elements of a simulated system change their state in a continuous fashion over time and as a consequence to continuous stimuli. Following Lückemeyer (2007), "continuous simulation time can only be approximated on digital computers by mapping it to a function that displays system development over time an then taking an increasingly small time increment to the limit as it approaches zero" (p. 31).

4.1.2 Discrete Models

Discrete models assume that the state of all simulated entities changes abruptly at determined points in time. Discrete models are further subdivided into *discrete time flow* and *discrete event* models.

Discrete time flow models[1] are used for time-oriented simulations in which the model time is advanced at an appropriately chosen unit time, namely

[1]Discrete time flow models are also frequently referred to as *synchronous time flow* models.

Δt (Lieberman and Rathi, 2005; Lückemeyer, 2007; Barceló, 2010b). For each time interval, the simulation engine computes the activities that change the state of a simulated element and applies these changes. The discrete time flow approach, entails the significant disadvantage that most of the simulated entities are idle much of the time.

Discrete event models[2] avoid this computational overhead and advance only between points in time in which certain incidents, namely *events*[3] cause changes in the simulated system (Lieberman and Rathi, 2005; Lückemeyer, 2007).

While the former approach is highly recommended for computer systems of limited size or for traffic systems with entities whose state changes infrequently, the latter approach is clearly the better choice for traffic systems where most entities experience a continuous change, or where detailed descriptions are required by the simulation's objectives.

4.2 The Traffic Flow Model

There are three commonly used mechanisms to represent traffic flows in traffic simulations (Cascetta, 2001; Lieberman and Rathi, 2005; Barceló, 2010b).

To start with, traffic flow can be modeled *macroscopically*, that is, in an aggregated fashion. Models that conceptualize traffic in a macroscopic fashion are called *macroscopic models*. Macroscopic models are frequently based on a hydrodynamic analogy and conceptualize traffic flows as a fluid process whose state is determined by the three aggregate variables: *density*, *volume*[4], and *speed* (Barceló, 2010b).

The second category of traffic models are *microscopic models*. Microscopic models are bottom-up models, that is, the behavior of the entire traffic system is derived from the detailed description of its entities. In other words, the traffic flow "evolves" from the dynamics of individual traffic entities (Barceló, 2010b).

[2]Discrete event models are also referred to as *variable time increment* models.
[3]Events are also frequently referred to as *activities*.
[4]The volume variable is also frequently referred to as *flow* (Gazis, 2002).

Finally, *mesoscopic models* combine the microscopic and the macroscopic view and conceptualize traffic flows by means of a simplification of vehicular dynamics.

I present the particulars of all three categories below.

4.2.1 Macroscopic Modeling of Traffic

Macroscopic traffic flow models describe all traffic entities as well as their activities and interactions at a low level of detail (Lieberman and Rathi, 2005). In the most cases, the vehicles are not represented as individuals but as a fluid that flows through a street network (Gazis, 2002). Detailed maneuvers such as lane changing or gap acceptance are usually not conceptualized (Lieberman and Rathi, 2005).

Macroscopic models are based on the *continuum traffic flow theory*, which describes the time-space evolution by means variables that determine the characteristics of a macroscopic flows, namely volume $q(x,t)$, speed $u(x,t)$, and density $k(x,t)$. These variables have to be defined at every instant in time t and every point in space x (Barceló, 2010b).

The equation which expresses this connection is the *conservation*, or *continuity equation*, which was described by Gerlough and Huber (1975):

$$\frac{\partial q}{\partial x} + \frac{\partial k}{\partial t} = 0.$$

The continuity equation formally describes that the number of vehicles remains constant between two locations on a motorway section without entrances and exits (Barceló, 2010b). The equation is complemented by the following relationship:

$$q(x,t) = k(x,t) \cdot u(x,t).$$

A popular and well-established macroscopic traffic flow model is the *Phenomenological Model for Dynamic Traffic Flow on Highway Networks*, which was presented by Hilliges (1995). The model formally describes dynamic traffic flow on a complex highway network. Another example for a popular macroscopic traffic flow model is the *Kerner-Konhäuser Model*, or *KK-Model* (Kerner and Konhäuser, 1993), which accounts for the fact that even

in stable and homogeneous traffic flows, regions with high density and low average speed (so called clusters), can suddenly emerge. A whole set of popular macroscopic traffic flow models are grouped under the umbrella of *Boltzmann-like models*. Boltzmann-like models are kinetic models that apply the theory of ideal gases on traffic streams. In doing so, Boltzmann-like models describe the dynamics of the flow phase density (Shvetsov, 2003).

4.2.2 Microscopic Modeling of Traffic

Microscopic traffic flow models describe the system's entities as well as their interactions at a high level of detail (Lieberman and Rathi, 2005). Where macroscopic models do not conceptualize motions of individual vehicles, microscopic approaches account for all actions, such as acceleration, decelerations, gap acceptances, or lane changes, to name but a few (Lieberman and Rathi, 2005; Barceló, 2010b). To this effect, the overall traffic flow is the result of the motions of the vehicles that form the traffic stream (Barceló, 2010b).

A common way to conceptualize microscopic traffic flows is to describe how one vehicle follows the other. Models that describe how one vehicle follows the other are commonly referred to as: *car-following models*. Car-following models were mainly developed in the 1950s and 1960s, after Reuschel (1950a, also Reuschel, 1950b) and Pipes (1953) presented their seminal works on car-following theories (Barceló, 2010b, after May, 1990).

Barceló (2010b) argues that the first approaches (cf. Reuschel, 1950b; Pipes, 1953) implemented the suggestion that was proposed by the *California Motor Vehicle Code*, namely "to allow yourself at least the length of a car between your vehicle and the vehicle ahead for every ten miles per hour of speed at which you are travelling" (p. 18).

Gerlough and Huber (1975) argue that all car-following models are basically stimulus-response equations, which comply with:

$$Response(t + T) = Sensitivity \times Stimulus(t), \tag{4.1}$$

where the driver's response is defined as their reaction to the motion of the vehicle immediately preceding them and their response is either an acceleration or a deceleration in proportion to the magnitude of the stimulus at

time t. This response begins after a time lag T—the reaction time of the follower. Following Gerlough and Huber (1975), most microscopic traffic flow models comply with Equation 4.1, but differ in two fundamental questions, namely:

- What is the nature of the driver's response?
- To what stimulus does they react and how do we measure their sensitivity?

The *linear car-following model* is the simplest model that answers these questions. The model is based on the assumption that a driver's response is limited to acceleration and deceleration maneuvers. Furthermore, the model assumes that the stimulus to what a driver reacts is a variation in the relative speeds, while the driver's sensitivity is constant.

Barceló (2010b) formalizes this connection as follows:

$$\ddot{x}_{n+1}\ (t+T) = \lambda\left[\dot{x}_n\ (t) - \dot{x}_{n+1}\ (t)\right],$$

where $x_n(t)$ and x_{n+1} are the positions of the leader and the follower, at a given time t. The model is based on the assumption that a driver's behavior is only influenced by the driver in front of them, though, Herman et al. (1959) argue, that drivers also take the next-nearest neighbor into account.

The work of Herman et al. (1959) triggered the development of approaches that additionally accounted for concepts like traffic density and traffic flow. Gazis et al. (1959), for instance propose a model that uses the traffic stream's density as an additional stimulus and thus account for individual behavior in traffic jams. Newell (1961) describes a similar approach and uses the traffic stream's density in order to describe shockwaves in traffic systems. Edie and Foote (1960) present another approach that falls into this category and that is able to account for sudden state-changes which occur in a traffic stream in the transition between relatively free-flowing conditions and a crawling stop-and-go condition, and vice versa.

The first work that ever explicitly integrated human factors into the mathematical equations was presented by Gipps (1981). The model reflects

the goal oriented nature of drivers[5] and conceptualizes the driver's desire to drive at an intended speed. The model comprises two components. The first component conceptualizes the driver as intentional system and accounts for the intention of a driver to reach a certain target speed. The second component reproduces the limitations that are imposed by the preceding vehicle when the driver tries to drive at the target speed.

Extending car-following models to account for behavioral factors became increasingly popular, especially when Parker (1996) argued that real drivers do not always act in compliance with the California Motor Vehicle Code—the fundamental assumption of car-following models.

To this end, there were many attempts to combine regular car-following models with behavioral elements. Hidas (1998), for instance, proposed a model which is based on the assumption that a follower vehicle $n+1$ follows closer than a "safe distance" and, when approaching and following a leader vehicle n, has to adjust their acceleration so as to reach a "desired spacing" at any time t, after τ seconds. Following Barceló (2010b, after Hidas, 1998), this dependency can be formalized as follows:

$$x_n\ (t+\tau) - x_{n+1}\ (t+\tau) = D_{n+1}\ (t+\tau),$$

where D, the desired spacing, is designed as a linear function:

$$D_{n+1}\ (t+\tau) = \alpha \cdot \dot{x}_{n+1}\ (t+\tau) + \beta,$$

where α and β are constants and $\dot{x}_{n+1}\ (t+\tau)$ is the speed of the follower vehicle.

While the work of Hidas (1998) was only one of the more popular approaches, there were many attempts to extend car-following models with behavioral factors. A comprehensive survey of such models was done by Ranney (1999), who classified these factors into two categories, namely *individual differences* and *situational factors*.

Individual differences refer to attributes of the driver but also to the driver's personality. Determining factors that fall into this category

[5] A comprehensive discussion on the goal oriented nature of drivers from a psychological perspective was provided in Section 3.4.1.

are the driver's: age, gender, risk-taking propensity, driving skills, vehicle size, or vehicle performance characteristics. Psychological models account for similar concepts. In Section 3.4.2, however, I argued that psychological approaches further subdivide individual differences into the driver's personality and their experience and knowledge.

Situational factors are further subdivided into *environmental* and *individual* situational factors. As examples for environmental situational factors, Ranney (1999) referred to the time of the day, the day of the week, weather and road conditions. Examples for individual situational factors are situations of distraction, hurrying, impairment due to alcohol, drugs, stress and fatigue, trip purpose, length of driving. In Section 3.4.2, I argued that psychological models reflect environmental situational factors by means of environmental factors. Individual situational factors are reflected by internal factors or the driver's personality.

Despite the differences of microscopic traffic simulation models, Barceló (2010b) provides a generic description for microscopic approaches. In more detail, Barceló (2010b) argues that microscopic traffic simulations can be represented as a generic process, which is iteratively executed. In a simplified form, this generic process looks as follows (adapted from Barceló, 2010b, p. 33):

1. Initialization:
   (a) Define a cycle time to update paths in the network.
   (b) Calculate initial shortest paths for each vehicle on the basis of some definition of initial link costs, e.g., free-flow link travel times.
2. Repeat until all vehicles have been loaded onto the network:
   (a) Calculate path flow rates according to a route choice model.
   (b) Dynamic network loading: propagate the flows along the paths in accordance with the microscopic flow dynamics. At every simulation step, update the position of every vehicle in the model:

- Determine the next move at the current simulation step and the associated model.
- Apply the corresponding model: lane change, car following, etc.
- Calculate the new position at the end of the simulation step.

(c) Collect statistics according to a predefined data collection plan.

(d) Update link costs.

(e) Update shortest paths with the updated link costs, for use in the next cycle.

Barceló (2010b) argues, that the various microscopic simulators only differ in the way they implement this generic iterative process.

4.2.3 Mesoscopic Modeling of Traffic

The third mechanism that is commonly used to conceptualize traffic flows is mesoscopic modeling. Where the macroscopic perspective can be considered as a high-level representation of traffic flows and microscopic approaches can be considered as detailed representations, mesoscopic models are somewhere in-between.

Mesoscopic models generally represent most entities at a high level of detail but describe their activities and interactions at a much lower level of detail than microscopic models (Lieberman and Rathi, 2005).

In fact, mesoscopic modeling is a simplification of microscopic models. The simplification results in less data demand and an increased computational efficiency (Barceló, 2010b). Mesoscopic models differ in two determining characteristics. First, available approaches use different concepts to model vehicles. Several approaches consider vehicles in packages or "platoons". These platoons move along links. Contrary, there are approaches that determine the overall traffic flow by means of simplified dynamics of individual vehicles (Barceló, 2010b).

The second characteristic that determines the category of a mesoscopic traffic flow model is the applied time flow mechanism (Barceló, 2010b). Most approaches are based on discrete (or synchronous) time flow models, however, there are models that use a discrete event (or asynchronous) time flow model.

4.3 The Variable Model

The third model category, which is required for a traffic simulation framework is the variable model. Lieberman and Rathi (2005) argue that variable models in traffic simulation frameworks can be classified either as *deterministic* or *stochastic*.

Following Lieberman and Rathi (2005), deterministic models do not use random variables for the simulation process. To this end, all entity interactions are described by exact relationships.

Contrary, stochastic approaches use probability functions to conceptualize the interaction between simulated entities.

The difference between deterministic and stochastic variable models can be clarified by means of the above-presented car-following models. Deterministic models (cf. Herman et al., 1959; Gazis et al., 1959; Newell, 1961; Edie and Foote, 1960) express the driver's reaction time as a constant value. Contrary, stochastic models (cf. Gipps, 1981; Parker, 1996; Hidas, 1998) use a random variable for the same attribute and thus account for a statistical derivation in the driver's response time.

4.4 Conclusion

The purpose of this chapter was to introduce the reader to the basic operation principle of traffic simulation frameworks. It was my intention to answer the question: "What are the fundamental models of a computer-aided traffic simulation?"

Traffic simulations are basically a collection of computational models. At least three models are required—each one belonging to a different category. First, a time flow model describes how time, the basic independent variable, is being reflected. Time flow models can be further divided into continuous and discrete models. Secondly, a traffic flow model describes how traffic is represented in the simulation. There are three common ways to conceptualize traffic, namely macroscopic, microscopic, and mesoscopic models. Finally, the variable model determines the nature of the variables that are used for the simulation. There are two common types of variable models, namely deterministic and stochastic variable models.

The reason for the versatility of models is the variety of applications in which traffic simulations are used. As an example, traffic simulation frameworks can be used to determine the effects of closed lanes, e.g., due to construction. Such examination requires a highly detailed traffic model in order to account for lane change maneuvers or gap acceptances. Contrary, traffic simulations can be used to determine the effects of blocking major intersections or important roads (e.g., city highways) on large-scale traffic systems. Despite the increased level of detail, microscopic models would not increase the quality of results, but rather reduce the simulation performance. Thus, for such kind of examinations macroscopic models are the clearly the better choice. The bottom line is, the choice of the model depends on the area of application!

The objective of my work is to present a model for strategic level driver behavior. This very focus narrows down the choice of models considerably. I discuss the above-presented model categories in the light of this work below.

4.4.1 Time Flow Model

There are generally two options for a time flow model, namely a continuous and a discrete approach.

Following Section 3.4.2, drivers are continuously influenced by factors that determine the outcome of their strategic level decisions. To this end, a continuous model would be the right choice to reproduce strategic level decision-making processes in a lifelike fashion. Yet, following Section 4.1.1, continuous time flow models can only be approximated in digital computer systems (e.g., by limit value generation).

In Chapter 3, I have outlined the complexity of human decision-making processes. Given this complexity, the choice of an infinitesimal time interval will cause significant performance problems. Furthermore, according to Definition 3.1, action plans that evolve from strategic level decision-making processes can not be completed in a matter of seconds. To this end, I conclude that discrete approaches are clearly the better choice for this work.

Discrete approaches can be subdivided into discrete event and discrete time flow models. In fact, both approaches fit purposes for my work, yet, I decided to apply the latter category for the following reason:

Traffic simulations with a discrete event model advance between instants in time in which simulated elements change their state. In more detail, the simulation interval Δt changes during the simulation and has to be recalculated at the end of each simulation interval in order to determine the specifics of the next simulation step—a computationally intensive process.

In the case that the simulated entities are idle most of the time, discrete event models are generally superior to discrete time models. Though, in Section 3.4.2, I showed that drivers are constantly affected by disturbances that may trigger strategic level decision-making, thus, a discrete event approach may result in a large number of events that have to be simulated.

In order to avoid any computational overhead that results from calculating the specifics of the next simulation interval, respectively, I decided to use a constant value for Δt and to apply a time discrete approach. Based on the above discussion, I conclude:

Conclusion 4.1 *Discrete time modeling is the most effective option for the development of a simulation model for strategic level driver behavior.*

4.4.2 Traffic Flow Model

There are three common categories of traffic flow models that can be used to represent traffic flows in a traffic simulation. These models are: macroscopic models, microscopic models, and mesoscopic models. The choice the right traffic flow model is significantly narrowed down by the objective of this work.

It is my objective to present a simulation model for strategic level driver behavior, thus, there is an innate focus on the driver and the their actions. In order to reproduce the driver's decision-making process it is necessary to consider this driver in isolation and not in an aggregated fashion.

In Section 4.2.2, I argued that microscopic approaches describe both, the system entities and their interaction at a high level of detail. Mesoscopic and macroscopic approaches neglect such level of detail and conceptualize traffic as compounds or platoons.

In fact, it is also possible to analyze the effects of individual strategic level behavior on a larger scale, though, such consideration still requires

a decision-making model for each simulated entity. Based on the above discussion, I conclude:

Conclusion 4.2 *Human decision-making processes in traffic environments are an innate part of the conceptualized subject. The focus on individual drivers and their behavior implies a microscopic point of view and thus narrows down the choice of applicable traffic models to microscopic traffic flow modeling.*

4.4.3 Variable Model

There are basically two categories of variable models, a stochastic and a deterministic one. Psychological driver behavior conceptualizations neglect a discussion on variables, therefore, it is difficult to decide whether stochastic or deterministic models fit better.

Intuitively, I would argue that human behavior is determined by a set of random factors, though, there is no proof in psychological literature.

In the end, it comes down to a design decision. Deterministic variable models have the advantage that simulation results become comprehensible and explainable. Results of stochastic models may be closer to reality but can be difficult to analyze.

A look into contemporary traffic simulation frameworks will show how this design decision is answered by contemporary approaches. As for now, I leave this question open.

5. A State-of-the-Art

The high complexity of traffic systems as well as the increased demand for alternatives to expensive and complex real world field tests have attracted developers from both, academia and industry. Currently, there are many traffic simulation frameworks available, each one focusing on particular aspects of traffic systems.

In this chapter, I outline the capabilities of existing frameworks to mimic strategic level behavior of simulated drivers. I also show how strategic level capabilities can be represented in traffic simulation frameworks. Finally, I determine to what extend existing approaches are able to reproduce the psychological understanding of human strategic level driver behavior.

The purpose of this chapter is to answer the following questions:

- Is human strategic level driver behavior a factor for the outcome of contemporary traffic simulations?
- What is an appropriate approach to simulate strategic level driver behavior?
- Where are the frontiers in simulating human strategic level driver behavior?

To answer these questions, I analyze the latest versions of well-established traffic simulation frameworks. In doing so, I respectively put emphasis on

the representation of human factors in general, and on the representation of strategic level decision-making in particular.

To provide some structure to this chapter, I distinguish between two categories of traffic simulation frameworks. In Section 5.1, I present academic approaches. Academic approaches are freely available and mostly open source, thus, it is easy to get information about implementation details. In Section 5.2, I present commercial approaches. Commercial software packages feature a high degree of performance and reliability, yet, since the source code is not directly accessible, it can be difficult to get accurate information about implementation details. I conclude this chapter in Section 5.3.

5.1 Academic Approaches

Most academic approaches that I present in this section were (and still are) developed by research groups at universities. One particular feature which characterizes these frameworks is their experimental nature. Most frameworks that I present in this section account for simulation features that have not been studied well enough for an appliance in professional software packages.

5.1.1 Multi-Agent Transport Simulation

The *Multi-Agent Transport Simulation* framework, or *MATSim* (Illenberger et al., 2007, after Balmer et al., 2004), is a microscopic traffic simulation framework, which uses a discrete event model to conceptualize the time flow. The framework evolved from its successful predecessor, the *TRANSIMS* traffic simulator. MATSim is based on the multi-agent paradigm and conceptualizes simulated vehicles (or their drivers) as autonomous agents.[1]

MATSim uses an activity-based approach to generate the events that are required for the event-based simulation engine. In more detail, each simulated agent receives a set of activities that the agent has to accomplish throughout the simulation time. In order to accomplish the list of activities, the agent computes a plan, which meets the requirements that are given by the activities.

[1] A more comprehensive introduction into the multi-agent paradigm and multi-agent systems is provided in Section 7.1.

A plan consists of the agent's intended schedule of activities for the day and the travel legs that connect these activities (Illenberger et al., 2007). A leg corresponds to an event in an event-based time flow model and describes the travel from one activity to another. A leg also specifies several attributes, such as: departure time, expected arrival time and the intended route or transportation mode (Illenberger et al., 2007).

MATSim is based on the *user equilibrium*, that is, the simulation is done under the assumption that (simulated) drivers aim to maximize the efficiency of their travel plans (Illenberger et al., 2007). The user equilibrium is implemented by means of evolution strategy (Rechenberg, 1973), an iterative optimization procedure.

At the beginning, a set of initial plans is generated. These plans are used as input data for a traffic flow simulation, namely the *physical layer* (Illenberger et al., 2007). Based on the results of the physical layer, the plans are assessed by means of a fitness function. Plans with the highest quality are selected and used as input for the *mental* or *strategic layer* (Illenberger et al., 2007), where the agents "mutate" or "recombine" (or both, mutate and recombine) their plans. Examples for mutation operations that are implemented in MATSim are the replacement of routes by other routes or the variation of departure times. Physical layer and strategic layer simulations iterate until the quality of the plans (which is determined by the fitness function) converges to an approximate user equilibrium.

The two fundamental processes of the MATSim framework, namely the physical and the strategic layer, as well as the interplay of both layers, are illustrated in Figure 5.1.

While the physical layer complies with a regular microscopic traffic simulation and implements facets of tactical level behavior, strategic level planning capability is implemented in the strategic layer.

The strategic layer comprises two distinct phases, namely the activity generation and the mode/route choice (Balmer et al., 2004). The activity generation disaggregates census data in order to produce a 24-hour activity plan that includes locations and times of activities. The mode-and-route choice mechanism connects these activities by the above-introduced legs. The connection is done by using travel times as cost function and by using the *Dijkstra shortest path* algorithm (Dijkstra, 1959).

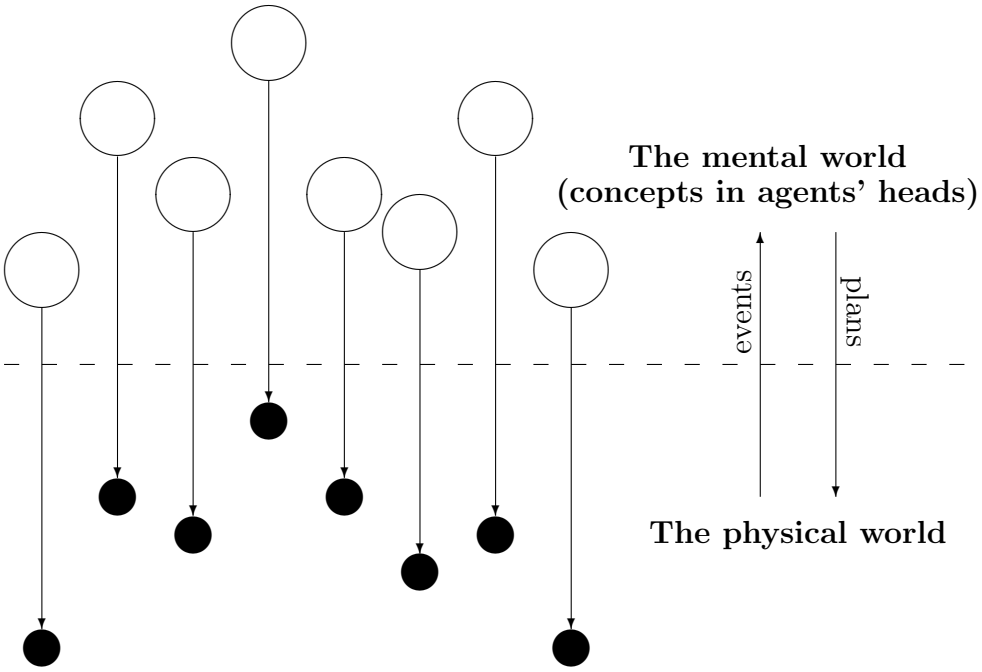

Figure 5.1: The two fundamental simulation layers, namely the strategic layer and the physical layer. On the strategic layer, traffic participants compute routes and select their means of travel. On the physical level these "plans" are simulated and assessed. The process iterates until a user equilibirium is reached (adapted from Balmer et al., 2004, Figure 1, p. 60).

On the physical layer, MATSim uses current traffic flow values for estimating the travel costs and thus reflects the dynamics of traffic systems. The mode-choice, however, is implemented as offline process and thus done before the simulation. For this process, a fitness function (also utility function) is used to assess the quality of available modes of transport (Balmer et al., 2004). The utility for using a bus U_{bus}, for instance, can be determined by several factors, such as the required time T, monetary costs C or personal attributes, such as the agent's gender G and several weight factors: α, γ, μ. Following Balmer et al. (2004), U_{bus} is computed as follows:

$$U_{bus} = -\alpha T_{bus} - \gamma C_{bus} + \mu G,$$

while the probability for using a car is computed as follows:

$$U_{car} = -\alpha' T_{bus} - \gamma' C_{bus} + \mu' G.$$

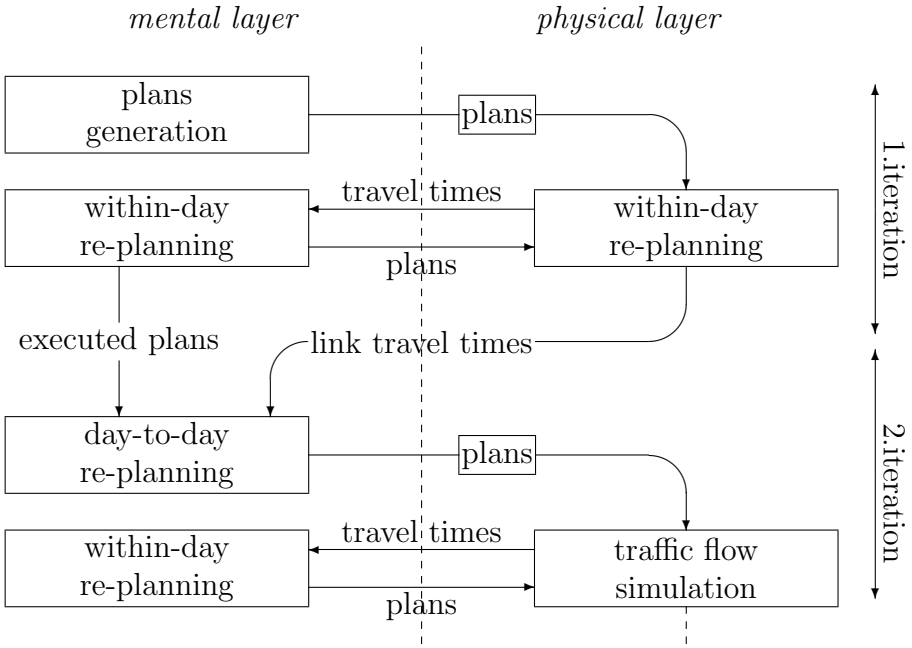

Figure 5.2: Two iterations of within-day re-planning in *MATSim*. The system iterates between the mental layer, where plans are being generated and the physical layer, where a traffic flow simulation is done (adapted from Illenberger et al., 2007, Figure 2, p. 95).

Based on these two utility functions, MATSim computes the probability for each mode of transport. Following Balmer et al. (2004), MATSim determines the probability for using a bus as follows:

$$p_{bus} = \frac{e^{\beta U_{bus}}}{e^{\beta U_{bus}} + e^{\beta U_{car}}},$$

where β is another weight factor that has to be adjusted.

MATSim allows agents to update their travel behavior in two different ways (Illenberger et al., 2007). First, agents are capable of *day-to-day* planning, that is, plans can be updated in a 24-hour interval. Secondly, agents are able to respond to unforeseeable incidents by updating their plans "en route". This second mechanism, namely *within-day re-planning*, is illustrated in Figure 5.2.

Both processes, day-to-day and within-day re-planning are similar—the only difference it the knowledge the agent possesses (Illenberger et al., 2007). While in the former case, the agents use information that has been collected during the previous simulation runs (learning), the agents access "locally

available" information in the latter case. This locally available information comprises data that is stored in a local memory, the *agent-brain*. Furthermore, locally available information comprises information about the agent's environment—the agent's current perception. Following Illenberger et al. (2007), this perception is "given by the current traffic state" (p. 96). The agent's awareness is thus limited to the surrounding traffic.

5.1.2 Simulation of Urban Mobility

Simulation of Urban Mobility, or *SUMO* (Krajzewicz, 2010, also Krajzewicz et al., 2002) is one of the most efficient traffic simulation frameworks there is. SUMO is a time discrete traffic simulation, which uses a microscopic traffic flow model and represents simulated vehicles in a high level of detail. The development of SUMO was driven by the objective to provide a universal evaluation platform for different models and algorithms that are either related to traffic or to traffic management. In more detail, the development of SUMO was driven by two major design objectives, namely portability and extensibility. Furthermore, the framework was geared towards performance. To this effect, highly efficient car-following models were developed and implemented. These car-following models conceptualize vehicles in a microscopic fashion, though, account for human factors as well.

Human factors are directly included in SUMO's car-following model and thus an innate part of the simulation engine. The car-following model which is used by SUMO comprises two separate models. The first model, namely the *longitudinal model*, is used to compute a vehicle's movements relative to a leading vehicle. The second model, namely the *lateral* or *lane change model*, is used to determine whether a simulated vehicle changes its lane. Both models, the longitudinal and the lateral model, account for human factors. I present both models in more detail below.

The longitudinal model which is used in SUMO is an extension of the time-discrete car-following model which was originally proposed by Krauß (1998). Like most microscopic approaches, the model is based on the assumption that a driver aims to maintain a distance to a leading vehicle that allows them to stop without risking a collision[2]. Based on the distance to

[2]The assumption that drivers aim to maintain a distance to a leading vehicle that allows them to stop without risking a collision is actually an implementation of the California Motor Vehicle Code (see also Section 4.2.2).

a leading vehicle g_{leader}, the velocity of the leading vehicle v_{leader}, and a set of vehicle and driver-specific attributes, namely the driver's reaction time τ and the vehicle's maximum deceleration ability b, the vehicle's velocity v_{safe} is computed as follows (Krauß, 1998):

$$v_{safe}(t) = -\tau \cdot b + \sqrt{(\tau \cdot b)^2 + v_{leader}(t-1)^2 + 2 \cdot b \cdot g_{leader}(t-1)}.$$

In order to avoid accelerations and velocities that are beyond the limits of the vehicle, the "desired" velocity v_{des} is computed as follows (Krauß, 1998):

$$v_{des}(t) = min\{v_{safe}(t), v(t-1) + a, v_{max}\},$$

where $v(t)$ is the current vehicle's velocity, a is its maximum acceleration ability and v_{max} is its maximum velocity.

So far, the equations lack human factors. Yet, Krauß (1998) argues that a driver is not perfect in realizing the desired velocity. To account for this imperfection, the final velocity $v(t)$ is computed as follows (Krauß, 1998):

$$v(t) = max\{0, v_{des}(t) - r \cdot a \cdot \epsilon\},$$

where r is a random factor and ϵ reflects the driver's imperfection in maintaining a given velocity.

Krajzewicz (2010) used the work of Krauß (1998) as a foundation and refined the above-presented model to its current form. Two additions were done. First, the ability to accelerate with an increasing speed was aggravated by a decay. Secondly, the driver's imperfection to maintain a desired speed was decreased for low velocities. Furthermore, additional factors (different from the leading vehicle) were included in the computation of a vehicle's velocity. These factors comprise: the allowed speed, right-of-way rules, and the driver's visual range.

The second model, which is used in SUMO, is the lateral model (Krajzewicz, 2010). The lateral model accounts for the ability of drivers to

change their lanes. The model also accounts for human factors. In order to determine whether a driver changes lanes, the road in front of the current vehicle is examined (up to a viewing distance) and occupancies are collected. Based on this perception, the driver computes "safe velocities" for all neighbor lanes and determines whether a lane change provides any profit. The computational process is implemented in compliance with the work of Ehmanns (2001), such that drivers constantly assess the benefit of lane changes. Whenever the calculated profit exceeds a driver-specific threshold, a lane change is initiated.

5.1.3 AVENUE

The *Advanced & Visual Evaluator for road Networks in Urban arEas*, or *AVENUE* simulation framework (Kuwahara et al., 2010), was developed under the objective to provide a tool for the analysis of local traffic management strategies.

AVENUE is a time discrete simulation framework, which uses hybrid approach to represent traffic flows. The traffic flow model for itself is based on fluid dynamics—a macroscopic approach. Nevertheless, the framework also provides visual representations for selected intersections. In order to visually represent vehicles at intersections, AVENUE implements a mechanism that is able to refine the applied macroscopic model to a microscopic one. The applied traffic flow models account for human factors.

To start with, two different dynamic route choice model are implemented. The first route choice model is based on dynamic user optima, the second on stochastic user optimum principles (Kuwahara et al., 2010). Both route choice models can be used to assess routes with respect to several factors, e.g., travel time, route length, number of turns, toll fee, etc. These factors—or the assessment of these factors—represent the personality of simulated drivers. A fixed-path routing version is also implemented in order to account for vehicles that usually follow fixed routes (e.g., busses or delivery trucks).

The second model in AVENUE which accounts for human factors is the is the lane change model. For each discrete simulation interval, the AVENUE engine determines whether a driver remains on the current lane or changes. Decision-making is determined by two factors, namely the observed flow rate of neighbor lanes and the driver's lane change preference. The latter can be specified by means of a numerical value.

5.1.4 Microscopic Traffic Simulation Laboratory

The *Microscopic Traffic Simulation Laboratory*, or *MITSIMLab* (Ben-Akiva et al., 2010b) is a time discrete traffic simulation framework. MITSIMLab uses a microscopic model to represent traffic flows. The framework was developed under the objective to analyze the effects of traffic management systems (Ben-Akiva et al., 2010b). The driver model, which is used in MITSIMLab, accounts for human factors and was calibrated by using behavior data of real drivers (Ben-Akiva et al., 2010b).

MITSIMLab comprehensively accounts for tactical level behavior. Tactical level behavior is modeled as a series of interdependent choices that comply with a superior plan (Ben-Akiva et al., 2010b). Behavior can also be adapted to the situations, e.g., to the behavior of other drivers or to traffic control systems. The driver's decisions can also be affected by previous plan choices. This mechanism is realized by means of a *hidden markov model*. Furthermore, anticipated future conditions are able to affect a driver's decisions. This mechanism is implemented by means of predicted conditions that are based on current information in the decision-making. Random factors are incorporated as well, in order to account for factors that differ between drivers, e.g., aggressiveness or varying levels of planning capability. Being a microscopic framework, MITSIMLab implements the stimulus-response mechanism (see Equation 4.1). The framework is able to mimic highly realistic lane change or gap acceptance behavior.

MITSIMLab also accounts for strategic level behavior and implements a sophisticated travel behavior model (Ben-Akiva et al., 2010b). The travel behavior model accounts for pre-trip and en route path choices. Drivers either use predefined paths or compute their route dynamically. Route selection is realized in two different ways, namely *path-based* route choice and *link-based* route generation. The path-based route choice model uses a set of predefined paths through the traffic network and respectively computes the probability that a driver will choose one of the routes. This calculation is based on several path attributes such as path travel times or a freeway bias. The second travel behavior model that is used in MITSIMLab does not require a predefined set of routes, as drivers choose only the next link at each intersection (Ben-Akiva et al., 2010b). In order to determine the next link, drivers assess the "systematic utility" for all available links. To

calculate this utility, the expected travel time to the destination as well as other factors, such as the distance to the destination or previous route choices, are used.

5.1.5 DRACULA

The *DRACULA*, or *Dynamic Route Assignment Combining User Learning and Microsimulation* package (Liu, 2010) is a microscopic traffic simulation framework. DRACULA is on of the few simulation frameworks that uses a continuous time model. The focus of the development was to account for individual trip makers' choices and individual vehicles' movements (Liu, 2010),.

DRACULA implements the car-following model, which was presented by Wang et al. (2005). The model is a classical car-following model, which means that it basically implements the rules that were proposed by Gipps (1981) (see also Section 4.2.2). DRACULA's car-following model accounts for human factors such as individual reaction times or gap acceptances. Furthermore, more complex elements of human behavior, such as particular motorway flow characteristics (e.g., traffic breakdown, hysteresis, or shockwave propagation) and close-following behavior are included (Liu, 2010).

DRACULA implements an activity-based approach to generate traffic demand (Liu, 2010, after Liu et al., 2006). The operation principle is based on the assumption that drivers aim to maximize their profit—the user equilibrium. Optimization is implemented as an iterative process. For each driver, activities for one day are generated. Using these activities, drivers compute a fitting strategy, including routes and departure times. The calculated strategies are simulated and their efficiency is assessed. Based on this assessment, the drivers adapt their knowledge and their experience. Experiences are used for the strategy generation process in the next iteration. The process iterates until the driver's profit remains constant.

5.1.6 DynaMIT

The *Dynamic network assignment for the Management of Information to Travelers*, or *DynaMIT* traffic simulation framework (Ben-Akiva et al., 2010a), is a simulation-based model system, which estimates and predicts traffic conditions. DynaMIT was developed under the objective to provide

anticipatory route guidance in real-time settings. Based on a set of input parameters (e.g., departure time, arrival times, preferred routes, or preferred modes of transport), DynaMIT simulates a set of possible route options on a given traffic network. This network contains predicted and time-dependent travel times.

DynaMIT is based on the user equilibrium and thus implements the assumption that drivers aim to optimize their travel time through the road network (Ben-Akiva et al., 2010a). In order to do so, the simulation engine shifts departure and arrival times within allowed ranges and respectively computes the benefit of these variations. The simulation engine is able to account for public transport and computes multi-modal routes. The modal choice, is done either before the route is simulated or during the simulation, which means that DynaMIT allows drivers to act spontaneously.

The drivers' dynamic perception, however, is limited to the current traffic situation. Other factors, e.g., available transport options, are known before the simulation and also used for route choice process. DynaMIT is therefore not able to conceptualize spontaneous reactions that are triggered by the driver's changing awareness for their surrounding infrastructure. Drivers in DynaMIT have—at any time—full information about the traffic and transport system.

5.1.7 FEATHERS

The *Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS*, or *FEATHERS* activity generator (Bellemans et al., 2010) was developed under the objective to facilitate the development of activity-based models for transport demand.

FEATHERS implements a development trajectory that consists of four-stages Bellemans et al. (2010). On the first stage, a static activity-based model is developed. On the second stage, this model is refined to a semi-static model that accounts for evolutionary and non-stationary behavior. On the third stage, a fully dynamic activity-based model is developed. This model accounts for short-term adaptation behavior and learning. Finally, on the fourth stage, a fully dynamic and agent-based microscopic simulation framework is developed. This level accounts for a high level of detail, e.g., microscopic traffic flow simulation and route assignment.

FEATHERS was developed under the objective to generate highly realistic, microscopic demand model for a particular traffic and transport network, namely the region of Flanders in the Kingdom of Belgium (Bellemans et al., 2010). In order to develop such activity generator, a considerable amount of data was required. Five different channels were used to collect this data (Bellemans et al., 2010). First, an automated *GPS*[3]-enhanced data collection tool was used. Secondly, a survey was done. Thirdly, social network data was analyzed. Fourthly, a specific internet-based stated preference experiment was undertaken. Finally, a long-term panel survey has been carried out. Collected data was used to create a synthetic population, which comprises more than six million agents. This synthetic population is used to create activity patterns in four consecutive phases.

In the first phase, a set of initial static schedules is generated. Decisions which are done in this phase are based on a number of attributes, e.g., the inhabitant's age or gender, vehicles per household, population density, or the number of shops close by. In the second phase, namely the semi-static activity-based modeling, the drivers' schedules are adapted to dynamics of the environment. Bellemans et al. (2010) argue that travel behavior is highly evolutionary and non-stationary, thus, the original schedules are adapted to several "non-stationary" conditions. These conditions include but are not limited to: the day of the week, holidays, or information about the weather. In the third phase, the dynamic activity-based model is generated. In doing so, the agents reschedule their previously defined activities, re-program their decisions and learn. Dynamical options, e.g., to change destinations or to use other means of transportation are considered as well. Finally, in the fourth phase, origin-destination matrices are derived from the previously generated activity-schedules. These origin-destination matrices are used to generate the traffic demand which is ultimately simulated on a highly precise representation of Flanders' traffic and transport system.

5.1.8 Discussion

The analysis showed that several frameworks account for human factors. Most factors that are represented are tactical, though, strategic level behavior is conceptualized as well.

[3]GPS is the abbreviation for *Global Positioning System*.

The MATSim framework comprehensively reflects the capability of human drivers to perform strategic level planning. Being one of the most sophisticated solutions for simulating strategic level driver behavior, I want to emphasize some aspects MATSim—especially in the light of the of the psychological description of human strategic level driver behavior.

To start with, following Conclusion 3.2, strategic level driver behavior is affected by the outcome of tactical level decisions. Furthermore, Conclusion 3.2 shows that is possible to neglect this factor of disturbance if one wants to focus on analyzing the effects of strategic level behavior in isolation. MATSim makes use of this option and refrains from integrating tactical level decisions into the strategic level decision-making process.

Secondly, following Conclusion 3.3, a driver's strategic level decisions are affected by two categories of external factors, namely alternative options and environmental factors. MATSim implements concepts for both categories of factors. In the case of alternative options, MATSim allows drivers to access the public transportation network. This representation fits purposes, though, I argue that MATSim restricts driver's awareness for alternative options to public transportation exclusively. Psychological works, on the other hand, have no such restriction but account for any other means of transportation as well. In the case of environmental factors, MATSim uses a similar restriction as the driver's awareness is restricted to the current traffic situation. Psychological works use a more generic approach to conceptualized environmental factors, such that their particular nature is not restricted. In other words, psychological works account for a more comprehensive spectrum of disturbances that evolve from the driver's environment and have the capability to affect their decisions.

Finally, MATSim is based on the assumption that drivers intend to optimize their strategies with respect to their preferences or their personality. Optimization is done in an iterative process. Following Conclusion 3.4, strategic level decisions can be affected by the driver's personality. MATSim comprehensively implements this source of distraction and uses a utility function, which is used by the drivers to assess the quality of the generated action plans. The strategy with the highest quality is selected for the next iteration, where the concept of mutation and recombination is used to increase the quality of the original strategy. In doing so, the drivers iteratively

gain experience about the effects of their decisions and ultimately strive towards an optimal action pattern.

This mechanism can be understood as a form of experience and knowledge and according Conclusion 3.5, experience and knowledge is a significant factor for the outcome of strategic level driver behavior. MATSim, however, interprets the concept of experience and knowledge a bit differently.

MATSim implements the user equilibrium, which means that simulated drivers consecutively optimize their actions until the quality of the selected strategy converges. In doing so, the drivers gain experience about the consequences of their action plans and finally select their strategies based on knowledge of future states. As an example consider the search for a parking lot. Drivers have no information about the parking situation in a target area before they actually arrive in the area. In other words, their knowledge is incomplete. Given a high utilization of the target area, there is a good chance that real drivers may search for a parking lot for several minutes. The situation may even cause drivers to change their strategies and combine the use of their vehicles with public transportation.

MATSim is not able to reflect this kind of behavior as simulated drivers always find an optimal solution. In MATSim, drivers iteratively gain experience about their actions and learn how to reach a target location most effectively. The iterative simulation process allows drivers to collect experience that real drivers do not possess, e.g., information about a journey before the journey is actually done. This mechanism is popular around traffic simulation frameworks and on the large scale, it provides reliable results. Yet, with an increasing focus on individuals, the metaphor of the "perfect driver" dissolves. This imperfection is mainly a consequence to limited knowledge, e.g., unavailable information about target areas.

The bottom-line is that MATSim implements a concept of experience and knowledge, though, interprets this mechanism differently—compared to the psychological concept. The main difference is that in MATSim, the knowledge of drivers iteratively increases. Psychological works account for learning procedures as well, though, knowledge can be limited—in other words, the knowledge of drivers can be incomplete. This limitation makes the psychological approach more accurate, more realistic. Especially smaller analysis, e.g., simulations of selected infrastructural facilities such as a park-

and-ride service, may profit from an implementation of the psychological concept, though, for large-scale evaluations, the user equilibrium is clearly the better choice.

The second framework that I presented in this analysis is SUMO. Like MATSim, SUMO accounts for human factors. SUMO directly reflects these factors in the computational models of the framework. Two processes were implemented, namely the way in which drivers determine their velocity and the way in which drivers determine whether the current lane is changed or not. Both maneuvers can be classified as tactical level behavior.

SUMO also accounts for elementary strategic level behavior. Simulated driver's constantly perceive the current flow rate of the surrounding traffic. In the case that the observed value drops below a given threshold, the current route is being rejected and re-calculated based on the current perception.

The mechanism accounts for drivers that change their strategy as a consequence to unexpected congestion and emphasizes that SUMO accounts for a connection between the driver's environment (environmental factors), their personality (the user-specific threshold) and their strategic level decisions. Like in MATSim, the driver's awareness for their environment is limited to the surrounding traffic situation. A more generic model for external factors is not provide.

The AVENUE framework works in a manner similar to SUMO. Most human factors that are supported can be classified as tactical level behavior (e.g., lane choice and distance behavior), though, strategic level factors, in the form of a route choice model, can be found as well. This model accounts for the driver's personality, such that travel time or route length are used to determine the individual quality of selected routes. Strategic level decisions are not subjected to external factors or experience and knowledge.

The focus of MITSIMLab is clearly on tactical level behavior, though, elements of strategic level behavior are included as well. The implemented route finding mechanism represents strategic level decision-making and accounts for individual personalities (in the form of individual utilities) and experiences. Like MATSim, the framework is based on the assumption that drivers aim to optimize their schedule, thus, the simulation results have to

be interpreted on a large scale—the focus on individual drivers is imprecisely. Furthermore, MITSIMLab uses no connection between the drivers strategic level decision-making process and their perception. Only the second travel behavior mode implements some form of perception, such that drivers respectively select the next link when they arrive at an intersection. A more comprehensive connection to the driver's environment is missing.

Similar mechanisms were implemented in DRACULA and DynaMIT. Both frameworks are activity-based and use the assumption that drivers aim to optimize their schedule. Optimization is done in an interactive process, such that routes and departure times are determined, simulated, assessed, and improved. Both frameworks allow drivers to access previous simulation results, thus, concepts of knowledge and experience are reflected in a way as it is done by MATSim. DynaMIT also accounts for individual preferences, e.g., preferred routes or preferred mode choices, thus, the driver's personality is reflected as well. Both frameworks allow drivers to evaluate the travel time that was required for a given choice of routes, thus, a connection between the strategic level route assessment and the driver's traffic environment is implicitly defined. Furthermore, drivers in DynaMIT are aware of alternative means of transport. This information is used for the route generation process, though, before the simulation is started. The feature mostly complies with the concept of alternative options, only that the mechanism is clearly implemented as "off-line" feature. Drivers are aware of the transport network before the simulation and can not change their strategy during the simulation, e.g., as a reaction to unexpected congestion. The mechanism complies with the framework's basic assumption, namely that drivers aim to optimize their routes, though, it is not possible to examine the effects of incomplete knowledge and sudden disturbances that occur "en route".

Finally, FEATHERS comprehensively accounts for strategic level planning capability. The framework produces activities which reflect several parameters. First, individual attributes, such as age or gender are used for the generation of the initial activity-schedule. Thus, there is an explicit connection between the drivers' strategic level decisions and the driver's personality or internal factors. Secondly, activities and journeys are adapted to a set of external factors, such as the day of the week, holidays or extreme weather. Thus, simulated drivers are also able to account for factors that

evolve from the environment, environmental factors. Thirdly, drivers are able to re-program and to reschedule their trips, including departure and arrival times, as well as their mode of transport. In order to do so, drivers access results from previous decision processes, thus, the concept of experience and knowledge represented in the strategic level decision-making. The implementation of this concept, however, is similar to MATSim, such that drivers learn about their actions and optimize those. A limitation and support for incomplete knowledge is not supported. In FEATHERS, drivers are assumed to act optimal. FEATHERS was developed under the objective to generate highly realistic activity patterns on a large scale (the entire region of Flanders). I already argued that the user equilibrium is suitable approach for large-scale analyses, tough, I also argued that the approach looses precision with an increasing level of detail. This also applies for MATSim, DRACULA, and DynaMIT, the other approaches that implement the user equilibrium.

While on the large scale, these frameworks provide high quality results, an improvement of the applied strategic level behavior model in terms of psychological findings may increase the quality of simulations in which selected spots or situations have to examined. Consider transfer hubs, car parks, park-and-ride services, car sharing stations, or charging stations for electric vehicles as facilities where an improved strategic level driver behavior behavior may contribute to the simulation results' quality.

Above, I presented the latest development from the academic world. I proceed by presenting commercial state-of-the-art solutions.

5.2 Commercial Approaches

The second category, which I present in this work, is the category of commercial approaches. I explicitly differentiate between academic and commercial frameworks as it is generally difficult to get information about implementation details of commercial approaches. Nevertheless, analyzing commercial frameworks provides an idea about what kind of features are required by professionals. The focus of my analysis is to identify to what extend strategic level driver behavior is represented and reproduced by commercial traffic simulation frameworks.

5.2.1 Verkehr In Städten – SImulationsModell

VISSIM, or *Verkehr In Städten – SImulationsModell* (Fellendorf and Vortisch, 2010), is a commercial simulation software for multi-modal traffic flow modeling. VISSIM was developed by *PTV Planung Transport Verkehr AG*. By the year 2010, more than 7.000 licenses were distributed (Fellendorf and Vortisch, 2010).

VISSIM is a microscopic and time-discrete traffic simulation Fellendorf and Vortisch (2010) and uses a traffic flow model which accounts for behavioral factors of drivers. In total, three behavioral elements are integrated. First, VISSIM provides a model for *anticipated driving at conflict areas*. In VISSIM, conflict areas are defined as areas in which at least two roads overlap. Drivers in VISSIM are able to determine plans to cross these conflict areas safely. In order to compute such plan, drivers observe approaching vehicles, anticipate their behavior, assess the situation behind the conflict area and consider characteristics of their own vehicle, e.g., acceleration or breaking distance. The result of this planning process is an acceleration profile for "the next seconds". This acceleration profile allows the driver to cross the conflict area. VISSIM uses a generalized from of the anticipated driving model, such that simulated drivers (not necessarily being located at an intersection) constantly compute an acceleration profile for the next seconds (Fellendorf and Vortisch, 2010).

The second complex behavior that is implemented in VISSIM is cooperative merging. Cooperative merging describes the capability of simulated drivers to perform lane change maneuvers which account for two factors. First, the situation on the target lane is assessed, secondly, the drivers on the target lane act cooperatively. Drivers that intend to change lanes observe gaps in the target lane. If there is no gap available, the velocity is adapted in order to find a gap. Drivers on the target lane recognize vehicles that attempt to change their lane and accelerate or decelerate in order to provide enough room for the changing vehicle.

Following Michon (1985) both features can be classified as tactical level behavior. Yet, elements of strategic level behavior can be found in the form of dynamic routing.

Dynamic routing in VISSIM accounts for the ability of simulated drivers to perceive and to anticipate traffic conditions and to adapt their routes to

this perception (Fellendorf and Vortisch, 2010). Simulated drivers use a set of preferred routes and respectively compare the efficiency of these routes to alternative ways. Whenever an alternative is superior to a preferred route, the driver rejects their current strategy and use the alternative one. VISSIM implements this mechanism by means of a rule-based approach (Fellendorf and Vortisch, 2010).

5.2.2 S-Paramics

S-Paramics, or simply *Paramics*, is a commercial traffic simulation framework, which was mainly developed by *SIAS*, a transport-planning consultancy based in Edinburgh, Scotland (Sykes, 2010). Paramics accounts for individual vehicle movements and facilitates the examination of small-scale effects of vehicle behavior.

Vehicle behavior is restricted to tactical level decisions and implemented in three steps (Sykes, 2010). First, simulated drivers observe their environment and assess their options (e.g., changing the distance to other vehicles, accelerate, decelerate, changing lanes). Secondly, the drivers select a target lane and an acceleration profile from the previously assessed options and update their location. Finally, statistics are generated for calibration or for comparison.

Paramics comprehensively implements a structured hierarchy of lane choice and lane change decisions (Sykes, 2010). The driver's decision is based on a range of available lanes that can be used to reach a target location. Paramics also accounts for special cases, such as bus lanes, lane restrictions, lane closures, road confluence, road diverge, and junctions. The selection is mainly determined by the situation on the lanes, this includes: congestion, lane drops, or the presence of extremely slow vehicles (e.g., busses or trucks).

Route calculations are not done by the drivers themselves but by a central instance (Sykes, 2010). This instance returns either highly accurate routes for targets that are in close distance, or a list of key points if the destination is further away. Route computation in Paramics also distinguishes between drivers, which are familiar with the road network and drivers that are not. This mechanism reflects the concept of experience and knowledge, though, other factors, e.g., the drivers' personality or external factors are

not represented. Dynamic re-routing during the simulation is not supported either.

5.2.3 Aimsun

The *Advanced interactive microscopic simulator for urban and non-urban networks*, or *Aimsun* (Casas et al., 2010) traffic simulation framework was initiated at the University of Catalonia and is currently in its sixth major commercial version.

The applied driver model comprehensively accounts for tactical level decision-making. The car-following model, for instance, is based on the work of Gipps (1981) and accounts for the driver's desire to reach a target velocity. Lane change behavior is implemented as well. The mechanism is designed as decision process, which accounts for the desirability or necessity of a lane change, the benefits of a lane change, and feasibility conditions (Casas et al., 2010).

Elements of strategic level decision-making can be found as well. Aimsun implements a sophisticated route choice mechanism, which is based on the concept of user equilibrium. Casas et al. (2010) argues that in Aimsun "vehicles try to minimize their individual travel times, that is, drivers choose the routes that they perceive as the shortest under the prevailing traffic conditions" (p. 192). Furthermore, drivers are allowed to dynamically reroute their strategies as a consequence to traffic incidents. This process is referred to as *Stochastic Route Choice* (Casas et al., 2010) and implemented by means of *discrete choice theory*. Incidents are limited to traffic conditions, such that there are no other external factors that are able to trigger rerouting. Both mechanisms use a utility function in order to determine the quality of selected routes.

5.2.4 Dynameq

Dynameq (Mahut and Florian, 2010) stands for *dynamic equilibrium* and is a dynamic traffic assignment model. The model comprises two components, namely an event discrete, microscopic traffic flow simulation model and a routing model. The latter model comprehensively integrates strategic level behavior.

Dynameq operates in an interactive process, such that routes are computed, simulated, adapted, and simulated, again. The objective is to maximize the utility of the drivers. This process is in compliance with the user equilibrium. Drivers respectively adapt their decisions to the results of previous iterations, thus, the concept of experience and knowledge is implemented in a way that is typical for approaches that are based on the user equilibrium. During the simulation, the drivers perceive the surrounding traffic condition inasmuch as travel times are observed. Other connections between the driver's decision-making process and the driver's environment are not mentioned.

5.2.5 TransModeler

TransModeler (Caliper Corporation, 2014) is a commercial traffic simulation package, which simulates traffic by means of microscopic and macroscopic models.

For the simulation, a time discrete approach is used. The approach is able to simulate the behavior of vehicles every one-tenth of a second. Behavioral elements are included, though, mostly limited to tactical level decision-making, such as car-following and lane changing. Both models account for the driver's personality, e.g., their aggressiveness.

Strategic level decision-making is represented in the form of dynamic route choice. Drivers are able to determine their routes autonomously. Route computation is done in compliance with the user equilibrium hypothesis. During the simulation, drivers are able to learn the efficiency of their routes and constantly perceive the surrounding traffic situation.

5.2.6 Strategic Transport Model

The *Strategic Transport Model*, or *STM* (TRL Software, 2014), is a strategic model, which can be used for regional transportation planning, structure plan development and other applications where there is a need for strategic level transport policy assessment.

The tool uses a macroscopic traffic flow model. Yet, despite the macroscopic representation, human strategic level behavior is reflected in the form of trip generation, trip distribution and mode choice.

Based on the results from the strategic level planning phase, the traffic flow is derived and simulated. The approach supports only offline planning, that is, planning before the simulation is started. Dynamic adaptations and re-routing processes are not supported.

5.2.7 EMME

The *EMME* framework (INRO, 2014) is a macroscopic travel demand modeling system for urban, regional and national transportation forecasting. EMME is currently in its fourth incarnation and includes a set of tools which can be used for the development and analysis of traffic simulation scenarios.

EMME includes a simple route finding model, which implements the user equilibrium, yet, it is possible to define custom choice models as well. Route choices account for the driver's personality, which is implemented as utility function. The impact of external factors is included as well, though, support for external factors in is restricted to the surrounding traffic situation and the public transportation network.

5.2.8 Discussion

The analysis showed that commercial providers have recognized the need to account for human factors in their traffic simulation models. Most factors, however, are limited to tactical level decisions. The only strategic level capability which is comprehensively covered is route finding. The applied implementations, however, do not account for all factors that psychologists identify as relevant for the outcome of this strategic level capability.

VISSIM, for instance comprehensively supports tactical level problem solving. This capability is directly implemented in the car following and lane change models of VISSIM. The framework accounts for anticipatory behavior of drivers that pass conflict areas and for cooperative merging. Strategic level behavior is integrated in the form of dynamic routing. Simulated drivers constantly perceive and anticipate the surrounding traffic situation and compare the efficiency of their currently pursued strategy to other alternatives. The drivers' decisions, are therefore connected to their environment. This environment, however, is limited to the surrounding traffic situation. When calculating alternative routes, drivers compare potential candidates to preferred choices. Individual preferences or the drivers'

personality is therefore represented by the capability to individually assess strategies. Experience and knowledge is reflected by a given set of preferred routes.

Paramics works in a manner similar to VISSIM. Tactical level decision-making is comprehensively covered. Strategic level behavior is reflected by a route choice mechanism, yet, route choice is not done by the drivers, but by a central instance. This instance has global knowledge and distinguishes between drivers that are familiar with the environment and drivers that are not. While the former category receives highly accurate routes, the routes for the latter category contain only a list of key destinations. The mechanism can be interpreted as an implementation of experience and knowledge.

The strategic level capabilities of Aimsun are also limited to route choice models. Aimsun implements a sophisticated route choice mechanism, which is based on the concept of user equilibrium. Drivers are also allowed to dynamically adapt their strategies to traffic condition, yet, adaptations always aim to maximize the driver's utility in an iterative process. Therefore, the framework fits purposes for analyzing traffic on a large scale. A focus on effects of sub-optimal decisions (as a consequence to incomplete knowledge) of individual drivers is not possible. Route selection is done by means of discrete choice theory. This approach works fine, though, it emphasizes that the strength of discrete choice theory is the computation of optimal solutions for offline problems. Sub-optimal decisions that result from incomplete knowledge or dynamic adaptations require a different mechanism.

A similar route finding mechanism was implemented in Dynameq. Routes are computed, simulated, adapted, and simulated, again. The objective is to maximize the utility for drivers. Drivers adapt their choices to previous simulations, thus, experience and knowledge is reflected. The driver's perception is limited to the surrounding traffic.

Strategic level capabilities in TransModeler are also restricted to dynamic route choice. For this purpose the user equilibrium hypothesis is used. The applied approach accounts for the driver's perception, though, like most other commercial approaches, the driver's perception is limited to the traffic situation. A more comprehensive approach which accounts for alternative options and environmental conditions is missing. Concepts of experience

and knowledge are reflected by the iterative optimization of routes and the ability of drivers to access the results of previous iterations.

The same applies for the Strategic Transport Model. Strategic level planning is limited to route choices. The approach accounts for offline planning, only. Dynamic reactions during the simulation are not conceptualized.

Finally, EMME implements a simple route finding model. The model complies with the user equilibrium hypothesis and accounts for experience and knowledge as well as the driver's personality, which is implemented by means of a utility function. Due to the application of the user equilibrium, sub-optimal decisions that evolve from incomplete knowledge, are not supported. Nevertheless, the model accounts for alternative options in the form of the public transportation network. The effects of environmental factors are not represented for strategic level decision-making, though, EMME allows customers to define their very own choice models.

5.3 Conclusion

The analysis of contemporary traffic simulation frameworks emphasized several facts.

To start with, it appears that need for human behavior in simulation models has been recognized. All analyzed frameworks account for human factors. The focus of most approaches, however, is on tactical level rather than on strategic level behavior. Human factors on tactical level are mostly integrated in the framework's computational models, namely the car-following and in the lane changing models.

Despite the focus on tactical level behavior, there are also representations of strategic level driver behavior. All analyzed frameworks account for strategic level behavior in the one or the other form, thus, the importance of this form of human behavior has clearly been recognized. Nevertheless, the way in which strategic level behavior is implemented, as well as the factors that are used to affect strategic level decision-making processes significantly differ.

Table 5.1 shows what kind of behavioral levels are supported by the analyzed frameworks. Furthermore, the table shows which frameworks account

Table 5.1: Capabilities of analyzed traffic simulation frameworks. The table shows supported behavior levels (x for explicit focus, o for implicit support) as well as factors that are used to determine the outcome of strategic level behavior and their particular realization (UE indicates that the mechanism is realized by means of the user equilibrium, M indicates that the mechanism is directly implemented in the microscopic traffic flow model).

	Behavior Level			Factors for Strategic Level Driver Behavior				
					External Factors			
	c	t	s	Other Levels	Alternative Options	Environmental Factors	Internal Factors	Experience
MATSim			x		public transport	traffic (UE)	utility	complete (UE)
SUMO		x	o	tactical		flow rate (M)	speed threshold	
AVENUE		x	o	tactical		traffic (UE)	utility	complete (UE)
MITSIMLab		x	o	tactical		traffic (UE)	utility	complete (UE)
DRACULA		x	o	tactical		traffic (UE)	utility	complete (UE)
DynaMIT		x	o	tactical	public transport	traffic (UE)	utility	complete (UE)
FEATHERS			x		public transport	traffic (UE), day, weather	utility	complete (UE)
VISSIM		x	o	tactical		flow rate (M)	expected arrival	routes
S-Paramics		x	o	tactical				traffic network
Aimsun		x	o	tactical		traffic (UE)	utility	complete (UE)
Dynameq		x	o	tactical		traffic (UE)	utility	complete (UE)
TransModeler		x	o			traffic (UE)	utility	complete (UE)
STM			x		public transport	traffic (UE)	utility	complete (UE)
EMME		x	o		public transport	traffic (UE)	utility	complete (UE)

for the factors that psychologists identify as relevant for the outcome of strategic level driver behavior.

There are three frameworks, namely MATSim, FEATHERS, and Strategic Transport Model, that put particular emphasis on reproducing strategic level driver behavior.

The Strategic Transport Model framework uses a macroscopic approach and neglects re-planning during the simulation, thus, there is no dynamic interaction between the simulated drivers and their environment. The driver's choices are done before the simulation and not adjusted to factors that occur spontaneously. Therefore, the implemented model does not fully comply with strategic level behavior as it is described by psychologists, e.g., drivers constantly perceive their environment and adapt their strategies to their perception, etc. The reason for this discrepancy is the objective of Strategic Transport Model. The framework was developed under the objective to facilitate analyses of the efficiency of traffic and transport systems on a large scale. Microscopic considerations may change the results for distinct locations, e.g., selected transfer hubs such as a metro station or a bus stops, though, on the large scale these situations are evened out and thus negligible.

MATSim and FEATHERS were implemented in a different way. Both frameworks are activity-based, use a microscopic approach, and conceptualize the simulated drivers as agents[4]. Models for strategic level driver behavior are deeply anchored in both frameworks, such that drivers are able to determine their routes, to shift or to re-order their activities, or to adapt their strategies to unforeseen events. In both frameworks, the drivers' strategic level decision-making process is directly connected to their environment. The models for the environment respectively accounts for one particular alternative option, namely public transportation and several environmental factors, e.g., the awareness for the current traffic density, the current day of the week, or the current weather condition.

Furthermore, both approaches provide models for a driver-specific personality. In both cases, this representation is done by means of a utility function. The representation of internal factors thus complies with psycho-

[4]A more comprehensive introduction into the multi-agent paradigm and multi-agent systems is provided in Section 7.1.

logical works (see Conclusion 3.4). Both approaches are highly sophisticated, state-of-the-art, and have been applied in a number of analyses, e.g., Hatzopoulou et al. (2011), Dons et al. (2014), and Lee et al. (2014).

Nevertheless, there are also discrepancies between simulation-based implementations and psychological works which have to be discussed.

To start with, MATSim and FEATHERS are based on the assumption that drivers aim to maximize their utility. This mechanism is commonly known as user equilibrium and is applied by most of the above-presented approaches (cf. AVENUE, MITSIMLab, DRACULA, DynaMIT, Aimsun, Dynameq, TransModeler, EMME). The user equilibrium is a condition where the actions of all drivers are optimal. This optimum is reached in an iterative process in which the driver's choices are simulated, assessed, improved, and simulated once more—until a steady state has been reached. The mechanism fits purposes on the large scale, though, does not account for sub-optimal decisions that result from incomplete knowledge about the traffic and transport system. As an example, consider a driver that—out of habit—uses a particular metro line without knowing that a bus line departs at the same metro station and arrives faster at the driver's target location. The user equilibrium does account for situations in which incomplete knowledge is a factor. Drivers iteratively increase their performance by learning the consequences of their actions. The user equilibrium makes it impossible to analyze the effects or the impact of sub-optimal behavior on the traffic situation.

It is important to mention that both, MATSim and FEATHERS are state-of-the-art solutions and highly accurate when it comes to large scale analyses where human strategic level driver behavior is a factor. Nevertheless, from a psychological point of view, both approaches lack precision if one wants to go in detail, e.g., if one wants to analyze the effects of incomplete knowledge on isolated spots, such as a selected bus stop or a particular metro line.

The second discrepancy between psychological works and those models that are used for the implementation of MATSim and FEATHERS is the representation of alternative options. Both works restrict this source of distraction to the awareness for public transportation. Depending on the application, this focus fits purposes, though, psychological works do not

restrict the nature of alternative options, but allow for any other mean of transportation as well.

Alternative options, as factor for strategic level decision-making, are not only supported by MATSim and FEATHERS, but also by DynaMIT, STM, and EMME. All approaches restrict their implementation to account for public transportation exclusively.

The third discrepancy between psychological works and the representation of human strategic level driver behavior in contemporary traffic simulation frameworks is the connection of the driver's decision-making process to environmental factors. Approaches that account for such connection are generally restricted to an awareness for the surrounding traffic situation. Two categories of approaches can be found. First, there are some approaches with a strong focus on tactical level behavior (cf. SUMO and VISSIM). These approaches define a connection between the driver's strategic level behavior and their current flow rate. Whenever the driver recognizes that the perceived flow rate drops below a threshold, the driver reacts and tries to find alternative routes.

The second mechanism uses an implicit connection between the drivers' strategic level behavior and their environment. This connection is substantiated by allowing drivers to access information about the duration of trips in iterative optimization procedures. Drivers use this information in order to assess their strategies in terms of utility. Frameworks that apply this mechanism (cf. MATSim, AVENUE, DRACULA, DynaMIT, FEATHERS, Aimsun, Dynameq, TransModeler) apply the user equilibrium. The only framework that uses a more comprehensive approach to represent environmental factors is FEATHERS. In addition to connecting the driver's strategic level decision-making to the traffic environment, FEATHERS also accounts for day-of-week effects and varying weather conditions. Despite the more comprehensive representation of environmental factors, there is still a discrepancy between FEATHERS and psychological models. In Section 3.4.2, I showed that psychological works describe environmental factors as a certain condition which resides at a certain location and affects the driver physically as well as psychologically. In FEATHERS, environmental factors affect drivers globally and not only at a certain location. For day-of-week effects, this mechanism may work, as it is in fact a global disturbance.

For weather conditions, however, the global approach may lack precision if one wants to analyze the effects of local conditions (e.g., scattered rain or snow) on the global transportation network. Moreover, FEATHERS indisputably determines the nature of environmental factors, psychological works define no such constraint and refer to this factor of irritation as "certain condition". In order to reflect this psychological concept adequately, a more generic approach is required—an approach, which also allows for a custom specification of environmental factors.

To wrap up, the analysis showed that the importance of strategic level decision-making has been recognized. All analyzed frameworks include this particular form of human decision-making to a greater or lesser extend. The level of detail in which strategic level behavior is included highly depends on the objective of the simulation software.

The most sophisticated models for human strategic level driver behavior are implemented by MATSim and FEATHERS. Despite the comprehensive representation, there are still discrepancies between the models that are used in the frameworks and psychological conceptualizations. These discrepancies can be classified into four categories. First, the appliance of the user equilibrium fits purposes on the large scale, but lacks precision if one wants to analyze selected situations. Secondly, psychological works do not restrict the nature of alternative options, while simulation based approaches generally restrict this factor of disturbance to public transportation. This limitation, however, makes it difficult to account for other means of travel, such as walking or using bicycles, or other forms of transportation, such as car and ride sharing. Thirdly, simulation based approaches restrict the nature of environmental factors. Most frameworks account for traffic conditions exclusively. Only FEATHERS extends this limitation and additionally accounts for day-of-week effects and weather conditions. These additional factors, however, affect drivers globally and do not allow for custom additions. A generic and location-specific representation in compliance with psychological works is generally missing.

Based on the analysis of contemporary simulation frameworks and the above-discussion, I can answer the questions that I presented at the beginning of this chapter. To start with: "Is human strategic level driver behavior a factor for the outcome of contemporary traffic simulations?"

Yes, it is indeed! From all analyzed frameworks, there is no implementation which does not account for strategic level traffic behavior. Concepts are not only provided by academic approaches, but also by commercial ones, which emphasizes that simulation models for strategic level behavior are not only an experimental game, but a significant factor for the outcome of contemporary traffic simulations.

Secondly: "What is an appropriate approach to simulate strategic level driver behavior?"

It depends! Analyzed approaches use different mechanisms to account for strategic level decision-making. The most common way to represent strategic level decisions is the user equilibrium, though, based on the analysis of psychological works I argue that this approach has drawbacks. A different approach, based on discrete choice theory, was implemented in Aimsun, yet, discrete choice theory is not able to account for the dynamics of human strategic level driver behavior, as it is pictured by psychological works. Nevertheless, despite the general heterogeneity, is striking that those approaches that put a particular focus on analyzing the effects of strategic level behavior, namely MATSim and FEATHERS, use very similar concepts to conceptualize the driver's behavior. To start with, both frameworks use an agent-based approach to conceptualize the drivers and their behavior. Furthermore, both approaches use a microscopic traffic model to represent traffic flows. Finally, both frameworks use a discrete event (or activity) time flow model. Given the popularity and the success of both frameworks, it appears that these three mechanisms are adequate concepts for representing human strategic level driver behavior. These findings substantiate Conclusion 4.1 and Conclusion 4.2.

Finally: "Where are the frontiers in simulating human strategic level driver behavior?"

Compared to psychological works, the frontiers are primarily in the limitations of external factors. Both categories of external factors, namely alternative options and environmental factors are represented, though, any form of representation is done in a predefined way. A more generic representation, as pictured by psychologists, is missing. In the case of alternative options, contemporary works restrict strategic level considerations to public transportation. Further concepts, e.g., other means of travel, such as walk-

ing or using bicycles, or other forms of transportation, such as car sharing or ride sharing or the use of taxis, are not reflected. The same applies for environmental factors. Despite the fact, that environmental factors are represented in contemporary framework, their nature is predefined. Furthermore, the implemented concepts occur globally, while psychological works explicitly account for factors that occur at selected locations. Finally, most approaches are focused on large-scale analyses and apply the user equilibrium for this purpose. On the large-scale, this approach provides reliable results, since human beings in traffic situations attempt to act "efficiently". Nevertheless, the user equilibrium looses precision with an increasing level of detail. Sub-optimal decisions, which result from incomplete knowledge, are currently not reflected.

Based on the analysis, we finally arrive at the problem statement, which I anticipated in Section 1.2 and which I repeat below.

5.3.1 Problem Statement

Despite the fact that strategic level driver behavior is reflected in contemporary traffic simulations, available approaches do not comply with requirements and connections that are defined by psychologists. Current works fall short in at least three aspects:

1. The assumption that drivers aim to optimize their efficiency applies to large-scale analysis but looses precision with increasing level of detail. Sub-optimal decisions, which result from incomplete knowledge, are currently not reflected.

2. Alternative options are limited to public transportation. A more generic concept, which accounts for other means of travel or other forms of transportation is missing.

3. Environmental factors are represented in a predefined fashion and occur globally. A generic representation, as described by psychological works, with distinct occurrences, is not possible.

In the following part, I present a model, which solves this problem.

Part IV

Engineering Behavior

The aim of this part is to present a simulation model that complies with psychological works and extends available approaches by a more generic representation of alternative options and environmental factors. In order to account for sub-optimal choices, the presented model is not based on the user equilibrium.

This part is based on the publications Lützenberger et al. (2011d), Lützenberger et al. (2011c), Lützenberger et al. (2011b), Lützenberger et al. (2011a), and Lützenberger et al. (2012a).

The conference paper Lützenberger et al. (2011d) was nominated for the best paper award at the 9th Industrial Simulation Conference.

The conference paper Lützenberger et al. (2011a) was nominated for the best applied paper award at the Winter Simulation Conference 2011.

6. Preliminary Work

Whenever something new is being developed, one is well advised to reuse existing approaches as much as possible.

I have already outlined the high level of sophistication of available traffic simulation solutions. There are many approaches available, including approaches with support for strategic level driver behavior. Nevertheless, I also emphasized that most of the presented approaches derivate from the picture that is painted by psychologists.

The fundamental assumption that drivers strive towards an optimal action plan (the mechanism is commonly known as user equilibrium), is somewhat in conflict with the "intuitive nature" of human beings and their willingness to make mistakes. Nevertheless, the user equilibrium is central to most traffic simulation frameworks with support for strategic level driver behavior, thus, it is difficult to use these frameworks as a foundation for this work.

Yet, there are also approaches available that were not intended to mimic strategic level driver behavior in the first place, though, provide the required prerequisites. The aim of this chapter is to present such an approach (Lützenberger et al., 2011d) in more detail. In fact, this very approach pointed out the necessity for a more comprehensive examination of strategic level driver behavior in the first place and ultimately triggered this work.

As mentioned above, the aim of this approach was not to reproduce strategic level driver behavior, but rather to provide a simulation-based evaluation platform for applications in the context of *electric mobility*, or *e-mobility*, which refers to any from of transportation that involves electric vehicles.

The particular problem of simulating electric vehicles is their significantly reduced range (compared to conventional vehicles). In order to avoid uncomfortable situations, drivers permanently have to ensure that the vehicle's battery provides enough energy for the intended trips. In doing so, vehicle usages have to be planned and charging processes have to be scheduled. Following Michon (1985), this form of behavior can be identified as strategic level driver behavior.

I already mentioned that it was never intended to use the framework as a platform for a comprehensive model of strategic level driver behavior, though, given the fact that particular facets of human strategic level behavior were already included, the framework fit purposes for this work.

The purpose of this chapter is to present the fundamental models of this simulation framework in detail and thus to answer the following question:

- Are there available implementations that can be used for the development of a simulation model for strategic level driver behavior?

In order to answer this question, I provide some background and motivate the need for a simulation model which explicitly accounts for the characteristics of electric vehicles in Section 6.1. Subsequently, in Section 6.2, I describe the applied models as well as the simulation routine in more particular. Finally, in Section 6.3, I discuss the presented simulation framework in the light of this work.

6.1 Background

The development of a simulation model for electric vehicles was driven by many factors, but mainly by the unavailability of practical information about the performance of electric vehicles.

When this simulation framework was developed, e-mobility was investigated only in prototypical pilot projects and both, industry and government

invested large amounts of money in research and development in order to accelerate a breakthrough of the electric powertrain. There were good reasons to support these efforts, though, a lot of problems had to be considered.

These problems can be explained with the differences in using conventional or electric vehicles. The most prominent difference is without a doubt the charging process. Depending on the model, fuel-driven vehicles provide ranges beyond 600 km. A fully developed fuel station network assures untroubled mobility, however, the electric vehicle case is a different one. The charging infrastructure of many major cities is patchy at best. In addition to that, the range of electric vehicles hardly exceeds the 200 km barrier, which aggravates the infrastructural deficiency, because charging will be required at least thrice as often as conventional refueling. Beyond that, considering the required time for a recharging process, the situation becomes even more difficult. Depending on the station and the battery's state of charge, charging can last up to several hours, which makes it necessary to schedule charging during the driver's daily routine. To sum up, the mentioned limitations force each electric vehicle use to devise plans regarding the scheduled rides, the overall range and the regional charging infrastructure.

The traffic simulation framework (Lützenberger et al., 2011d), which I present in this chapter, was developed under the objective to serve as a tool for the detection of problems that are related to e-mobility. The aim was to anticipate and to reproduce the usage of electric vehicles and to identify weaknesses of such form of mobility.

Consider the examination of charging infrastructures as a potential application for this framework. With a highly realistic model for the usage of electric vehicles, varying charging infrastructure configurations can be evaluated. As an example, it is possible to determine the maximum number of vehicles for which the given infrastructure will provide sufficient service. Combined with other mechanisms (e.g., an activity-based approach), it is possible to determine particular regions of deficiencies and to collect valuable information, e.g., for a determined and well-directed urban development of infrastructure for electric mobility.

Yet, given a flexible user or vehicle model, other examinations are possible as well. As an example, estimates on the practicability of particular vehicle models can be done as well. Depending on the given vehicle type's

attributes, it is possible to classify vehicle types as being suitable, adequate or unsuitable for a given user and usage profile. Furthermore, it will become possible to determine a fitting vehicle type to a given usage pattern.

In order to facilitate such analyses it was necessary to extend common traffic simulation concepts by three particular models. In the following, I present these models in more detail.

6.2 Concepts

As mentioned above, there are three aspects in which conventional simulation models have to be extended in order to account for electric mobility. These categories are: the vehicle characteristics, the charging infrastructure, and the user profile. The categories are explained in the following.

6.2.1 A Model for Electric Vehicles

Conventional vehicles provide ranges beyond 600 km, while a fully developed fuel station network assures mobility. Usually, it is not necessary to integrate range and consumption issues for traffic simulations[1], though, electric vehicles are limited by these factors, thus, in order to account for these limitations, I defined a domain model and described all limitations in a designated class type, namely `ElectricVehicle`.

Extending common vehicle attributes like dimensions, maximum speed or acceleration, the `ElectricVehicle` class additionally references a battery type (which is modeled by the `EV_Battery` class type) and a consumption table (modeled as a method). The modular assembly of class types allows for adaptations of charging and battery characteristics (e.g., to more detailed charging profiles or improved battery types). Furthermore, the battery itself, or the charging profile, can be used as simulation parameter and thus facilitates analyses that include fictitious performances or estimates on critical required capacities for given driving purposes. In addition to capacity characteristics, the battery model also supports current conduction values. The latter can be used to simulate charging and feeding processes in a lifelike fashion. The specific part of the model that shows the integration of the battery and the charging characteristics is illustrated in Figure 6.1.

[1] In fact, I was not able to find one traffic simulation framework that accounts for range and consumption issues (see also Chapter 5).

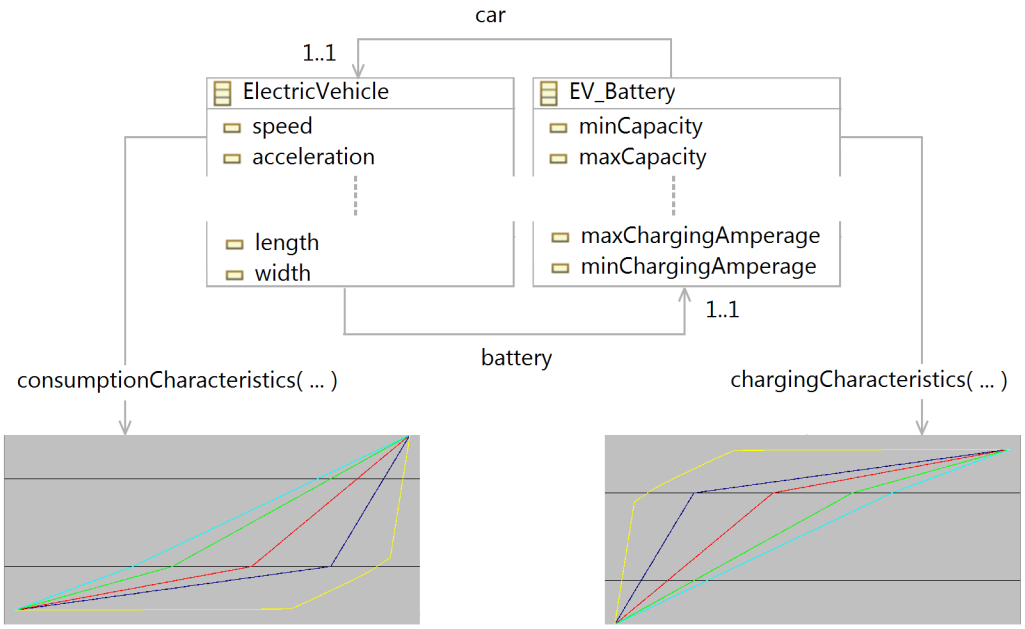

Figure 6.1: Specific part of the simulation's domain model with exemplary consumption and charging characteristics (after Lützenberger et al., 2011d, Figure 2, p. 172).

The above-presented vehicle model was applied in practical examinations, e.g., presented by Hoch et al. (2011), by Keiser et al. (2011), by Steuer et al. (2013), or by Vattenfall Europe Innovation GmbH et al. (2011), in order to represent particular characteristics of several vehicle types.[2]

6.2.2 A Charging Infrastructure Model

The second model that significantly differs from conventional simulation models, is the infrastructure model. Following the annual report of the *Nationale Plattform Elektromobilität* (Nationale Plattform Elektromobilität, 2011), the German government aims to deploy one million electric vehicles by the year 2020. To support this large number of electric vehicles, comprehensive charging infrastructure extensions are required. Any simulation model has to reflect the availability of charging stations as well as their locations and particular device-specific characteristics.

[2]Vehicle types that were conceptualized by means of the vehicle model include: *Aixam Mega Multitruck*, *Aixam Mega E-City*, *BMW Mini E*, *Compact Power Motors GK1*, *EcoCraft Automotive EcoCarrier*, *Fiat Karabag Micro-Vett 500*, *Fine Mobile Tyike Active*, *Fort Transit BEV*, *German E Cars Stromos*, *Goupil* Goupil G3*, *Mitsubishi i MiEV*, *Volkswagen E-Up*, *Reva Reva i*, *Smart Fortwo Electric Drive*, *Smiles CityEL*, *Tazzari Zero*, *Tesla Motors Tesla Roadster*, and *Think Global AS Think City*.

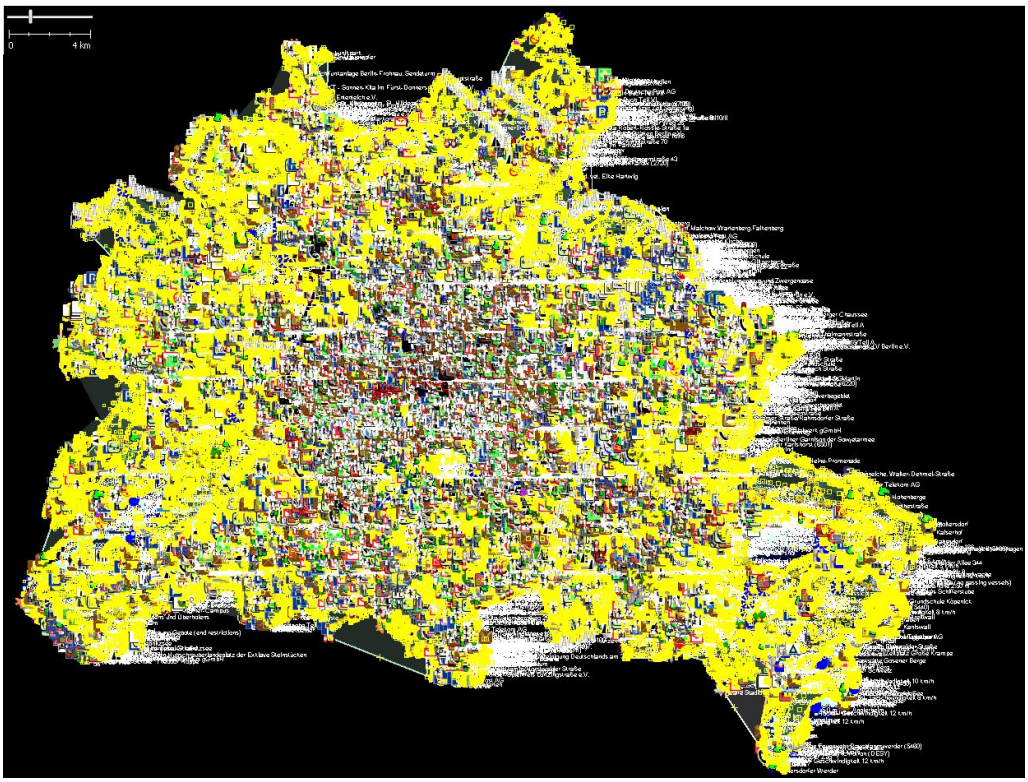

Figure 6.2: Visualized *OpenStreetMap* data, showing the city of Berlin (after Lützenberger et al., 2011d, Figure 3, p. 172).

To ensure flexible analyses, there must be an option to configure and adapt these characteristics. I included this information in the simulation topology and used the *OpenStreetMap*, or *OSM* framework (Ramm et al., 2010) for this purpose. OpenStreetMap is a collaborative project, which provides free, *GPS*[3]-precision road maps. In addition to geographic locations of road networks, OpenStreetMap provides a large amount of semantic information on speed limits, the amount of lanes, traffic lights, traffic signs, car parks and even comprises information on present charging stations. OpenStreetMap data is represented by means of *XML*[4], thus, it is easy to extend the data for custom purposes. An exemplary OpenStreetMap map, with the entire set of additional information showing is illustrated in Figure 6.2.

In order to use OpenStreetMap as a simulation topology, I developed a special editing tool, which is able to process the semantic information of the applied maps, illustrate them in a visual manner and supports custom

[3]GPS is the abbreviation for *Global Positioning System*.
[4]XML is the abbreviation for *Extensible Markup Language*.

adaptations as well. This mechanism ensures the use of up-to-date map material and allows for custom extensions of the charging infrastructure for fictitious scenarios.

The editor for itself is a tool, a byproduct, rather than a part of the simulation model that I present in this work. As it was developed and frequently used within the course of this work, I decided to include a brief description of the editor. This description can be found in Appendix D.

6.2.3 A Driver Model

The third model that significantly differs from conventional simulation models, is the driver model. As mentioned in the introduction of this chapter, the use of an electric vehicle requires some form of high-level consideration, e.g., to schedule charging processes or vehicle usages within the driver's daily routine. In order to predict in how far the limitations of electric mobility affect a user in their daily schedule, the driver's schedule had to become a simulation parameter.

I decided to use an activity-based approach in which each vehicle (or the driver of the vehicle) is assigned to a home position. The day schedule is assembled by randomly generating a set of appointments for the user. To account for the home positions, the underlying simulation topology was extended by census data. Target locations were generated by the same mechanism, though, it is possible to explicitly specify home and target areas as well. The capability to custom define home and target locations is also provided by the above-mentioned editing tool, which allows for the specification of "clusters", from which home or target locations are (randomly) selected. Figure 6.3 illustrates an exemplary target specification with three clusters and different radiuses. Simulated vehicles are assigned to a home location and a set of activities—each one assigned to a target location. The resulting activity pattern is then assigned to the vehicle and used for the simulation.

For the implementation, the domain model was extended by a `User` class type, representing the driver, and a `Calendar` class type, representing the driver's activities. Both class types were connected in order to express the relation between the driver and their calendar. Furthermore, I defined a reference between the `Calendar` and the `ElectricVehicle` class type. The

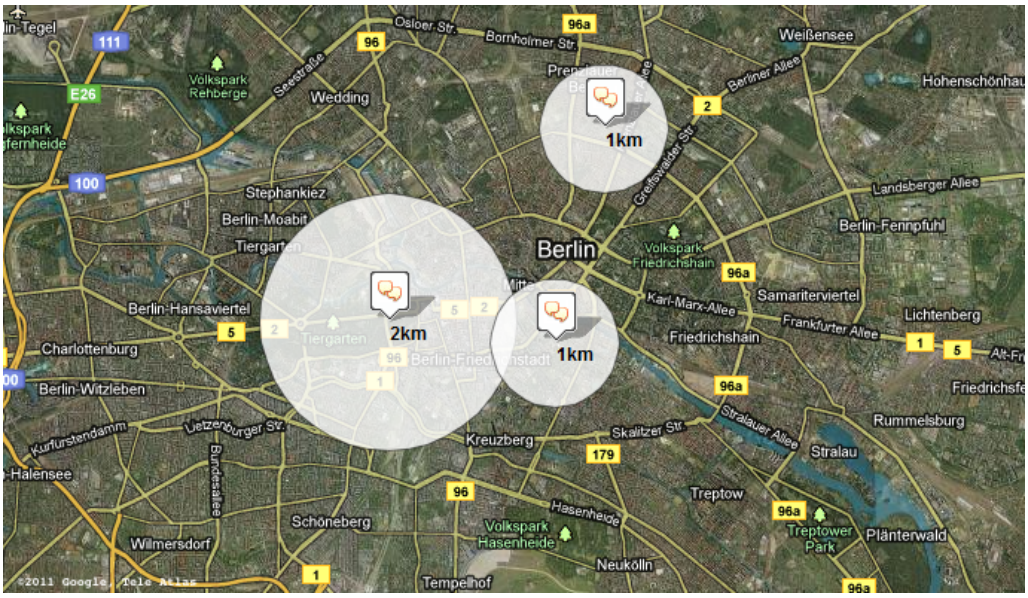

Figure 6.3: Target specification with three different target clusters for the capitol region Berlin (after Lützenberger et al., 2011d, Figure 4, p. 173).

vehicle's activity pattern is stored in this this calendar in the form of `Event` class types. `Event` class types are either `MoveOffEvent`, `AppointmentEvent`, `ParkingEvent`, or `ChargingEvent` class types—each type featuring a starting time. `MoveOffEvent` class types additionally feature a target location. While parking and charging events occur during a running simulation exclusively, only the `MoveOffEvent` types are required for the user profile generation.

The appointment generation process was implemented under the objective to make the generated schedules feasible. Given an empty calendar, a starting time for a potential activity is randomly created. Three different distribution functions were implemented for this purpose (Gaussian distribution with one cluster around 12 p.m., Gaussian distribution with two clusters around 7 a.m. and 7 p.m., and uniform distribution). Subsequently, potential target locations are retrieved from the target position cluster and assigned to the activity. Finally, the activity's duration is generated. The simulation frameworks provides capability to limit the activities' duration by defining minimum and maximum values. Once the activity is generated, it is placed within the vehicle's `Calendar` instance.

At the beginning, this calendar is empty and the first generation succeeds. Additional activities, however, may conflict. In order to detect conflicts, routes and cruising times from potentially previous activities and to potential succeeding activities are calculated. To make this approach more flexible, the simulation framework allows to define a tolerance time, which is granted by the activity generation process. This tolerance reflects the time between the arrival of the car and the actual starting time of the appointment and helps to avoid problems that are caused by delays of the vehicle (e.g., caused by severe congestion). In case the appointment fits into the schedule, a `MoveOffEvent` object is instantiated and—together with the activity—added to the vehicle's `Calendar` instance. The simulation framework also allows to define the overall number of activities per day. The entire domain model, as it is used by the simulation framework, is illustrated in Figure 6.4.

The three above-presented concepts, namely the vehicle model, the infrastructure model, and the driver model, were implemented as a microscopic traffic simulation framework with a discrete time flow model. In the following, I present the operation principle of this traffic simulation framework. In doing so, I put particular emphasis on the simulation routine.

6.2.4 Implementation

The simulation starts with each vehicle at its distinguished home location. The starting of a vehicle is indicated by the first `MoveOffEvent` instance in the vehicle's `Calendar` instance. In compliance with the discrete time flow model (see also Section 4.1.2), the simulation routine processes the day in discrete intervals of one minute and respectively checks if a `MoveOffEvent` is scheduled for a vehicle at the current simulation time. Whenever such event is detected, the target location is retrieved from the corresponding `AppointmentEvent` instance and a route from the current location to this target is calculated and stored in the form of a `Route` instance. The simulation engine uses this route object to simulate the vehicle on the underlying simulation topology.

In order to determine the velocity of simulated vehicles, the simulation engine uses data from the simulation topology (e.g., speed limits or available lanes), the domain model (e.g., particular vehicle characteristics), a traffic light factor and the current road congestion. The vehicles are simulated in

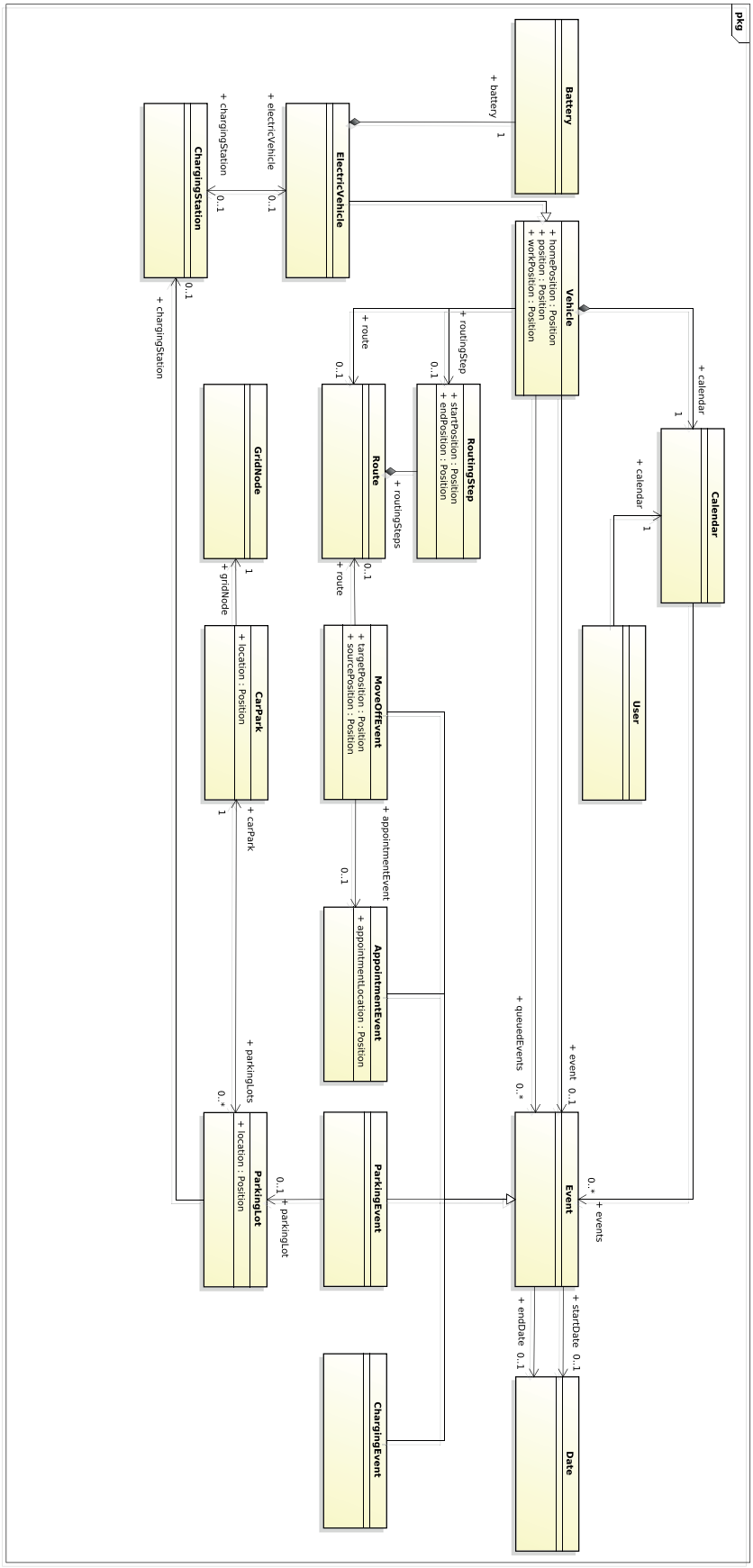

Figure 6.4: The entire domain model, showing all involved class types, including `ElectricVehicle`, `Battery`, `Calendar`, and `MoveOffEvent`, as well as their relation and multiplicities.

a discrete minute interval until the current route object is processed and the activity location has been reached.

Once the vehicle arrives, a parking lot is located (again, by using data that is stored in the underlying simulation topology). A route is calculated and used to navigate the vehicle to the next parking lot. This is done in the same manner as described above. Once the vehicle arrived at the parking lot, the simulation engine checks for available parking and either initiates the parking process (or charging respectively) or determines the next parking lot from the simulation topology. It is important to mention, that the time that is required to find a parking lot is not reflected by the activity generation process. The only parameter that reflects this time is the level of tolerance that can be defined as a simulation parameter. This mechanism allows vehicles to fall behind schedule. Whenever the simulation engine determines that a vehicle is delayed, the vehicle is either re-routed to its home location or forwarded to the next scheduled appointment. Once a vehicle arrived at parking lot, the vehicle's state of charge, that is, the energy level of the vehicle's battery, is evaluated and compared to a threshold value. Depending on the state of charge, either a `ChargingEvent` or a `ParkingEvent` is generated and added to the vehicle's calendar. In the next simulation cycle, the simulation uses this information to switch the vehicle to the according state, in which it remains until the next `MoveOffEvent` occurs. Figure 6.5 illustrates the simulation routine as a *BPMN*[5] process diagram.

6.3 Discussion

While the above-presented approach was never intended to reproduce strategic level decision-making, there are several aspects that reflect this particular form of human driver behavior. To start with, the activity generation was designed to make activities feasible. In order to ensure feasibility, routes between the activities are calculated and travel times are derived. These travel times are used to arrange the activities in the vehicle's schedule, clearly a planning process that complies with strategic level traffic behavior after Michon (1985).

[5]BPMN is the abbreviation for *Business Process Model and Notation*.

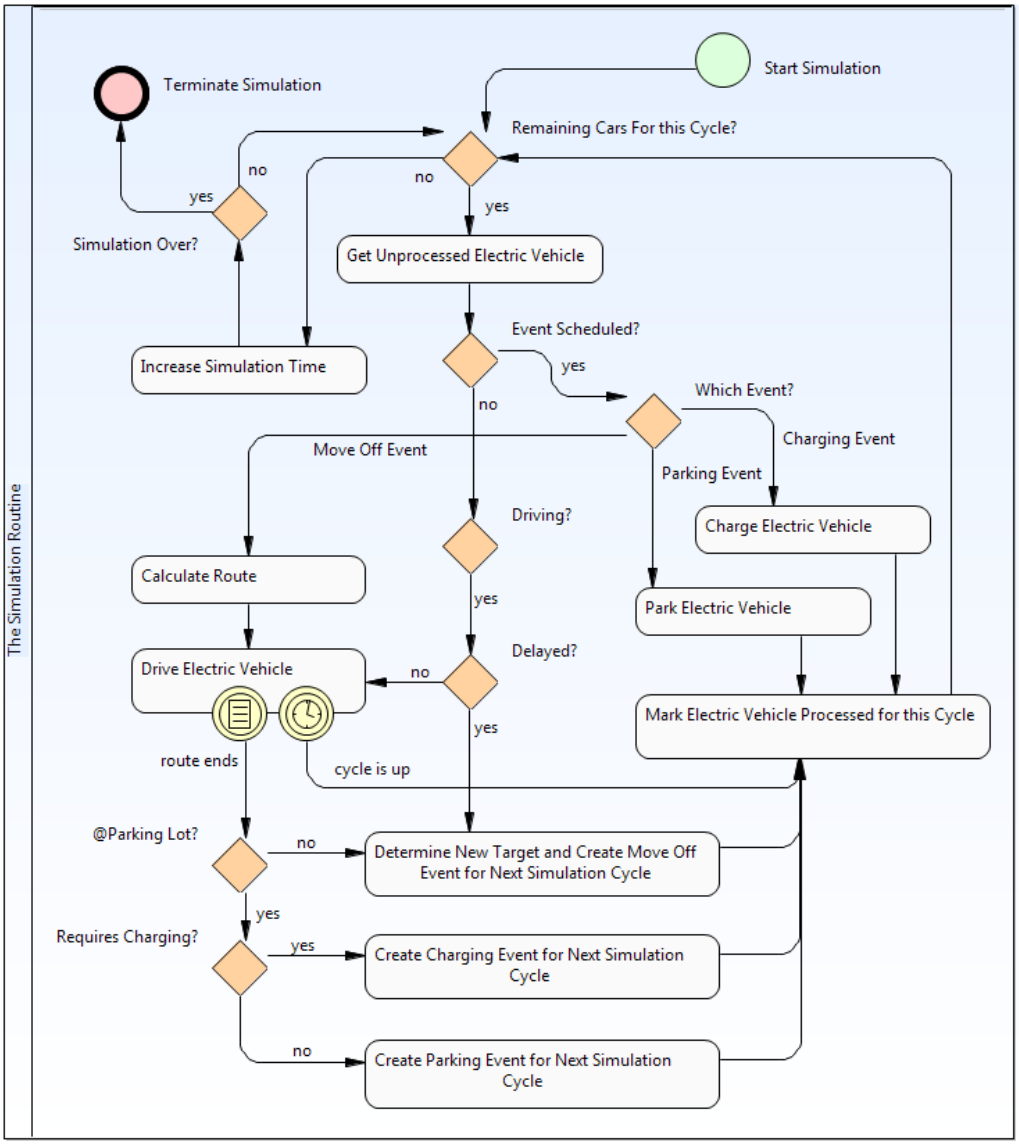

Figure 6.5: The original simulation principle, illustrated as BPMN Diagram (after Lützenberger et al., 2011d, p. 174).

While this form of planning is done before the simulation, there are also several situations in which strategic level behavior is applied dynamically, that is, during the simulation.

First, whenever a vehicle arrives at a designated target location, the closest parking lot is retrieved. This information is retrieved from the underlying topology and not from the driver's "knowledge", therefore the mechanism is not in compliance with human strategic level decision-making, which is

characterized by incomplete knowledge, though, the process for itself is the same, the only difference is the number of available options.

The second form of strategic level driver behavior, which is reflected by the simulation, is the mechanism which is used to deal with delayed vehicles. Delays may either result from congestion or from unavailable parking. Depending on the delay and depending on the location and the time of the next scheduled activity, vehicles either proceed to their home location or directly to the next activity. The decision-making is also affected by a custom factor that represents the vehicle's tolerance to arrive early at a location. This factor can be understood as a preference value. It substantiates a connection between the driver's strategic level decision-making and their personality.

Finally, it is decided whether vehicles are charged or simply parked. This decision is based on the driver's tolerance for low battery levels. Tolerance, however, can be considered as an internal factor. Strategic level decisions are therefore connected to a very specific form of the driver's personality.

To sum up, despite the fact the focus of the simulation was not on strategic level behavior, the implementation shows traces of this behavioral pattern. The conclusion is that the use of electric vehicles requires some form of strategic level problem solving.

Due to the innate support for strategic level driver behavior, the framework is also suitable as a foundation for a more comprehensive consideration.

Based on the above-presented discussion, I can provide an answer the question that I presented at the beginning of this chapter, namely: "Are there available implementations that can be used for the development of a simulation model for strategic level driver behavior?"

Yes, the simulation framework after Lützenberger et al. (2011d) is suitable as a foundation for a more comprehensive, simulation-based model for strategic level driver behavior. The calendar-based approach as well as the distinction between driver (represented by the `User` class) and vehicle (represented by the `Vehicle`) supports this thesis. The driver's goals (in the form of appointments at selected target locations) can be stored in a time-dependent fashion, which allows for re-arrangement. Furthermore, the reference between the driver and their vehicle is volatile, such that the

model-representation accounts for drivers that occur as pedestrians. The applied inheritance mechanism between the class type `Vehicle` and `ElectricVehicle` supports the definition of further means of transport without affecting the model as it is. Finally, the applied topology mechanism accounts for custom extensions (as it was done in the case of the charging infrastructure). Such mechanism can be useful when it comes to the representation of external factors.

Based on the above-presented discussion, I decided to use the simulation framework as foundation for this work. In the following chapter, I outline required extensions and present concepts that can be used to facilitate an effective implementation process in compliance with psychological findings.

7. Design Decisions

Having presented a foundation for the development in the previous chapter, the purpose of this chapter is to identify required extensions as well as concepts that can be used for the implementation of these extensions.

Following Section 3.4, strategic level decisions evolve from the driver themselves and are affected either by the driver's personality or by the driver's awareness for their environment. Thus, at least one model for each active part of the strategic level decision making-process, namely the driver and the driver's environment, is required. In this chapter, I discuss requirements for the development of both model categories. Furthermore I present concepts and mechanisms that can be used for an efficient implementation of human strategic level driver behavior. The purpose of this chapter is to answer the following question:

- Are there established concepts that can be used to facilitate the development of a simulation model for human strategic level driver behavior?

To provide some structure to this chapter, I present these concepts separately for both active parts of the strategic level decision-making process. In Section 7.1, I present concepts that can be applied for the implementation of a driver model and in Section 7.2, I present mechanisms that can be used to facilitate the development of the infrastructure model. Subsequently, in Section 7.3, I discuss the requirements that are necessary to integrate both

models and outline such integration. Finally, in Section 7.4, I discuss the steps that are required to implement the outlined approach.

7.1 Drivers and Agents

The first task that has to be solved is to find a model that can be used to represent the driver. This search becomes more simple if one focuses on the distinguishing attributes and characteristics of drivers. Following Conclusion 3.1, a driver's strategic level behavior can be considered as goal directed. Furthermore, in Section 3.4.2, I argued that a driver's strategic level decision-making is affected by factors that evolve from the driver themself, namely the driver's personality or internal factors, and their experience and knowledge. I also showed that strategic level decisions are not only affected by internal factors, but also by the driver's awareness for their environment.

When looking at the particular characteristics of drivers, it becomes clear that any computer-based representation of a driver is a *software agent*. Wooldridge and Jennings (1995) argue that it is difficult to define the term agent. Instead of providing a definition, Wooldridge and Jennings (1995) characterize software agents as program parts that enjoy one of the following properties: autonomy, social ability, reactivity, or pro-activeness. Wooldridge and Jennings (1995) describe these properties as follows:

autonomy refers to the ability of a software-based computer system to act without the intervention of a human being.

social ability refers to the ability of a software-based computer system to communicate either with other software-based computer systems (also other software agents) or human beings. The content of any form of communication is arbitrary, while for the conversation usually some kind of *agent communication language* is used.

reactivity refers to the ability of a software-based computer system to perceive its surrounding environment. This environment may comprise a physical world, a (human) user, a collection of other agents, the Internet, or all four factors in combination. Agents have to respond to changes that occur in their environment in a timely fashion.

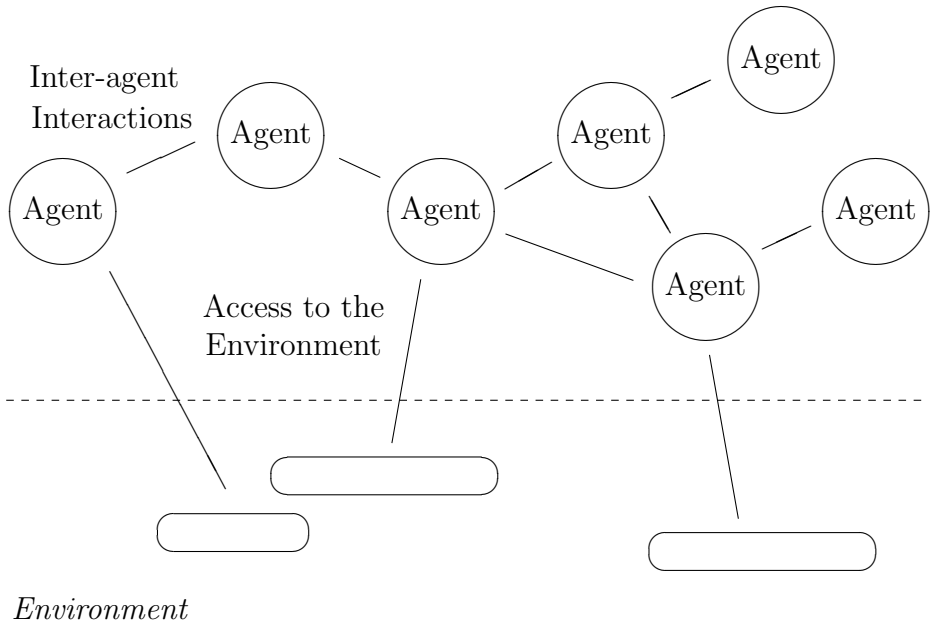

Figure 7.1: Typical structure of a multi-agent system. Agents are able to interact with each other and to perceive elements of their environment (adapted from Jennings, 2001, Figure 2, p. 37).

pro-activeness refines the reactivity attribute of software agents, such that agents do not only react on changes in their environment, but also feature some form of goal directed behavior and take the initiative.

The characteristics and principles of software agents lead to the immediate conclusion, that agents are most effective when interacting in some kind of agent network. Decentralization is innately implied within this network and thus individual agents are encouraged to satisfy their design objectives by acting as a team—although, opposing intentions are possible as well (Jennings, 2001). A network which provides communication as well as interaction of loosely coupled agents is called a *multi-agent system*.

7.1.1 Multi-Agent Systems

A multi-agent system collects a number of agents within some kind of surrounding environment (Sycara, 1998). The agents are able to interact with each other and thus realize problem solving in a distributed fashion. A typical multi-agent system architecture is illustrated in Figure 7.1.

For multi-agent systems, one or more of the following conditions applies (Sycara, 1998):

1. there is no agent that is able to solve the overall problem on its own,
2. there is no centralized entity which controls global process,
3. information is distributed across the entire system, and
4. computation is asynchronous.

If one uses the agent paradigm to represent drivers, the multi-agent system paradigm can be used to represent traffic systems—which comprise a large number of drivers. This analogy is not a novelty. In Section 5.3, I showed that several state-of-the-art solutions use the agent paradigm to conceptualize drivers and the multi-agent system paradigm to represent traffic and transport systems (cf. Illenberger et al., 2007; Bellemans et al., 2010. The advantage of using the agent paradigm for the development of software is of a practical nature.

Decades of research have enabled the *agent-oriented software engineering*, or *AOSE* Jennings and Wooldridge (2000) community to provide a whole set of tools, mechanisms and frameworks that make the development of agent-based software easier. Whenever system entities can be identified as agents, agent-oriented software engineering can be used for the development of the system. Most importantly for this work are models that can be used to conceptualize agent behavior—one of them is the belief-desire-intention programming model (Rao and Georgeff, 1995).

7.1.2 Belief-Desire-Intention

The belief-desire-intention, or BDI model (Rao and Georgeff, 1995) can be used to conceptualize autonomous systems, or agents. BDI regards agents as intentional systems, whose behavior is predictable in terms of attitudes like belief, desire and intention. This approach provides several advantages—not only in predicting and explaining an agent's behavior, but also in developing models that generate this behavior. Instead of writing code, it is possible to specify an agent's behavior by providing definitions for the agent's attitudes. The architecture of an agent, which is built by means

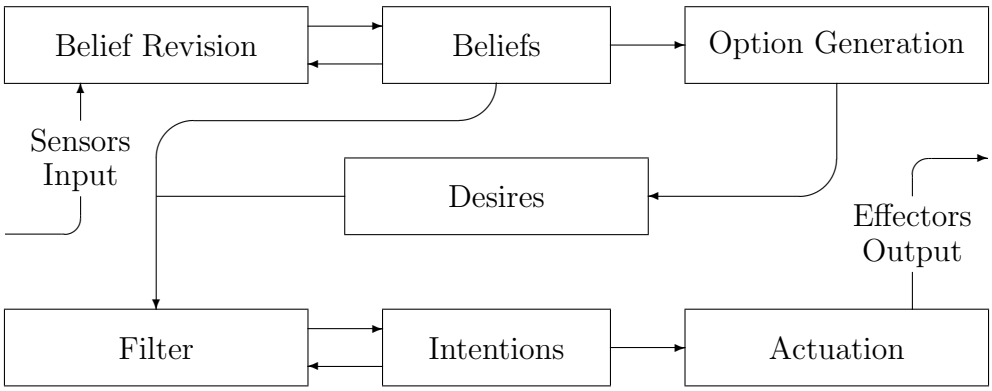

Figure 7.2: The process of practical reasoning in a BDI agent (adapted from Wooldridge, 2002, Figure 5, p. 31).

of the BDI model commonly consists of beliefs, desires, and intentions and is thus called *BDI-agent*.

BDI-agents are equipped with assumptions about their environment (beliefs), knowledge about their intended goals (desires) and plan-elements (intentions), which describe how to achieve these goals. In addition to belief, desires, and intentions, BDI-agents are equipped with a set of basic capabilities, namely *plans*. The practical reasoning process in a BDI agent comprises four phases, namely: *belief revision*, *option generation*, *filter*, and *actuation*. The practical BDI-reasoning process is illustrated in Figure 7.2.

Following Conclusion 3.1, drivers are intentional systems. Thus, BDI can be used to formally represent their behavior. The particular characteristic of drivers to follow a goal until it is reached, is supported by BDI as well. In BDI, this mechanism is represented by the single-minded principle (Cohen and Levesque, 1990).

In order to use BDI for the conceptualization of strategic level driver behavior, it is necessary to find beliefs, desires, and intentions in a driver's world. This mapping, however, almost comes from the definition itself. Beliefs, for instance, can be understood as everything the driver knows (or believes) about the traffic and transport system they are located in. Desires can be understood as their "motivation" or their "drive" to reach a certain target location. Finally, intentions are the driver's action plans, which comprise combinations of the driver's basic capabilities. Examples for basic capabilities are the ability to walk, to drive, or to use other means of transportation (e.g., bus, metro, bicycle, etc.).

Since BDI features the expressiveness to capture behavioral concepts that are required for strategic level driver behavior, I decided to use BDI as a foundation for the driver model that I present in this work.

Nevertheless, above I argued that a simulation model for strategic level driver comprises two models: one for the driver and one for the driver's environment. BDI does not explicitly account for this environment but only specifies how the agent's perception is processed. Thus, a second model is required. One suitable paradigm which is also frequently combined with the agent metaphor is the *service* paradigm.

7.2 Stimuli and Services

Following Conclusion 3.3 external factors are able to affect a driver's behavior. I distinguished between two categories of factors. First, there are alternative options. Factors from this category may cause drivers to reconsider their original strategy, e.g., to use a different route or to use another means of transportation. Secondly, there are factors that affect drivers psychologically and physically and—as a consequence to this disturbance—also cause deviations from the originally selected strategy. I referred to this second category of external factors as environmental factors.

In Section 5.3, I showed that simulation-based approaches account for external factors, though, significantly restrict their scope to concrete concepts, e.g., weather conditions or public transportation. In order to overcome this limitation, a generic model is required, preferably, a model that can be used to conceptualize both, alternative options and environmental factors. In order to develop a joint representation, it is necessary to find similarities between both categories.

The one thing that both categories do have in common is a state that occurs when the drivers respond to the awareness of an external factor. What makes the categories different is the freedom of drivers to decide whether or not they respond to such awareness. In the case of alternative options, drivers have the choice to make use of it or not, e.g., different means of transportation. In Section 3.4.2, I argued that each decision is usually accompanied by a check, which helps drivers to determine whether it is possible to make use of a newly perceived alternative option or not. The choice is also accompanied by a calculation, which determines the drivers' benefit

in using alternative option. In the case of the second category, the drivers have no option. The effects of environmental factors occur immediately, no matter if the drivers agree or not.

The concept of options that are selected on the basis of expected states, added values, and capabilities that are required to use these options is not a novelty in computer science. Here, these options are commonly know as *service*. MacKenzie et al. (2006) define a service as:

> "...a mechanism to enable access to one or more capabilities, where the access is provided using a prescribed interface and is exercised consistent with constraints and policies as specified by the service description." (MacKenzie et al., 2006, p. 12)

The invocation of a service causes to the realization of one or more real world effects. Following MacKenzie et al. (2006, p. 12), these effects are defined as follows:

1. information returned in response to a request for that information,
2. a change to the shared state of defined entities, or
3. some combination of (1) and (2).

To sum up, a service is able to change the state of defined entities. These changes are described in a so called: "service description". Access to a service is controlled by a prescribed interface. This interface defines the requirements that are necessary to use the service, or the preconditions of the service. Thus, in order to describe a service, two specifications are required, namely:

1. a specification of the service's effects and
2. a specification of the service's preconditions.

Below, I show how these concepts can be used to describe external factors in a traffic environment. Subsequently, I show how the service paradigm and the agent metaphor can be connected and what kind of additions are required to use these two mechanisms as a computer-processable model for strategic level traffic behavior.

7.3 The BDI Driver in a Service City

To make this approach work, two topics have to be addressed. First, a model which conceptualizes factors that evolve from the environment and affect a driver's strategic level decisions is required. Secondly, a behavioral model is required. The behavioral model has to comprehend disturbances that evolve from the driver's environment. Furthermore, the behavioral model has to generate the driver's action plans. I continue by outlining the first model—a model for external factors.

As mentioned above, there are two categories of factors that affect a driver's strategic level decisions. For a start, I only deal with factors that can be classified as alternative options.[1]

In Section 3.4.2, I argued that alternative options have the capability to support drivers to achieve their goals or influence their strategy in doing so. These options are a part of the infrastructure and drivers are able to perceive and to interact with them.

While I referred to the psychological concept of this source of distraction as "alternative options", I refer to the formal conceptualization of this concept as *infrastructural features*. I use the following definition:

Definition 7.1 *An Infrastructural Feature can be everything which is able to fulfil a desire (or parts of it) of a person at a certain location of an infrastructure (after Lützenberger et al., 2011c, p. 1257).*

According to this definition, public transport can be considered as infrastructural feature. Public transport provides a service at many places of an infrastructure and supports a person's desire to reach a certain location.

Yet, the concept is not limited to the representation of public transport. As an example for an infrastructural feature which is different from public transport, consider a car park. Located somewhere in a traffic and transport infrastructure, car parks provide service for drivers that want to park their vehicle. Moreover, according to Definition 7.1 infrastructural features are not necessarily related to traffic, but can also be interpreted as: shop,

[1] The development and integration of a model for environmental factors is comprehensively described in Chapter 9.

restaurant, takeaway, telephone booth and many more, or in other words, everything which is located in an urban infrastructure and which might help the drivers to achieve their goals.

The broad definition of infrastructural features emphasizes that it is nearly impossible to provide a complete model for any larger city. The problem statement of this thesis substantiates that this is not my intention.

Rather, it is my objective to provide a generic model that facilitates a uniform and generic specification of external factors. The advantage of such representation is the possibility to examine and to evaluate the mutual dependencies between concurrent factors, e.g., the impact of parking space on a nearby metro station.

As mentioned above, I decided to use the service metaphor for the development of a model for infrastructural features. Services are described by preconditions and effects. Both concepts are easily transferred to infrastructural features.

To start with, the access to infrastructural features is basically restricted. Consider a metro station as an example for an infrastructural feature with restricted access. Driving a vehicle makes it difficult to use this source of distraction. Contrary, a pedestrian may use metro service at any time. The conclusion is that a valid precondition for a metro service requires drivers to become pedestrians.

Secondly, services require an effect specification. Such concept applies for infrastructural features as well. Again, consider the metro service as an example. The use of a metro usually causes traffic participants to occur (after a certain time) at a different position. Services specify these effects in a so called service description. Thus, in order to use the service metaphor for infrastructural features, such description is also required. Later, I will show that simulated drivers can use this description for their cost-risk evaluation and to assess their expected benefit in adapting their strategy to make use of newly perceived infrastructural features. Finally, such description is also required by the simulation engine in order to implement the effects of an infrastructural feature whenever drivers decide to use it.

Having a specification for preconditions and effects, the description of a service is complete. Yet, exceeding the attributes of a regular service, infrastructural features require additional specifications. First, infrastructural

features reside "...at a certain location of an infrastructure" (Lützenberger et al., 2011c, p. 1257), thus, a location attribute is required. Later, I will show that this location can be used to include an infrastructural feature into a simulation topology. Secondly, drivers somehow have to perceive infrastructural features. To make drivers aware of infrastructural features, I use an additional attribute, namely a visual scope. This visual scope determines the visibility of infrastructural features, such that the simulation engine can use this scope in order to determine whether a driver perceives an infrastructural feature or not. Thirdly, following Lieberman and Rathi (2005), traffic simulation frameworks describe traffic systems as a dynamical system where "time is always the basic independent variable" (p. 10–5). Thus, some form of duration function is required in order to determine the time after which the effects of an infrastructural feature occur.

The above-presented mapping can be used to express infrastructural features by means of the service metaphor. Only minor extensions to the common attributes (preconditions and effects) of services are required, namely a location, a scope and a duration function.

The second model which is required is a behavior model for the drivers. Above, I argued that simulated drivers comply with the determining characteristics of software agents after Wooldridge and Jennings (1995). Due to this resemblance, agent-technology, tools, and concepts can be used for the development of agent-oriented models.

Following Conclusion 3.1, drivers are intentional systems, thus, it is possible to use belief-desire-intention paradigm (Rao and Georgeff, 1995), which provides a scheme for the formal conceptualization of intentional entities. The appliance of BDI provides a clear specification for the implementation and a validation for drivers' behavior. Critical processes can be implemented in terms of several distinct modules, each one realizing a particular phase of the driver agents' overall behavior.

In Section 7.1.2, I outlined a mapping from belief, desires and intentions to objects in a driver's world. Based on this mapping, beliefs can be understood as everything the driver knows (or believes) about the traffic and transport system, they are located in. Desires can be understood as a driver's motivation to reach a certain target location. Finally, intentions are the driver's capabilities, e.g., to walk, to drive, or to use other means

of transportation. A mapping that remains open is a specification of the behavior phases. In Section 7.1.2, I argued that practical reasoning in BDI comprises four phases. To make this approach work, these four phases have to be interpreted in the light of practical reasoning in traffic and transport environments.

Such interpretation, in the form of a simulation process which accounts for all four phases of the BDI reasoning, as well as for infrastructural features which are specified in compliance with the description that I presented above, may look as follows:

- The simulation engine uses the driver's current location as well as the location and the visual scope of all infrastructural features in order to determine whether infrastructural features are being perceived.
- In the case that the driver has entered the visual scope of an infrastructural feature, the agent starts with the belief revision phase, in which they extend the belief base by newly perceived infrastructural features and remove outdated beliefs which are no longer required.
- Using the updated belief base and current intentions, the agent proceeds with the generate options phase, in which the preconditions of all infrastructural features in the belief base are evaluated.
- In case of a positive evaluation of the precondition, the desire to make use of the infrastructural feature will be stored in the form of a goal within the goal base of the agent. Two different types of goals are required. First, a main goal expresses the agent's main objective (or motivation), to reach a certain location. Secondly, sub-goals emerge dynamically, indicating an agent's desire to make use of a perceived infrastructural feature.
- In combination with the agent's basic capabilities (walk and drive) and current intentions, the new set of goals constitutes the input for the filter phase.
- By accessing the effects of an infrastructural feature, the agent computes any possible permutation of option usages and measures which strategy is able to support them best in achieving the main goal.

- Finally, the favorite strategy is selected and inserted into the agent's intention repository, from which the actuation is derived in the actuation phase. Whenever a driver's strategy contains the use of an infrastructural feature, the simulation engine uses the duration function of such feature in order to determine the time after which the effects occur.

The above-presented steps show how infrastructural features can be integrated into the BDI reasoning process of drivers in a traffic environment. Distinguishing specifications of infrastructural features (preconditions, effects, location, scope, and duration function) are translated to BDI objects and used within the BDI reasoning process, which comprises the four stages, namely: belief revision, option generation, filter and actuation.

The above-presented model features all factors that are relevant for strategic level decision making in traffic environments, e.g., goal-oriented behavior, support for incomplete knowledge, perception, continuous reasoning, or personality, to name but a few. I decided to use this very concept as foundation for my simulation model.

In the following chapter, I describe a prototypical implementation of this concept. Before, I conclude this chapter and discuss the steps that are required for the implementation of this prototype.

7.4 Discussion

In this chapter, I identified concepts that can be used for the modeling and implementation of drivers with strategic level planning capabilities in traffic environments. I argued that simulated drivers have a strong resemblance to software agents. The analysis of contemporary traffic simulation simulation frameworks substantiated this consideration, as the agent paradigm was frequently used for the implementation—especially in frameworks with a particular focus on strategic level driver behavior (see also Section 5.3).

For the above-mentioned reasons, I selected the agent metaphor as a foundation for the development of my own driver model. I argued that the main benefit in using an agent-oriented view is the comprehensive set

of tools which can be used for the development. One of these tools being the belief-desire-intention programming model. BDI guides the formal conceptualization of intentional systems, thus, I decided to use BDI for the specification of the drivers' behavior. While BDI comprehensively supports the specification of agent behavior, it mostly neglects particulars of the agent's environment, thus, a second model was needed.

I compared the particular characteristics of external factors to the service concept and emphasized that services and external factors enjoy similar attributes. While services are determined by preconditions and effects, external factors feature the same characteristics. The original service description is easily extended by further simulation-specific attributes, e.g., a location, a scope, and a function that returns the duration of a service invocation—the bottom line is that the service metaphor perfectly fits as a foundation for the infrastructure model. Moreover, I argued that the service approach can be used to represent both categories of external factors, (alternative options and environmental factors), which are similar but feature differences as well. For the above-reasons, I decided to use the service metaphor for the development of the infrastructure model.

Once I determined promising mechanisms for the implementation, I introduced infrastructural features as the formal conceptualization of alternative options and presented an approach to integrate the BDI-based driver model and the service-based representation of alternative options.

Compared to available works, I consider the application of BDI as the most significant advancement. The BDI model accounts for all factors that are relevant for strategic level decision-making in traffic environments. To start with, BDI implies goal directed and intentional behavior. I already showed that the drivers enjoy these characteristics. Secondly, BDI accounts for the individual personality traits of drivers. In BDI, personality is implemented in the filter module, where agents select a strategy that best matches their personality. Such selection can be implemented by means of a utility function. Finally, and most importantly, BDI innately accounts for the representation of knowledge. BDI is commonly accepted to adequately transfer psychology into computer-processable models, thus, the way in which "knowledge" is implemented in BDI absolutely complies with psychological findings. In BDI, knowledge is realized by means of a belief

base in which agent can store and revise their belief base artifacts, namely beliefs. This belief base can be easily adjusted to feature different levels of knowledge. This can be done by simply adding or removing beliefs.

The BDI-based approach improves the representation of knowledge in a simulation environment compared to contemporary frameworks, which are based on the assumption that drivers have thorough knowledge and act in an optimal fashion. I already outlined an alternative option to conceptualize a driver's knowledge. The above-presented approach uses a visual distance and thus mimics some form of "exploratory behavior". Another option is to add beliefs to the driver's belief base before the simulation is started. This mechanism can be used to account for basic knowledge. Yet another option is to combine exploratory behavior and basic knowledge. Either way, the BDI driver model is highly flexible and provides many options that exceed the capabilities of contemporary works.

Finally, I demonstrated that the service-based infrastructure model and the BDI driver model can be integrated. This integration comprises mapping from service and BDI-specific terms to the traffic and transport environment. Furthermore, I sketched an approach to include the driver's changing awareness for infrastructural features in the BDI reasoning cycle.

To wrap up, the purpose of this chapter was to answer the question: "Are there established concepts that can be used to facilitate the development of a simulation model for human strategic level driver behavior?"

Yes, there are indeed! Due to the strong resemblance of simulated drivers and software agents, the agent metaphor can be used as a pattern for the development. The main benefit of using an agent-oriented view is the comprehensive set of tools which can be used for the development. Particularly interesting for this work is the BDI approach, which facilitates the behavior specification of intentional systems. The capabilities of BDI, however, are limited to the specification of behavior, thus, a second model is required to conceptualize the impact of external factors.

External factors enjoy similar properties as services, thus, a service-based approach may facilitate the implementation of external factors. A service is described by providing specifications for the service's preconditions and effects. Infrastructural features require additional attributes, such as a lo-

cation, a scope, and a duration, though, any common format to describe services is easily extended to account for these additional attributes as well.

The application of the service metaphor is extremely helpful, especially in the light of the agent-based driver model. Services and agents share many similarities and often occur together. An application of both concepts will significantly ease the implementation process.

While it was the purpose of this chapter to identify concepts that facilitate the development of a simulation model for strategic level driver behavior, the implementation of such model requires more detailed specifications. First, the entire service mechanism requires a more detailed description which explains how infrastructural features can be integrated into a simulation topology. Secondly, the particulars of the driver model have to be described. Specifications that are required are those of the drivers' goal mechanism and their basic capabilities. Furthermore, the entire belief revision phase (and the removal of outdated beliefs in particular) requires a more detailed specification.

In the following chapter, I provide these details and present a first functional prototype.

8. A Functional Prototype

In the previous chapter, I presented concepts that can be used for capturing human strategic level behavior in traffic environments. The aim of this chapter is to connect these concepts to form a first operational prototype.

In total, I presented three concepts, namely software agents, BDI and the service metaphor. The idea is to consider simulated drivers as software agents and to use the BDI approach to conceptualize their behavior. The service metaphor is used to capture the impact of disturbances that evolve from the driver's environment. In the previous chapter, I concluded that a working prototype requires a more detailed description of infrastructural features. Furthermore, the driver's goal mechanism, their belief revision, as well as their basic capabilities have to be refined.

While any comprehensive approach requires a consideration of alternative options and environmental factors, this chapter focuses on presenting a model for infrastructural features (the formal representation of alternative options), only. The purpose of this chapter is to demonstrate that it is feasible to combine a BDI-based conceptualization of human strategic level driver behavior and and service-based conceptualization of the driver's infrastructure. To this end, this chapter aims to answer the following question:

- Is it generally possible to produce human strategic level driver behavior by using a BDI-based driver behavior conceptualization and a service-based infrastructure representation?

In order to answer this question, I present the service-based infrastructure model in Section 8.1. Subsequently, in Section 8.2, I describe the behavioral model for the driver which comprehends distractions from the service-based environment and generates the driver's actions accordingly. Both models are integrated into an existing framework, thus, in Section 8.3, I elaborate on the extensions that were required to make the integration work. In Section 8.4, I provide an exemplarily model with different traits of acceptance towards a park-and-ride service combination and demonstrate the functionality of the approach by presenting the simulation results of this example. Finally, in Section 8.5, I discuss collected experiences and elaborate on required additions.

8.1 The Service City

A simulation model for strategic level driver behavior comprises at least to sub-models: a driver behavior conceptualization as well as a model for the infrastructure. The purpose of this section is to present a model for the latter category, namely a model for the infrastructure. It is important to mention, that, at this stage, the model comprises a prototype rather than a comprehensive approach. Missing aspects will be added throughout the remainder of this thesis.

Following Conclusion 3.3, external factors comprise alternative options as well as environmental factors. The purpose of this chapter is to present a functional prototype that can be used for further refinements.

For the matter of simplicity, I refrain from accounting for the latter source of distraction in this first prototype and focus on presenting a model for alternative options. Later in this work (see Chapter 3.4.2), I extend this implementation prototype to account for environmental factors as well.

In the previous chapter, I introduced the concept of infrastructural features as a formal conceptualization of alternative options. Using a definition for the "abstract concept" of alternative options will help to clarify the limits of the presented approach. Thus, following Definition 7.1, by infrastructural features, I understand:

> "...everything which is able to fulfil a desire ...of a person at a certain location of an infrastructure."

Admittedly, the broad definition makes it difficult to provide a complete description of reality—in fact, this was never intended. Rather, it was my objective to provide a generic model that facilitates a uniform specification of external factors.

I decided to use the service metaphor as foundation for the development of such model. The service metaphor already accounts for precondition and effects, two attributes which are also required for infrastructural features. Yet, infrastructural features require further specifications. Following Section 7.3, an infrastructural feature is given by providing specification for five attributes, namely:

1. preconditions,
2. effects,
3. a scope,
4. a location, and
5. a duration.

Below, I discuss these attributes in more detail and provide exemplary specifications in order to clarify the approach.

8.1.1 Preconditions

Preconditions determine whether a driver can use an infrastructural feature or not. Following Definition 7.1, a fuel station is an infrastructural feature, as it helps the driver to achieve their goal(s). In order to use a fuel station, the driver's vehicle has to run with a fuel type which is sold at the fuel station. In first-order logic, this condition may look as follows:

$$\exists\, type \in f.fuelTypes : d.vehicle.fuelType = type,$$

where d is a driver and f is a service representation of a fuel station.

Drivers have to decide for themselves whether an infrastructural feature can be used or not, thus, from an engineering perspective, it is most comfortable to design this evaluation as an instance method of the driver. This method must return true whenever the following condition is satisfied:

$$d.canUse(s) \rightarrow p = true \mid \forall p \in s.preconditions. \tag{8.1}$$

where `canUse(Service s)` is the instance method, s is the service representation of the infrastructural feature, and d is the driver that wants to determine whether s can be used or not.

8.1.2 Effects

Alongside the preconditions, the usage of each infrastructural feature serves a purpose—an effect. In the case of the exemplary fuel service, this effect can be defined as follows:

$$d'.vehicle.fuelLevel := d.vehicle.maxFuelLevel,$$

where d is the driver before the service was invoked and d' refers to the driver after the fuel service was used.

Effects are used for two purposes. First, the description of the effects can be used by the simulated drivers in order to assess the benefits of using an infrastructural feature. Secondly, effects are used by the simulation engine in order to apply effects on those drivers that decided to make use of an infrastructural feature. A method which applies the effects of an infrastructural feature must return true for the following condition:

$$s.execute(d) \rightarrow e \mid \forall e \in s.effects \cup d.effects, \tag{8.2}$$

where `execute(Driver d)` is the instance method of an infrastructural feature, which applies the effects on both, the driver and the feature itself. Equation 8.2 states that any successful execution of an infrastructural feature results in the validity of all effects.

8.1.3 Location & Scope

Beyond specifications that are required to describe a common service, infrastructural features require additional attributes. Following Definition 7.1, infrastructural features provide service "... at a certain location of an infrastructure...". Thus, in order to represent them in a traffic simulation, a location attribute is required. Furthermore, the infrastructural feature's scope

has to be defined. This scope will be used to determine whether a driver is able to perceive the service. In real life, this scope can be interpreted as the visual range of the particular source of distraction.

8.1.4 Duration

The last attribute, which is required to specify an infrastructural feature is a duration method. This method is required by the simulation engine in order to determine the time after which effects occur.

To sum up, an infrastructural feature can be specified by providing definitions for five distinguishing attributes, namely: preconditions, effects, location, scope, as well as information about the execution duration.

Below, I present a driver behavior model, which is able to comprehend information that evolves from the above-presented infrastructure model and which generates actions that reflect this information.

8.2 The BDI Driver

Following Conclusion 3.1, drivers are intentional systems, thus, their behavior can specified by means of BDI. In order to make this work, all four BDI phases (belief revision, option generation, filter, actuation) have to be integrated into practical reasoning within traffic environments. The operation principle and behavior phases of the driver agents are illustrated in Figure 8.1.

In more detail, the integration may look as follows: Triggered by their perception (1), the agent starts with the belief revision, in which they update (3) their belief base with their current perception (2a) and their so far beliefs (2b). With their updated new belief base (4a) and their current intentions (4b), the agent updates (5) their current set of goals in the generate options phase. In combination with the agent's plans and their current intentions, the new set of goals constitutes the input (6a, 6b, 6c) for the filter phase, which generates a new set of intentions (7). Finally, the new set of intentions is used (8) to determine the agent's actuation, by which they influence (9) their environment.

The mechanism includes all relevant BDI phases and integrates them with human practical reasoning in traffic environments. In the following, I

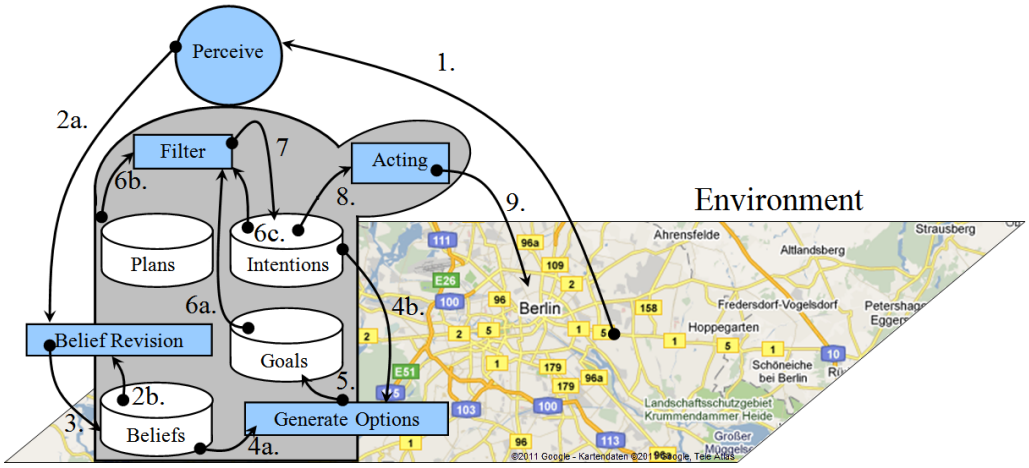

Figure 8.1: The architecture and actuation principle of the BDI driver agents (after Lützenberger et al., 2011c, Figure 1, p. 1258, adapted from Wooldridge, 2002).

present all phases in more detail. In doing so, I put particular emphasis on how infrastructural features are included. Furthermore, I demonstrate how the mechanism can be used within a traffic simulation.

8.2.1 Prerequisites

In Section 7.3, I argued that a functional prototype requires the specification of a driver's basic capabilities or basic plans[1].

Since both plans require a whole set of additional usage information, I defined an extra class type, namely the `PlanObject`, which I additionally furnished with information on the plan's preconditions, its effects and a function which returns the duration for an intended trip.

To avoid confusion, I renamed the `User` class type (see also Section 6.2.3, Figure 6.4) to the `Driver` class type and extended the type to provide a walk and a drive plan—both instances of the `PlanObject` class. Simulated drivers are able to access and to use these plans to either walk or drive from a location A to a location B.

Walk and drive plans are implemented straightforward, such that the *A-Star* algorithm (Russel and Norvig, 2003, pp. 97–101) is used for route-finding. In order to calculate the required duration, information from the

[1]BDI refers to basic capabilities as "plans".

underlying OpenStreetMap simulation topology can be accessed (see also Section 6.2.2). Preconditions of walk and drive plans are easily defined, such that an agent has to be in possession of a vehicle in order to have driving capability. In comparison, the walk capability requires the agent to be on foot. The effects of both plans are to move an agent from their current location to the desired target within the period of time which is returned by the duration function of the respective `PlanObject` instance. With one plan object for the walking capability and one plan object for the driving capability, the prerequisites for the BDI driver agents are given.

8.2.2 Perception and Belief Revision

In this phase, the agents perceive their environment. The simulation engine uses the location and the scope of the integrated infrastructural features to determine if drivers are within a feature's range or not and to produce the perception for the drivers accordingly. Whenever a driver senses an infrastructural feature, it is inserted into their belief base. Concurrently the belief revision process checks whether already stored services are still being perceived by the agent. If that is not the case the corresponding service is being removed from the belief base.

The above-presented belief mechanism directly addresses the requirement to account for the driver's knowledge in the strategic level decision making process. Following Conclusion 3.5, knowledge is a factor for the outcome of strategic level driver behavior. BDI innately provides such concept in the form of a belief base. During the simulation, this belief base is used to store new knowledge, e.g., the awareness for infrastructural features. Later in the reasoning process, this knowledge can be used for the computation of strategies. It is also possible to store knowledge before the simulation is started. This concept can be used to account for basic knowledge, while knowledge that results from the driver's perception can be considered as a learning process.

The BDI-based knowledge representation also tackles one of the problems that I have identified in contemporary traffic simulation frameworks, namely their lacking support for "incomplete knowledge". The BDI-based approach makes knowledge configurable, thus, it is by all means possible to equip drivers with complete knowledge, yet, it is also possible to configure varying levels of knowledge an to analyze the effects of this particular

source of distraction on the drivers' strategic level behavior. To sum up, BDI innately provides a highly flexible way to incorporate knowledge as a factor for strategic level driver behavior.

8.2.3 Option Generation

In this phase, the agents determine whether they are able to make use of any of the perceived infrastructural features, by evaluating the feature's preconditions.

A failed precondition check will not change the state of the agent, but in case of a successful evaluation, the desire to make use of the infrastructural feature will be stored in the form of a goal within the goal base of the agent. There are two different types of goals. First, a superior goal expresses an agent's main objective to reach a certain location. Secondly, (sub-)goals emerge dynamically and express the agent's desire to make use of an infrastructural feature. The agent is compelled to their superior goal, exclusively. Other goals can be considered as alternative options in reaching their ultimate target. Whether or not an alternative option is chosen is determined by the agent's personality—or internal factors. This decision is done within the subsequent phase, the filter phase.

8.2.4 Filter

In this phase, the agent retrieves their goals from the goal base and tries to find ways to achieve them. As mentioned above, there are two types of goals. One goal is superior to any other goals and expresses the agent's main objective to reach a certain location. This goal is placed within the goal base of any agent whenever they are starting their journey.

The implementation is based on the framework that I presented in Chapter 6, thus, drivers are equipped with a `Calendar` instance which collects appointments and/or selection of `Event` class instances. The calendar is used to store instructions to start a journey to a certain location and at a certain time. This information is stored in the form of a `MoveOffEvent` instance. During a simulation, the simulation engine scans the drivers' calendars and whenever an event for the current simulation time is detected, a goal is created and placed within the goal base of the driver. Following Conclusion 3.1, the behavior of drivers complies with the single-minded

principle (Cohen and Levesque, 1990), thus, the newly created goal will remain within the goal base of the agent until it has been achieved, or until it is no longer possible to reach the goal. Other goals can only be generated by perceiving infrastructural features from the topology and they simply express an agent's desire to make use of a perceived feature.

What happens just after a superior goal has been placed within an agent's goal-base is straightforward. By considering their plan object's, the agent determine if they either use their drive or walk capability. Since the first option requires less time for reaching the goal, an execution of the drive method is likely to be chosen.

When a second goal emerges "en route" (as a consequence to the awareness of an infrastructural feature), the original strategy gets competition. The filter function will now compute a strategy to make use of the feature. Usually, this strategy starts with a drive to the location of the infrastructural feature. Subsequently, the filter function assumes an execution of the feature and computes a strategy to achieve the superior goal (just as it did initially), based on the state which is defined by the features' effects.

Again, this is quite a simple case, since it is of course possible that an agent is located within the scope of more than one infrastructural feature. In case of more available features, each possible composition of features is evaluated and temporarily stored in combination with the measured quality. The quality is determined by means of a utility function, which—following Conclusion 3.4—is able to represent the driver's personality and to account for internal factors. The utility function maps strategies to a numeric value and thus represents the agent's personality, because here it is decided which criteria an agent selects from many proposed strategies.

The mechanism allows for a creative implementation of this process, since the programmer is able to access the duration methods of the services and plan objects involved in the strategy, and can therefore define a time-based selection, or custom acceptances for each strategy element.

Once each possible strategy has been computed, the filter phase will come to end and place the best strategy into the agent's intention repository.

8.2.5 Actuation

In this phase, the computed strategy is executed. A strategy can only comprise the method execution of a plan object, or the execution of infrastructural features. While I defined the implementation for the walk and drive methods earlier, I did not mention the implementation of a features' execution method so far. Next to preconditions, effects and a duration method, an infrastructural feature specification has to implement the actual execution method. Equation 8.2 determines that the result of this method is an adaptation of the internal values and parameters of the feature, the driver, and the environment. The simulation engine uses this method to apply the effects of a service usage to the simulated system. This appliance is done after the execution time of the feature has passed. Subsequently, the agent can start to perceive their environment, again.

I already mentioned that the above-presented approach was integrated into the simulation engine, which I presented in Chapter 6. Due to the implicit consideration of strategic level driver behavior, the framework provided several concepts that were required for the implementation of a more comprehensive approach. Thus, the framework provided a good foundation for this work. Nevertheless, several additions were required as well. I elaborate on these additions below.

8.3 Framework Additions

There were a couple of factors that determined my decision to integrate the above-presented model into the simulation framework that I have presented in Chapter 6. The framework already uses discrete time modeling as well as a microscopic perspective, two patterns which I identified to be necessary for the development of a simulation model for strategic level driver behavior (see Conclusion 4.1 and Conclusion 4.2). Furthermore, the framework uses events (or activities) to generate driving profiles. In Section 5.3, I showed that such approach is used by most frameworks with a focus on strategic level driver behavior. Nevertheless, there were also several additions required in order to make the integration work.

The first addition that was required was to disconnect the driver from their vehicle (the original framework considered both as one) in order to allow simulated drivers to use other means of transportation. To account

for this volatile connection, I extended the `Driver` class by a reference, which either points to an instance of the `Vehicle` class (in case the driver currently uses a vehicle) or to `null` in case the driver walks. Like in the original version, particular vehicle characteristics are stored within vehicle class. The `Driver` class was extended to provide particular attributes of walking drivers.

As mentioned in Section 8.2.1, the capabilities to walk and to drive were implemented as plan objects. For this purpose, I developed a `PlanObject` class with the capability to store information about the plan's preconditions, its effects and a function which returns the duration for an intended trip, and used two different instantiations of this class for the drive and walk capability.

Both plans were implemented straightforward, such that the *A-Star* algorithm (Russel and Norvig, 2003, pp. 97–101) was used for route-finding. The required duration was calculated on the basis of the underlying OpenStreetMap topology. To calculate the effective travel time for the driving capability, the `maxspeed` tags of all roads on the route were accessed. For the walking capability, a constant velocity of 4 km/h (or 2.49 m/h) was assumed. Preconditions of walk and drive plans were easily defined, such that a particular `Driver` instance has to define connection to a `Vehicle` instance in order to have driving capability. Contrary, the walk capability requires the `Driver` instance to have `null` as a value for the vehicle reference. I designed the effects to move the `Driver` instance from their current location to the desired target within the period of time which is returned by the duration function of the respective `PlanObject` instance.

In addition to changes to the driver mechanism, it was necessary to extend the simulation topology to account for infrastructural features. Most of this capability was already provided by OpenStreetMap, which allows to extend maps by additional `Node` elements and to annotate these nodes with key-value tags. I implemented the map-parser to analyze key-value tags of all available nodes and to identify those as infrastructural features that contain an annotation with a `iFeatureCategory` key. For the implementation prototype, I used the values to determine the category of the infrastructural feature and provided specifications in terms of preconditions and effects directly in the source code.

Finally, the simulation engine was adapted. At the beginning, drivers are located within their vehicle and wait for instances of `MoveOffEvent` types in their calendar.

Whenever a `MoveOffEvent` occurs, drivers become aware of their environment, meaning that the simulation engine determines infrastructural features that are currently perceived. The implementation was done on a visual basis, thus, the simulation engine uses the infrastructural features' locations and scopes, as well as the location of the currently focused driver and determines if the latter is currently aware of external factors. Following Section 8.2.2, this perception is stored within the belief base of the driver, which is a complex member of the `Driver` class.

In the case that infrastructural features are perceived, the driver starts with the belief revision phase in which they extend the belief base by newly perceived infrastructural features and remove outdated beliefs which are no longer required.

Using the updated belief base and current intentions, the driver agent proceeds with the generate options phase, in which the preconditions of each infrastructural feature in the belief base are evaluated. In case of a positive evaluation of the precondition, the desire to make use of the infrastructural feature will be stored in the form of a goal within the goal base of the driver—also a complex member of the `Driver` class. In combination with the driver's basic plans (walk and drive) and current intentions, the new set of goals constitutes the input for the filter phase. Following Section 8.2.3, two different types of goals are required. First, a `MainGoal` expresses the driver's main objective (or motivation), to reach a certain location. Secondly, `SubGoals` emerge dynamically, indicating an agent's desire to make use of a perceived infrastructural feature.

By accessing the effects of an infrastructural feature, the driver computes any possible permutation of option usages. Subsequently, the driver's utility function is used to determine which strategy is able to support them best in achieving the main goal. Finally, the favorite strategy is selected and inserted into the driver's intention repository, which is also implemented as a complex member of the `Driver` class.

The intention repository is used to store the currently pursued strategy, which is executed by the simulation engine until the current simulation

cycle (discrete time modeling) terminates. After that, the driver is marked as "processed" by the simulation engine. Drivers that are "en route", begin each simulation cycle with the same perception process as drivers that just received a `MoveOffEvent` instance. Moving drivers initiate the strategy (re-)computation in order to reflect their current perception. This mechanism complies with the requirement that human drivers continuously perceive their surrounding environment (see Conclusion 3.3).

The only difference between moving and waiting drivers is the currently pursued strategy, which is stored in the driver's intention repository. For waiting drivers, this strategy is empty. Moving drivers, on the other hand consider their currently pursued strategy as option and—depending on the implementation of the utility function—the quality of this strategy can be surpassed by other options. This mechanism allows for a dynamic implementation of the driver's flexibility—an individual personality trait. The adapted simulation principle, is illustrated in Figure 8.2.

In order to establish that the above-presented simulation principle works, the approach was evaluated in an exemplary simulation scenario. In the following, I present evaluation results as well as the particulars of this scenario.

8.4 Evaluation

The purpose of this evaluation was to show that the approach is applicable. In more detail, it was my intention to demonstrate that the connection between the decision-making model and the infrastructure model works. For this purpose, I selected a simple but expressive simulation scenario.

The simulation scenario comprised two categories of common infrastructural features, namely a car park category and a metro station category. Drivers were located at one end of a topology with target locations at the other end of the topology[2]. On their way, a set of infrastructural features were passed. In order to demonstrate the interplay between all relevant factors, several simulations with respectively different acceptances towards the use of infrastructural features were done and the effects observed. The aim was to show that different acceptances towards the infrastructural features—ergo different personalities—have different effects on the traffic system. In

[2]The capability to custom define home and target locations is provided by the original simulation framework (see also Section 6.2.3).

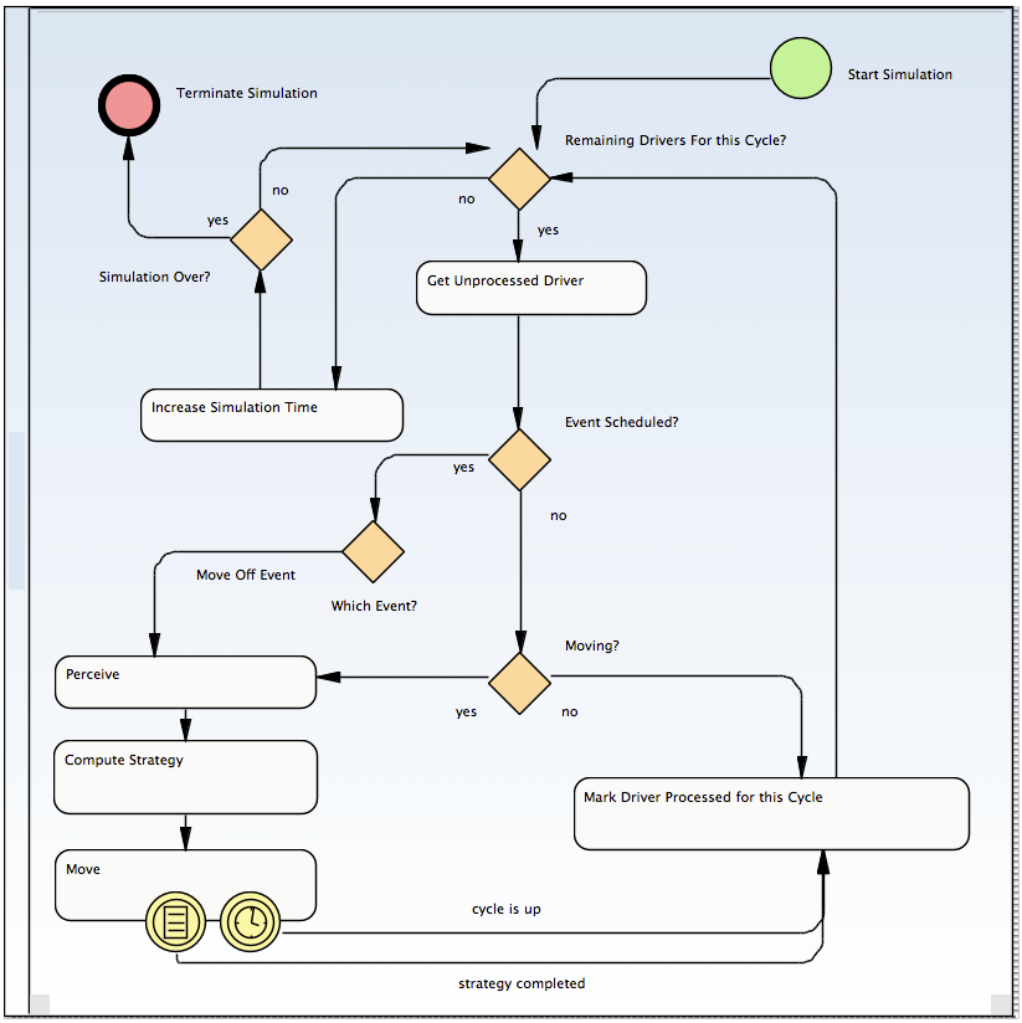

Figure 8.2: The adapted simulation principle, illustrated as BPMN Diagram.

Section 8.2.2, I argued that knowledge—as a factor—is already represented by the BDI-concept, thus, I will not explicitly mention this factor, but justify its representation with the application of BDI.

In the following, I present the evaluation scenario in more detail. First, I explain the instantiation of both infrastructural feature categories, namely the metro station and the car park. Subsequently, I explain how the personality of the drivers was configured. After this, I explain the simulation setup, which includes the start and target locations of the drivers and the arrangement of all infrastructural features. Finally, I present collected simulation results.

8.4.1 Metro Stations

In compliance with Section 8.1.1, the integration of infrastructural features was done by providing a specification for the feature's preconditions.

Using public transportation implies that no other means of transportation are used at the same time, thus, the following precondition makes sure that the driver d is currently not located in a vehicle:

$$d.getVehicle() = \emptyset. \tag{8.3}$$

Although a metro system is a complex and cross-linked service, a rather simple implementation for the infrastructural feature's effects was used. In this scenario, three instances of the metro station were placed into the simulation topology. While the different instances are located at different positions, each infrastructural feature moves the executing driver to the same target location. To this end, a metro network with three entrance points, but only one exit point was created. The only effect of the service is to move a driver to the target position p:

$$d'.position = p.$$

Due to the different access points of the metro service, the duration method was designed to return the duration from the respective instance of the infrastructural feature to the universal target location.

8.4.2 Car Parks

Like the metro station, car parks require a specification of preconditions. In this scenario, I assume that each driver who wants to make use of a car park is currently driving a vehicle. Furthermore, I assumed that the car park provides enough available capacity, which I initially set on 2.000 parking lots for each car park service instance. In first-order logic, these preconditions look as follows:

$$d.getVehicle() \neq \emptyset,$$

$$cP.currentCapacity > 0,$$

where d is a driver and cP is an instance of the infrastructural feature for the car park. Parking a vehicle causes the capacity of the car park to decrease. Furthermore, drivers that make use of a car park will no longer be in possession of their vehicle. These dependencies can be modeled as follows:

$$d'.getVehicle() = \emptyset,$$

$$cP'.currentCapacity = cP.currentCapacity - 1.$$

For the matter of simplicity, I decided to implement the duration method of the car park to constantly return one minute.

8.4.3 The Drivers

In order to demonstrate that different acceptances towards available infrastructural features cause different effects on the traffic infrastructure, the filter module of the drivers was adapted. In more detail, a configurable `acceptance` attribute was added to the module, representing the driver's acceptance towards the metro service. The utility function was designed to evaluate proposed strategies by accumulating the regular durations for any walk, drive and parking service usage and artificially lengthen the required time for the metro service inversely proportional to the driver's acceptance towards the service. The higher a driver's acceptance for the metro service, the lower the chance for artificially increased costs (for this part of the strategy) and the higher the probability for a service usage.

8.4.4 The Example

In order to set up a simulation scenario, it was necessary to integrate instances of the designed infrastructural features into a simulation topology. For each car park, I defined a total capacity of 2.000 parking lots. Furthermore, I integrated three metro services into the topology, each one at a different location but altogether with the same target. In total, I specified a total amount of 10.000 vehicles for each simulation run and defined an area of potential start locations and an area of potential target locations. The specification of start and target locations was done by means of the

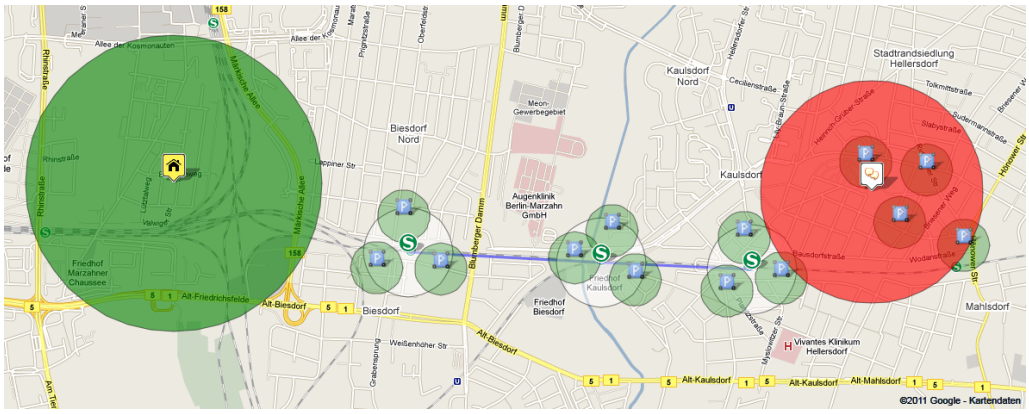

Figure 8.3: The simulation scenario, including three metro services (white), thirteen car parks (green), as well as markers for start and target areas (dark green and red) of the vehicles (after Lützenberger et al., 2011b, Figure 2, p. 152).

editor tool that was provided by the original framework. The arrangement of start and target locations was selected to make sure that simulated vehicles pass the influence of all instantiated infrastructural features. The entire simulation setup is illustrated in Figure 8.3.

In total, four scenarios were simulated—respectively one for a 20%, 40%, 60% and 80% acceptance towards a potential use of the metro service. Each scenario was simulated 1.000 times in order to avoid statistical outliers.

At the beginning of the simulation, the drivers are located at random places within the start area and in possession of a vehicle. Their calendar contains one `MoveOffEvent` with an instruction to proceed to a random location within the target area. Once the simulation engine detects a scheduled event, a `MainGoal` object is instantiated and placed within the goal base of the driver. The driver now starts their journey. Since no other option is available (no infrastructural feature is perceived and the walk capability requires the driver to be on foot), the driver computes and executes a strategy involving their drive capability. Once a driver enters the visibility scope of a service, further concurrent strategies are be proposed. In case of entering the scope of a car park, the driver computes a strategy to park their car and walk to the target location. Usually this option will fail because I used a strategy selection, which is based on the required time to the target location and walking strategies tend to be highly expensive. In case of entering the scope of a metro station, any evaluation on making use of the service will

fail as Equation 8.3 determines that the driver has to be on foot. Only when the simulated vehicle is within the scope of both infrastructural features at the same time, the filter module will be able to compute a valid strategy, involving a ride to the car park, its execution, a walk to the metro service, its execution and a walk to the target location. Depending on the driver's acceptance towards the metro service, this optional strategy either replaces the original one or is rejected. The results of all four simulation scenarios are illustrated in Figure 8.4. Presented numbers were averaged from all 1.000 simulations that were done for each scenario.

The acceptance for the metro service increases from the top to the bottom, such that the topmost illustration features an acceptance of 20% and the lowermost illustration features an acceptance of 80%. Each illustration shows the capacity utilization of respectively one parking service by means of colored circles. Red circles represent utilizations beyond 90%, yellow circles represent utilizations beyond 50% and green circles represent utilizations below 50%. One can clearly see that different user profiles tend to influence the overall traffic situation differently. Where a low metro service acceptance results in a high utilization of the car parks within the target area, an increasing acceptance causes a migration of the utilization peak, until—in case of an acceptance of 60% and more—it is not possible to make use of the first metro station, because its parking capabilities are exhausted. A more detailed illustration of all car park utilizations around the three metro stations is provided in Table 8.1.

Table 8.1: Collected simulation results. The table illustrates the utilization (in percent) of car parks around all three metro stations and the target area. Presented numbers were averaged from all 1.000 simulations that were done for each scenario. The standard deviation of the utilization variable (combined for all areas of a scenario) is presented as well.

Acceptance Rate	Station 1	Station 2	Station 3	Target	σ_{util}
20	33.3	26.6	21.3	85.0	1.48
40	66.3	40.0	24.0	36.0	.99
60	100.0	40.3	16.0	10.8	1.12
80	100.0	53.3	10.7	2.8	1.26

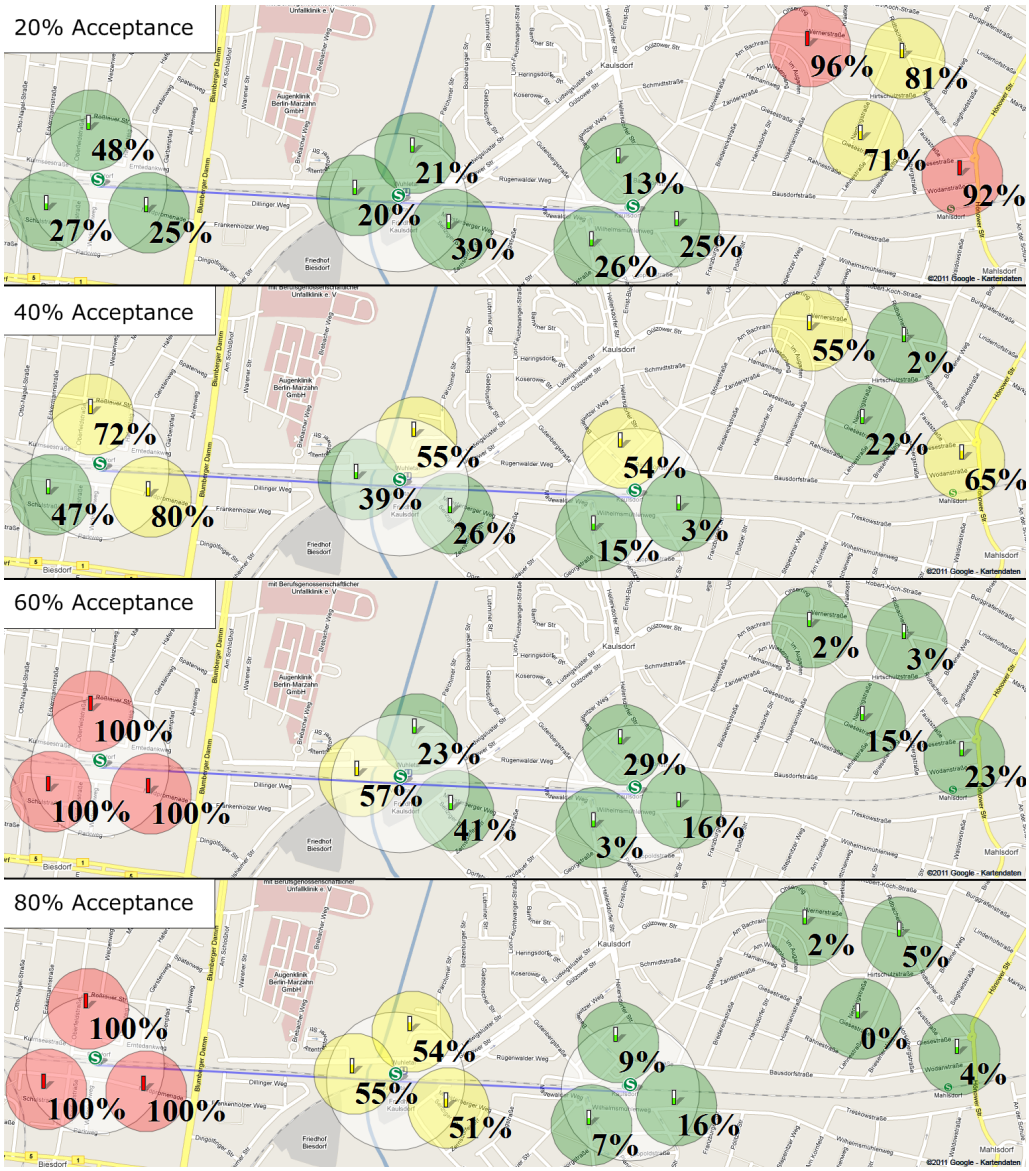

Figure 8.4: Results of the four simulations, showing the parking service's utilization in percentage values.

The simulation results substantiate two aspects. First, the relatively small standard deviation σ_{util} emphasizes that similar behavior profiles cause similar effects in the traffic infrastructure. This correlation substantiates that simulation results are reproducible. Secondly, changes in the behavior profiles have an impact on the infrastructure. This dependency is emphasized by the infrastructure utilization, which significantly varies between all four simulation scenarios. Based on these results, I argue that

the approach is applicable. Different user profiles affect traffic situations differently. □

8.5 Discussion

The purpose of this chapter was to demonstrate that it is generally possible to use the combination of BDI and services for the development of a simulation model for strategic level driver behavior. In order to do so, I presented implementation details for both, the service-based infrastructure model and the BDI-based driver behavior model, and explicitly emphasized how both models were connected.

I designed the infrastructure model to account for factors that evolve from the driver's environment. In more detail, I described a formalism to specify alternative options. I referred to this formalism as "infrastructural features". Subsequently, I presented the driver model in more detail and discussed prerequisites that were necessary to make the driver model functional. There was only one requirement, namely an implementation for the agents' basic capabilities or plans. I identified two different plans, namely to walk and to drive, and provided an implementation which mostly[3] complies with the specification of an infrastructural feature. The advantage of this approach is the fact that the simulation engine can treat plans and infrastructural features in the exact same way. The joint design significantly simplified the implementation of the simulation engine. After presenting the prerequisites, I described how the drivers' BDI reasoning cycle had to be designed in order to account for distractions that evolve from the previously presented service-based infrastructure. In doing so I presented the drivers' belief mechanism and argued that BDI innately accounts for the concept of knowledge—following Conclusion 3.5, a significant factor for the outcome of strategic level driver behavior. Furthermore, I showed that the flexible representation of knowledge in BDI tackles the problem of most contemporary traffic simulation framework, namely to support the concept of "incomplete knowledge". The BDI-based approach makes knowledge configurable, thus, it is by all means possible to equip drivers with complete knowledge, yet, it is also possible to configure varying levels of knowledge and to analyze the effects of this particular source of distraction on the drivers' strategic

[3]The only difference between infrastructural features and plan objects is the location attribute, which is only provided by infrastructural features.

level behavior. To sum up, BDI innately provides a highly flexible way to incorporate knowledge as a factor for strategic level driver behavior.

The prototype was evaluated by using an exemplary simulation setup. I continued by presenting the setup. This setup involved different instances of a parking and a metro service. The purpose of this evaluation was to show that the approach is generally applicable. In more detail, it was my intention to demonstrate that the model is able to account for the fact that different driver personalities have different effects on a fixed traffic and transport infrastructure. In order to do so, I selected a simple but expressive simulation scenario in which drivers pass the influence of several infrastructural features. In total, four simulation scenarios were simulated, each one with a different acceptance towards public transportation. The simulation results established that different driver personalities indeed have a different effect on the underlying infrastructure. While lower acceptances for public transportation usually resulted in highly utilized target regions, higher acceptances caused congested parking infrastructures close to the source region.

The bottom-line is that the presented prototype is able to account for varying driver personalities and to express the impact of these personalities on the traffic and transport system. Based on this finding, it is now possible to answer the question which I presented at the beginning of this chapter, namely: "Is it generally possible to produce human strategic level driver behavior by using a BDI-based driver behavior conceptualization and a service-based infrastructure representation?"

Yes, it is indeed possible to extend a common simulation topology by service-based representations of alternative options and to use the BDI paradigm to conceptualize a strategic level driver behavior model which accounts for these sources of distraction. The connection between both paradigms is mainly done in the driver's perception phase, where the calculated awareness for infrastructural features is translated into objects that are BDI-processable, in this case: sub-goals. It is also necessary to equip the driver with some form of basic capability, namely elementary actions.

To wrap up, the combination of BDI and services generally fit its purpose for the development of a simulation model for strategic level driver behavior. Yet, there are also some deficiencies that should be mentioned. First, the

way in which the simulation engine determines whether drivers are aware of infrastructural features is incorrect and was chosen for the matter of simplicity. Infrastructural features might have an area of influence, though, the capability to perceive an infrastructural feature is ultimately determined by the driver's skills. I correct this simplified design in the following chapter.

Secondly, the current approach is not able to account for interconnected infrastructural features. Alternative options are generally interconnected. As an example, consider a metro network, which can be entered and exited at any station. In the above-presented example, I used a simplified approach to include a metro service. Although there were several occurrences of metro stations, all instances provided service only to one target metro station. This setup does not account for the ability of traffic participants to exit the metro at an intermediate stop and to use yet another transport option (e.g., public bus) from this intermediate location to the ultimate target location. To this effect, the so far model has to be extended to account for interconnected infrastructural features. This extension is also described in the following chapter.

Finally, the above-presented infrastructure model is limited to one particular external factor only, namely alternative options. Yet, in Section 3.4.2, I argued that distractions may originate from a second source, namely: environmental factors. Thus, any simulation model that aims to cope with psychological findings requires a concept for this second category of external factors as well.

In the following chapter I show how the so far prototype can be extended with the above-mentioned requirements.

9. The Living Environment

The aim of the previous chapter was to show that the service metaphor and a BDI-based behavior conceptualization can be used as foundation for the development of a simulation model for strategic level driver behavior. I established that the concepts are connectable and that the approach generally works, though, I also argued that the model is not complete. To start with, I used a simplified infrastructure representation and neglected environmental factors as a source of distraction for strategic level decision-making of drivers. Secondly, I emphasized the necessity to connect occurrences of infrastructural features in order to account for more complex transportation networks. Finally, I argued that the awareness for infrastructural features is determined by the driver's skills rather than by the infrastructural feature.

The purpose of this chapter is to correct these issues and to refine the current simulation model. It is my intention to answer the following question:

- Is it possible to use the BDI-based approach and the service paradigm to implement a simulation model for strategic level driver behavior which accounts for the entire spectrum of external disturbances, namely environmental factors and alternative options?

In order to answer this question, I informally introduce characteristics of environmental factors and emphasize the resemblance between environmental factors and alternative options in Section 9.1. Subsequently, in Sec-

tion 9.2, I revise the current infrastructure model to account for both categories of external factors. In Section 9.3, I elaborate on additions that are required to make the driver model compatible with the revised infrastructure model. Again, I evaluated the refined models in an exemplary setup. In Section 9.4, I explain the particulars of this evaluation scenario and present collected simulation results. Finally, in Section 9.5, I wrap up with a conclusion.

9.1 Regional Conditions

In Section 3.4.2, I showed that psychologists distinguish between two categories of external factors that may affect the strategic level decision-making of drivers. In the previous chapter, I introduced infrastructural features as a formal conceptualization of factors that psychologists refer to as alternative options. In this section I present the complete infrastructure model, which accounts for alternative options and environmental factors. While I conceptualized alternative options as infrastructural features, I refer to the formal conceptualization of environmental factors as *regional conditions*. To clarify the limits of my approach, I provide a definition for the term:

Definition 9.1 *A Regional Condition can be everything which is able to affect or influence a person, its behavior, or its vehicle (physically) at a certain location of an infrastructure (after Lützenberger et al., 2011a, p. 247).*

In Section 7.3, I argued that a uniform specification of external factors facilitates the examination of mutual dependencies between concurrent factors. To this effect, it is necessary to express regional conditions with the same model that I have used for infrastructural features.

On first sight, both categories appear to be different in nature, though, on closer inspection there are certain similarities. An example will help to emphasize the similarities between regional conditions and infrastructural features. Consider the sudden occurrence of freezing rain in close distance to a metro station with parking capabilities. While the metro station and the parking facility can be considered as alternative option, the freezing rain is a good example for an environmental factor. The entire situation is determined by the driver's personality and by the characteristics of the alternative options and the environmental factor. While impassable road conditions

and sufficient parking capabilities may even influence established drivers, a slight chill and a crowded car park may only convince careful individuals to use the metro. As mentioned above, the determining characteristics of alternative options are not too different from the environmental factors. In order to formally conceptualize alternative options, a specification for their location, their scope, their preconditions, their effects, and their duration is required. Similar specifications are required to represent environmental factors.

To start with, the freezing rain is located somewhere in the simulation topology, thus, a location attribute is needed as well. Yet, contrary to infrastructural features, the freezing rain is not located at a distinct position, but covers an entire area. The model for regional conditions has to account for this aspect. The same situation applies for effects. The use of infrastructural features has an effect on drivers. Simulated drivers are able to access these effects in order to determine the benefit of using an infrastructural feature. The simulation engine uses the same specification in order to apply the effects on simulated drivers that decided to use an infrastructural feature. When it comes to environmental factors, drivers have no option but to accept the effects (this is in the nature of environmental factors). Nevertheless, some form of effect specification is still required in order to provide information for the simulation engine, which applies these effects (e.g., by changing the physics or the range of vision) to drivers that are under the influence of regional conditions. The next thing that has to be considered is a precondition. For infrastructural features, preconditions are used by the drivers in order to assess their capability to make use of perceived features. For the freezing rain, the situation is a bit different as the awareness for uncomfortable weather is not constrained. Thus, contrary to infrastructural features, regional conditions require no preconditions. Finally, a duration method is required. In the case of infrastructural features, this duration method can be highly complex, depending on the feature. For regional conditions, this function is rather simple—their effects occur immediately.

The above-presented discussion shows that there is a strong resemblance between the nature of regional conditions and infrastructural features. Based on this informal discussion, I proceed by providing a formal specification for all required attributes. I use the infrastructural feature model from the pre-

vious chapter as a foundation and refine this model to account for both, infrastructural features and regional conditions.

9.2 The Living Environment

In Section 8.1, I provided a formal conceptualization for alternative options which requires specifications for the following attributes: a location (and a scope)[1], preconditions, effects, and a duration. Above, I have motivated the necessity to use a homogeneous representation for infrastructural features and regional conditions. I proceed by presenting this generic representation in more detail.

9.2.1 $\mathbb{L}$ocations

Traffic simulation frameworks move vehicles either on existing or fictitious maps. For realistic results, I assume that these maps are based on geographic coordinates. A common way for representing locations on map is the *GPS Exchange Format* (*GPX*)[2]. Using GPX syntax, it is possible to describe distinct positions. Yet, as mentioned above, environmental factors are not limited to locations, but comprise entire "areas of influence". A regional conditions has to account for that, thus, I extend the GPX format by an additional attribute which expresses the range of the respective source of distraction. In the case of the freezing rain, the GPX coordinate can be understood as the rain's epicenter, while the range attribute can be understood as its radius. I define the location l of an external factor as follows:

$$l = (x, y),\ x \in GPX, y \in \mathbb{R}. \tag{9.1}$$

For the matter of simplicity, I refer to the set of locations as $\mathbb{L}$.

9.2.2 $\mathbb{P}$reconditions

In Section 8.1.1, I used first-order logic for the specification of preconditions. A single precondition can thus be considered as predicate which either

[1]In Section 8.1, I allowed to specify an external factors location and scope separately, however, for practical reasons, I decided to represent the external factor's location and scope in a joint representation.

[2]The GPS Exchange Format website: `http://www.topografix.com/gpx.asp`.

becomes true or false. Regional conditions imply no valid preconditions, yet, the use of infrastructural features may require several preconditions to be fulfilled. Reflecting these requirements, I design the preconditions $s.preconditions$ of an external factor s as a relation between the attributes of s and the attributes of a driver d. This relation contains all attribute combinations which allow for an execution of s, such that:

$$s.preconditions = \langle domain(s) \times domain(d), Graph(s.preconditions) \rangle,$$

where

$$Graph(s.preconditions) := \{(attributes(s), attributes(d)) \mid d \text{ can execute } s\}.$$

I refer to the set of preconditions as $\mathbb{P}$. Furthermore, I re-design the specification of the `canUse(Factor s)` method (see Equation 8.1, such that a driver d is able to make use of an external factor s, when the tuple of the current attributes of s and d are in $Graph(s.preconditions)$, such that:

$$d.canUse(s) := (attributes(s), attributes(d)) \in Graph(s.preconditions). \tag{9.2}$$

9.2.3 Effects

Effects define some kind of target state, which applies after the external factor has affected the driver or their vehicle. In the case of infrastructural features, drivers use these effects to measure if a potential application helps to reach the target state and whether to make use of it or not. In case of the regional conditions, the situation is different. Regional conditions affect the driver (physically or psychologically) without their permission. Accounting for both categories of external factors, I allow for any specification of an effect e, which applies for a driver d as a consequence the execution of an external factor s, which complies with:

$$e = \{f \mid f : X \rightarrow X, where\ X = \{x \mid x\ is\ a\ driver\ or\ x\ is\ an\ external\ factor\}\}. \quad (9.3)$$

I refer to the set of effects as $\mathbb{E}$. Due to the fact that in the applied traffic simulation framework vehicles are basically attributes of the driver (see Section 8.3), Equation 9.3 allows to express both, psychological effects on the driver as well as physical effects on the vehicle (e.g., an affected stopping distance, varying consumption or road grip, to name but a few).

9.2.4 $\mathbb{D}$uration

Finally, the duration method has to be defined. The duration method is used by the simulation engine to determine the time t after which the effects of the external factor s occur. For regional conditions, this function is quite simple, since their effects occur immediately. For infrastructural features, this function can be highly complex and can include many parameters. Basically, the combination of current attributes of a driver d and current attributes of an external factor s are mapped to an execution time. I refer to such mapping as *dur* and define *dur* in compliance with:

$$dur : domain(d) \times domain(s) \rightarrow Time.$$

I refer to the set of duration functions as $\mathbb{D}ur$.

So far, the definition fits purposes, yet, in the previous chapter, I argued that complex systems can not be captured (see Section 8.5). A metro service, for instance, provides access at many distinct entrances, while the entire system is somehow interconnected.

For this reason, the current model has to be extended from single occurrences to complex systems. I elaborate on this extension below.

9.2.5 The External Factor $\mathbb{S}$ystem

I define an external factor system as follows:

$$\mathbb{S} := \{(l, p, e, dur) \mid l \in \mathbb{L}, p \in \mathbb{P}, e \in \mathbb{E}, dur \in \mathbb{D}ur\} \quad (9.4)$$

Based on the above-presented definition, it is possible to conceptualize both categories of external factors by using the same model. I proceed by adjusting the driver model to account for the refined version of the infrastructure model.

9.3 The Driver Model

The improved driver model mostly complies with the model that I have presented in Section 8.2. Only the `Driver` class was slightly adapted and features an additional variable, namely `rangeOfSight`. This variable determines the driver's range of vision and is used by the simulation engine to determine whether drivers are able to "see" infrastructural features. This mechanism directly addresses the issue, which I discussed in Section 8.5, namely the way in which the simulation engine determines whether drivers are aware of infrastructural features or not. Instead of using an approach which is based on the feature's area of influence the new design is based on the driver's skills—a more realistic approach.

The general model structure remains the same, such that the driver model is based on the agent metaphor and the BDI approach is used for the conceptualization of the agents' behavior. The behavioral process remains unchanged and still complies with the schematic representation which is given in Figure 8.1.

In total, the driver's actuation comprises four phases (belief revision, generate options, filter, and acting). The simulation process, however, was extended to account for regional conditions. To this effect, each simulation interval begins with an application of the effects of regional conditions to drivers that are currently under the influence of these regional conditions. By accessing current positions of drivers and the installed regional conditions' location and range, the simulation engine determines if drivers are affected. Whenever drivers are affected the attributes of the drivers are altered according to the respective conditions' effects. Due to the discrete time flow model, it is important to make sure that regional conditions are evaluated first, before the current interval is being simulated. The reason for this is that the effects of regional conditions affect a driver's state and attributes, and may lead to different decisions in the decision-making process. In a discrete time flow model all actions of the same simulation interval

occur at the same time. Yet, in order to account for a given condition in a discrete time step, the condition has to be applied before the driver proceeds with their decision-making process. I conclude:

Conclusion 9.1 *In order to account for effects of regional conditions in the decision-making process of d_t, where d is a simulated driver and t is the discrete simulation interval, which d is about to execute, the effects of regional conditions have be applied before the perception phase is triggered.*

The freezing rain for instance may increase a driver's affinity for public transport and result in a lower cruising speed. Fog, as a second example for a regional condition may reduce a driver's range of sight and result in the situation that infrastructural features are recognized later than usual.

The remaining actuation process complies with process that I presented in Section 8.2, such that the consecutive numbers refer to the numbers that were illustrated in Figure 8.1. After the effects of regional conditions have been applied on drivers that are located within a regional condition, the simulation engine uses the drivers' position and `rangeOfSight` variable to determine if infrastructural features are perceived (1.). The perception is then forwarded to the belief revision, where the agent updates their belief base (3.) by merging their current perception (2a.) with stored knowledge (2b.). Using their updated belief base (4a.) and their former intentions (4b.), the agent proceeds with the generate options phase, where preconditions of all infrastructural features in the belief base are evaluated by means of the agent's `canUse(s)` method, which has to comply with Equation 9.2. For each positive evaluation, the sub-goal to utilize the infrastructural features is stored within the goal base of the agent (5.). In combination with the agent's basic plans (walk and drive) and their current intentions, the new set of goals constitutes the input (6a., 6b., 6c.) for the filter phase. There are two different types of goals. While the superior goal expresses the agent's overall objective to reach a certain location, only sub-goals can emerge dynamically indicating an agent's desire to utilize an infrastructural feature. By accessing the infrastructural features' effects and by making use of their basic plans, the agent computes alternative strategies to their target location involving any possible permutation of infrastructural feature utilizations. The resulting strategies are evaluated by using the agent's utility

function and finally, the favorite strategy is selected and inserted into the agent's intention repository (7.), from which their actuation is derived (8.) and their environment influenced (9.) once more.

To substantiate the functionality of the driver and the infrastructure model, I used an exemplary simulation setup in which simulated drivers pass the influence of regional conditions with changing characteristics. I present this evaluation below.

9.4 Evaluation

In order to evaluate the functionality of the concept, I present results of three simulation scenarios. While the first simulation was done without any influence, I integrated a regional condition, namely an oil puddle into the simulation topology of the second scenario. Finally, in the third scenario, I changed the attributes of the regional condition.

After demonstrating the capability of the simulation model to account for infrastructural features, the objective of this experiment was to show that the extended model is able to account for the effects of regional conditions on the driver's strategic level decision-making process and the traffic situation, respectively. In more detail, it was my intention to demonstrate that the model accounts for the fact that different regional conditions affect traffic situations differently. Below, I elaborate on the particular nature of the applied regional condition, explain the simulation scenarios, and present collected simulation results.

9.4.1 The Oil Puddle

I selected an oil puddle as an example for a regional condition. An oil puddle o complies with Definition 9.1 and thus requires a rather simple specification for their preconditions $o.preconditions$ and duration function dur. Both can be defined as follows:

$$o.preconditions = \emptyset,$$

and

$$dur(domain(d), domain(o)) = now,$$

where d is a driver. Contrary, location and effects require more complex assignments. In compliance with Equation 9.1, I assigned position and scope ($l = (x,y)$, where x=(52.510965, 13.397272) and y=100)) and specified the effects in compliance with Equation 9.3 as a function f, which manipulates the driver's velocity according to their distance to the oil puddle's epicenter (x), such that:

$$f(d) \Leftrightarrow d'.velocity = V_{new}(d.velocity, d.position, l), \tag{9.5}$$

where $V_{new} : \mathbb{R} \times GPX \times \mathbb{L} \rightarrow \mathbb{R}$ is defined as follows:

$$V_{new}(d_v, d_l, (x, y)) := \begin{cases} \frac{1}{3}d_v & , beeline(d_l, x) < \frac{y}{2} \\ \frac{2}{3}d_v & , \frac{y}{2} \leq beeline(d_l, x) < y, \end{cases}$$

where $beeline : GPX \times GPX \rightarrow \mathbb{R}$ is an auxiliary function, which determines the beeline between two positions.

In order to demonstrate that changes in the specification of the regional condition have an effect on the traffic situation, I slightly changed the scope of the oil puddle to $y' = 150$, such that $l' = (x, y')$ and reused the previously applied effect specification $\{f\}$.

9.4.2 The Scenarios

I selected a small map segment from the road network of Berlin, Germany. I assigned each driver a vehicle and defined an area of start locations in which the vehicles were initially located. Furthermore, I specified an area of target locations, from which the simulation engine retrieved positions when generating superior goals for the simulated drivers.

In total I compared the results of three simulation scenarios. In the first scenario, no regional condition was added, such that the external factor system for scenario one, or $\mathbb{S}_1$, looked as follows:

$$\mathbb{S}_1 = \emptyset.$$

In the second scenario, I added one regional condition, such that the external factor system $\mathbb{S}_2$ looked as follows:

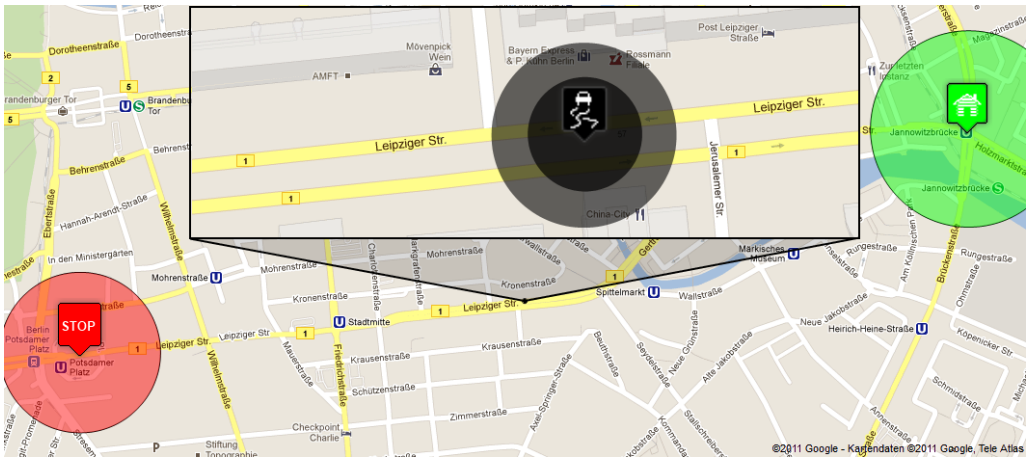

Figure 9.1: The topology for the second simulation scenario, including start area (green, right), target area (red, left) and oil puddle (black, center) with a radius of 100m.

$$\mathbb{S}_2 = \{(l, \emptyset, \{f\}, dur)\}.$$

In the third scenario I manipulated the attributes of the oil puddle and used the following external factor system:

$$\mathbb{S}_3 = \{(l', \emptyset, \{f\}, dur)\}.$$

The simulation setup for the second scenario, in which $\mathbb{S}_2$ was used, is illustrated in Figure 9.1.

Finally, I defined the utility function of the simulated drivers to measure the proposed strategies according to the required time—the least time, the best value.

In total, I specified a total amount of 10.000 vehicles for each simulation run, while each scenario was simulated 1.000 times in order to compensate statistical outliers. In the following, I elaborate on the collected simulation results. Presented numbers were averaged from all 1.000 simulations that were done for each scenario.

9.4.3 The Results

To demonstrate the effects of varying oil puddle definitions, I determined both, the average velocity and the average time that drivers required to

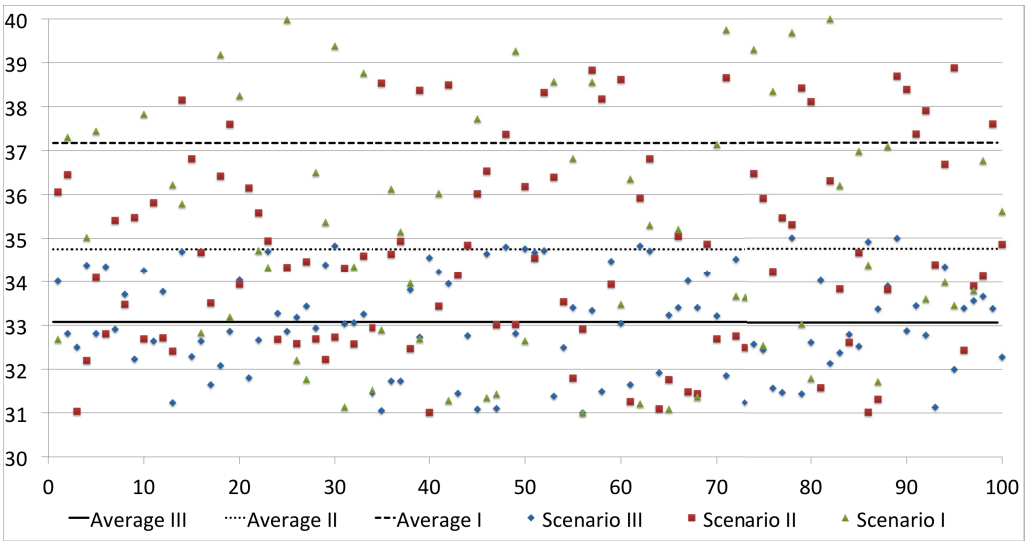

Figure 9.2: Average velocity (y-axis in km/h) of 100 randomly selected vehicles (x-axis) from Scenario I (triangle), Scenario II (box), and Scenario III (diamond) and average velocities from the entire simulation.

reach their designated target locations. Figure 9.2 compares the effective velocity that was driven by 100 randomly selected vehicles from the first (diamond), the second (box), and the third (triangle) scenario. Average values for all three scenarios are illustrated as linear trend line.

Simulation results for all three scenarios are comprehensively presented in Table 9.1. The effects of the oil puddle are reflected by the decrease in the driver's velocity from scenario to scenario. In Scenario I, where no regional condition was installed, the average cruising speed was determined with 37.18 km/h. In Scenario II, this value dropped by 5.1% to 34.98 km/h. In Scenario III, this value dropped again, by another 5.9% to 33.07 km/h.

The results emphasize two things. First, the approach is able to reflect the effects of regional conditions in general. This effect is emphasized by the significant velocity decrease between Scenario I (where no regional condition was used) and Scenario II (where one form of the oil puddle was integrated into the simulation topology).

Secondly, the approach is able to reflect the effects of varying characteristics of regional conditions. This impact is emphasized by the decreased average velocity of vehicles in Scenario II and vehicles in Scenario III. Thus,

Table 9.1: Collected results of the performed simulation scenarios. In each scenario, 10.000 vehicles were simulated, while the scenarios were simulated 1.000 times in order to minimize statistical outliers. Presented numbers were averaged.

	Simulation Scenario		
$\emptyset$ Values for	I ($\mathbb{S}_1$)	II ($\mathbb{S}_2$)	III ($\mathbb{S}_3$)
Effective velocity (in km/h)	37.18	34.98	33.07
Driven distance (in km)	3.34	3.34	3.34
Required time (in sec)	323.40	343.74	363.59

the simulation results emphasize that different regional conditions indeed affect traffic situations differently.

Based on these results, I can argue that the extended model is able to account for the effects of regional conditions on the driver's strategic level decision-making process and the traffic situation, respectively. □

9.5 Discussion

The aim of this chapter was to extend the existing simulation framework with the capability to represent environmental factors. In order to do so I introduced regional conditions as formal conceptualization of environmental factors.

To make the extension compatible with the representation of infrastructural features, I conceptualized regional conditions by means of a service-based approach.

A complete representation of a regional condition requires specifications for two determining attributes. First, there has to be a locational attribute, comprising a position and a scope. While the former represents the regional condition's epicenter, the later provides information about the condition's expansion. Since the locational attribute of a regional condition is given by a position and a scope, only concentrically shaped regional conditions are possible. Yet, in reality, environmental factors may feature more complex shapes. The presented approach, however, can be easily extended to feature more complex representations. In the end, the locational attribute

is used by the simulation engine in order to determine whether a driver is located within the sphere of a regional conditions. If one replaces the static representation with a function, which maps a given angle to the regional condition's epicenter to a distance, arbitrary shapes can be captured. To make this work, the simulation engine has to be adapted to calculate the angle between a driver and a regional condition and to compare the function's return value for this angle to the geographical distance between driver and regional condition. Despite the feasibility to make the approach more realistic, I refrain from using this more complex option. The objective of this thesis is to show that it is generally possible to develop a simulation model that reproduces strategic level driver behavior in compliance with psychological findings, not to present a universal and life-like implementation. Above, I sketched a possibility to make the initial approach more realistic, yet, for this thesis, I use a concentric representation of regional conditions.

The second attribute which is necessary to specify a regional condition is an effect. The effect definition of regional conditions is not different from the effect definition of infrastructural features.

Nevertheless, in order to be compatible with the representation of infrastructural features, regional conditions have to provide additional specifications for preconditions. These specifications are easily given as there are no preconditions for regional conditions. Furthermore, a duration method has to be provided. This duration method, however, can be defined universally, such that the current simulation time *now* is returned. The reason for this is that the effects of regional conditions occur immediately.

Another addition that was done is the consideration of the driver's range of vision. In the previous chapter, I defined that the visibility of an infrastructural feature is determined by the feature itself, yet, in Section 8.5, I argued that a skill-based approach is more realistic. To this effect, I adapted the driver model to account for a perception mechanism which is based on a range of vision. This range is driver-specific and implemented as `Driver` class attribute. The simulation engine uses the value in this field in order to determine whether drivers are able to "see" infrastructural features or not. While the perception mechanism for infrastructural features was adapted, I still use the old mechanism for regional conditions, which—following Con-

clusion 9.1—are evaluated before infrastructural features. The reason for this separation is the different nature of alternative options and environmental conditions. While the awareness for factors from the former category is also determined by the driver's skills (their range of vision), the latter source of distraction affect drivers in any case. For this reason, I decided to apply different perception mechanisms for regional conditions and infrastructural features.

I used an exemplary simulation setup in order to show that the extended model is able to conceptualize the effect of regional conditions on the strategic level decision-making of simulated drivers. The idea was to use driver's with fixed personality specifications and to simulate these drivers on infrastructures with varying regional conditions. My assumption was that the varying environmental conditions cause drivers to adapt their behavior and to affect the traffic situation differently.

To substantiate this assumption, I simulated three different scenarios; one scenario in which the strategic level decisions of the simulated drivers were not affected, one scenario in which the existing topology was extended by an oil puddle (as an example for a regional condition), and yet another scenario in which I used a more expanded version of this oil puddle.

The results established that the traffic situation significantly varied. This variation was reflected by the average velocity (and time) of the simulated vehicles. While in the first scenario the simulated vehicles travelled with an average velocity of roughly 37 km/h, the occurrence of the oil puddle caused drivers to decrease their velocity by roughly 5%. The expansion of the oil puddle aggravated this effect, such that the effective traveling speed dropped to roughly 33 km/h.

Based on the above-presented results I can answer the question that I presented at the beginning of this chapter, namely: "Is it possible to use the BDI-based approach and the service paradigm to implement a simulation model for strategic level driver behavior which accounts for the entire spectrum of external disturbances, namely environmental factors and alternative options?"

Yes, it is indeed possible to integrate both mechanisms to form a simulation model for strategic level driver behavior. While BDI can be used to conceptualize the drivers' behavior, sources of external distraction can be

captured in compliance with the service paradigm. In order to make this connection work, the driver has to become aware of the sources of distraction. This can be done by using a driver-specific attribute which determines the driver's visual scope. In order to account for basic knowledge (also a factor for the outcome of strategic level driver behavior), the driver's belief base can be custom-extended by the awareness for selected external factors or other belief artifacts. BDI innately accounts for this feature. Implementing the service paradigm, external factors have to provide specifications for the following attributes: a location & scope, preconditions, effects, and a duration. Due to the resemblance between both categories of external features I decided to use a joint model for their representation. The joint approach was feasible, though, for both categories of external factors there are respectively unused attributes. Infrastructural features for instance require no specification for a scope. Contrary, regional conditions require not specification for preconditions. To make the joint approach work it is necessary to allow the model to contain empty fields.

So far, I focused on demonstrating the general feasibility of the approach. For this purpose, the concept was mainly geared towards the evaluation scenarios, yet, precision and clarity were missing in the one or the other aspect.

As it was possible to demonstrate that the approach is feasible, I used the model as a foundation for a complete and generic behavior model for strategic level driver behavior. I present the complete model in the following chapter. The final version of the model was strongly influenced by the experiences that I have collected during the development and application of the previously presented versions.

10. Cause and Effect

Where those models that I presented in the previous chapters were geared towards the evaluation scenario, I continue this work by presenting a complete and generic behavior model for strategic level driver behavior in this chapter. The model presented in this chapter is based on collected experiences from practical applications of its predecessors.

Practical applications showed that the infrastructure model mostly coped with the requirements that are needed to conceptualize the impact of external factors on human strategic level behavior. Yet, the same applications also showed that the driver behavior model required further refinements—especially in terms of flexibility.

I present these refinements and thus the complete version of my simulation model in this chapter. The purpose of this chapter is to answer the following question:

- Is it possible to develop a simulation model for strategic level driver behavior which complies with psychological findings and accounts for all factors that psychological literature deems to be relevant for the outcome of human strategic level decision-making in traffic environments?

To make this essential chapter self-contained, I begin by repeating the definitions for regional conditions and infrastructural features, the formal

conceptualizations for environmental factors and alternative options, in Section 10.1. Subsequently, I present the complete infrastructure model, including one model for regional conditions and one model for infrastructural features, in Section 10.2. In Section 10.3, I present the strategic level driver behavior model, which is able to comprehend disturbances that evolve from the previously described infrastructure model. I demonstrate the functionality of the simulation model by presenting simulation results that were collected from an exemplary setup. In Section 10.4, I present both, this setup as well as collected simulation results. Finally, in Section 10.5, I discuss the presented approach in the light of this thesis.

10.1 External Factors

Following Conclusion 3.3, strategic level driver behavior can be affected by two types of external factors, namely alternative options and environmental factors. I refer to the formal conceptualization of environmental factors as regional conditions and to the formal conceptualization of alternative options as infrastructural features. In compliance with Definition 9.1, by regional conditions I understand:

> "...everything which is able to affect or influence a person, its behavior, or its vehicle (physically) at a certain location of an infrastructure." (after Lützenberger et al., 2011a, p. 247)

Following this definition, regional conditions describe sources of irritation which have some kind of effect on a driver or their vehicle. In compliance with psychological models (see also Section 3.4.2), the nature of this effect is either physical and psychological. Physical influences directly affect a driver or their vehicle. The driver has no alternative but to accept the effects until the affected area is left. By contrast, the results of psychological effects are individual—it is usually up to the driver on how they respond to different irritations. As an example consider the effects of extreme and freezing rain respectively. On a physical level, both conditions have a similar effect. Extreme rain may compromise the vision of a driver and also increase their breaking distance. Freezing rain does not affect a driver on visual level, but increase their breaking distance (more severely). Similarities can not only be identified on a physical but also on a psychological level. Potential

reactions of drivers to the occurrence of heavy or freezing rain are careful driving, deceleration and increasing the distance to other traffic participants for safety reasons.

I conceptualize the second category of external factors, namely alternative options as infrastructural features. In compliance with Definition 7.1, by infrastructural feature I understand:

> "...everything which is able to fulfil a desire (or parts of it) of a person at a certain location of an infrastructure." (Lützenberger et al., 2011c, p. 1257)

In compliance with psychological works (see also Section 3.4.2, infrastructural features constitute options or alternative ways which support a driver in achieving a particular goal. While this is rather broadly stated, an example will help to show the practical implications. In order to successfully keep an appointment (goal), a car park is indispensable, as regular appointments usually require the driver to be on foot. Since the car park helps the driver to fulfill their desire, the car park can be considered as an infrastructural feature. Consider public transport as another example for an infrastructural feature. Public transport provides a service at many places of an infrastructure and supports a person's desire to reach a certain location. According to Definition 7.1, any place where public transport service is offered can be considered as infrastructural feature as well.

Thus, from a psychological perspective, the impact of the driver's environment on their strategic level decision-making process can be conceptualized by means of two models, respectively one for regional conditions and one for infrastructural features. In the following, I provide formal specifications for these models.

10.2 The Infrastructure Model

On first sight, regional conditions and infrastructural features appear to be different in nature, though, on closer inspection there are certain similarities.

In fact, the resemblance is strong enough to represent both categories of external factors with the same model (the feasibility to account both factors of disturbance by means of a joint representation was demonstrated in

Chapter 9). In total, the representation of a regional condition or an infrastructural feature requires specifications for four determining characteristics. Thus, external factors can be represented as quadruple, consisting of:

1. a locational attribute (comprising a location and a scope),
2. preconditions,
3. effects, and
4. a duration function.

In the following, I present specifications for the four determining characteristics of external factors. These specifications mostly comply with the specifications that I presented in Section 9.2, though, refinements were also required.

10.2.1 $\mathbb{L}$ocations

While infrastructural features are immovably anchored at a distinct position, regional conditions may be located either on a single position or comprise entire areas. Traffic simulation frameworks move vehicles either on existing or fictitious maps. For realistic results, I assume that these maps are based on geographic coordinates and can be represented as GPX data. To support not only distinct positions, but also areas of influence, or scopes, I extend GPX by an additional attribute which expresses the range of the respective influence. Given that $i.position$ determines the geographical location of an external factor i and $i.scope$ determines its geographical extent, the location l of i is defined as follows:

$$l := (i.position, i.scope),\ where\ i.position \in GPX\ and\ i.scope \in \mathbb{R}.$$

By analogy with Section 9.2.1, I refer to the set of locations as $\mathbb{L}$.

10.2.2 $\mathbb{P}$reconditions

For regional conditions, the situation is simple, as there is no precondition to sense environmental factors. Infrastructural features on the other hand may require several preconditions to be fulfilled. Reflecting these requirements, I design the preconditions $i.preconditions$ of an external factor i as a relation between the attributes of i and the attributes of a driver d. This relation contains all attribute combinations which allow for an execution of i, such that:

$$i.preconditions = \langle domain(i) \times domain(d), Graph(i.preconditions) \rangle,$$

where

$$Graph(i.preconditions) := \{(attributes(i), attributes(d)) \mid d \ can \ execute \ i\}.$$

In compliance with Section 9.2.2, I refer to the set of preconditions as $\mathbb{P}$ and argue that d is able to make use i if the factor's preconditions are satisfied.

In order to evaluate whether a driver is able to use an infrastructural feature[1], I equip drivers with an instance method, namely `canUse`.

Henceforth, I refer to the set of infrastructural features as $\mathbb{I}$. Furthermore, I design $canUse : \mathbb{I} \rightarrow Boolean$ to return `true` whenever d is able to use i, such that:

$$d.canUse(i) := (attributes(i), attributes(d)) \in Graph(i.preconditions). \tag{10.1}$$

[1] I refrain from mentioning regional conditions since regional conditions have no preconditions and thus require no specification for their `canUse` method.

10.2.3 $\mathbb{E}$ffects

Effects define an estimated target state which applies after an external factor has affected the driver. This estimation can be used by the drivers in order to determine if the external factor is useful or not. In case of the infrastructural features, these effects can be used by the agents to measure if it helps reaching the potential target state and whether to make use of it or not. Regional conditions affect the driver (physically or psychologically) without their permission. Accounting for both categories of external factors, I allow for any specification of an effect e, which applies for a driver d as a consequence to the execution of an external factor s, which complies with:

$$e := \{f \mid f : X \rightarrow X, where \;\; X = \mathbb{D} \; or \; X = \mathbb{I}\}.$$

Henceforth, I refer to the set of drivers as $\mathbb{D}$. In compliance with Section 9.2, I refer to the set of effects as $\mathbb{E}$. For the matter of simplicity, I use $\mathit{eff}_i(d)$ to express that the effects of an external factor i are applied on a driver d, such that:

$$d' \Leftrightarrow \mathit{eff}_i(d). \tag{10.2}$$

10.2.4 $\mathbb{D}$uration

Finally, the duration method has to be defined. The duration method is used by the simulation engine to determine the time t after which the effects of the external factor i occur. For regional conditions, this function is quite simple as their effects occur immediately. For infrastructural features, this function can be highly complex and involve many parameters. Basically, the combination of current attributes of a driver d and current attributes of an external factor i are mapped to an execution time. I refer to such mapping as dur and allow for definitions of dur in compliance with:

$$dur : \mathbb{D} \times \mathbb{I} \cup \mathbb{R}eg \rightarrow Time. \tag{10.3}$$

Henceforthe, I refer to the set of regional conditions as $\mathbb{R}eg$ and to the set of duration functions as $\mathbb{D}ur$.

While for infrastructural features, the implementation of *dur* highly depends on the nature of the feature, it is possible to provide a universal definition for the duration method of regional conditions. A universal specification for *dur* could be done as follows:

$$\forall r \in \mathbb{R}eg : dur(d, r) := now.$$

So far, the definition fits purposes, however, more complex systems which comprise several external factors that are somehow interconnected cannot be captured, yet. As an example for a complex system of external factors consider a public transportation network or several regionally distinct but logically connected car parks (e.g., car parks that belong to the same operator). In order to account for such systems as well, the above-presented model has to be extended. I present this extension below.

10.2.5 The External Factor $\mathbb{S}$ystem

Multiple occurrences of somehow interconnected external factors are external factors systems. An external factor system Sys is a set of external factors, such that:

$$Sys := \{(l, p, e, dur) \mid l \in \mathbb{L}, p \in \mathbb{P}, e \in \mathbb{E}, dur \in \mathbb{D}ur\}.$$

For the matter of simplicity, I refer to the set of external factor systems as $\mathbb{S}$. Together with the definitions that I used for $\mathbb{I}$ and $\mathbb{R}eg$, the following statments can be derived:

$$\mathbb{I} \subseteq \mathbb{S} \; and \; \mathbb{R}eg \subseteq \mathbb{S} \; and \; \mathbb{I} \cap \mathbb{R}eg = \emptyset.$$

Based on the above-presented formalism, it is possible to include regional conditions or infrastructural features into GPX-based simulation topologies. I continue by presenting the driver model which is able to comprehend disturbances that evolve from the above presented infrastructure model.

10.3 The Driver Model

In order to make our approach work, the driver model has to be able to comprehend influences which evolve from the above-presented infrastruc-

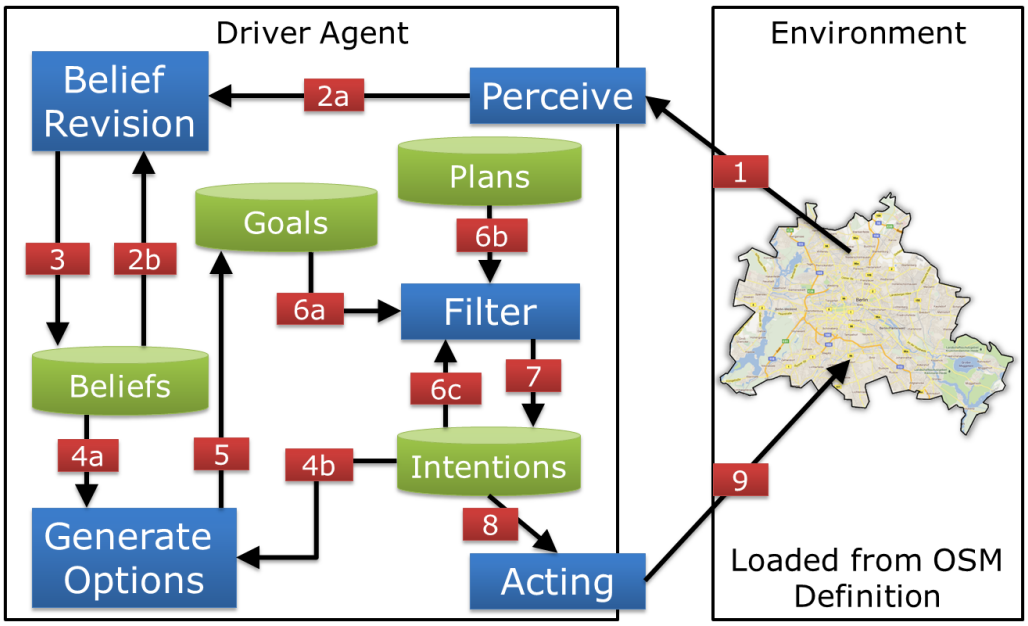

Figure 10.1: The architecture and actuation principle of the BDI-driver agents (after Lützenberger et al., 2012a, p. 342).

ture model. Simulated drivers have to act autonomous, reactive, pro-active and socially competent to changes in their environment. Thus, following Wooldridge and Jennings (1995), the driver is an agent. Furthermore, following Conclusion 3.1, drivers are intentional systems, thus, their behavior can specified by means of BDI (Rao and Georgeff, 1995). In order to make this work, all four BDI phases (belief revision, option generation, filter, actuation) have to be integrated into practical reasoning within traffic environments. The operation principle and behavior phases of the BDI-driver agents are illustrated in Figure 10.1.

In compliance with Section 9.3, the agent's execution cycle comprises four phases. Triggered by their perception (1), the agent starts with the belief revision and updates (3) their belief base with their current perception (2a) and their current beliefs (2b). With their updated new belief base (4a) and their current intentions (4b), the agent updates (5) their current set of goals in the generate options phase. In combination with the agent's plans and their current intentions, the new set of goals constitutes the input (6a, 6b, 6c) for the filter phase, which generates (7) a new set of intentions. Finally, the new set of intentions is used (8) to determine the agent's actuation, by

which they influence (9) their environment. In more detail, the different phases look as follows:

10.3.1 Prerequisites

Following Section 7.3, each simulated driver has to provide basic capabilities, namely plans. I defined a walk and a drive plan, which the agent uses to either walk or drive from a location A to a location B. Additional information on the usage of both plans are bundled into an extra class type, namely the `PlanObject`, which is furnished with information on the plan's preconditions, its effects and a function which returns the duration for an intended trip. Routing in both plan objects is implemented in compliance with the A-Star algorithm (Russel and Norvig, 2003, pp. 97–101), while the required duration is calculated by accessing the max-speed fields of the simulation topology, which is based on the OpenStreetMap framework (Ramm et al., 2010).[2]

Regarding the preconditions, I defined that the agent is in possession of a vehicle in order to have driving capability. By contrast, the walk capability requires the agent to be on foot. Effects of both plans are defined to move an agent from their current location to the desired target within the period of time which is returned by the duration function of the respective plan object. I refer to the set of plan objects of a driver as $\mathbb{P}lan$.

Next, an initial perception radius for the drivers is required. This attribute will be used by the simulation runtime to determine the current perception of the drivers. During the simulation, it is possible that the driver's initial perception radius is changed due to the effects regional conditions. In compliance with Section 9.3, I implemented this perception radius as additional variable, namely `rangeOfSight`, in the `Driver` class. This variable determines the driver's range of vision and is used by the simulation engine in order to determine whether drivers are able to "see" infrastructural features. Having both, a specification for plans and a concept for the perception radius, the prerequisites for the drivers given.

[2]While the velocity of vehicles was derived from the OpenStreetMap max-speed fields, I assumed a constant velocity of 4 km/h (or 2.49 m/h) for the walk plan.

10.3.2 Perception and Belief Revision

The phase comprises two parts. Following Conclusion 9.1, the effects of regional conditions are applied before the perception of infrastructural features is triggered. Thus, the currently perceived regional conditions are determined. In order to do so, locations and scope of elements in $\mathbb{R}eg$ are analyzed and compared to the positions of the simulated drivers. In compliance with Equation 10.2, effects are directly applied as long as a driver is located within the scope of a regional condition:

$$\forall d \in \mathbb{D}, \forall r \in \mathbb{R}eg : d' := \begin{cases} eff_r(d) & , dist(d.pos, r.pos) \leq r.scope \\ d & , else, \end{cases}$$

where

dist(x,y)	Complies with $dist : GPX \times GPX \rightarrow \mathbb{R}$ and calculates the *Euclidian Distance* between x and y.
d.pos	The current location l_d of driver d, such that $l_d \in GPX$.
r.pos	The location l_r of a regional condition r, such that $l_r \in GPX$.

After regional conditions have been applied, the simulation engine proceeds by updating the driver's knowledge about infrastructural features. In order to do so, distances between the elements in $\mathbb{I}$ and the simulated drivers are computed and compared with the driver's perception radius. Whenever a driver "senses" an infrastructural feature, it is inserted into their belief base. Also, the simulation routine verifies whether already stored infrastructural features are still being perceived by the agent. In case they are no longer perceived, the features are removed from the agent's belief base. This process complies with:

$$\forall d \in \mathbb{D}, \forall i \in \mathbb{I} : d'.bBase = update(d.bBase, i),$$

where *update* complies with:

$$update : X \times \mathbb{I} \rightarrow X, X \subseteq \mathbb{B},$$

and is defined by:

$$update(b, i) := \begin{cases} b \cup \{g_b(i)\} & , dist(d.pos, i.pos) \leq d.sight \\ b \setminus \{g_b(i)\} & , else, \end{cases}$$

where

$d.bBase$	Is the belief base of driver d.
$g_b(x)$	A function, which generates a belief from an infrastructural feature, such that $g_b : \mathbb{I} \rightarrow \mathbb{B}$, where $\mathbb{B}$ constitutes the set of believes.
b	Is a belief base, such that $b \subseteq \mathbb{B}$.

10.3.3 Option Generation

In this phase, the agents determine if they are able to make use of any of the perceived infrastructural features by evaluating their preconditions in compliance with Equation 10.1. A failed precondition check will not change the state of the agent, but in case of a successful evaluation, the desire to make use of the infrastructural feature will be stored in the form of a goal within the goal base of the agent. In this goal base two categories of goals are stored. First, there is one designated superior goal, which expresses an agent's main objective to reach a certain location. Following Conclusion 3.1, the behavior of drivers complies with the single-minded principle (Cohen and Levesque, 1990), thus, the agent is compelled to their superior goal, exclusively. Secondly, there are several sub-goals which emerge dynamically as an agent's desire to make use of an infrastructural feature. Sub-goals express the agent's desire to make use of infrastructural features and thus reflect the impact of alternative transport options on the driver's currently pursued strategy. Whether or not an alternative option is selected, however, is determined by the driver's internal factors. This decision is done within the subsequent filter phase. I formalize the option generation process as follows:

$$\forall d \in \mathbb{D}, b \in d.bBase :$$
$$d'.gBase := \begin{cases} d.gBase \cup \{g_g(b)\} & , d.canUse(b.iFeature) \\ d.gBase \setminus \{g_g(b)\} & , else, \end{cases} \tag{10.4}$$

where

d.gBase	Is the goal base of driver *d*.
g_g(x)	Is a function, which generates a goal from a belief, such that $g_g : \mathbb{B} \rightarrow \mathbb{G}$, where $\mathbb{G}$ constitutes the set of goals.
b.iFeature	Is the infrastructural feature which is associated with the belief b.

10.3.4 Filter

In this phase, the agent retrieves their goals from the goal base and tries to find ways to achieve them. As mentioned above, there are two categories of goals. One goal is superior to any other goals and expresses the agent's main objective to reach a certain location. This goal is placed within the goal base of any agent whenever they are starting their journey. Following Section 8.3, the simulation engine checks whether events are scheduled for the current simulation time *now*. Whenever an event is detected, a superior goal is created and placed within the goal base of the driver. This is done in compliance with:

$$\forall d \in \mathbb{D} : d'.gBase := d.gBase \cup \{g_e(e) \mid e \in \mathbb{E}, e.start = now\}, \tag{10.5}$$

where

$\mathbb{E}$	Is the set of events.
g_e(x)	A function, which generates a goal from an event, such that $g_e : \mathbb{E} \rightarrow \mathbb{G}$.
e.start	The scheduled start for an event *e*, where $e \in \mathbb{E}$.
now	The current simulation interval.

In compliance with the single-minded principle (Cohen and Levesque, 1990), the superior goal will remain within the goal base of the agent until it has been achieved, or until it is no longer possible to reach the goal. Sub-goals can only be generated as a result of Equation 10.5, by perceiving infrastructural features in the simulation topology. These sub-goals express an agent's desire to exploit their environment.

Whenever a superior goal in the goal base of the agent is detected, a planning algorithm is used to compute actions that fulfill this goal. In more detail, backtracking search (Russel and Norvig, 2003, p. 142) is used to compute available action plans, which are able to satisfy the agent's superior goal. I refer to these action plans as *strategy*. A strategy looks as follows:

$$s_1 \dots s_n \mid s \in \mathbb{P}lan \cup \mathbb{G}, n \in \mathbb{N}. \tag{10.6}$$

Henceforth, I refer to the set of strategies as $\mathbb{S}trat$.

In order to compute strategies, the applied planning algorithm calculates any possible sub-goal permutation and respectively tries to accomplish the agent's superior goal by extending this permutation with their basic capabilities. To assure consistency, the planning algorithm accesses preconditions and effects from the infrastructural feature, which is—as a consequence to Equation 10.4 and Equation 10.5—directly associated with the sub-goal. Preconditions and effects of the agent's basic capabilities are derived from the corresponding `PlanObject` instance.

As each valid course of action is temporarily retained, the result of the planning process is a set of potential strategies:

$$\forall d \in \mathbb{D} : Strat_d := genStrat(d.gBase), Strat_d \subseteq \mathbb{S}trat,$$

where

genStrat(x)	Is a function, which generates the set of consistent strategies from the current goal base of a driver, such that $genStrat : \mathbb{G} \rightarrow X, X \subseteq \mathbb{S}trat$.

After the set of potential strategies has been generated, the agent's favorite strategy has to be determined. For this purpose each agent is equipped with a utility function *util*, which complies with:

$$util : \mathbb{S}trat \rightarrow \mathbb{R}.$$

The utility function measures the quality of a proposed strategy. This measurement process represents the driver's internal factors, or their personality, following Conclusion 3.4, a significant factor for the outcome of strategic level driver behavior. Here, it is decided by which criteria an agent selects their course of action. Using *util*, the strategy with the highest quality is determined from the proposed set of options:

$$s = best(\mathbb{S}trat_d),$$

where *best* complies with:

$$best : X \rightarrow \mathbb{S}trat, X \subseteq \mathbb{S}trat,$$

and is defined by:

$$best(\mathbb{S}trat_d) := y, \nexists s \in \mathbb{S}trat_d, s \neq y : util(y) \leq util(s). \tag{10.7}$$

Once the agent's favorite strategy has been computed, the filter phase will come to end and place the best strategy into the agent's intention repository.

10.3.5 Actuation

In this phase, the computed strategy is executed. Following Equation 10.6, a strategy can only comprise the execution of an agent's basic capability, or an infrastructural feature. Both options are executed by the simulation engine.

In the case of an infrastructural feature, the specification is provided by the feature's effects (defined by Equation 10.2) and its duration (defined by

Equation 10.3). Thus, in order to execute an infrastructural feature, the simulation engine has to apply the specified effects after the given duration. Furthermore—as the presented approach is based on a discrete simulation model—the simulation engine has to exclude the driver from the simulation whilst they are executing the infrastructural feature.

By contrast, the process of executing an agent's basic capabilities is just applying Newton's laws of motion in order to move a vehicle (or a person) from a given location A to a given location B. The result to this application are altered values for the vehicle's position, heading and velocity. These are returned to the simulation engine and assigned to the respective agent. In the subsequent simulation cycle, the simulation engine uses the altered values in order to determine the agent's new perception. The process iterates until the simulation's end has been reached.

10.3.6 Simulation-Specific Improvements

So far, the driver agents are designed to constantly perceive their environment, which is not far off from reality. Yet, this principle is not feasible, if only for efficiency reasons. Moreover, it is not even necessary to compute a new strategy as long as the perception of an agent has not significantly changed. The strategy generation process for itself is a deterministic process, thus, the strategy generation can be optimized as follows:

$$s'_d := \begin{cases} oGen, filter & , d.bBase' \setminus d.bBase \neq \emptyset \\ s_d & , else, \end{cases} \tag{10.8}$$

where

s_d	Is the strategy of a driver d. While s_d describes the driver's strategy at a given time t, s'_d describes his strategy at a given time t+1.
oGen, filter	Constitutes the regular strategy computation mechanism as including the option generation and the filter phase.

An important implication of this definition is that a strategy update is not performed if a known influence has been left but only in the case when a new influence is being perceived.

In fact, this optimization only works for deterministic variable models (see also discussion in Section 4.4.3). I decided to design the entire BDI-reasoning process in a deterministic fashion, though, I never determined the nature of the involved functions, e.g. the validity check that is used to determine whether drivers are able to use infrastructural features or not or the utility function, which is used to determine the quality of a strategy.

Given that all involved functions are deterministic, the driver's strategic level decision-making remains a deterministic process and the above-presented optimization can be applied. Yet, this implementation is somewhat in conflict with psychologists. These argue that drivers constantly perceive their environment. In Section 4.4.3, I argued that it is difficult to rule out a stochastic or a deterministic variable model. After presenting my approach, I still have no answer to this question. In fact, it is not even necessary to answer it as long as it is possible to account for both options.

The deterministic approach is somewhat in conflict with the psychological understanding of human driver behavior, though, simulation is only an imitation of reality. If it is necessary to produce deterministic and comprehensible results, a deterministic set of functions is suggested. If one wants to reflect the volatility of human behavior, a carefully calibrated set of stochastic functions can be used. Bear in mind that in the latter case the above-presented optimization is not applicable.

10.4 Evaluation

Previously presented evaluations were aimed to proof that the connection between the drivers' personality, their experience, and infrastructural features as well as the connection between the drivers' personality, their experience, and regional conditions worked. Now that all relevant sources of distraction are integrated, the purpose of this evaluation is to show that the approach is able to produce strategic level decisions that are subject to the driver's internal factors, their experience, and their simultaneous awareness for alternative options and environmental factors.

In total, I performed two series of experiments. In the first test series, I configured a simulation topology with four metro stations and several car parks as examples for infrastructural features und simulated four scenarios with respectively different acceptance rates towards public transportation. In the second test series, I used the exact same configuration but additionally added freezing rain, as an example for a regional condition. Thus, in total, I simulated eight scenarios, respectively with different characteristics.

In the following, I explain the preconditions, effects, and duration functions that were used for the involved infrastructural features and regional conditions. Subsequently I describe how the driver model was configured in order to account for these external factors and how I assigned the involved external factors to locations. Finally, I present collected results from this experiment.

10.4.1 The Metro Service

In order to make use of the metro service, the driver is not allowed to use any other form of transportation. For a driver d, this constraint looks as follows:

$$d.getVehicle() = \emptyset. \tag{10.9}$$

Although metro systems can be highly complex and cross-linked, I used a rather simple implementation for its effects. I selected a map with four metro stations and while the different instances are located at different positions, each station moves the driver to a universal target position $p \in GPX$. Thus, the effects of the metro service were defined as follows:

$$d'.position = p.$$

In compliance with Equation 10.3, I applied Newton's law of motion and defined *dur* to return the required time for the beeline distance between the location of an instance i and the universal target location *target*. For this calculation, I assumed an average velocity of 34.52 km/h (or 21.45 m/h , which was derived from the schedule of *Berliner Verkehrsbetriebe*[3], Berlin's transportation company. In more detail, *dur* looks as follows:

[3]Berliner Verkehrsbetriebe website: `http://www.bvg.de`

$$dur(d, i) := \frac{beeline(d.position, i.position)}{34.52\frac{km}{h}}.$$

10.4.2 The Car Parks

For the car parks, I assumed that each driver d who wants to make use of a car park instance c, is currently using a vehicle:

$$d.vehicle \neq \emptyset.$$

Furthermore, I assumed that the instance provides enough capacity:

$$c.capacity > 0.$$

For the effects, I defined that the driver is no longer within their vehicle:

$$d'.vehicle = \emptyset.$$

Furthermore, I assumed that the current capacity of the car park is decreased by one:

$$c.capacity' = c.capacity - 1.$$

For the matter of simplicity, I designed the duration method dur of the car park to constantly return one.

I continue by presenting how the scenario—which currently comprises only a set of infrastructural features—can be extended by an exemplary regional condition. For this purpose, I selected the freezing rain.

10.4.3 The Freezing Rain

Except for a location, the only thing regional conditions require is a specification of their effects. I designed the effects e of the freezing rain r as a set with one function f, which increases the metro service acceptance rate (psychological effect) of a driver d in dependency to their distance to the freezing rain's epicenter $r.position$:

$$f(d) \Leftrightarrow d'.metroAcceptance = \\ mAccept_{new}(d.position, r.position, d.acceptance),$$

where $mAccept_{new} : GPX \times GPX \times \mathbb{R} \rightarrow \mathbb{R}$ is defined as follows:

$$mAccept_{new}(d_{pos}, r_{pos}, a) := \begin{cases} 6a & , beeline(d_{pos}, r_{pos}) < 1\ km \\ 4a & , 1\ km \leq beeline(d_{pos}, r_{pos}) < 2\ km \\ 2a & , else. \end{cases}$$

10.4.4 The Drivers

To configure the drivers' acceptance towards public transportation, I used the same approach as presented in Section 8.4.3. In more particular, I used the `acceptance` field of the `Driver` class to reflect and to configure the drivers' acceptance towards the metro service.

Following the *Mobilität in Deutschland 2008* study (Federal Ministry of Transport, Building and Urban Development, 2010), a commonly accepted work, which analyses mobility patterns in the Federal Republic of Germany, I assigned an acceptance of 15%[4]. Note that this mechanism is based on a stochastic function. Out of 100 drivers only 15 will consider a nearby metro station as potential alternative and generate strategies that include this option. The stochastic approach prevents me from using the optimized simulation procedure which I presented in Section 10.3.6.

Finally, I manipulated the filter module of the driver agents to perform an evaluation of the proposed strategies by accumulating the regular durations for any walk, drive, parking, and metro process.

10.4.5 The Setup

I selected Berlin as simulation environment and extracted a fitting map fragment for the example. The selected topology comprised several car

[4]The real acceptance which was used to reflect the driver's acceptance towards the metro service was 14.58%, to be more accurate.

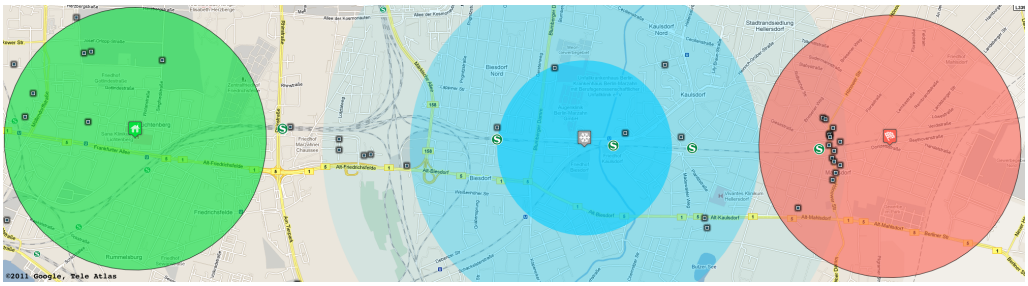

Figure 10.2: The evaluation scenario, including four metro stations, one car park for each metro station and several others in the target area, one zone with freezing rain (middle, light blue), as well as start and target areas (left, green and right, red) for the vehicles (after Lützenberger et al., 2011a, p. 253).

parks, to which I assigned a capacity of 3.000 parking lots, respectively. The map also comprised four metro stations to which I assigned the above-mentioned definitions for preconditions and effects. In total, I used an amount of 10.000 vehicles for each simulation run. Furthermore, I used the existing framework's capability to define start and target locations for the simulated drivers, ensuring that simulated vehicles pass the scope of all external factors. The simulation setup is illustrated in Figure 10.4.5.

In total, two series of scenarios were simulated. In the first test series, I configured a simulation topology with four metro stations and several car parks as examples for infrastructural features and simulated four scenarios with respectively different acceptance rates (5%, 10%, 15%, and 20%) towards public transportation.

In the second test series, I used the exact same configuration but additionally added freezing rain with a radius of 3.000 m between the start and target area. Thus, in total, I simulated eight scenarios, respectively with different characteristics. The course of events in both scenarios can be described as follows:

At the beginning, the drivers are located within a parked vehicle at some random location within the start area. During runtime, the simulation engine randomly generates superior goals to reach a location from the target pool and places them in the goal base of a driver. Triggered by the goal, the agent starts the journey. As no other option is available, the agent computes and executes a strategy involving their drive plan. Once a driver perceives an external factor, further concurrent strategies will be proposed. In the

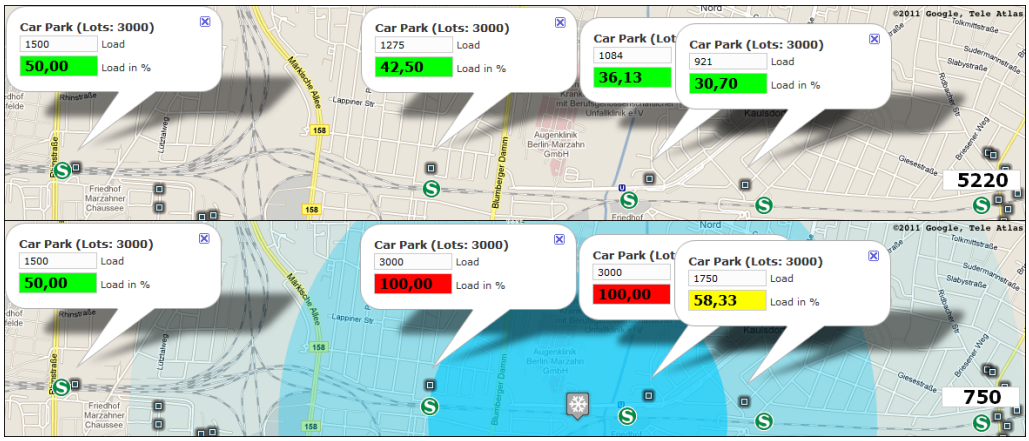

Figure 10.3: Averaged results for two simulation scenarios. In the first scenario a 15second scenario freezing was added, while the acceptance rate remained the same. Results are illustrated by showing the car parks' utilization in absolute and percentage values (after Lützenberger et al., 2011a, p. 254).

case of a car park, the driver computes a strategy to park their car and walk to the target location. Usually this option will fail since the applied strategy selection is based on the required time to the target and walking strategies tend to be highly expensive. In the case of a metro station, any evaluation on making use of the service will fail, since Equation 10.9 requires the driver to be on foot. Only when the driver senses both external factors (and the stochastic strategic generation process considered the metro station as an option), the filter module will be able to compute a valid strategy, involving a ride to the car park, a walk to the metro station and a walk to the target location. Depending on the quality of the newly perceived route, this optional strategy either replaces the original one or is rejected.

In order to avoid statistical outliers, both scenarios were simulated 1.000 times. Averaged results for two selected scenarios are illustrated in Figure 10.4.5.

The upper illustration shows simulation results for a 15% acceptance rate and without an integration of freezing rain. The lower illustration emphasizes the effects of that regional condition (with the same acceptance rate). Simulation results from all eight scenarios (averaged from all 1.000 simulation runs that were done for each scenario) are presented in Table 10.6.

The results establish that the parking situation is significantly affected by the regional condition. For the first car park (namely *Parking Area*

Table 10.6: Averaged evaluation results. The table shows the utilization of each car park in absolute numbers. In total, four different acceptance rates were simulated in two different test series. While the first series contained no regional condition, freezing rain was added in the second test series.

		Parking Area				
Regional Condition	Acceptance	1	2	3	4	Target
None	5%	439	399	503	393	8266
	10%	908	847	899	674	6672
	15%	1500	1275	1084	921	5220
	20%	2043	1595	1271	999	4092
Freezing Rain	5%	427	557	540	409	8067
	10%	1003	3000	2929	1212	1856
	15%	1500	3000	3000	1750	750
	20%	1978	3000	3000	1607	415

1), the utilization between the scenarios that included the freezing rain and those that did not include the freezing rain is roughly the same (1.1% difference). This result was foreseeable as Parking Area 1 was not affected by the regional condition, thus, drivers act exactly as in the scenarios without the freezing rain.

For the other car parks, however, the difference became more apparent. The utilization of the car parks varied significantly. The average utilization for *Parking Area 4*, for instance, dropped by the factor .59. Contrary, for *Parking Area 3*, the average utilization climbed up by the factor 1.36.

Due to different utilizations of the parking areas, the utilization of the target area was affected as well and dropped by the factor .63—although the target area was not directly affected by the freezing rain. This difference is a direct consequence to the adapted strategic level behavior of the simulated drivers in the affected area.

The purpose of the evaluation was to show that the approach is able to reproduce strategic level driver behavior as a result of three distinct factors,

namely: the driver's personality, alternative options and environmental factors. [5]

In each scenario a number of drivers make use of alternative transport options, thus, there is indeed a connection between the drivers' behavior and their awareness for infrastructural features. There is also a connection between the drivers' personality and infrastructural features as varying personalities result in different utilizations of alternative options. Moreover, there is a connection between the driver's behavior, their awareness for infrastructural features, and their awareness for regional conditions. This connection is established by differing utilizations of alternative options for respectively the same acceptance rate but different regional condition setups. Finally, the results show that this utilization is significantly determined by the driver's personality profile.

The results show that the presented approach is able to reproduce human strategic level driver behavior as a result of the driver's personality, their awareness for alternative options and their awareness for environmental factors. □

10.5 Discussion

In this chapter, I presented a simulation model which conceptualizes human strategic level driver behavior by considering those factors that psychologists identify as significant for the outcome of strategic level decision-making. In total, four input channels were connected. First, there was experience and knowledge. In compliance with Conclusion 3.5, the former was conceptualized by means of a utility function, the latter was integrated as an innate part of the driver model, namely the driver's goal base. Secondly, the driver's personality was conceptualized. In compliance with Conclusion 3.4 this was also done by means of a utility function. Thirdly, a connection to alternative options was established. This source of distraction was conceptualized by means of a separate model, namely infrastructural features. Finally, a connection to environmental factors was established, again by means of a separate model, namely regional conditions.

[5] I already established that the impact of knowledge as a factor for the outcome of strategic level driver behavior is innately provided by the BDI approach (see also Section 8.5.

I began this chapter by providing definitions for both categories of external factors in order to clarify the capabilities, the scope, and the limits of the presented approach. Subsequently, I presented a joint model both external factors. Based on positive experiences, I designed this model in compliance with the service metaphor, such that infrastructural features and regional conditions can be defined by providing specifications for their preconditions, their effects, and a duration function. To account for applications in a traffic simulation environment, a locational attribute is required as well. In the case of regional conditions, this locational attribute comprises a position and a scope. The former can be interpreted as the external factor's epicenter, the latter as the factor's extend. Contrary, infrastructural features require only a position. To facilitate a joint representation of infrastructural features and regional conditions, I allowed the model to contain empty fields in order to account for unused attributes (e.g., preconditions for regional conditions or a scope for infrastructural features).

After presenting the joint model for regional conditions and infrastructural features, I introduced the external factor system as a way to represent occurrences of interconnected external factors. Examples for external factor systems that comprise two or more infrastructural features are metro systems or bus network. External factor systems for regional conditions are imaginable as well, yet, regional conditions usually feature no "logical connection", therefore it is not necessary to define multiple occurrences of regional conditions—e.g., three distinct rain cells—as external factor system; three separate regional conditions fit the purpose as well.

After presenting the infrastructure model, I continued by presenting the driver model. The driver model comprehends disturbances that evolve from the infrastructure model and generates a strategy, which reflects the driver's individual personality as well as their experience and knowledge. Based on successful appliances, I used an agent-based model and conceptualized the drivers' behavior with the belief-desire-intention approach. For a behavior conceptualization in compliance with BDI, four phases of human practical reasoning have to be specified. Thus, I provided definitions for the belief revision, the option generation, the filtering as well as the acting phase, respectively for traffic and transport environments. Furthermore I emphasized where and how the driver's awareness for external factors affect these phases.

I used an exemplary setup in order to establish that the presented approach is able to reproduce strategic level driver behavior as a result to the drivers knowledge (provided by the BDI-based driver representation) as well as three further distinct factors, namely: the driver's personality, alternative options and environmental factors.

In more detail, I used varying behavior profiles and regional conditions on a simulation topology, which I furnished with a set of infrastructural features. Collected simulation results establish that each source of distraction significantly affects the strategic level decision-making process of simulated drivers and the traffic situation, respectively.

It is important to mention that the purpose of this experiment was not to demonstrate that the approach accounts for realistic results, but rather to show that the identified and conceptualized input channels have a significant impact on the outcome of the driver's strategic level decision-making process. The exact configuration depends on the application of the model and differs from use case to use case.

Base on these results I can answer the question that I presented at the beginning of this chapter, namely: "Is it possible to develop a simulation model for strategic level driver behavior which complies with psychological findings and accounts for all factors that psychological literature deems to be relevant for the outcome of human strategic level decision-making in traffic environments?"

Yes, it is possible! The answer to this question lies within a carefully adjusted combination of the belief-desire-intention programming model and the service-based approach. In more detail, the belief-desire-intention model can be used to conceptualize behavior of drivers such that strategic level problem solving is mimicked. BDI innately accounts for a flexible configuration of the driver's belief—their knowledge—an thus accounts for the first factor that is relevant for the outcome of strategic level problem solving in traffic and transport environments. Furthermore, it is possible to custom-define the mechanism which determines after which criteria a driver selects from available strategies. This feature directly addresses the requirement to account for the driver's personality in the strategic level decision-making process. I already established that it is possible to refrain from accounting for the impact of other levels of behavior (psychologists agree with

that). Thus, there remains only one source of distraction, namely external factors. External factors are not innately supported by BDI, therefore a second model is required. External factors have a strong resemblance to software services, thus, a service-based representation is suggested. In order to make this work, the distinguishing attributes of services have to be identified within the concept of external factors. From a service-perspective, there are two attributes that require a mapping, namely preconditions and effects. To properly account for external conditions in a traffic environment, the service metaphor, however, has to be extended by further attributes, namely a locational attribute (including a location and a scope) and a duration function. The connection between BDI and the service-based representation can be done in the driver's perception phase. Here the drivers awareness for their environment is determined. The services' location and scope as well as driver-specific parameters (e.g., the drivers range of vision) can be used to connect the driver's reasoning process to their environment and to generate BDI objects (e.g., beliefs or goals) that represent the driver's perception during the subsequent reasoning phase. This mechanism integrates the BDI-based driver model and the service-based infrastructure representation and connects the driver's strategic level behavior to their awareness for the surrounding infrastructure—the fourth factor that, following human factors psychology, determines the outcome of strategic level driver behavior.

The purpose of this part was to present a functional simulation model that is able to produce strategic level driver behavior in compliance with psychological requirements. In the following part I demonstrate that the model can be calibrated and adjusted to different application domains and that the presented simulation model advances the state-of-the-art in a meaningful manner.

Part V

Evaluation

In the previous part, I presented a functional simulation model for strategic level driver behavior. This model is a skeleton rather than a generally applicable solution. Strategic level driver behavior highly depends on the situation, thus, the simulation model has to be tailored to the application context.

While I already established that the strategic level decision-making model accounts for all relevant sources of distraction, namely external factors and the driver's personality, I use this part to demonstrate that the model can be calibrated to reproduce human strategic level driver behavior in selected situations. In order to do so, I present three scenarios in which the approach was comprehensively applied and evaluated.

This part is based on the publications Hoch et al. (2011), Keiser et al. (2011), and Lützenberger et al. (2012b).

11. The Volkswagen Case

The first evaluation that was done by means of the presented simulation model was a part of a joint project with *Volkswagen AG*.

The objective of the project was the development of an assistance system (Hoch et al., 2011) for the drivers of electric vehicles. In more detail, it was planned to develop a user-centric, constrained-based, in-vehicle travel planning system, which schedules a daily travel plan of a user by exploiting knowledge about current and future states of the vehicle-user-infrastructure network.

In order to assess the capabilities of such system, it was necessary to compare its performance to those of regular drivers. The project context did not allow for a comprehensive field test, thus, a simulation-based approach was applied in order to evaluate the system.

In more detail, two categories of drivers were simulated, namely those drivers that are in possession of the assistance system and those drivers that are not. While the behavior of the former category was generated by the assistance system itself, my approach was used to generate the behavior of those drivers that are not in possession of the assistance system.

This chapter is structured as follows: In Section 11.1, I describe the objective as well as the particulars of the above-mentioned assistance system. Subsequently, in Section 11.2, I present the evaluation scenarios and establish how the simulation model was calibrated in order to account for realistic

results. I present these results in Section 11.3 and wrap up with a discussion in Section 11.4.

11.1 The Application

The objective of this project was the development of a user-centric, constrained-based, in-vehicle travel planning system, which schedules a daily travel plan of a user by exploiting knowledge about current and future states of the vehicle-user-infrastructure network.

In order to evaluate the capabilities of such approach, it is necessary to compare the performance of drivers that were assisted by the system with the performance of drivers that act on their own. Yet, due to the fact that most services that were used by the assistance systems (e.g., information on the utilization of parking infrastructure) were not available for real, it was not possible to deploy the system on real hardware and to evaluate its capabilities in a field test, but only by means of simulation.

The assistance system was developed to optimize the driver's strategic level decisions, thus, it was possible to use the assistance system to generate driver behavior and compare the efficiency of this behavior to the efficiency of drivers whose behavior is generated by my model.

To clarify the evaluation procedure, I continue by presenting the mechanism of the assistance system.

11.1.1 The Objective

The assistance system (Hoch et al., 2011) was developed under the assumption that intelligent electric vehicles interact with their surrounding infrastructure components. This interaction helps to gain information about past, current, and future infrastructure states by means of telematics services.

Based on this interaction, we designed the assistance system in a joint effort, to govern their users by their preferences as well as their appointment sequence. In addition, the assistance system was designed to obey the technical constraints of the driver's vehicle, such as power output or recuperation restrictions.

Furthermore, being in a traffic environment, the electric vehicle is competing for resources whilst obeying driver, vehicle and infrastructure hard constraints.

In order to assess the quality of the proposals that were made by the assistance system, we established that a route sequence is *feasible* if:

- The vehicle can reach each user-defined calendar appointment in time.
- Each route contains both available and suitable parking and charging lots.
- The vehicle's state-of-charge never decreases a limit energy value of the battery.

Furthermore, we established that a route sequence is *optimal*, if battery state-of-charge, adherence to user schedule and choice of parking and charging lot are optimally matched against the user preferences and if minimal travel time and energy are consumed.

The assistance system was designed to optimally fulfill user preferences whilst raising time efficiency of the daily vehicle travel plan. In total, the following four mobility-related user preferences were used as key performance indicators:

1. Reduction in travel time and distance
2. Increase in usable time throughout the schedule
3. Adherence to user schedule
4. Adherence to user preferences

To optimize a user's daily mobility patterns can be understood as a multi-criteria optimization problem dealing with different objective functions, such as the maximization of usable working time, the minimization of driving time and the minimization of appointment conflicts. Based on this understanding we developed the assistance system.

11.1.2 Implementation Details

The assistance system was assembled around the user's daily calendar, which was used as main input. The user's appointments were used to generate a user-specific *travel plan*, which includes tailored pedestrian and vehicle routes. While the former connect the appointment location to the parking lot, the latter connect parking lots of consecutive but different appointment locations. The assistance system generates route sequences with respect to user-specific constraints, such as a maximum tolerated walking distance between the parked vehicle and the appointment location. The assistance systems also accounts for infrastructural factors, such as the traffic flow or available parking capacity.

Travel plan generation is done in three stages. First, the user's calendar is examined. The purpose of this examination is to detect conflicting appointments. While overlapping appointments are rather easy to detect, it is more difficult to identify conflicts that appear to be feasible on first sight (e.g., no overlap in time) but turn out to be infeasible upon closer look (e.g., not enough time to overcome physical distance between appointments). In the second stage, the user's appointments are organized, such that the usable time between appointments is maximized. Finally, in stage three, resource allocation (e.g., parking lots) is integrated into the generation process.

The assistance system was designed as a multi-agent system, using the latest version of the *Java-based Intelligent Agent Componentware*, namely *JIAC V* (Lützenberger et al., 2013). Below, I describe the architecture of the assistance system.

System Architecture

In order to account for scalability, adaptability and privacy requirements we applied the multi-agent paradigm and developed our assistance as a decentralized system, where the systems entities (e.g., the user, the vehicle, or the parking-lot operator) were represented as autonomous JIAC V agents.

Due to the modular assembly, the agent paradigm facilitated the scalability and adaptability of the assistance system. Privacy was also ensured due to the distributed representation of knowledge. The system's architecture is illustrated in Figure 11.1.

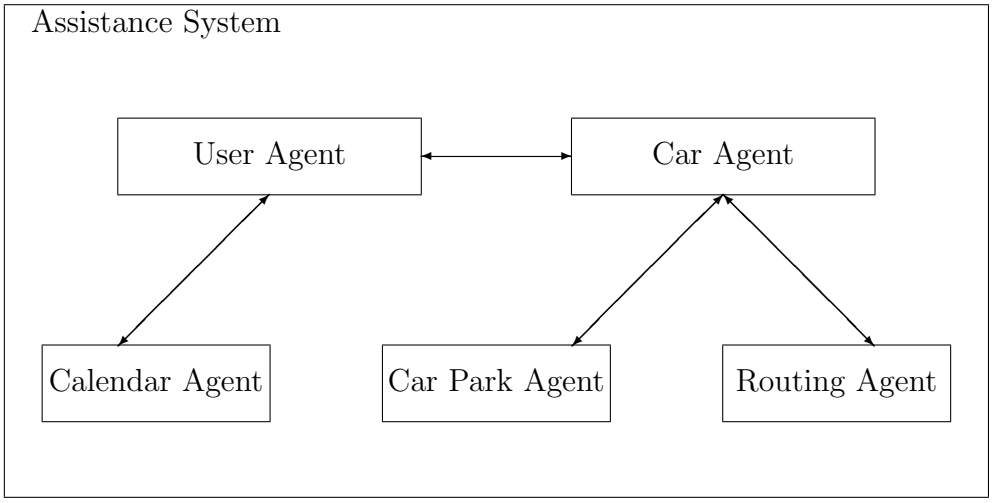

Figure 11.1: The architecture of our assistance system. Entities are represented by JIAC V agents (boxes). Communication between the agents is indicated by arrows (adapted from Hoch et al., 2011, Figure 1, p. 189).

The assistance system comprises five different agent types with respectively different tasks. The *user agent* represents the user perspective and analyses appointments with regard to location and time. The user agent identifies conflicting activities and initiates interaction with the user to resolve the conflict.

The *car agent* is responsible for route and parking related decision-making. The car agent receives planning requests from the user agent and selects routes and parking lot from all proposed options. The *calendar agent* provides access to a user calendar and offers additional functionality (e.g., modification, insertion of appointments) to other agents. The *car park agent* represents the car park operator and features resource management capabilities. The car park agent is able to process simple booking request, but also more complex inquiries, e.g., to return the nearest car park with available parking for a given location. Finally, the *routing agent* features routing capability and determines routes and travel times for a given start and a given target location.

The agents interact in order to optimize the user's mobility profile. This interaction is presented below.

Operation Principle

The optimization process is initiated by the user agent, who queries a list of all user appointments from the calendar agent. The user agent processes

these appointments in several steps. First, the location of the appointment is evaluated. For appointments without location entry the agent uses the user's office location. A user's default location, however, can be specified by means of user-specific settings.

Additional appointments are integrated, such that the time and location of the previous and the subsequent appointments are determined and forwarded to the car agent. The car agent uses this information to determine parking lots for each appointment location. In order to do so, the car agent sends a request to the car park agent, who manages and supervises parking capabilities and also provides a reservation service. Having a designated target location (the parking lot), the car agent requests the routing agent to determine vehicle routes between the parking locations of all appointments and pedestrian routes between the parking locations and the appointments, respectively.

Routes and parking lot locations are returned to the user agent, who examines the feasibility of the overall schedule. In the case that conflicts are identified, the system tries to resolve these conflicts automatically, e.g., by slightly shifting appointments within user-specific tolerance zones. As an example, there are situations in which it might not be possible to get from one appointment another within the allocated time. In such case, the user agent would inform the user about this conflict either by email or by sending message to a designated mobile device in order to solve the conflict interactively.

The above-presented process is iteratively done for each appointment in the user's calendar, until each appointment has been marked "processed". The process terminates when all appointments have been marked processed and the schedule becomes feasible. Journey information, such as a suggested departure time or route and target parking lot locations are added to the user's calendar.

The assistance system's operation principle is illustrated in Figure 11.2

In the following, I explain how the above-presented planning system was integrated into the simulation framework that I have presented in the previous part. Furthermore, I show how the simulation model was calibrated in order to serve as a benchmark for assessing the performance of our assistance system.

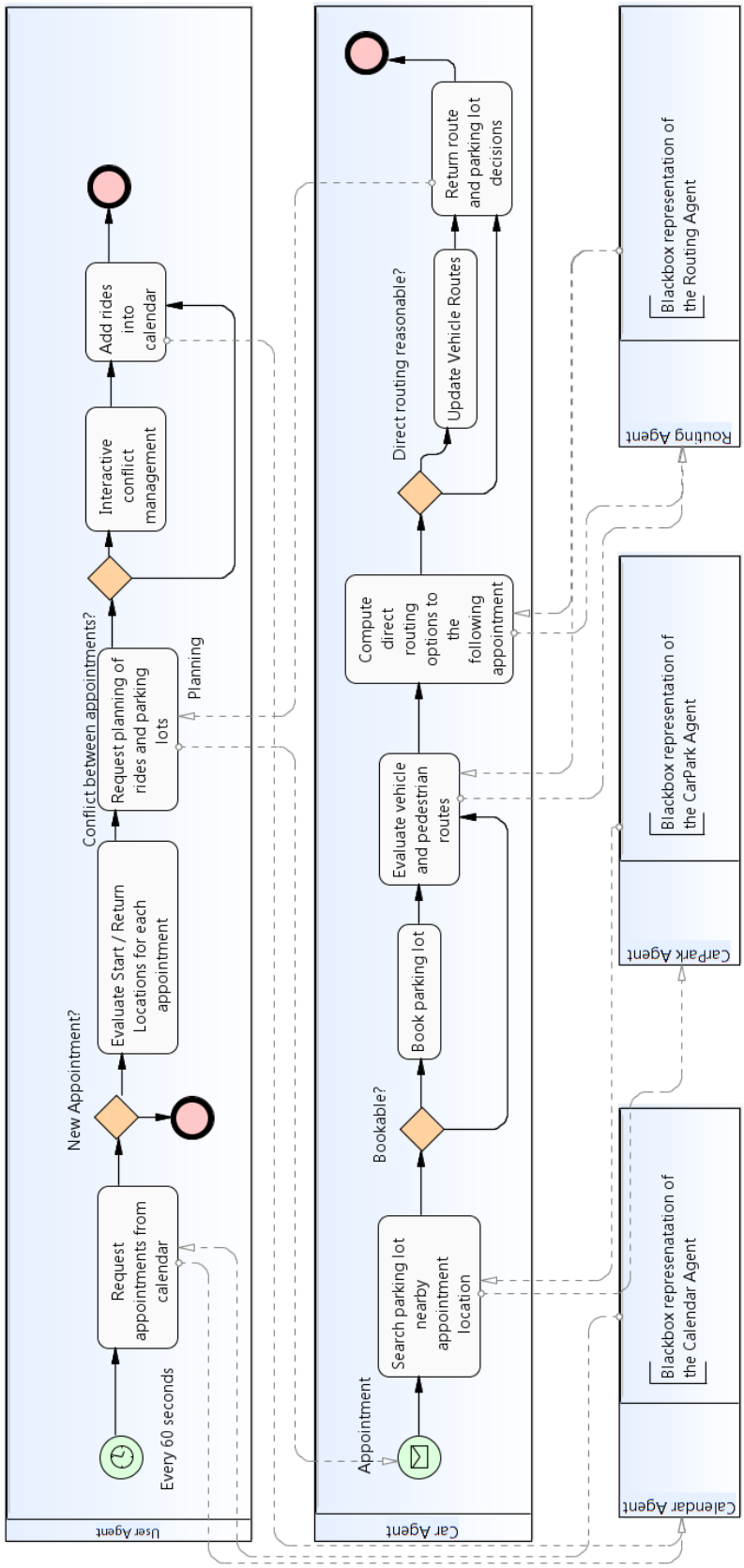

Figure 11.2: The automated planning approach, illustrated as a BPMN diagram (after Hoch et al., 2011, Figure 2, p. 190).

11.2 Configuration & Calibration

The simulation model was used to evaluate both, the efficiency of the assistance system, as well as the efficiency of regular human behavior.

In order to evaluate the performance of the assistance system, I used my simulation framework, but simply replaced the entire BDI reasoning cycle with the planning of the assistance system. Before the simulation, the simulated drivers received a set of appointments, which were processed by the system. The result of this planning process was a list of routes, including vehicle routes to selected (and reserved) parking lots, as well pedestrian route from the parking lot to the appointment location and vice versa. The route objects also contained departure and arrival times and I used this list to generate a corresponding list of `MoveOffEvent` objects for the simulation framework. The simulated drivers were adjusted to skip their perception phase. Furthermore, I re-programmed the drivers to avoid the computation of routes, but to take the predefined ones—which I stored within the `MoveOffEvent` instance, respectively. As a consequence to these adjustments, the drivers followed the schedule which was predetermined by the planning system. Due to their connection to the planning system, I henceforth refer to vehicles that were controlled by drivers that use the planning system as *planned vehicles*.

In order to evaluate the performance of drivers that are not in possession of an assistance system, I used the same list of `MoveOffEvent` objects as for the planned vehicles. The departure times account for the human capability to estimate trip durations—it is difficult to use my reasoning model (which is focused on reactive behavior rather than on proactive behavior) to reproduce this capability. To make the simulated drivers find their own routes, I removed all pedestrian routes (initially computed by the assistance system) from the list and replaced the locations of the `MoveOffEvent` objects (which is a parking lot) with the original appointment location. Finally, I assigned a precondition to the superior goals which are referenced by the `MoveOffEvent` objects. In order to account for the fact that drivers are required to arrive at an appointment location on foot, I defined this precondition as follows:

$$driver.vehicle = \emptyset. \tag{11.1}$$

The simulation was done for the capital region of Berlin, Germany, thus I selected a fitting map as simulation topology. I used the previously described editing tool (see Section 6.2.2, also Appendix D) to automatically extract all car park occurrences in this map and to assign infrastructural features to these locations. In total, 390 car parks were identified. I specified their preconditions as follows:

$$driver.vehicle \neq \emptyset.$$

For the effects, I defined that the driver is no longer within their vehicle and that the current capacity of the car park is decreased by one. In more detail, these effects look as follows:

$$driver'.vehicle = \emptyset,$$

and

$$c'.capacity = c.capacity - 1.$$

I designed the duration method *dur* of the car park to constantly return $now + 1$. The capacity of the car parks was also derived by the editor. OpenStreetMap provides capacity values for most car parks, yet, values that were not available were derived by the car park's geographical size.

For the simulation, I assumed that drivers were aware of all car park locations from the beginning. For the matter of simplicity, I refrained from adding all car parks to the driver's belief base. Instead, I decided to set the drivers' `rangeOfSight` attribute to infinity—which has the same effect, namely that driver's are aware of all car park locations from the beginning:

$$\forall d \in \mathbb{D} : d.rangeOfSight = \infty.$$

Finally, I designed the utility function of the simulated drivers to measure the proposed strategies according to the required time—the least time, the best value. As a consequence to this configuration, unplanned drivers wait at their home locations until a `MoveOffEvent` occurs. Whenever such event

is triggered, the associated superior goal is placed within the goal base of the driver.

Evaluating their options, the drivers recognize that it is currently not possible to achieve the superior goal (as a consequence to Equation 11.1), thus, the drivers compute (vehicle) routes to all know car parks and pedestrian routes from the car parks to the appointment location. These sequences are assessed by the utility function and the fastest combination is selected.

I consciously defined no precondition that checks whether the car park provides enough capacity or not in order to account for the fact that drivers do not know about the car park's utilization. This is the exact point where other approaches fail. Contemporary traffic simulation models do not allow to distinguish between the driver's assumptions about a given situation and the situation in reality. The BDI-based approach, however, makes it possible to define such discrepancy and to simulate strategic level decision-making which results from this incomplete (or in this incorrect) knowledge (see also Section 8.2.2).

Yet, in order to make this mechanism work, I had to adapt the simulation engine to perform a check before the effects of an infrastructural feature are applied. In the case that a driver aims to use a car park with no available parking, the simulation engine detects the inconsistency and removes the infrastructural feature from the driver's belief base. Subsequently the driver's reasoning process is initiated and an alternative option is computed.

To make the performance of unplanned and planned vehicles comparable, the same appointment sequences were used as input parameter. These appointment sequences comprised a maximum of six appointments and a minimum of two appointments with an average of four appointments per day. The average appointment duration was 60 minutes, while the minimum and maximum duration was limited to 15 mintes and 120 minutes, respectively.

The appointment sequence was conflict free, that is, it was feasible to find a route/car park selection. Vehicle energy levels were also sufficient, that is, the battery provided enough energy for the entire day.

Unplanned vehicles receive their travel instructions not from the travel planner. Instead, they are following a scheme, which "arguably represents

the real world behaviour of drivers" (Hoch et al., 2011, p. 191). The scheme cannot revert to experience or intuition for a particular route or destination. The unplanned vehicle's appointment sequence is transformed into the vehicle travel plan as follows:

The unplanned vehicle heads towards the parking lot which is closest to the appointment location. Upon arrival, the vehicle executes the car park's effect method eff. In the case that parking is available, the invocation succeeds and the effects are applied. The driver will park their vehicle and proceed to the appointment location on foot. In the case the invocation fails, the infrastructural feature is removed from the driver's belief base and the reasoning cycle is initiated. As a consequence, the driver proceeds to the next car park. The simulation records the route travel time and distance of the unplanned vehicle, which includes the walking time and distance.

Due to the search process, it is by all means possible that a driver is delayed or misses an appointment. The driver considers an appointment as missed if they have unsuccessfully searched for an available parking space before exceeding the start time of the appointment by more than 15% of the appointment duration. When an appointment is missed the appointment-related parameters, e.g., walking distance and time, are filtered from the results.

The traffic scenario is restricted to a 100 km by 120 km map section of Berlin, Germany. Appointments can be generated for each available street number within the map. The average walking distance from any appointment location to its nearest car park was determined with 1.398 meters. The mean route length between two equally distributed appointment locations within the scenario was determined with 18.6 kilometers.

11.3 Simulation Results

The purpose of this evaluation was to show that resource scheduling has the potential to improve the quality of the daily travel plan. The user wants to get from A to B in the least possible time. The user also expects adherence to their schedule, which requires an accurate travel time prediction and shorter walking distances from the parking lot to the appointment locations.

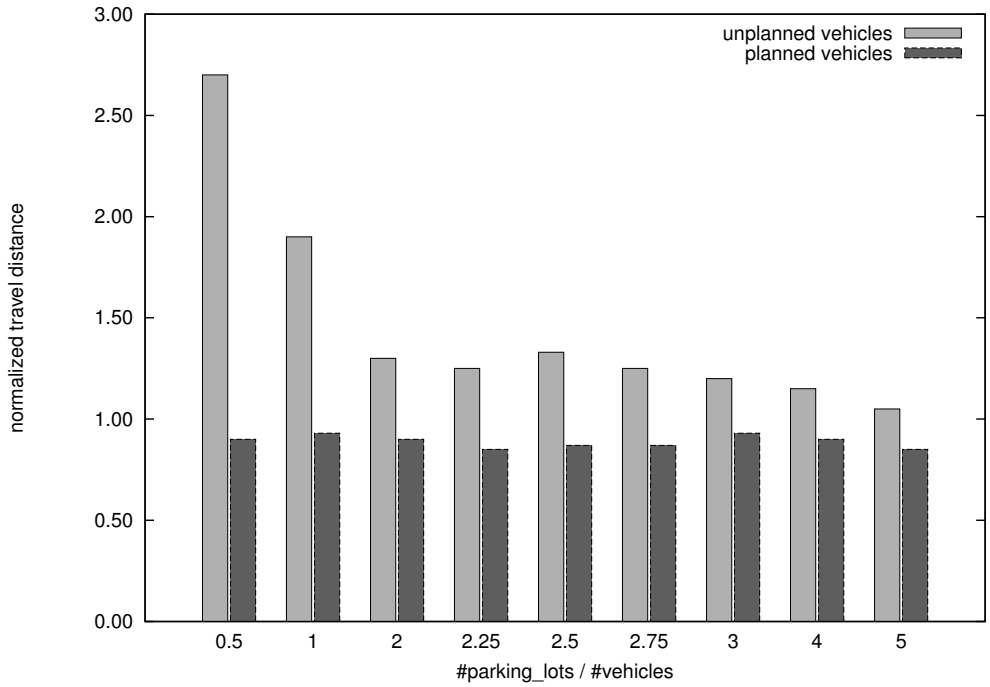

Figure 11.3: Average travel distance (per trip) of planned and unplanned vehicles over varying degrees of parking lot availability (adapted from Hoch et al., 2011, Figure 3, p. 193).

Resource scheduling was measured with respect to singular appointments. The individual user's benefit from the planning system was quantified over the varying availability of parking spaces.

The performance of the assistance system was measured by four parameters, namely the travel distance, the travel speed, the overall journey time, and the amount of failed appointments. I present the simulation results for all three parameters below.

11.3.1 Travel Distance

The first value that was determined was the average distance that was driven for each appointment. The travel distance was normalized over the scenario's average route length. Figure 11.3 compares the average travel distance per journey for planned and unplanned vehicles.

It can be seen that planned vehicles travel an average of 87% of the scenario's mean route length. Travel distance of planned vehicles is constant over parking space availability. With the reduction of available re-

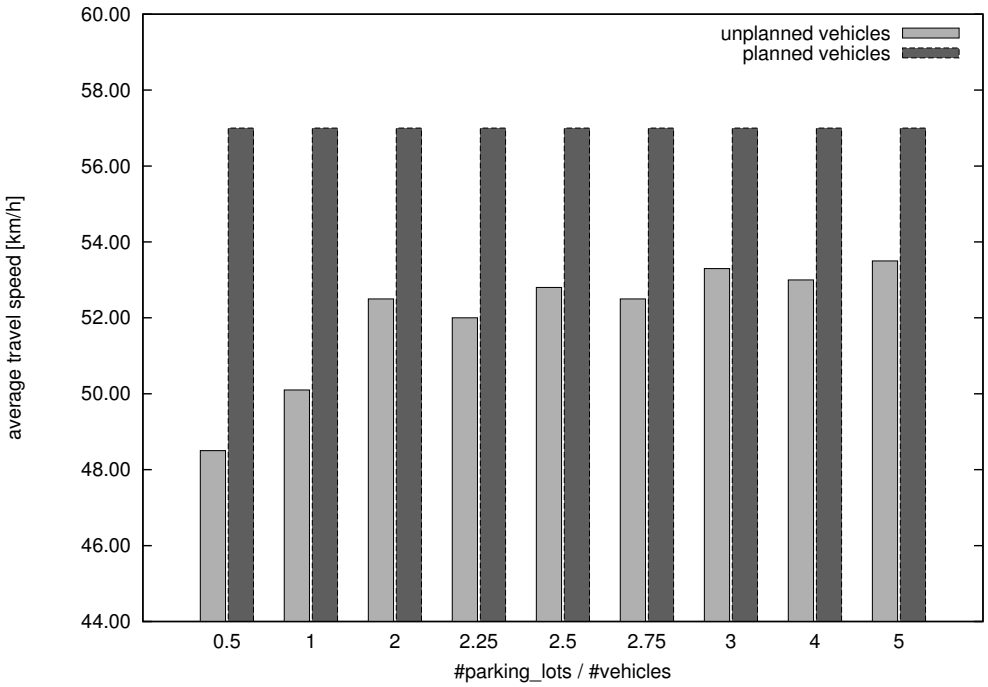

Figure 11.4: Average travel speed (per trip) of planned and unplanned vehicles over varying degrees of parking lot availability (adapted from Hoch et al., 2011, Figure 4, p. 194).

sources, planned vehicles gain distinct advantage over unplanned vehicles. Figure 11.3 also emphasizes that resource planning can reduce driving distance up to 67%. Towards high resource availability, travel route distance for planned and unplanned vehicles converges.

11.3.2 Travel Speed

Searching for parking spaces generally increases the time that is required to reach an appointment. In order to measure this increase, the average distance from source locations to appointment locations was divided by the average time that was required to reach the parking location that was used for the appointments. The result is the trip's average travel speed. Figure 11.4 shows the average travel speed of planned vehicles to be 57 km/h and remains constant over parking lot availability. The travel speed of the unplanned vehicles is on average 4.9 km/h lower the travel speed of planned vehicles. Once again, planned vehicles become increasingly advantageous with decreasing parking space availability.

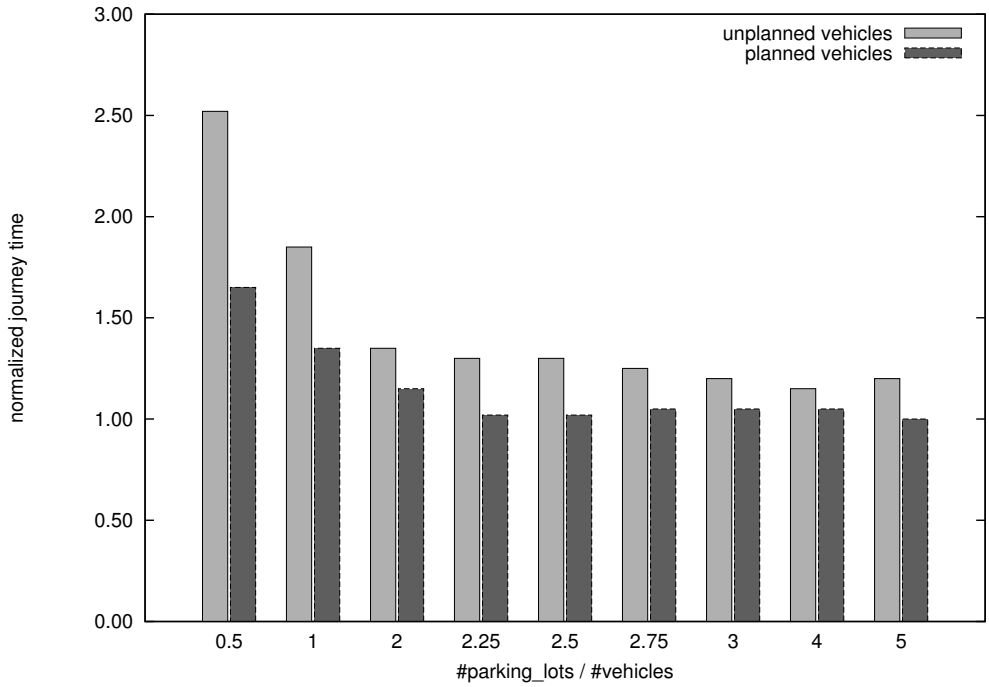

Figure 11.5: Complete journey times (per trip) of planned and unplanned vehicles over varying degrees of parking lot availability (adapted from Hoch et al., 2011, Figure 5, p. 195).

11.3.3 Total Journey Time

The third parameter that was used to compare the efficiency of the assistance system to human behavior is the total journey time. The total journey time is considered to be the sum of the vehicle travel time and the walking time from the parking lot to the appointment location. Journey time is normalized with respect to the simulated journey time at the ratio:

$$\frac{parking\_lots}{vehicles} = 5.$$

Total journey times for planned and unplanned vehicles are illustrated in Figure 11.5.

11.3.4 Failed Appointments

The last parameter that was used to determine the performance of the assistance system was the count of failed appointments. Figure 11.6 displays the rate of failed appointments of planned and unplanned vehicles

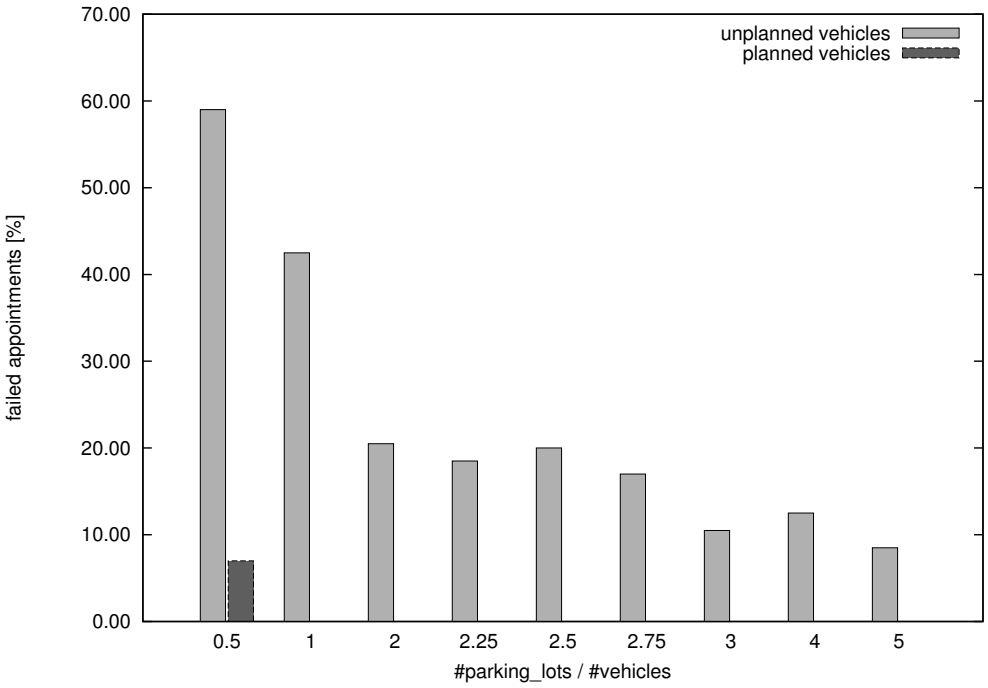

Figure 11.6: Rate of failed appointments (per day) of planned and unplanned vehicles over parking space availability (adapted from Hoch et al., 2011, Figure 6, p. 195).

with respect to parking availability. With a decreasing parking availability, unplanned vehicles increasingly miss appointments. At a ratio of .5, unplanned vehicles miss nearly 60% of their appointments. Vehicles that miss appointments are not counted for evaluation of route distance, walking time or journey time. This explains the unexpectedly low difference in journey time (see Figure 11.5).

11.3.5 Result Discussion

As can be expected from Figure 11.3 and Figure 11.4, the planned vehicles' savings in journey time are especially significant in an environment of low parking space availability. However, at the ratio of .5 and 1, the difference in journey time between planned and unplanned vehicles is unexpectedly small. For example, at .5 parking space availability, the journey times of unplanned vehicles appear to not replicate the significant drop in average travel speed (see Figure 11.4) and the dramatic increase in average travel distance (see Figure 11.3). As has been stated in (Section 11.2), appointments are considered missed if the vehicle does not succeed to find a

parking space before the start time of the appointment is exceeded by 15% of the appointment duration.

The simulation results emphasize that resource scheduling reduces the average travel distance and in particular reduces the parking search distance. Additionally, average travel speed can be increased whilst overall journey time can be reduced. Most importantly, the rate of missed appointments can be significantly reduced. The advantage of planned over unplanned vehicles increases in environments of sparse resource availability.

Based on these results, it can be argued that resource scheduling has the potential to improve the quality of the daily travel plan. □

11.4 Discussion

In this chapter, I presented the first comprehensive evaluation that was done by means of the simulation model that I presented in this thesis.

The purpose of this evaluation was to compare the performance of drivers that apply an assistance system to drivers that are not in possession of such system. The purpose of the assistance system was to optimize the driver's travel pattern with respect to time and efficiency.

In more detail, the assistance system determined available parking lots in close distance to appointment locations and proposed departure times as well as routes from the current location to the parking lot, from the parking lot to the appointment location, and back to the parking lot. The advantage of such system is the knowledge about available parking spaces—regular driver's have no such knowledge. This is the exact point where other simulation-based approaches fail. In Section 5.3, I showed that contemporary approaches do not allow to use varying levels of knowledge for the simulated drivers. Furthermore, most approaches are based on the user-equilibrium and do not account for the fact that drivers are not able to act optimal in situations where their knowledge is incomplete. The BDI-based approach—and the belief base in particular—makes it possible to define discrepancies between assumed states and real situations (see also Section 8.2.2. Such feature becomes most important if one wants to analyze the capabilities of information systems (such as the above-presented assistance system). These systems mainly aim to maximize the driver's knowledge, yet, in order

to assess the effects of such systems, one has to compare their performance to drivers that act on their own. Nevertheless, in order to simulate drivers that act on their own, a flexible knowledge configuration is indispensible.

The simulation model accounts for this exact feature, thus, it was possible to determine the capabilities of the assistance system by simulating drivers that have access to the system (namely planned vehicles) and comparing their performance to drivers that find routes and parking lots on their own (namely unplanned vehicles).

I used my simulation framework for both categories of drivers. For unplanned vehicles, I adapted the agent model such that the behavior was not generated by the BDI reasoning cycle, but by the assistance system. Contrary, I used the original BDI reasoning cycle to mimic the behavior of unplanned vehicles. In order to properly define the infrastructure model, I used the editing tool, which I introduced in Section 6.2.2, to automatically extract car park occurrences in the OpenStreetMap representation of Berlin, Germany.

In total, 390 car parks were identified. After specifying their preconditions, effects and duration methods, I extended the simulation engine with the capability to validate the applicability of the eff method. This extension was required in order to account for the fact that drivers are aware of the presence of car parks, but not aware of their current utilization—a good example for incomplete knowledge.

Finally, I conceptualized the drivers' personality by means of a utility function. This function was designed to measure the proposed strategies according to the required time—the least time, the best value.

I used randomly generated appointment sequences to assess the efficiency of the assistance system and the behavior of unplanned vehicles (generated by the BDI-based approach), respectively. In total, I used four parameters to determine the assistance system's superiority over human behavior, namely: travel distance, travel speed, journey time, and number of failed appointments.

The simulation results emphasize that resource scheduling reduces the average travel distance and also the parking search distance. Additionally, average travel speed can be increased whilst overall journey time can be

reduced. Most importantly, the rate of missed appointments can be significantly reduced. The advantage of planned over unplanned vehicles increases in environments of sparse resource availability.

The simulation model fit purposes for this evaluation. It was possible adjust the simulated drivers' personality, to tailor their knowledge and their awareness for external factors. To sum up, the drivers' behavior reflected was in compliance with reality.

The generic simulation model was able to account for most of the scenario-specific requirements—only few additions were needed. To start with, the application of the effect method eff had to be validated. This additional validation, however, is actually a useful extension to the generic model. It can be used to safeguard the simulation engine against inconsistencies. Furthermore, the goal-mechanism had to be adjusted to account for preconditions for superior goals. This addition, however, was easily done as the same class-type is used to represent superior and sub-goals—the required field was already available.

12. The Mini E Case

The second evaluation that was done by means of the presented simulation model was done within the government-funded research project *MINI E powered by Vattenfall*, or *Mini E 1.0* (Keiser et al., 2011, also Steuer et al., 2013).

The purpose of the Mini E 1.0 project was to develop a decentralized control system for the charging processes of electric vehicles. The vehicles were equipped with the vehicle-to-grid (V2G) technology. The V2G technology allows vehicles to feed their energy back to the energy grid and thus to act as a controllable energy source.

The control system was supposed to assist the drivers of electric vehicles to schedule their charging intervals. The objective was to decrease to the overall CO_2 consumption of the vehicle.

In order to account for that objective, the system acquired information on current and future CO_2 emissions of energy from the energy grid and shifted charging intervals to periods with low CO_2 emission. Feeding processes, on the other hand, were scheduled for periods with high CO_2 values.

Although the system was deployed in reality, it was necessary to assess its quality by means of simulation. My simulation model was used for this very purpose. The idea was to compare the efficiency of the control system to charging as it is intuitively done by human drivers—clearly a strategic level decision. In more detail, two categories of drivers were simulated. First, there were those drivers that follow the suggestions of the control system

and charge their vehicles in compliance with the proposed charging schedules. Secondly, there were drivers that have no access to the optimization system and determine charging and feeding periods for themselves. While the behavior of the former category was generated by the control system, my BDI-based decision-making model was used to generate the behavior of those drivers that were not in possession of such system. The aim of this evaluation was to show that it is generally possible to decrease the effective CO_2 emissions of electric vehicles by anticipatory planning.

In this chapter, I present the developed control system and put particular emphasis on its objective and its implementation (see Section 12.1). Subsequently, in Section 12.2, I explain the evaluation scenarios and show how the simulation model was adjusted to account for realistic evaluation results. I present these results in Section 12.3 and wrap up with a discussion in Section 12.4.

12.1 The Application

The purpose of the Mini E 1.0 (Keiser et al., 2011, also Steuer et al., 2013). project was the development of a decentralized control system for the charging processes of electric vehicles. The control system was designed to reduce the effective CO_2 emissions of electric vehicles and to maximize the benefit of all stakeholders that are involved in electric mobility. In total, we accounted for three stakeholders, namely the driver, the vehicle manufacturer, and the charging station operator.

The system was deployed in reality, yet, it was considerably difficult to assess its efficiency. The reason for this is that real CO_2 calculations can only be done in an enclosed test-bed with detailed knowledge about the composition of the energy mix from the grid. At the time when the system was developed, we were not in possession of such test-bed, thus, in order to estimate the capabilities of the control system, we used a simulation-based approach.

It was necessary to simulate two categories of drivers. First, there was a category of drivers which have access to the control system. These drivers use their electric vehicles in compliance with the charging and feeding plans that were proposed by the control system. Secondly, there were drivers

that have no access to the optimization system and determine charging and feeding periods for themselves.

Based on experiences that we collected in the joint project with Volkswagen AG (see Chapter 11), we derived the behavior of drivers with access to the control system directly from the control system. Contrary, actions for drivers without access to the control system, were generated from the BDI-based decision-making model.

In the following, I present the control system in more detail.

12.1.1 The Objective

The purpose of the control system (Keiser et al., 2011, also Steuer et al., 2013). was twofold. First, it was our intention to minimize the effective CO_2 emissions of electric vehicles that were operated by our control system. This objective appears to be paradoxical—is it not that electric vehicles produce no emissions? As a matter of fact, it is true: electric vehicles produce no direct CO_2 emissions! Nevertheless, in order to charge electric vehicles, energy is required. In the most cases, this energy comes from the public power grid, thus, the energy for itself is indirectly burdened by the emissions of those production processes that are required to produce this energy. The fact is that the composition of these processes varies over time. At sunny or windy days, for example, an increased share of the overall energy production is supported by energy from renewable energy sources. As a consequence, the resulting CO_2 fingerprint decreases. Contrary, the CO_2 fingerprint increases when most energy is produced by conventional procedures (e.g., nuclear or coal power plants). The time-dependency, however, allows to adapt consumption patterns towards the effective CO_2 fingerprint of the energy grid and thus to decrease the emissions of consumers. The idea of the control system was to exploit this very connection in order to arrange charging and feeding processes, such that the effective emissions of electric vehicles are optimized.

The second objective of our development was to represent the objectives of all stakeholders that are involved in the charging process of an electric vehicle. In this project, we accounted for three stakeholders, namely the driver, the battery manufacturer, and the charging station operator. To start with, the driver is mainly interested in unrestricted mobility, that is,

batteries should never decrease a certain threshold in order to reflect the driver's interests. Secondly, the battery manufacturer (we did not distinguish between the battery and the vehicle, thus the battery manufacturer is also referred to as: the vehicle) is interested in maximizing the lifetime of the battery, thus, the battery manufacturer is interested in the implementation of specific charging and feeding profiles that maintain the operability of the battery. Finally, the charging station operator aims to have a reliable additional energy source, which can be used in order to balance the local energy grid (e.g., by means of the V2G technology).

The interests of the stakeholders are conflicting.

12.1.2 Implementation Details

We considered the driver to be the most critical stakeholder in the system. The acceptance of electric vehicles is measured by the experience of drivers, thus, we decided to make the driver—and their interests—vital for the system.

In order to learn about the requirements of drivers in our system, we accessed the drivers' calendar and extracted appointments, respectively for the next 24 hours. We used these information as input parameters for the control system.

Due to the involvement of different parties with different interests we applied a negotiation-based approach and used agent-technology for the implementation of the system. In more detail, we used the JIAC V agent framework (Lützenberger et al., 2013) and represented the active negotiation roles as agents. I proceed by presenting the system's architecture.

System Architecture

Given that the system was supposed to be deployed in reality, we had to assume that the representations of the stakeholders are truly distributed, such that parts of the overall application might be running on user devices (e.g., the representation of the driver), on the charging station, on backend servers, or on the vehicles' hardware. We dealt with a truly distributed environment, where software instances negotiate autonomously in order to maximize the profit of their stakeholders.

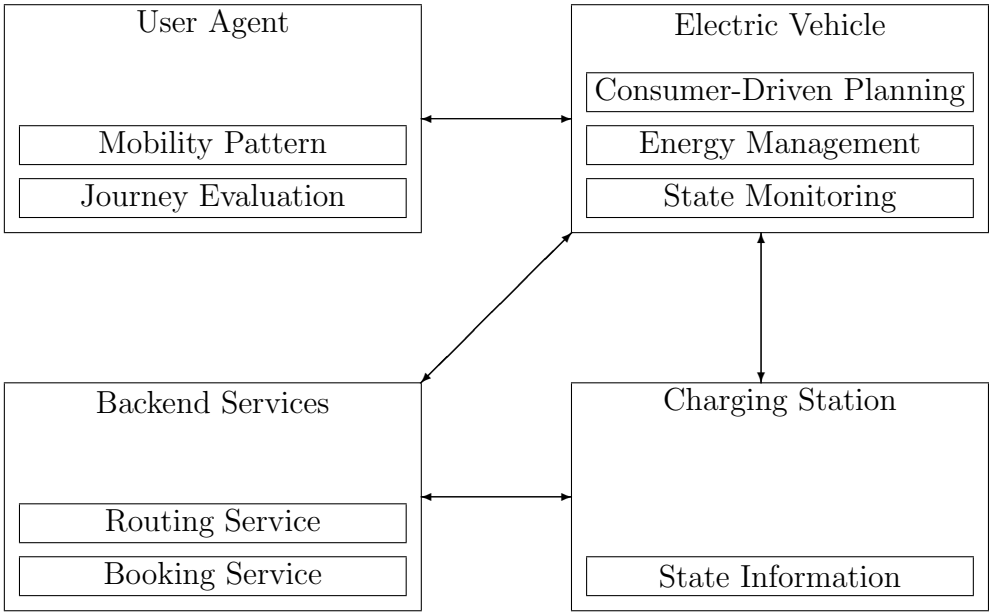

Figure 12.1: The architecture of our energy management system. Entities are represented by JIAC V agents (boxes). Functional components, namely *Agent Beans* (inner boxes) and communication between the agents (arrows) are indicated as well (adapted from Keiser et al., 2011, Figure 1, p. 274).

The development of software, which comprises distributed, autonomous and negotiating components is significantly eased by agent-oriented software engineering. The implementation of distributed application is actively supported by agent technology. Due to the innate distribution of the problem domain, we decided to develop our energy management system as decentralized multi-agent project, where components that actively participate in the negotiation process were represented as software agents. For the implementation we selected the JIAC V agentframework (Lützenberger et al., 2013). The assembly of our multi-agent system is illustrated in Figure 12.1

All software agents were designed to optimize their profit by means of negotiation. Their engagement was based on several factors, e.g., the planned usage of the vehicle, the availability of the charging stations, the energy consumption, the current battery level, and the grid load. Furthermore, weather forecasts were used to predict periods with high shares of renewable energy (and respectively low emissions).

The distributed system was able to act as energy management system, which used available information (e.g., the user's schedule, the current battery level, the expected amount of renewable energy) to calculate a charg-

ing and feeding pattern with maximized profits of all involved stakeholders. Stakeholder-specific interests as well as responsibilities of the software agents that reflect these stakeholders in the system are illustrated in Table 12.1.

Table 12.1: Stakeholder-related constraints as well as responsibilities of agents that reflect these stakeholders in the system (adapted from Keiser et al., 2011, Table 1, p. 274).

Stakeholder	Constraints	Responsibilities
User	ensure given range, ensured mobility	definition of the ecological attitude and risk attitude of the user
Vehicle/Battery	ensured mobility, reasonable charging- and feeding processes	energy management
Charging Station	consumption of available renewable energy, feeding from batteries during peak load hours	capacity management, grid demand- and wind forecasts

In order to act as an energy management system, the agents communicate, negotiate, and cooperate. I describe this interaction mechanism in the following.

Operation Principle

Due to the fact that the user determines the vehicle's utilization, the energy management process is initiated by the *User Agent*. The User Agent accesses the user's mobility pattern, which mainly comprises future appointments in a calendar.

Utilization data is send to the *Car Agent*, which uses the information to calculate the expected energy consumption of the vehicle. In order to do so, the Car Agent determines routes from the user's current location to the appointments and between the appointments, or, if time allows, back to the current location. Routing capability is provided by backend-services. Based on these routes and vehicle-specific information, the Car Agent determines

the battery's state-of-charge for the next 24 hours. This estimation is used as input for the energy management behavior of our multi-agent system. This mechanism works as follows:

The Car Agent constantly observes the estimated energy profile for the vehicle. Whenever the vehicle's state-of-charge drops below a user-specific threshold, the Car Agent tries to schedule an additional charging process (or to re-schedule an existing one). What happens is that all potential charging periods (time intervals where the vehicle is parked and has access to some form of charging infrastructure) before the identified threshold violation are examined. From all potential periods, the algorithm removes those periods that are not able to increase the battery's state-of-charge beyond the threshold. All remaining options are assessed by the interval-specific quotient of the portion of energy from renewable energy sources and the expected energy demand from the grid. "Profitable" charging intervals should feature a high share of renewable energy and a low grid demand. To be more precisely: A charging interval is preferred to another if the interval-specific quotient is higher. Interval selection which is based on this mechanism contributes to the utilization of renewable energy. Furthermore, due to the consideration of the grid-sided demand, grid load balancing is done as a positive side effect.

While the above-presented mechanism only accounts for the charging of electric vehicles, the vehicles' V2G capability has not been used so far. V2G capability is considered by the second part of the system's energy management capability and, again, triggered by the Car Agent. The planning process is initiated whenever the mobility pattern of the user changes. In this case, existing feeding intervals are rejected and completely recalculated. Feeding actually does not contribute to the driver's interests, thus, only grid-related aspects are considered for selecting feeding intervals. Possible feeding intervals are assessed by means of the reciprocal for the quotient that was used above in order to determine the quality of charging intervals. Once the most promising interval has been identified, the Car Agent determines whether the feeding violates the user-specific battery threshold. If the threshold is violated, the next best interval is tested, and so forth. In the case that none of the candidates features a certain quality, the Car Agent tries to compensate the violation by adding another charging process. If the agent fails, the V2G scheduling terminates.

The system assumes that users are initially located at their designated home location and that these users return to their home locations at the end of the day. Furthermore, the system assumes that the users' home locations are equipped with some charging infrastructure.

Information on external charging capabilities is provided by a backend-service, namely the charging station booking service (see also Figure 12.1, backend-services). The charging station booking service provides detailed information on availability, particular characteristics, as well as the location of charging stations. Furthermore, the charging station booking service provides reservation capability and thus ensures access to the charging infrastructure for a desired time slot.

12.2 Configuration & Calibration

The efficiency of our energy management system was determined by means of simulation. Based on the positive experiences (see also Section 11), we used the simulation framework that I presented in this work. To assess the capability of our energy management system it was necessary to simulate drivers that are in possession of such system and compare their performance to drivers that act on their own.

In order to simulate the former category of drivers, I used the same approach as in the previous section and simply replaced the entire BDI-based reasoning cycle with the planning capability of our energy management system. The system uses a driver's calendar as input parameter, computes a set of routes (including departure and arrival time), and proposes charging periods. This information is used to generate valid input parameters for the simulation framework. Departure times were used to generate `MoveOffEvent` objects. These objects were used to store the routes that were calculated by the energy management system. The drivers were configured to avoid computing routes on their own but to use those from the `MoveOffEvent` objects. Furthermore, the drivers were programmed to skip their perception phase in order to exactly follow the scheme that was generated by the energy management system. To account for charging processes, I reused the `ChargingEvent` type, which I introduced in Section 6.2.3. `ChargingEvent` objects contain information about the start and end time of charging processes. Information about the applied amperage for the process is stored as

well. Whenever a `ChargingEvent` instance is scheduled for the current simulation interval, the simulation engine uses the amperage and the current energy level of the vehicle's battery to calculate the battery's energy level for the simulation cycle. The simulated charging process terminates when the `ChargingEvent`'s end time has been reached.

As a consequence to the above-described adjustments, the drivers followed the guideline that was proposed from the energy management system. For the matter of simplicity, I refer to vehicles that were controlled by drivers with access to the energy management system as *planned vehicles*.

Contrary to planned vehicles, I used my original approach to mimic the behavior of drivers that are not in possession of the energy management system, but schedule the charging processes on their own. I refer to vehicles that were controlled by drivers whose behavior is generated by my model as *unplanned vehicles*. To make the performance comparable, I used the same list of `MoveOffEvent` objects as I used for planned vehicles. From these `MoveOffEvent`s, I removed the predetermined routes and replaced the target location (which is either a parking lot or a charging station) with the original appointment location. The energy management system includes some form of parking guidance, yet, drivers without such system have no information about the utilization of parking and charging infrastructure. Thus, they have to determine parking locations for themselves.

In order to account for the fact that drivers have to arrive at appointment locations on foot, I added the following precondition to the goals that were connected to the `MoveOffEvent` objects.

$$driver.vehicle = \emptyset. \tag{12.1}$$

Simulation was done for the capital region of Berlin, Germany. I used the same mechanism as presented in the previous chapter to extract information about the location of car parks (see also Section 11.2). In total, 390 car parks were identified. It was necessary to account for charging infrastructure in this scenario, thus, I respectively specified two infrastructural features (one for parking capability and one for charging capability) for each car park.[1]

[1] The real charging infrastructure in Berlin was not as far developed as in this scenario. For this evaluation, I used "fictitious" but fixed configurations.

I defined the following precondition for both infrastructural features:

$$driver.vehicle \neq \emptyset.$$

For the parking capability I additionally defined that the vehicle's energy level has to be above 20%:

$$driver.vehicle.battery.soc > .2 \cdot soc\_max. \tag{12.2}$$

I specified the following effect for both infrastructural features:

$$driver'.vehicle = \emptyset.$$

For the charging capability, I specified an additional effect, that is:

$$driver'.vehicle.amperage = \begin{cases} 64 & , driver.vehicle.battery.soc \leq .2 \cdot soc\_max \\ 0 & , else. \end{cases}$$

The effect implies that a charging process is started whenever the battery's state of charge drops below 20%. The energy management uses a similar concept, namely a user-specific state of charge threshold. To make the approaches comparable the thresholds of planned as well as unplanned vehicles was set to 20%.

To make this approach work, I had to adjust the drive plan of the drivers. Plan objects provide information about the driver's walking and driving capability, e.g., the required time. The drivers use this information to assess their options, thus, I extended the `PlanObject` for the driving capability to not only return the required time for a route, but also the expected state of charge. For the consumption of the vehicles, I assumed 0.2083 kWh/km, the specific consumption rate of a *Mini E*.[2] Drivers can use this information to validate applicability of infrastructural features.

[2]Detailed characteristics can be found at the Mini E website: `http://www.mini.com/minimalism/product/mini_e/`.

As an example consider a driver that expects to arrive at a target location with a battery level below 20%. As a consequence to Equation 12.2, any execution of a parking service will fail. The only option is to find the closest charging service—or a car park which is closer to the departure location and can be reached without violating the driver's battery-level tolerance.

I designed the duration method *dur* for both infrastructural features to constantly return $now + 1$.

Like in the previous chapter, I assumed that drivers were aware of all car park locations from the beginning.

$$\forall d \in \mathbb{D} : d.sight = \infty.$$

Finally, I defined the utility function of the simulated drivers to measure the proposed strategies according to the required time, the faster, the better.

During the simulation, unplanned drivers wait at their home locations until a `MoveOffEvent` is detected. Whenever such event is triggered, the associated superior goal is placed within the goal base of the driver. The driver recognizes that the preconditions for achieving the superior goal are currently not given (due to Equation 12.1). Thus, routes to all know infrastructural features and pedestrian routes from the infrastructural features to the appointment location are computed. These sequences are assessed by the utility function and the fastest combination is selected.

Contrary to the evaluation that I presented in the previous chapter, I equipped the car parks and the charging stations with unlimited capacity. It was not my intention to assess the resource-management capability of our system, but to evaluate the energy management system's capability to decrease the effective CO_2 emissions of controlled vehicles. Thus, whenever a vehicle arrived at parking (or charging) location, the simulation engine directly executed the feature's effect method eff (without validating its applicability).

Charging processes were recorded by the simulation engine and later assessed with respect to the grid energy's time-dependent CO_2 fingerprint. For this assessment, I used the same information as it was used by the energy management system. The energy management system was aware of

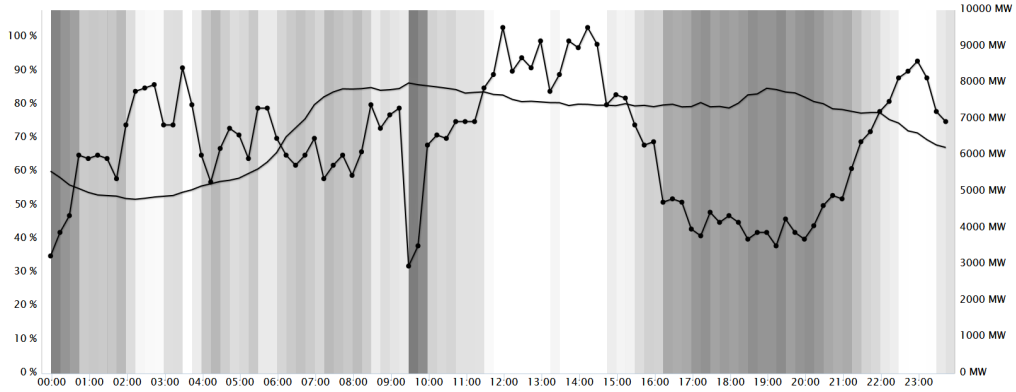

Figure 12.2: The illustration shows all relevant input parameters for the energy management system (and also for the simulation-based assessment). The available amout of wind energy (dotted line) as well as the expected energy demand (regular line) are illustrated. The quotient which is used to determine the efficiency of charging and feeding intervals is presented as well (dark areas indicate profitable feeding intervals, while light areas indicate profitable charging intervals) (after Keiser et al., 2011, Figure 2, p. 295).

both, the CO_2 fingerprint as well as the expected grid demand. To make the scenario as realistic as possible, I selected real data for both, the total amount of renewable energy[3] and the grid-sided energy demand. Input values for our scenario are illustrated in Figure 12.2.

The appointment sequences were generated by random, yet, I configured the production process to generate patterns that were in compliance with the *Mobilität in Deutschland 2008* study (Federal Ministry of Transport, Building and Urban Development, 2010).

Appointment sequences were based on a regular working day. This working day was extended by further appointments before and after the user's working time. In total, the daily mileage for all appointments was 133.28 kilometers (or 82.82 miles). Although the first use of the vehicle was scheduled not before 7 a.m., the simulation starts at 10 p.m. of the previous day—when the user connects their electric vehicle to their home charging station. This design decision was made in order to account for the night time, which, in fact, was only interesting for planned vehicles. Unplanned vehicles were not able to utilize the "pre-simulation" night time, as their initial battery level was set to 100%. Furthermore, by definition, unplanned

[3]In this scenario, we only accounted for energy that was produced by wind turbines.

vehicles were not capable of V2G, thus, only planned vehicles were able to utilize this particular time interval.

To compensate statistical outliers, 1.000 unplanned and 1.000 planned vehicles were simulated. To assess the capability of the energy management system, I respectively determined the drivers' CO_2 efficiency. In order to compare the performance of electric vehicles to conventional vehicles, a third simulation was done. In this third simulation, I removed all charging infrastructural features from the map and replaced the electric vehicles' consumption model with a fuel driven consumption model.[4] In the following I present collected simulation results.

12.3 Simulation Results

The purpose of this evaluation was to show that it is generally possible to decrease the effective CO_2 emissions of electric vehicles by anticipatory planning.

For the fuel-driven vehicle, an overall CO_2 fingerprint of 18.126 gram was determined. The determined value is independent from any grid load or wind availability forecast but was only used to emphasizes the difference between the fuel-driven and the electric powertrain.

To calculate the performance of planned and unplanned electric vehicles, it was necessary to define the CO_2 fingerprint of energy that is stored within the vehicle's battery at the beginning of the simulation. It was assumed that this energy comprised a share of 20% from nuclear and fossil energy with an emission fingerprint of 683.80 g/kWh and a share of 80% from wind energy with an emission fingerprint of 24.00 g/kWh.

Using these initial values, I determined the effective CO_2 emissions of unplanned vehicles with 4.283,53 gram. The energy management, however, was able to cut these emissions in half, such that an emission fingerprint of 2.364,57 gram was determined for planned vehicles. The order of magnitude of these results is illustrated in Figure 12.3.

12.3.1 Result Discussion

The results are significant. Compared to unplanned vehicles, the energy management was able to decrease the effective CO_2 emissions by almost

[4]Particulars can be found at the at the Mini website: `http://www.mini.com`.

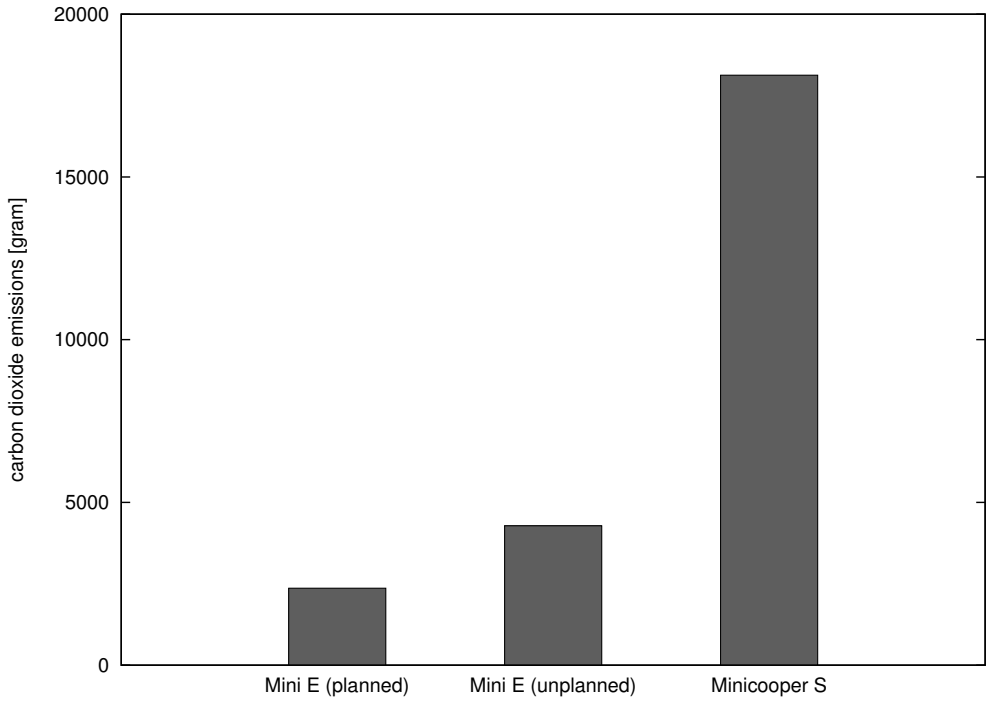

Figure 12.3: Effective CO_2 emissions for the simulated scenarios. All three categories are illustrated. From left to right: Mini E planned, Mini E unplanned, Minicooper S unplanned (adapted from Keiser et al., 2011, Figure 3, p. 295).

50% (44.8% to be accurate). This significant difference can be explained by the different selection of charging intervals. While driver's of unplanned vehicles "selfishly" decide to execute a charging process, the planning system preserves a bigger picture and takes additional criteria, such grid stability or CO_2 efficiency into account.

The results establish that it is possible to decrease the effective CO_2 emissions of electric vehicles by anticipatory planning. □

12.4 Discussion

In this chapter, I presented particulars about the second project in which the developed simulation model was comprehensively used for the evaluation.

The purpose of this evaluation was to show that automated anticipatory planning is superior to regular human planning behavior due to the amount

of available information. In most cases, human beings are not aware—and also not interested—in particular knowledge about the current and future state of the energy grid. Yet, the evaluation showed that this exact information can be utilized in order to further sustainability.

The simulation model was used to compare the performance of two categories of electric vehicle drivers. First, there were drivers that were in possession of a system, which automatically controls their charging processes, secondly, there were drivers that control and manage their charging processes on their own—clearly a strategic behavior level capability.

The simulation model was used for both categories of drivers. For the former category, namely "planned vehicles", I removed the BDI reasoning cycle and the perception phase from my agent model and used the output of the energy management system as input for the simulation framework. The same mechanism was already used for the evaluation that I have presented in the previous chapter, thus, the framework accounted for this capability. For the second category of drivers, namely "unplanned vehicles", I used the BDI reasoning cycle as it is.

The simulation was done for the capital region of Berlin, Germany. In total, 390 car park locations were automatically retrieved from the applied simulation topology and each location was assigned to a parking and to a charging infrastructural feature.

To make this approach work, the agents' `PlanObject` for the driving capability had to be adjusted to return information about the estimated consumption for proposed routes.

The utility function of the drivers was designed to assess strategies according to required time—the shorter, the better.

The simulation scenario was generated by random, yet, in compliance with the specific characteristics of a commuter. To make the performance comparable, the same sequence of appointments were used for planned as well as unplanned vehicles.

To compare the performance of the electric powertrain to conventional vehicles, a third scenario was simulated. For this third scenario all charging-relevant objects (e.g., infrastructural features) were removed from the simulation model and the vehicle-specific characteristics were adjusted.

The simulation results emphasize that anticipatory planning is superior to planning as it is done by humans. The reason for this is the availability of information. Automated procedures are able to account for the current and the expected grid state, human beings are not aware of, and not even interested in such information. However, this exact information can be used to utilize intervals with an increased availability of energy from renewable energy sources and decreased energy demand. The utilization of these intervals contributes to a more sustainable mobility.

The presented simulation model was indispensible for the evaluation procedure of the energy management system. Although the system has been deployed in reality, it was not possible to assess its capability due to imprecise information about the current state of the energy grid, e.g., demand and current CO_2 emissions. By means of simulation it was possible to provide such information and to do the assessment. In doing so, it was necessary to produce the behavior of unplanned vehicles. For this purpose, I used the same appointments that were originally used for the simulation of planned vehicles, though, I configured the unplanned vehicles to find their routes themselves. The resulting driving characteristics were absolutely in compliance with the performance of real human drivers (based on the mobility study provided by Federal Ministry of Transport, Building and Urban Development (2010)), thus, it was possible to correctly calibrate the simulation model.

Only one minor addition was required, that is, the plan object mechanism had to be extended to return the consumption for proposed routes. To return valid information, the vehicle's specific consumption was stored within the `Vehicle` class. The respective `PlanObject` accesses this class and determines the expected consumption based on the length of the proposed route and the specific consumption value.

13. Gesteuertes Laden 2.0

The third evaluation that was done by means of the presented simulation model was done as a part of the government-funded research project *Gesteuertes Laden 2.0* (Vattenfall Europe Innovation GmbH et al., 2011, also Lützenberger et al., 2012b).

The Gesteuertes Laden 2.0 project picked up where the Mini E 1.0 left of, thus, the project aimed to refine the previously presented energy management system in terms of flexibility and performance.

I already mentioned that the energy management system was deployed in reality, yet, for the same reasons as in the Mini E 1.0 project, it was difficult to demonstrate its capability to decrease CO_2 emissions. Thus, in Gesteuertes Laden 2.0, we established this capability by means of simulation.

Again I used my simulation model to account for both, drivers that are in possession of the energy management system and drivers that are not. Drivers from the latter category manage and schedule charging processes on their own. For the evaluation, I used the exact same approach as in the predecessor project (see also Chapter 12), such that the energy management system was used to produce the behavior of drivers from the former category and the developed BDI-based model was used to mimic the behavior of drivers from the latter category.

Despite the resemblance to the Mini E 1.0 project, the evaluation that was done in Gesteuertes Laden 2.0 was significantly more complex as differ-

ent infrastructural configurations (e.g., limited availability of parking and charging infrastructure and support for different types of charging stations with varying characteristics) as well as varying driver profiles (e.g., commuters or field workers) had to be examined.

The purpose of this evaluation was to establish that anticipatory planning is able to significantly increase the performance of electric vehicles and to better exploit the available infrastructures. Furthermore, it was planned to establish that the performance can be increased for different types of mobility patterns.

I begin this chapter by presenting the energy management system in more detail (see Section 13.1). As the basic operation principle was presented in the previous chapter already, I keep this part rather brief and focused on novel aspects. Subsequently, in Section 13.2, I show how the simulation model was configured in order to work for this evaluation. Furthermore, I elaborate on the simulation scenarios that were used for the Gesteuertes Laden 2.0 project. In Section 13.3, I present and discuss collected simulation results. Finally, in Section 13.4, I wrap up with a discussion.

13.1 The Application

The objective of the energy management was explained in the previous chapter, already. In short, it was our objective to maximize the profit of all stakeholders that are involved in charging processes of electric vehicles. The application accounted for the driver, the vehicle manufacturer, and the charging station operator, basically the same stakeholders that were represented in Mini E 1.0, already. Yet, while in the MiniE 1.0 project we integrated information about the current and expected energy mix composition as static values, we designed the Gesteuertes Laden 2.0 application to include this important factor as an additional stakeholder, namely the *distribution system operator*. We designed the system as anticipatory approach in which software agents negotiate a charging and feeding profile for a given amount of time. The objective was to maximize the profit of all stakeholders, e.g., mobility of the driver, restrictions of the energy grid, utilization of charging infrastructure, utilization of renewable energies, to name but a few.

Compared to Mini E 1.0, we extended the capabilities of selected agents. To start with, the User Agent was redesigned to account for extended preferences. This extension accounted for individual levels of risk-tolerance, the factor that determines the driver's willingness to exploit profitable charging and feeding intervals on the expense of their mobility. Furthermore, a driver-specific "comfortability factor" was included. This factor was used to determine the tolerated distance from a charging station to an appointment location.

The charging station agent was extended to take infrastructural information into account. Due to this extension, the overall system was able to access detailed information about the charging infrastructure—including the exact location of charging stations and the available charging rates. Time-dependent information, e.g., the availability of charging stations, was provided as well. For this purpose, a charging station booking service was developed. The same service was used in the Mini E 1.0 project, yet, we put no focus on resource management and used unlimited capacities. In Gesteuertes Laden 2.0, however, resource management was explicitly considered by the planning procedure.

Finally, we implemented a completely new agent type, namely the *Distribution System Operator Agent*. This agent type was designed to represent the distribution system operator in the system. At runtime, the Distribution System Operator Agent provided detailed information about the current and the expected composition of the grid energy mix.

Despite the additions, both, the system architecture as well as the energy management's operation principle remained roughly the same.

The performance of our energy management system was determined within the Mini E 1.0 project, already. One conclusion that was drawn from the project was the fact that the applied charging infrastructure was not able to cope with an increasing number of electric vehicles. The main reason for this deficiency was the structural limitation of the applied energy grid architecture.

Given the relatively small number of electric vehicles, the inadequacies of the energy grid are negligible, yet, in the future, this deficiency will become a severe problem! Following the German government, a number of 200.000 electric vehicles can be expected for the capital region of Berlin,

Germany, by the year 2020 (Nationale Plattform Elektromobilität, 2011). The Mini E 1.0 project, however, showed that energy grids were not able to account for such high number of additional consumers (Steuer et al., 2013).

Countering this problem, we redesigned the energy management system to account for grid-related limitations. As a consequence, the evaluation of the Gesteuertes Laden 2.0 project was focused on assessing the energy management system's capability to exploit available (charging) infrastructures. Furthermore, we intended to identify the limits of our approach. For this purpose, varying driver profiles were simulated.

In the following, I present the particulars of the evaluation process as it was done in the Gesteuertes Laden 2.0 project. In doing so, I elaborate on the scenarios that were simulated as well as on how the simulation model had to be configured for this evaluation.

13.2 Configuration & Calibration

Like in the Mini E 1.0 project, two different categories of drivers were simulated. The first category of drivers was able to access the energy management system. These drivers used the proposals from the energy management system to charge their vehicles. By analogy with the previous chapter, I refer to vehicles that were controlled by drivers with access to the energy management system as *planned vehicles*. The second category of drivers were not able to access the energy management system. These drivers had no knowledge about the energy mix composition or the local energy grid constraints. These drivers scheduled their charging processes on their own. I refer to vehicles that were controlled by the second category of drivers as *unplanned vehicles*.

Both categories of drivers were simulated with the simulation framework that I have presented in this work. In order to simulate the first category of drivers I used the same approach as in the previous chapter and replaced the entire BDI reasoning cycle with the planning capability of our energy management system.

I conceptualized the behavior of drivers from the second category with the original BDI-based model. The applied configuration was similar to the configuration that I have used in the Mini E 1.0 project, though, some adaptations were done.

First, I added the following precondition to the superior goals of all drivers:

$$driver.vehicle = \emptyset. \tag{13.1}$$

The precondition ensures that drivers have to arrive at the target location on foot. I used original data as input for the parking infrastructure. This data was extracted by the editing tool which I described in Section 6.2.2 (see also Appendix D). For the simulation, I used OpenStreetMap data for the capital region of Berlin, Germany. In total, I extracted 390 car parks from this map.

As stated above, the objective of this evaluation was to investigate the performance of our energy management on different charging infrastructures. To make the simulation as realistic as possible, we comprehensively analyzed (Vattenfall Europe Innovation GmbH et al., 2011) the current situation as well as the expected development stages of the charging infrastructure in Berlin and configured our simulation scenarios in compliance with our findings.[1]

Based on this analysis, we distinguished between six different types of charging stations. Furthermore, we distinguished between three different development stages, namely the years 2015, 2020, and 2030, and respectively adapted the charging station mix to the figures from the survey. Particular characteristics of the applied charging infrastructures for all three development stages are illustrated in Table 13.1.

For each position that was retrieved from the map, I specified four infrastructural features: one for regular parking and three for the different charging station categories. Given that we actually identified six different types of charging stations, the definition of only three infrastructural feature categories for charging stations appears to be confusing in the first place—I explain this decision as follows:

Planned vehicles use the information from the energy management system for their charging procedures, thus, the perception/reasoning mecha-

[1] As a matter of fact, the charging infrastructure survey was also a part of the Gesteuertes Laden 2.0 project. The survey was compiled by one of the project partners, namely Vattenfall Europe Innovation GmbH—designated experts in the domain of charging infrastructures.

Table 13.1: Charging station types that were used for the simulation scenarios 2015, 2020 and 2030, including their charging and V2G specifications (given in ampere), as well as their absolute number and percentage distribution for each scenario (after Lützenberger et al., 2012b, p. 149).

			Mixture		
	Charging	V2G	2015	2020	2030
Type I	64A	64A	0%	0%	10%
Type II	64A	–	32%	32%	40%
Type III	32A	32A	6%	6%	0%
Type IV	32A	–	32%	32%	0%
Type V	16A	16A	14%	14%	10%
Type VI	16A	–	16%	16%	40%
Absolute number of charging stations			27.900	167.000	200.000

nism was only required for unplanned vehicles. Unplanned vehicles, however, were not capable of V2G.[2] As a consequence, it was not necessary to reflect the V2G capability of the charging station Type I, III, and V by means of infrastructural features. Nevertheless, the additional charging possibility had to be added. Charging characteristics, however, were already reflected by those charging station types that were not capable of V2G (Type II, Type IV, and Type VI). For this reason, I decided to use a joint configuration for the following pairs: Type I and II, Type III and IV, and Type V and VI. The occurrences of the individual types were respectively added together in order to determine the occurrences of the joint type. Joint types were only used for unplanned vehicles, the energy management used the original charging station distribution as presented in Table 13.1.

To ensure that parking or charging requires the driver to be in possession of a vehicle, I defined the following precondition for all four infrastructural features:

$$driver.vehicle \neq \emptyset.$$

[2]Making use of V2G requires knowledge about the current state of the grid. Feeding energy at the wrong time may cause energy grid architectures to collapse, thus, in Gesteuertes Laden 2.0, we decided to restrict the use of V2G to planned vehicles, only.

In addition, I defined the following precondition for the parking capability:

$$driver.vehicle.battery.soc > .2 \cdot soc\_max.$$

The preconditions ensures that only drivers of a vehicle with a battery level over 20% make use of a parking capability. The same value was defined as critical threshold for the energy management system.

For the mixed representation of Type I and Type II, I added the following precondition:

$$soc + \frac{230V \cdot 32A \cdot t}{1.000 \cdot soc\_max} < .2 \cdot soc\_max, \tag{13.2}$$

where soc refers to the current battery level, soc_max refers to the maximum battery level (both in absolute numbers) and t is the time difference between the current simulation time now and the occurrence of the next superior goal. A method which returns the time difference between two superior goals can easily be implemented as an instance method of the `Driver` class.

Equation 13.2 expresses that this type of charging station can only be used when charging stations with the next lower amperage (32 Ampere) are not able to increase the battery level beyond the user-specific threshold of 20% within the time t.

For the mixed representation of Type III and Type IV, I used the following precondition:

$$soc + \frac{230V \cdot 32A \cdot t}{1.000 \cdot soc\_max} \geq .2 \cdot soc\_max > soc + \frac{230V \cdot 16A \cdot t}{1.000 \cdot soc\_max}. \tag{13.3}$$

While the right-hand side of the statement ensures that this type of charging station can only be used when charging stations with the next lower amperage (16 Ampere) are not able to increase the battery level beyond the user-specific threshold of 20% within the time t, the left-hand side of the inequality ensures that this type of charging station is able to increase the battery level beyond the user-specific threshold (note that the left-hand side of the statement is complementary to Equation 13.2).

For the mixed representation of Type V and Type VI, I used the following precondition:

$$soc + \frac{230V \cdot 16A \cdot t}{1.000 \cdot soc\_max} \geq .2 \cdot soc. \tag{13.4}$$

Equation 13.4 ensures that this type of charging station can be used to increase the battery level beyond the user-specific threshold (note that this statement is complementary to right-hand side of Equation 13.3).

For the effects of all infrastructural features, I specified that drivers are no longer within their vehicle:

$$driver'.vehicle = \emptyset.$$

Furthermore, I specified that the capacity of the used infrastructural feature c is decreased by one:

$$c'.capacity = c.capacity - 1.$$

For the three categories of infrastructural features that were used to represent available charging capability, I designed the effects to increase the vehicle's battery level in dependency to the applied amperage. For Type I and Type II charging stations, this effect looks as follows:

$$driver'.vehicle.amperage = 64,$$

while for Type III and Type IV charging stations, this effect can be described by:

$$driver'.vehicle.amperage = 32.$$

For Type V and Type VI charging stations, the effect complies with:

$$driver'.vehicle.amperage = 16.$$

Contrary to the evaluation that was done in the Mini E 1.0 project, drivers in Gesteuertes Laden 2.0 were not allowed to park their vehicles at

charging stations without using the charging capability. As a matter of fact, in Germany, this regulation is enforced by the law.

I used the car parks' original locations (retrieved from the OpenStreetMap data) and equally distributed parking and charging capacities among all 390 locations. Furthermore, I designed the duration method *dur* for all infrastructural features to constantly return $now + 1$.

For the drivers, I used the same `PlanObject` instances as described in the previous chapter. I refrained from limiting their scope:

$$\forall d \in \mathbb{D} : d.sight = \infty.$$

Finally, I defined the utility function of the drivers to assess the proposed strategies according to the required time, the faster the higher the quality.

Contrary to the other evaluation scenarios, I generated appointment sequences for not only one, but three different driver types. These were in compliance with the *Mobilität in Deutschland 2008* study (Federal Ministry of Transport, Building and Urban Development, 2010). I generated mobility patterns for three different driver types, namely: commuters, field workers, and delivery service drivers. The schemes included specific values for the frequency in which vehicles are used and also for their daily mileage. As such, a typical commuter was defined to travel roughly 100 km per day, a field worker to drive around 200 km per day, and a deliverer with a daily mileage of approximately 400 km.

The simulation procedure was similar to the procedure that I have presented in the previous chapter. Unplanned vehicles wait at their home locations until a `MoveOffEvent` instance is detected in their calendar instance. Whenever such event is triggered, the assigned superior goal is placed within the goal base of the driver. Due to Equation 13.1, the driver recognizes that it is currently not possible to achieve the superior goal. As a consequence, routes to all know infrastructural features and pedestrian routes from the infrastructural features to the appointment location are computed. In order to do so, the consumption method of the driver's `PlanObject` instance is used to determine the estimated battery level. Furthermore, the new instance method (`Driver` class) is used to determine the time between the

expected arrival time and the next `MoveOffEvent`. Computed action sequences are assessed by the utility function and the fastest combination is selected. Once a strategy has been selected, the unplanned vehicle proceeds towards the selected parking or charging lot. Upon arrival, the vehicle executes the infrastructural feature's effect method eff. I used the same implementation as I have presented in Section 11.2, thus, the simulation engine validates whether it is possible to execute the effect method or not. In the case that enough capacity is available, the invocation succeeds and the effects are applied. The driver will park (or charge) the vehicle and proceed to the appointment location on foot. In the case that the invocation fails, the infrastructural feature is removed from the driver's belief base and the reasoning cycle is initiated once more. As a consequence, the driver proceeds to the next best option.

While the appointment patterns for all three driver profiles were derived from the *Mobilität in Deutschland 2008* study (Federal Ministry of Transport, Building and Urban Development, 2010), the compensatory behavior was specified in compliance with the results of a three-week field experiment (Vattenfall Europe Innovation GmbH et al., 2011) for which we deployed our application on real hardware components, such as charging stations, vehicles, or cell phones. We selected test drivers to evaluate the reliability and suitability of our system and respectively recorded the test driver's actions to compensate the lack of parking or charging availability. The above-presented specification was calibrated to match the results of this field test. Vehicle-specific input parameters, such as consumption and charging characteristics, vehicle ranges, etc. were adjusted as well.

During the simulation, the simulation engine recorded the start and end time of all charging processes—and particulars of the charging process, e.g., the applied amperage, grid-relevant data such as the grid energy's CO_2 fingerprint over time, and mobility restrictions. The latter may occur for both, planned as well as unplanned vehicles as a result to an insufficient energy level. The energy management system uses a reservation system to ensure parking or charging availability, hence, for planned vehicles, any insufficient state of charge can only be due to a large number of appointments and insufficient charging periods. In the case of unplanned vehicles, mobility issues can also be caused by the unavailability of parking or charging capability. Unplanned vehicles have no information about the infrastructure's

utilization until they arrive at the designated target location. Exhausted capacities cause the drivers to look for other opportunities. This "strolling" process, however, may cause the vehicle to run completely empty. The simulation engine counts these events as failure cases which are listed in the simulation report.

13.3 Simulation Results

All three driver profiles (commuter, field worker, and delivery service) were simulated on the expected infrastructure configuration for the years 2015, 2020, and 2030. The driver profiles were respectively simulated twice. During the first simulation, the behavior was generated by the energy management system, during the second simulation, the behavior was generated by the BDI-based approach. Thus, in total, 18 scenarios were simulated.

The performance of our energy management system was assessed by means of performance in two categories. First, it was my intention to determine the efficiency of our energy management system to increase the utilization of renewable energy. Secondly, it was my intention to determine in how far the energy management system is able to support the mobility of drivers.

In the following, I present collected simulation results and elaborate on how the performance of our assistance was assessed.

13.3.1 Utilization of Renewable Energy

The extend to which renewable energy is utilized is expressed by the so called *simultaneity factor*. The simultaneity factor can be understood as the average share of renewable energy for all time intervals in which electric energy was taken from the grid network.

In order to assess the capability of our energy management system to utilize available energy from renewable energy sources, I used the simulation results to determine the simultaneity factor.

The computation was done straightforward, by averaging the shares of renewable energy during which simulated vehicles were charged. The simulation results are illustrated in Table 13.2.

Table 13.2: Utilization of renewable energy without considering the current which is applied for charging intervals. The values indicate the average share of renewable energy which was used to charge the simulated vehicles (after Lützenberger et al., 2012b, p. 150).

	2015		2020		2030	
	upl	pl	upl	pl	upl	pl
Commuter	15.28%	16.00%	15.03%	15.59%	14.28%	15.98%
Field Worker	14.90%	16.83%	15.31%	16.81%	15.19%	16.61%
Delivery Service	15.31%	16.82%	15.19%	17.44%	15.84%	17.41%

Table 13.3: Utilization of renewable energy under consideration of the applied current. The values indicate the average share of renewable energy which was used to charge the simulated vehicles (after Lützenberger et al., 2012b, p. 151).

	2015		2020		2030	
	upl	pl	upl	pl	upl	pl
Commuter	12.80%	22.70%	12.36%	22.73%	12.39%	21.38%
Field Worker	15.24%	18.26%	15.43%	18.45%	14.75%	18.04%
Delivery Service	15.02%	17.49%	15.28%	17.82%	15.09%	17.69%

Differences between planned and unplanned drivers were comparably small. This phenomenon can be explained with the one-dimensional nature of the simultaneity factor, that is, the simultaneity factor takes the average share of wind energy into account but neglects the intensity of the current which is used to charge vehicles. This additional dimension, however, makes the difference.

To emphasize the importance of the applied current, a second analysis was done. In this second analysis, I determined the simultaneity factor, again. Yet, instead of calculating the average value, I weighted the charging intervals according to the applied current. The results for each simulation scenario are illustrated in Table 13.3.

Compared to the un-weighted simultaneity factor, the efficiency of the energy management system becomes more obvious. As an example, the difference between commuters that were using the assistance system and those

who were not, is almost 10%. With an increasing mileage, both factors literally converge, until—in the 2030 delivery service scenario—the difference between assisted- and unassisted drivers drops to a little over 2%.

The convergence can be explained with the fading optimization options for the assistance system—a direct consequence to the comprehensive usage of delivery vehicles. The excessive usage as well as short idle times make it difficult for the energy management system to find suitable charging periods with a high share of renewable energy. As a consequence, the performances of the energy management and the intuitive control pattern converge.

For a fixed driver profile, there was no significant discrepancy between the three infrastructural development stages. The simulation results do not explain this phenomenon.

13.3.2 Mobility Issues

After determining the energy management's system to utilize renewable energy, it was my intention to assess its capability to increase the drivers' mobility. For reliable figures, I analyzed the simulation results and determined vehicles that had to cancel at least one scheduled trip due to an insufficient energy level. The results are illustrated in Table 13.4.

Table 13.4: Share of electric vehicles that were affected in their mobility as a result to an insufficient state of charge (after Lützenberger et al., 2012b, p. 151).

	2015		2020		2030	
	upl	pl	upl	pl	upl	pl
Commuter	60.00%	10.00%	53.30%	10.00%	59.30%	07.69%
Field Worker	96.70%	03.33%	93.30%	10.00%	92.30%	13.19%
Delivery Service	100.00%	36.67%	100.00%	48.33%	100.00%	42.86%

The results substantiate the energy management system's capability to increase the drivers' mobility. For the commuters and for the field workers the amount of affected planned vehicles remained relatively constant, yet, there is a significant increase of affected vehicles between unplanned commuters and unplanned field workers. This number further increases in the delivery service scenario, where each unplanned vehicle was somehow

affected. The energy management system, however, was able to roughly halve this number.

Admittedly, the total number of affected vehicles may be misleading. For this purpose, a second analysis was done in which I determined the total amount of all scheduled trips and used this total number to standardize the number of trips that failed due to an insufficient energy level. The results of this second analysis are illustrated in Table 13.5.

Table 13.5: Share of trips that failed due to an insufficient state of charge (after Lützenberger et al., 2012b, p. 152).

	2015		2020		2030	
	upl	pl	upl	pl	upl	pl
Commuter	02.21%	00.78%	02.00%	00.60%	02.30%	00.47%
Field Worker	04.90%	00.13%	04.55%	00.39%	04.80%	00.51%
Delivery Service	08.68%	01.49%	08.33%	01.95%	08.71%	02.39%

The results establish the efficiency of the energy management system to support the mobility of their drivers. While planned commuters were affected in less than one percent of their scheduled trips, unplanned commuters had to deal with almost three times as many failures.

Moreover, results for planned commuters and planned field workers are roughly equal. Yet, results for the same but unplanned driver profiles significantly differ, such that the number of affections for unplanned field workers was doubled.

Finally, the number between unplanned field workers and unplanned delivery service drivers was almost doubled. Nevertheless, the energy management system was able to decrease the number of affections for delivery service drivers by the factor of four.

13.3.3 Result Discussion

The simulation results underlined the efficiency of our energy management system in all respects. To start with, collected simulation results establish that the energy management system was able to increase the utilization of renewable energy sources by almost 10%. This value decreases

with the utilization and the daily mileage of the vehicles. This phenomenon can be explained with the fading alternatives for the energy management system. The conclusion is that despite an intelligent arrangement of charging processes current technology is not able to facilitate the use of regular electric vehicles for delivery scenarios. Other technologies, such as battery changing stations are required to further the use of electric vehicles for delivery service providers.

Furthermore, the simulation results emphasize that the energy management system was able to increase the mobility of their drivers. Compared to unassisted drivers, mobility restrictions of assisted drivers were significantly decreased. The positive effect of the energy management system became most apparent for field workers. It was possible to decrease their mobility restrictions by up to 90%.

The simulation results emphasized that the presented energy management system was able to increase the performance of electric vehicles and to better exploit the available infrastructure. An improved performance was established for all simulated driver profiles. □

13.4 Discussion

In this chapter, I presented the third and the most comprehensive application of my simulation model, so far.

The objective of this study was to establish that anticipatory planning is superior to regular planning as it is done by human beings. My simulation framework was used for both category of drivers, those that were assisted by the energy management system (planned vehicles) and those that were not (unplanned vehicles).

The approach which was used to simulate the behaviors of planned vehicles was similar to the approach which I described in the previous chapter. In short, I removed the entire BDI reasoning cycle and the perception phase and used the output of the energy management system as input for the simulation framework. I used the original BDI-based approach to produce the behavior of unplanned vehicles.

The simulation was done for the capital region of Berlin, Germany. I used OpenStreetMap data as simulation topology and extracted occurrences of car parks.

The purpose of the evaluation was to analyze the energy management's capability to exploit varying configurations of the charging infrastructures, therefore, three infrastructural development stages were simulated. Furthermore, it was the objective to identify the energy management's capability to support different types of driver profiles. In total, three different profiles were simulated: a commuter profile, a field worker profile, and a delivery service profile.

The simulation model was essential for the evaluation procedure. Only few additions were required to make it work for the Gesteuertes Laden 2.0 project. To start with, it was necessary to use the extensions that I have described in the previous chapter, namely the extended `PlanObject` for the agents' driving capability. Secondly, the `Driver` class type had to be extended to feature a method which returns the time difference between a given simulation time and the occurrence of the next superior goal. This method was required to allow drivers to determine the amperage which has to be applied for charging intervals.

To make the simulation results as realistic as possible, the driver behavior model was calibrated by using results from a three week field trial that was also done as a part of the Gesteuertes Laden 2.0 project. The field trial established that drivers mainly optimize their actions with respect to the required time. It was possible to mimic this approach by adapting the utility function of the drivers.

The simulation model produced reliable results. To start with, the simulation results emphasize that anticipatory planning is able to increase the utilization of renewable energy by roughly 10%. This value decreases with the frequency in which the vehicles were being used, such that an increased mileage resulted in a decreased utilization of renewable energy. It was possible to explain this phenomenon with the fading options for the energy management system to place charging processes.

Furthermore, the simulation results substantiate the capability of the energy management system to increase the mobility of their drivers. Assisted vehicles encountered significantly less mobility restrictions than unassisted drivers. For field workers, the effect became most obvious. Mobility restrictions for this type of driver profile were reduced by up to 90%.

To wrap up, the developed simulation model was successfully applied within the Gesteuertes Laden 2.0 project. The approach made it possible to assess the energy management's performance and to compare this performance to intuitive behavior.

To make this evaluation work, the full capabilities of the simulation model were required. First, it was necessary to have an approach for strategic level decision-making in traffic environments in order to account for situations in which drivers had to find or had to adapt their strategies, e.g., in cases where charging capabilities were exhausted and alternative options had to be found. Secondly, it was necessary to make the decision-making subject to the driver's personality in order to account for the time-based strategy assessment that was observed during the field test. Thirdly, the drivers' awareness for external factors was required. This concept was used to make the drivers aware of available charging options. Finally, a concept for knowledge was required. This concept was used to account for the fact that drivers have incomplete knowledge about situations in target areas. In the Gesteuertes Laden 2.0 project, I used this mechanism to account for situations in which charging infrastructures were occupied and alternatives had to be found.

The analysis of contemporary traffic simulation frameworks showed that there are currently no solutions that express human driver behavior as a result of the above-mentioned sources of distraction. For the Gesteuertes Laden 2.0 project, however, such model was indispensible to compare the performance of the energy management system to the intuitive behavior of human beings. Thus, based on this discussion, I conclude that the presented simulation model for human strategic level driver behavior advances the state-of-the-art in a meaningful manner.

Part VI

Conclusion

14. Conclusion

The aim of this thesis was twofold. First, it is my intention to clarify in how far current approaches are able to reflect the characteristics of human strategic level driver behavior in a computer-aided traffic simulation. It was my objective to identify the current frontiers in simulating this particular form of human driver behavior in traffic environments.

The second objective of this thesis was to shift these borders and to present an improved model which implements psychological findings, better copes with reality, and increases the quality and precision of simulation results.

In order to identify the frontiers in simulating human strategic level driver behavior it was necessary to gain an understanding for human driver behavior in general and human strategic level driver behavior in particular.

There are no domains with more experience in explaining human behavior than human factors psychology, thus, I began this work by introducing the fundamentals of human driver behavior from a psychological perspective.

As a matter of fact, our current understanding of human driver behavior began with the work of Michon (1985). Michon (1985) analyzed available driver behavior conceptualizations in order to identify reasons for the communities' inability to present a commonly accepted and comprehensive model for human driver behavior.

Based on his analysis, Michon (1985) concluded that none of the examined approaches was able to account for his understanding of human

driver behavior (Michon, 1976) and proposed a novel and seminal approach to conceptualize human driver behavior, namely the Hierarchical Control Model (Michon, 1985). The Hierarchical Control Model combined all promising aspects and neglected all misleading components of those models that Michon analyzed. It was the first approach that overcame the formerly prevailing monolithical design.

Instead of applying a monolithical view, Michon (1985) introduced different levels of behavior and argued that decisions evolve not only from one but from different levels simultaneously—respectively with different intentions and goals. In more detail, Michon (1985) introduced three levels of human driver behavior, namely the control level, the tactical level, and—most importantly for my own work—the strategic level. Following Michon (1985),

strategic level driver behavior refers to the general planning stage of a trip. This stage includes the determination of trip goals, the route and the modal choice as well as a cost-risk evaluation. Furthermore, the behavior of drivers on this level is affected by general considerations about transport and mobility. Finally, concomitant factors such as aesthetic satisfaction and comfort are able to determine the outcome of this behavior level.

In order to identify the particulars of strategic level driver behavior and to determine whether the description of Michon (1985) is still in use, I analyzed recognized and well-established driver behavior conceptualizations (cf. van der Molen and Bötticher, 1988; Keskinen et al., 2004; Hale et al., 1990; Summala, 1996, 1997; Hatakka et al., 1997; Bekiaris et al., 2003; Salvucci et al., 2001; Krajzewicz and Wagner, 2002; Hollnagel, 1993; Engström and Hollnagel, 2007).

The analysis revealed three things. First, strategic level driver behavior is still used in a way which complies with the original description after Michon (1985). While Michon's definition was rather generic, the analysis of well-established driver behavior conceptualizations showed that it is common practice to categorize behavior according to the time which is required to complete actions that evolve from the particular level. While control level

behavior is in the milliseconds range and tactical level behavior is in the second's range, strategic level behavior is commonly seen beyond the seconds' range. To clarify the understanding of strategic level driver behavior that I use for this work, I provided a definition for the term:

> Strategic level driver behavior is the level of human traffic behavior on which action plans are generated that are not entirely related to the driving task per se and that cannot be completed within a matter of seconds (adapted from Michon, 1985).

Following this definition, the outcomes of strategic level behavior are action plans. Most of the analyzed approaches assume that the purpose of these action plans is to accomplish a driver's strategic level goals. This assumption was also substantiated by Michon (1985), who argued that a driver's strategic level behavior can be characterized as "goal directed" or "intentional". Thus, the second conclusion that I draw from the survey was that most frameworks provide an implementation for the driver that complies with the concept of intentional systems after Dennett (1989). Moreover, drivers were implemented such that a particular goal is followed until it is reached. This behavioral mechanism complies with the single-minded principle after Cohen and Levesque (1990).

Besides the definition for strategic level driver behavior and the particular behavior characteristics that traffic simulation frameworks implement, the survey revealed a third finding, namely the factors that psychologists consider to be relevant for the outcome of human strategic level driver behavior. I was able to identify four sources of distraction, these sources are:

1. other levels of behavior,
2. external factors,
3. the driver's personality, and
4. experience and knowledge.

Following human factors psychology, the above-presented sources of distraction are able to determine the outcome of a driver's strategic level decisions. I elaborate on this impact below:

Other levels of behavior: Psychologists commonly conceptualize human behavior by means of different levels. While each level of behavior is connected to factors of disturbance, the levels are also mutually connected, such that the outcome of a given level may affect those levels that are directly connected to this particular level. In the case of the strategic level behavior, decision-making is mostly affected by the tactical level behavior. Psychologists explicitly argue (van der Molen and Bötticher, 1988; Hale et al., 1990; Summala, 1996, 1997; Bekiaris et al., 2003; Hollnagel, 1993) that it is possible to analyze behavior levels in isolation, that is, to neglect the mutal dependencies to other levels of behavior.

External factors: Drivers constantly perceive their environment and adapt their strategic level behavior to changes that occur in this environment. Psychologists distinguish between two categories of distractions that may evolve from the environment of a driver. First, alternative options constitute alternative means of transportation. Drivers assess their capability to make use these alternatives and perform a cost-risk evaluation to determine their expected benefit in adapting their currently pursued strategy to make use of alternative options. Secondly, environmental factors directly evolve from the driver's environment and affect the driver physically and/or psychologically.

Internal factors: This factor evolves from the driver themselves. Internal factors can be considered as the driver's personality. This factor comprises elements like the driver's attitude, their motivation, their preferences, their lifestyle, their gender, and/or their emotional state, to name but a few. Following van der Molen and Bötticher (1988, also Keskinen, 1996), internal factors can be represented in an abbreviated form, such that a utility function reflects the personality of drivers. This utility function is used to assess in how far the driver is satisfied with the currently pursued or other potential strategies.

Experience & knowledge: A driver's experience and knowledge significantly affects their strategic level decision-making process. Salvucci et al. (2001) and Krajzewicz and Wagner (2002) argue that experience is also an innate part of the driver, thus, it is possible to reflect this factor in an abbreviated form by means of a utility function.

Knowledge however, is a separate factor that has to be considered in isolation.

Based on a detailed understanding for strategic level driver behavior it was possible to determine to what extend contemporary traffic simulation frameworks are able to reproduce the psychological understanding of human driver behavior.

I analyzed the most recognized and well-established works, respectively in their latest version. In doing so, I put particular emphasis on their support for human behavior in general and strategic level driver behavior in particular.

The analysis showed that contemporary works comprehensively account for traits of human behavior. The focus of most approaches, however, is on tactical level rather than on strategic level behavior. Human factors on tactical level are mostly integrated in the framework's computational models. Despite the focus on tactical level behavior, there was also support for strategic level driver behavior. In fact, there was no framework without support for this particular form of human problem solving. The most comprehensive solutions were—without a doubt— MATSim (Illenberger et al., 2007, after Balmer et al., 2004) and FEATHERS (Bellemans et al., 2010). Despite their comprehensive support for strategic level driver behavior, there were also a number of discrepancies between simulation-based implementations and psychological works.

To start with, MATSim and FEATHERS are based on the assumption that drivers aim to maximize their utility. This mechanism is referred to as the "user equilibrium" and is applied by most of the analyzed approaches (cf. AVENUE (Kuwahara et al., 2010), MITSIMLab (Ben-Akiva et al., 2010b), DRACULA (Liu, 2010), DynaMIT (Ben-Akiva et al., 2010a), Aimsun (Casas et al., 2010), Dynameq (Mahut and Florian, 2010), TransModeler (Caliper Corporation, 2014), EMME (INRO, 2014)). In short, approaches that implement the user equilibrium mechanism are based on the assumption that drivers act in an optimal fashion, that is, these drivers aim to reach a desired target location with minimal costs. The optimization process in these frameworks is mostly implemented in a stochastic fashion, such that routes are generated and then iteratively simulated, assessed, and

manipulated until a steady state has been reached—the user equilibrium. The mechanism fits its purpose on the large scale, though, it also looses precision if one wants to go in detail, e.g., if one wants to analyze the effects of sub-optimal decisions which can result from incomplete knowledge on selected locations, such as a particular bus stop or a metro line.

The second discrepancy between psychological works and those models that are actually implemented in contemporary traffic simulations is the representation and implementation of alternative options. Traffic simulation models use a rather fixed way and limit their models to account for public transportation, exclusively. Depending on the context, this limitation fits its purpose, though, psychological works do not restrict the nature of alternative options but allow for any form of alternative transportation, e.g., car sharing, ride sharing, bicycles, and even walking.

The third discrepancy between psychological works traffic simulation models is the connection of the driver's decision-making process to environmental factors. Again, traffic simulation frameworks limit their models to account for concrete forms of this source of distraction. In most frameworks this support is limited to the drivers' awareness for the surrounding traffic situation. Only FEATHERS (Bellemans et al., 2010) accounts for other forms of environmental factors and is able to connect the drivers' strategic level decision making process to their awareness for the current day-of-the-week and to weather conditions. Contrary to psychological models, these factors affect drivers globally and in concrete forms. A generic and location-specific representation in compliance with psychological works is generally missing in state-of-the-art implementations.

To wrap up, the analysis also showed that particular facets of human strategic level driver behavior are not represented in compliance with psychological findings. In short, current works fall short in at least three aspects, namely:

1. The assumption that drivers aim to optimize their efficiency applies to large-scale analysis but looses precision with increasing level of detail. Sub-optimal decisions, which result from incomplete knowledge, are currently not reflected.

2. Alternative options are limited to public transportation. A more generic concept, which accounts for other means of travel or other forms of transportation is missing.

3. Environmental factors are represented in a predefined fashion and occur globally. A generic representation, as described by psychological works, with distinct occurrences, is not possible.

Based on this problem statement I motivated the development of an approach which tackles these problems.

In order to ease and to facilitate the engineering of such approach, it was necessary to find approved mechanisms for the implementation. When analyzing contemporary simulation frameworks, I recognized that several frameworks—especially those that were focused on strategic level driver behavior—were based on the agent paradigm. A deeper look into this paradigm revealed that, following Wooldridge and Jennings (1995), (simulated) drivers are software agents. Due to this resemblance I decided to use the agent paradigm for the development of my approach. The main benefit of using an agent-oriented view is the comprehensive set of tools that can be used for the development. Particularly interesting for this work was the belief-desire-intention software model (Rao and Georgeff, 1995) which facilitates the behavior-specification of intentional systems after Dennett (1989). The capabilities of BDI, however, are limited to the specification of behavior, thus, a second model was required to conceptualize the impact that evolves from the driver's environment, namely external factors.

I already mentioned that, following human factors psychology, external factors can be classified either as alternative options or as environmental factors. As in the case with strategic level driver behavior, I provided definitions for both terms in order to clarify my understanding of both concepts, to avoid confusion with the psychological concepts, and to clearly determine the limits of my own approach. I introduced infrastructural features as the formal, simulation-based conceptualization of alternative options. Furthermore, I introduced regional conditions as the formal, simulation-based conceptualization of environmental factors. For infrastructural features, I used the following definition:

> "An Infrastructural Feature can be everything which is able to fulfil a desire (or parts of it) of a person at a certain location of an infrastructure." (after Lützenberger et al., 2011c, p. 1257)

For regional conditions, I used the following definition:

> "A Regional Condition can be everything which is able to affect or influence a person, its behavior, or its vehicle (physically) at a certain location of an infrastructure." (after Lützenberger et al., 2011a, p. 247)

In order to ease the development process and to facilitate analyses of the mutual dependencies between both categories of external factors, I decided to conceptualize both concepts with the same model. I compared the particular characteristics of external factors to the concept of software services (MacKenzie et al., 2006) and emphasized that services and external factors enjoy similar attributes. While services are determined by preconditions and effects, external factors feature the exact same characteristics. Due to this resemblance, I decided to conceptualized both categories of external factors by means of the service-metaphor.

Nevertheless, external factors are not determined by preconditions and effects exclusively—additional specifications are required. In order to account for these additional specifications, I extended the original service description to account for further attributes, such that infrastructural features and regional conditions can be defined by providing specifications for their preconditions, their effects, and a duration function. Furthermore, in order to account for applications in a traffic simulation environment, a locational attribute is required as well. In the case of regional conditions, this locational attribute comprises a position and a scope. The former can be interpreted as the external factor's epicenter, the latter as the factor's extend. Contrary, infrastructural features require only a position. To facilitate a joint representation of infrastructural features and regional conditions, I allowed the service-oriented infrastructure model to contain empty fields in order to account for unused attributes (e.g., preconditions for regional conditions or a scope for infrastructural features).

After presenting the infrastructure model, I continued by presenting the driver model. I designed this driver model to comprehend disturbances that evolve from the service-based infrastructure model and to generates a strategy, which reflects the driver's:

1. awareness for these disturbances,
2. their personality, and
3. their knowledge.

Based on collected experiences and many successful appliances, I developed the final simulation model by considering simulated drivers as software agents and by conceptualizing their strategy-generation process in compliance with the belief-desire-intention software model (Rao and Georgeff, 1995).

For a behavior conceptualization in compliance with BDI, four phases of human practical reasoning had to be mapped to the domain traffic and transportation. Thus, I provided definitions for the belief revision, the option generation, the filtering, and for the acting phase, respectively for traffic and transport environments. Furthermore I emphasized where and how the driver's awareness for external factors is generated and thus connected BDI-based driver model to the service-based representation of external factors. In its final form, the driver agent's reasoning process looks as follows:

Drivers wait at designated locations until the simulation engine triggers their departure. This is done by placing a a superior goal within the goal base of the agent. For both, moving and waiting driver agents, each simulation interval begins with an application of the effects of regional conditions to those drivers that are currently under the influence of these regional conditions. By accessing current positions of drivers and the installed regional conditions' location and range, the simulation engine determines if drivers are affected. Whenever drivers are affected, the attributes of the drivers are altered according to the respective conditions' effects.

After the effects of regional conditions have been applied to drivers that are located within a regional condition, the simulation engine uses the drivers' position and driver-specific "range of vision", in order to determine

if infrastructural features are perceived. The perception is then forwarded to the belief revision, where the agent updates their belief base by merging their current perception with stored knowledge. Using their updated belief base and their former intentions, the agent proceeds with the generate options phase, where preconditions of all infrastructural features in the belief base are evaluated. For each positive evaluation, the sub-goal to utilize the infrastructural features is stored within the goal base of the agent. In combination with the agent's basic plans (walk and drive) and their current intentions, the new set of goals constitutes the input for the filter phase. There are two different types of goals. While the superior goal expresses the agent's overall objective to reach a certain location, only sub-goals can emerge dynamically indicating an agent's desire to utilize an infrastructural feature. By accessing the infrastructural features' effects and by making use of their basic plans, the agent computes alternative strategies to their target location involving any possible permutation of infrastructural feature utilizations. The resulting strategies are evaluated by using the agent's utility function and finally, the favorite strategy is selected and inserted into the agent's intention repository, from which their actuation is derived and their environment influenced.

The presented driver model is able to produce strategic level decisions that account for all sources of disturbance that psychologists identified as relevant. First, the model accounts for the driver's personality, or internal factors. In compliance with psychological findings, I implemented this source of distraction as a utility function. I chose a rather generic specification for this utility function, such that developers are able to implement a broad spectrum of human personality traits. The only restriction that was defined is the function's scope. In its current form, the function has to return a real number for a given strategy. Driver agents use the utility function in order to assess the quality of proposed strategies. This assessment process determines how drivers select from available options and thus represents their personality profile.

Secondly, the concept of knowledge was integrated. The concept of knowledge is innately provided by the BDI programming model. BDI is a commonly accepted mechanism to conceptualize human behavior in compliance with psychological findings, thus, the application of BDI as a foundation for the development of my own model actively facilitated the at-

tempt to reproduce strategic level driver behavior in a life-like fashion. The way in which experience is represented in BDI directly addresses shortcomings of available traffic simulation frameworks. These are generally based on the user equilibrium and thus neglect the impact of incomplete knowledge or sub-optimal decisions on the traffic scene. The mere application of BDI for the engineering of the driver behavior model significantly improved the simulation-based representation of strategic level driver behavior—especially in terms of how knowledge is integrated.

Finally, the presented simulation model is able to produce strategic level driver behavior which accounts for the drivers' awareness for external factors. I designed the model to account for both categories of external factors, namely alternative options and environmental factors. I used a generic model for the representation of both external sources of distraction, thus, the model is not limited to concrete forms of distraction, but allows for any specification which complies with the presented model. This flexible representation directly addresses shortcomings of available models, which exclusively account for fixed sources of distraction (e.g., public transport or particular weather situations). Furthermore, the abstract infrastructure model allows for the automated configuration of simulation topologies based on semantic map data (such feature was implemented in the editor tool (see also Appendix D).

The presented simulation model was integrated into a simulation framework and evaluated in three comprehensive studies.

The first application was done in joint research project (Hoch et al., 2011) with Volkswagen AG. The aim of this project was the development of an assistance system for the drivers of electric vehicles. In more detail, it was planned to develop a user-centric, constrained-based, in-vehicle travel planning system, which schedules a daily travel plan of a user by exploiting knowledge about current and future states of the vehicle-user-infrastructure network. My simulation model was used in order to compare the performance of the assistance system to the performance of regular drivers. In order to do so, I connected the simulation framework to the assistance system, such that the driver's decision were generated by the assistance system. In a second experiment I used my own BDI reasoning cycle to generate the drivers' decisions. The project was highly successful and we were able to

show that resource scheduling reduces the average travel distance and also the parking search distance. We also showed that average travel speed can be increased whilst overall journey time can be reduced. Furthermore, we demonstrated that the rate of missed appointments can be significantly reduced. The evaluation showed that the advantage of the assistance system over "intuitive" behavior increases in environments of sparse resource availability.

The second evaluation was done within the government-funded research project *Mini E 1.0* (Keiser et al., 2011, also Steuer et al., 2013). The purpose of the Mini E 1.0 project was to develop a decentralized control system for the charging processes of electric vehicles. The vehicles were equipped with the vehicle-to-grid technology. The V2G technology allows vehicles to feed their energy back to the energy grid and thus to act as a controllable energy source. The control system was supposed to assist the drivers of electric vehicles to schedule their charging intervals. The objective was to decrease to the overall CO_2 consumption of the vehicle. Although the system was deployed in reality, it was necessary to assess its quality by means of simulation. My simulation model was used for this very purpose. The idea was to compare the efficiency of the control system to charging as it is intuitively done by human driver—clearly a strategic level decision.

I simulated two categories of drivers. First, there were those drivers that followed the suggestions of the control system and charge their vehicles in compliance with the proposed charging schedules. Secondly, there were drivers that had no access to the optimization system and determine charging and feeding periods for themselves. While the behavior of the former category was generated by the control system, my BDI-based decision-making model was used to generate the behavior of those drivers that were not in possession of such system. Collected simulation results showed that anticipatory planning is superior to human planning. The reason for this is the availability of information. Automated procedures are able to account for the current and the expected grid state, human beings are not aware of, and not even interested in such information. However, this exact information can be used to utilize intervals with an increased availability of energy from renewable energy sources and decreased energy demand and to contribute to a more sustainable mobility.

The presented simulation model was indispensible for the evaluation procedure of the energy management system. Although the system has been deployed in reality, it was not possible to assess its capability due to imprecise information about the current state of the energy grid, e.g., demand and current CO_2 emissions. By means of simulation it was possible to provide such information and to do the assessment. Drivers whose decisions were generated by the BDI reasoning cycle were calibrated by means of a generally accepted mobility study (Federal Ministry of Transport, Building and Urban Development, 2010). Their driving patterns were absolutely in compliance with the performance of real human drivers.

The third evaluation was done as a part of the government-funded research project *Gesteuertes Laden 2.0* (Vattenfall Europe Innovation GmbH et al., 2011). The Gesteuertes Laden 2.0 project picked up where the Mini E 1.0 left of, thus, the project aimed to refine the previously presented energy management system in terms of flexibility and performance. I already mentioned that the energy management system was deployed in reality, yet, for the same reasons as in the Mini E 1.0 project, it was difficult to demonstrate its capability to to decrease CO_2 emissions. Thus, in Gesteuertes Laden 2.0, we established this capability by means of simulation. Again I used my simulation model to account for both, drivers that are in possession of the energy management system and drivers that are not. Drivers from the latter category manage and schedule charging processes on their own. For the evaluation, I used the exact same approach as in the predecessor project, such that the energy management system was used to produce the behavior of drivers from the former category and the BDI-based model was used to mimic the behavior of drivers from the latter category.

Simulation results established that anticipatory planning significantly establishes the utilization of renewable energy. The same results showed that the utilization with the frequency in which the vehicles were being used, such that an increased mileage resulted in a decreased utilization of renewable energy. It was possible to explain this phenomenon with the fading options for the energy management system to place charging processes. Furthermore, it was possible to establish the energy management systems' capability to increase the mobility of their drivers. To make the simulation results as realistic as possible, the driver behavior model was calibrated by using results from a three week field trial that was also done as a part of the Gesteuertes

Laden 2.0 project. The field trial established that drivers mainly optimize their actions with respect to the required time. It was possible to mimic this behavior by adapting the utility function of the drivers.

For the evaluation of the Gesteuertes Laden 2.0 project, the full capabilities of the simulation model were required. First, it was necessary to have an approach for strategic level decision-making in traffic environments in order to account for situations in which drivers had to find or had to adapt their strategies, e.g., in cases where charging capabilities were exhausted and alternative options had to be found. Secondly, it was necessary to make the decision-making subject to the driver's personality in order to account for the time-based strategy assessment that was observed during the field test. Thirdly, the drivers' awareness for external factors was required. This concept was used to make the drivers aware of available charging options. Finally, a concept for knowledge was required. This concept was used to account for the fact that drivers have incomplete knowledge about situations in target areas. In the Gesteuertes Laden 2.0 project, I used this mechanism to account for situations in which charging infrastructures were occupied and alternatives had to be found.

The analysis of contemporary traffic simulation frameworks showed that there are currently no solutions that express human driver behavior as a result of the above-mentioned sources of distraction. For the Gesteuertes Laden 2.0 project, however, such model was indispensible to compare the performance of the energy management system to the intuitive behavior of human beings. Thus, based on this discussion, I conclude that the presented simulation model for human strategic level driver behavior advances the state-of-the-art in a meaningful manner.

14.1 Future Work

While the simulation model itself has reached a reasonable level of maturity, there is still room for improvements.

The most important issue is the model's performance. During the filter phase, drivers compute available strategies by means of the *genStrat* function. Depending on the available options, this process can be highly complex and may entail long calculating times. With an increasing number

of simulated drivers, the presented approach becomes increasingly inapplicable. The current limit of the approach (in terms of memory usage and computation time) are roughly 10.000 vehicles. This number was sufficient for the presented evaluation scenarios, though, if one wants to perform more comprehensive analyses, the simulation model has to be improved. This improvement is possible since drivers frequently compute and assess the same strategies several times. The mechanism can be improved by using a local memory in which strategies are stored in combination with their quality. It is also possible to store strategy parts in a similar fashion and to re-use these fragments for future strategy computations. First experiments showed that this mechanism is able to increase the model's performance by roughly 90%.

The second objective is to complete the presented simulation model by a comprehensive set of tools. I already presented an editing tool for the comfortable configuration of infrastructures. This editing tool was used in most applications and evaluation scenarios. Drivers and their behavior, however, had to be configured manually. During this manual configuration, most parts of the driver's program code remained the same—only selected parts had to be adjusted, e.g., the utility function or the initial belief-base of the agents. A visual tool might help to ease this process and thus further the use of the presented approach.

Finally, for the implementation of presented model, I selected an existing simulation framework due to its native support for strategic level driver behavior. This simulation framework fit its purpose, nevertheless, there are many professional implementations which represent microscopic traffic flows in a more realistic fashion—though, with a focus on another level of behavior. The SUMO framework Krajzewicz (2010), for instance, is one of the most sophisticated frameworks when it comes to the simulation of tactical level driver behavior.

In this thesis, I argue that it is possible to consider selected levels of behavior in isolation, though, the opportunity to connect my own model for strategic level decision-making to a framework which professionally accounts for tactical level driver behavior is extremely tempting. In fact, such combination has the potential to provide impetus for the development of a holistic representation of human driver behavior in traffic simulations.

Part VII

Appendix

A. List of Publications

Parts of this work have been published within the following publications:

Hoch, N., Werther, B., Bensler, H.-P., Masuch, N., Lützenberger, M., Heßler, A., Albayrak, S., and Siegwart, R. Y. (2011). A user-centric approach for efficient daily mobility planning in e-vehicle infrastructure networks. In Meyer, G. and Valldorf, J., editors, *Advanced Microsystems for Automotive Applications 2011 – Smart Systems for Electric, Safe and Networked Mobility*, VDI-Buch, pages 185–198. Springer.

Keiser, J., Glass, J., Masuch, N., Lützenberger, M., and Albayrak, S. (2011). A distributed multi-operator W2V2G management approach. In *Proceedings of the 2nd IEEE International Conference on Smart Grid Communications (SmartGridComm), Brussels, Belgium*, pages 291–296. IEEE.

Lützenberger, M. (2014). A driver's mind – psychology runs simulation. In Janssens, D., Yasar, A.-U.-H., and Knapen, L., editors, *Data Science and Simulation in Transportation Research*. pages 182–205. IGI Global.

Lützenberger, M., Ahrndt, S., Hirsch, B., Masuch, N., Heßler, A., and Albayrak, S. (2011a). Strategic behaviour in a living environment. In Jain, S., Creasey, R., Himmelspach, J., White, K., and Fu, M., editors, *Proceedings of the 2011 Winter Simulation Conference (WSC'11), Phoenix, AZ, USA*, pages 246–258. IEEE.

Lützenberger, M., Ahrndt, S., Hirsch, B., Masuch, N., Heßler, A., and Albayrak, S. (2012). Reconsider your strategy — an agent-based concep-

tualisation of compensatory driver behaviour. In *Proceedings of the 15th Intelligent Transportation Systems Conference (ITSC 2012), Anchorage, AK, USA*, pages 340–346. IEEE.

Lützenberger, M. and Albayrak, S. (2013). Can you simulate traffic psychology? an analysis. In Pasupathy, R., Kim, S.-H., Tolk, A., Hill, R., and Kuhl, E., editors, *Proceedings of the 2013 Winter Simulation Conference (WSC'13), Washington D.C., USA*, pages 1539–1550. IEEE.

Lützenberger, M. and Albayrak, S. (2014). Current frontiers in reproducing human driver behavior. In *Proceedings of the 46th Summer Computer Simulation Conference (SCSC 2014), Monterey, CA, USA*, pages 514–521.

Lützenberger, M., Keiser, J., Masuch, N., and Albayrak, S. (2012). Agent based assistance for electric vehicles — an evaluation. In Huang, R., Ghorbani, A. A., Pasi, G., Yamaguchi, T., Yen, N. Y., and Jin, B., editors, *Active Media Technology, 8th International Conference, AMT 2012, Macau, China, December 2012, Proceedings*, volume 7669 of *Lecture Notes in Computer Science*, pages 145–154. Springer.

Lützenberger, M., Masuch, N., Hirsch, B., Ahrndt, S., and Albayrak, S. (2011). Strategic behaviour in dynamic cities. In Weed, D., editor, *Proceedings of the 43rd Summer Computer Simulation Conference (SCSC 2011), The Hague, The Netherlands*, pages 148–155.

Lützenberger, M., Masuch, N., Hirsch, B., Ahrndt, S., Heßler, A., and Albayrak, S. (2011). The BDI driver in a service city (extended abstract). In Tumer, K., Yolum, P., Sonenberg, L., and Stone, P., editors, *Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2011), Taipei, Taiwan*, pages 1257–1258. IFAAMAS.

Lützenberger, M., Masuch, N., Hirsch, B., Heßler, A., and Albayrak, S. (2011). Predicting future(e-)traffic. In Balsamo, S. and Marin, A., editors, *Proceedings of the 9th Industrial Simulation Conference (ISC'2011), Venice, Italy*, pages 169–176. EUROSIS-ITI.

Steuer, F., Keiser, J., Geithner, T., Masuch, N., Lützenberger, M., and Ahrndt, S. (2013). Vehicle 2 grid – intelligentes laden und entladen verteilter energiespeicher. In Krems, J. F., Weinmann, O., Weber, J., Westermann, D., and Albayrak, S., editors, *Elektromobilität in Metropolregionen: Die Feldstudie MINI E Berlin powered by Vattenfall*, number 766 in Reihe 12: Verkehrstechnik/Fahrzeugtechnik, pages 114–135. VDI Verlag GmbH.

B. Research Questions

Throughout this thesis, I answered several research questions. I presented these questions in Section 1.3 and used them as a red thread to structure this thesis. Below, I repeat these questions and also their answers:

What is human driver behavior?

Our current understanding of human driver behavior began with the work of Michon (1985), who identified several problems of formerly available approaches. To counter these problems, Michon (1985) proposed his own approach which became widely accepted and helped the entire community of human factors research in driver behavior to gain new momentum.

Following Michon (1985), human driver behavior can be represented as a hierarchically ordered structure of loosely coupled behavioral levels, on which drivers attempt to solve problems. The higher the level, the more "detached" are problems that drivers attempt to solve. On the lowest level, for instance, drivers deal with fundamental car controlling processes, such as controlling speed, following the road, and keeping the vehicle on the road. On the highest level, drivers reason about the general planning of a trip and solve problems that are not entirely related to the driving task. The result of the problem solving process is an action that the driver executes. This action may solve the level-specific problem of the driver, however, it may also cause problems on adjacent levels of behavior, such that the mutual dependencies of all behavior levels can be described as nested hierarchy. Nevertheless, on each level, the drivers' decision-making process is affected

by their personality, their perception, their knowledge (as a consequence to learning processes), as well as by their cognitive abilities.

What is strategic level driver behavior?

Following Michon (1985), strategic level driver behavior refers to the general planning stage of a trip. This stage includes the determination of trip goals, the route and the modal choice as well as a cost-risk evaluation. The behavior of drivers on this level is affected by general considerations about transport and mobility. Finally, concomitant factors such as aesthetic satisfaction and comfort are able to determine the outcome of this behavior level.

What are the factors that determine the outcome of human strategic level decision-making in traffic environments?

Based on the analysis of well-established driver behavior conceptualizations, I conclude that strategic level driver behavior is affected by no less than four distinct factors. First, the outcome of other levels of behavior can affect a driver's strategic level decisions. This impact can be neglected if one wants to focus on analyzing the effects of strategic level behavior in isolation. Secondly, strategic level driver behavior can be affected by the driver's awareness for their surrounding environment. Factors that evolve from the driver's environment are either alternative options or environmental factors. Thirdly, a driver's strategic level decisions are affected by internal factors that represent the driver's personality. Internal factors can be expressed as utility function, which assesses in how far the driver is satisfied with their potential decisions. Finally, strategic level driver behavior is affected by the driver's experience and knowledge. Experience—as a part of the driver's personality— can also be reflected by means of a utility function.

What are the fundamental models of a computer-aided traffic simulation?

Traffic simulations are basically a collection of computational models. At least three models are required—each one belonging to a different category. First, a time flow model describes how time, the basic independent variable, is being reflected. Time flow models can be further divided into continuous and discrete models. Secondly, a traffic flow model describes how traffic is represented in the simulation. There are three common ways to conceptualize traffic, namely macroscopic, microscopic, and mesoscopic models.

Finally, the variable model determines the nature of the variables that are used for the simulation. There are two common types of variable models, namely deterministic and stochastic variable models.

Is human strategic level driver behavior a factor for the outcome of contemporary traffic simulations?

Yes, it is indeed! From all analyzed frameworks, there is no implementation which does not account for strategic level traffic behavior. Concepts are not only provided by academic approaches, but also by commercial ones, which emphasizes that simulation models for strategic level behavior are not only an experimental game, but a significant factor for the outcome of contemporary traffic simulations.

What is an appropriate approach to simulate strategic level driver behavior?

It depends! Analyzed approaches use different mechanisms to account for strategic level decision-making. The most common way to represent strategic level decisions is the user equilibrium, though, based on the analysis of psychological works I argue that this approach has drawbacks. A different approach, based on discrete choice theory, was implemented in Aimsun, yet, discrete choice theory is not able to account for the dynamics of human strategic level driver behavior, as it is pictured by psychological works. Nevertheless, despite the general heterogeneity, is striking that those approaches that put a particular focus on analyzing the effects of strategic level behavior, namely MATSim and FEATHERS, use very similar concepts to conceptualize the driver's behavior. To start with, both frameworks use an agent-based approach to conceptualize the drivers and their behavior. Furthermore, both approaches use a microscopic traffic model to represent traffic flows. Finally, both frameworks use a discrete event (or activity) time flow model. Given the popularity and the success of both frameworks, it appears that these three mechanisms are adequate concepts for representing human strategic level driver behavior. These findings substantiate Conclusion 4.1 and Conclusion 4.2.

Where are the frontiers in simulating human strategic level driver behavior?

Compared to psychological works, the frontiers are primarily in the limitations of external factors. Both categories of external factors, namely

alternative options and environmental factors are represented, though, any form of representation is done in a predefined way. A more generic representation, as pictured by psychologists, is missing. In the case of alternative options, contemporary works restrict strategic level considerations to public transportation. Further concepts, e.g., other means of travel, such as walking or using bicycles, or other forms of transportation, such as car sharing or ride sharing or the use of taxis, are not reflected. The same applies for environmental factors. Despite the fact, that environmental factors are represented in contemporary framework, their nature is predefined. Furthermore, the implemented concepts occur globally, while psychological works explicitly account for factors that occur at selected locations. Finally, most approaches are focused on large-scale analyses and apply the user equilibrium for this purpose. On the large-scale, this approach provides reliable results, since human beings in traffic situations attempt to act "efficiently". Nevertheless, the user equilibrium looses precision with an increasing level of detail. Sub-optimal decisions, which result from incomplete knowledge, are currently not reflected.

Are there available implementations that can be used for the development of a simulation model for strategic level driver behavior?

Yes, the simulation framework after Lützenberger et al. (2011d) is suitable as a foundation for a more comprehensive, simulation-based model for strategic level driver behavior. The calendar-based approach as well as the distinction between driver (represented by the `User` class) and vehicle (represented by the `Vehicle`) supports this thesis. The driver's goals (in the form of appointments at selected target locations) can be stored in a time-dependent fashion, which allows for re-arrangement. Furthermore, the reference between the driver and their vehicle is volatile, such that the model-representation accounts for drivers that occur as pedestrians. The applied inheritance mechanism between the class type `Vehicle` and `ElectricVehicle` supports the definition of further means of transport without affecting the model as it is. Finally, the applied topology mechanism accounts for custom extensions (as it was done in the case of the charging infrastructure). Such mechanism can be useful when it comes to the representation of external factors.

Are there established concepts that can be used to facilitate the development of a simulation model for human strategic level driver behavior?

Yes, there are indeed! Due to the strong resemblance of simulated drivers and software agents, the agent metaphor can be used as a pattern for the development. The main benefit of using an agent-oriented view is the comprehensive set of tools which can be used for the development. Particularly interesting for this work is the BDI approach, which facilitates the behavior specification of intentional systems. The capabilities of BDI, however, are limited to the specification of behavior, thus, a second model is required to conceptualize the impact of external factors.

External factors enjoy similar properties as services, thus, a service-based approach may facilitate the implementation of external factors. A service is described by providing specifications for the service's preconditions and effects. Infrastructural features require additional attributes, such as a location, a scope, and a duration, though, any common format to describe services is easily extended to account for these additional attributes as well.

The application of the service metaphor is extremely helpful, especially in the light of the agent-based driver model. Services and agents share many similarities and often occur together. An application of both concepts will significantly ease the implementation process.

Is it generally possible to produce human strategic level driver behavior by using a BDI-based driver behavior conceptualization and a service-based infrastructure representation?

Yes, it is indeed possible to extend a common simulation topology by service-based representations of alternative options and to use the BDI paradigm to conceptualize a strategic level driver behavior model which accounts for these sources of distraction. The connection between both paradigms is mainly done in the driver's perception phase, where the calculated awareness for infrastructural features is translated into objects that are BDI-processable, in this case: sub-goals. It is also necessary to equip the driver with some form of basic capability, namely elementary actions.

Is it possible to use the BDI-based approach and the service paradigm to implement a simulation model for strategic level

driver behavior which accounts for the entire spectrum of external disturbances, namely environmental factors and alternative options?

Yes, it is indeed possible to integrate both mechanisms to form a simulation model for strategic level driver behavior. While BDI can be used to conceptualize the drivers' behavior, sources of external distraction can be captured in compliance with the service paradigm. In order to make this connection work, the driver has to become aware of the sources of distraction. This can be done by using a driver-specific attribute which determines the driver's visual scope. In order to account for basic knowledge (also a factor for the outcome of strategic level driver behavior), the driver's belief base can be custom-extended by the awareness for selected external factors or other belief artifacts. BDI innately accounts for this feature. Implementing the service paradigm, external factors have to provide specifications for the following attributes: a location & scope, preconditions, effects, and a duration. Due to the resemblance between both categories of external features I decided to use a joint model for their representation. The joint approach was feasible, though, for both categories of external factors there are respectively unused attributes. Infrastructural features for instance require no specification for a scope. Contrary, regional conditions require not specification for preconditions. To make the joint approach work it is necessary to allow the model to contain empty fields.

Is it possible to develop a simulation model for strategic level driver behavior which complies with psychological findings and accounts for all factors that psychological literature deems to be relevant for the outcome of human strategic level decision-making in traffic environments?

Yes, it is possible! The answer to this question lies within a carefully adjusted combination of the belief-desire-intention programming model and the service-based approach. In more detail, the belief-desire-intention model can be used to conceptualize behavior of drivers such that strategic level problem solving is mimicked. BDI innately accounts for a flexible configuration of the driver's belief—their knowledge—an thus accounts for the first factor that is relevant for the outcome of strategic level problem solving in traffic and transport environments. Furthermore, it is possible to custom-

define the mechanism which determines after which criteria a driver selects from available strategies. This feature directly addresses the requirement to account for the driver's personality in the strategic level decision-making process. I already established that it is possible to refrain from accounting for the impact of other levels of behavior (psychologists agree with that). Thus, there remains only one source of distraction, namely external factors. External factors are not innately supported by BDI, therefore a second model is required. External factors have a strong resemblance to software services, thus, a service-based representation is suggested. In order to make this work, the distinguishing attributes of services have to be identified within the concept of external factors. From a service-perspective, there are two attributes that require a mapping, namely preconditions and effects. To properly account for external conditions in a traffic environment, the service metaphor, however, has to be extended by further attributes, namely a locational attribute (including a location and a scope) and a duration function. The connection between BDI and the service-based representation can be done in the driver's perception phase. Here the drivers awareness for their environment is determined. The services' location and scope as well as driver-specific parameters (e.g., the drivers range of vision) can be used to connect the driver's reasoning process to their environment and to generate BDI objects (e.g., beliefs or goals) that represent the driver's perception during the subsequent reasoning phase. This mechanism integrates the BDI-based driver model and the service-based infrastructure representation and connects the driver's strategic level behavior to their awareness for the surrounding infrastructure—the fourth factor that, following human factors psychology, determines the outcome of strategic level driver behavior.

C. List of Abbreviations

ACME	**A** **C**ommon **M**ental **E**nvironment
ACT-R	**A**daptive **C**ontrol of **T**hought-**R**ational
Aimsun	**A**dvanced **i**nteractive **m**icroscopic **s**imulator for **u**rban and non-urban **n**etworks
AOSE	**A**gent **O**riented **S**oftware **E**ngineering
AVENUE	**A**dvanced & **V**isual **E**valuator for road **N**etworks in **U**rban ar**E**as
BPMN	**B**usiness **P**rocess **M**odel and **N**otation
BDI	**B**elief **D**esire **I**ntention
COCOM	**CO**ntextual **CO**ntrol **M**odel
DRACULA	**D**ynamic **R**oute **A**ssignment **C**ombining **U**ser **L**earning and Microsimul**A**tion
Dynameq	**Dynam**ic **eq**uilibrium
DynaMIT	**Dy**namic **n**etwork **a**ssignment for the **M**anagement of **I**nformation to **T**ravelers
E-Mobility	**E**lectric-**Mobility**
ECOM	**E**xtended **C**ontrol **MO**del
FEATHERS	**F**orecasting **E**volutionary **A**ctivity-**T**ravel of **H**ouseholds and their **E**nvironmental **R**epercussion**S**
GPS	**G**lobal **P**ositioning **S**ystem
GPX	**GP**S E**X**change Format
JIAC	**J**ava-based **I**ntelligent **A**gent **C**omponentware
KK-Model	**K**erner-**K**onhäuser Model

MATSim	**M**ulti-**A**gent **T**ransport **Sim**ulation
MITSIMLab	**MI**croscopic **T**raffic **SIM**ulation **L**aboratory
OSM	**O**pen**S**treet**M**ap
STM	**S**trategic **T**ransport **M**odel
SUMO	**S**imulation of **U**rban **M**obility
V2G	**V**ehicle **2** **G**rid
VISSIM	**V**erkehr **I**n **S**tädten – **SI**mulations**M**odell
XML	E**X**tensible **M**arkup **L**anguage

D. The Editor

The simulation model that I presented in this thesis comprises two parts. First, there is one model to conceptualize the action-generation process of the driver, secondly, there is one model to conceptualize influences that evolve from the driver's environment and that are able to affect a driver's decision, namely external factors.

In practice, there are many scenarios where one wants to add a large number of external factors of the same type to a simulation topology and analyze their impact on the traffic scene. As an example, consider those applications which I presented in Chapter 11 and Chapter 13. What these project applications had in common was the requirement to represent parking availability in a realistic fashion. In both cases a map of Berlin, Germany was used as simulation topology. Due to the dimension of the map it becomes obvious that any realistic configuration which is done manually is cumbersome at best.

Yet, our practical experiences with the simulation framework showed that most simulation scenarios comprise a large number of factors that belong to the same type but have different locations. In other words, while the location attribute of external factor instances varies, specifications for the preconditions, the effects, and the duration function are mostly the same. For large scale scenarios, the location attribute constitutes a serious problem. The effort to define preconditions and effects for one and for one thousand car parks may be the same, yet, the effort for their distribution grows linear with the amount.

To solve this problem, I consciously designed the simulation engine to support the OpenStreetMap framework (Ramm et al., 2010) . In addition to GPS coordinates of traffic-relevant objects, OpenStreetMap maps feature an additional layer which enriches traffic objects by attributes. This mechanism allows for a selective identification of places, such as restaurants or fuel stations or even special tracks, such as hike, cycle or even seaways. OpenStreetmap is an open project, which collects geographic data and makes them publicly available. On the lowest hierarchy level, the data consists of GPS coordinates. On top of that, the data is grouped to collections, which reflect complex entities such as streets, bike paths, subway stations, bus stops, and many more. These complex entities are extended by tags, which carry the semantic enrichment. Additional information such as a street name, amount of lanes, or a subway station's lines are stored here.

In order to facilitate the configuration of simulation scenarios, a graphical editor was developed. This editor can import maps that comply with the OpenStreetMap syntax and automatically locate infrastructural features for which preconditions and effects have been defined. To provide a high degree of flexibility, the initially loaded map can be manipulated by adding, removing or configuring selected infrastructural feature instances. Further, the map can be extended by previously defined regional conditions.

The editor is able to import OpenStreetMap files and to retrieve particular points of interest from this map. The implementation of this mechanism was easy, since OSM simply extends GPS coordinates with key-value tags. Car parks for instance are tagged by the key-value combination: `amenity=parking`. Subway stations can be identified by the key-value combination: `railway=subway`. The editor does not support the entire key-value scope of OpenStreetMap, but an extension can be done quickly by an addition to the editors' list of known key-value pairs.

Using the editor, the locations of infrastructural features can be derived automatically, but to comply with the presented infrastructure model, further specifications for preconditions and effects are required. I developed a mechanism to store these information in separate files, which are loaded by the editor on startup. For the binding I use the OpenStreetMap key-value pair as identifier.

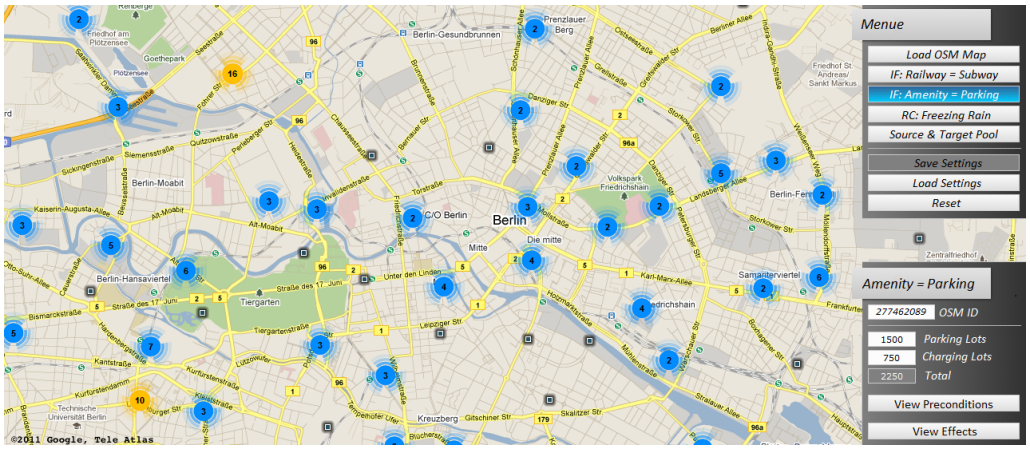

Figure D.1: The OpenStreetMap editor, showing original car park occurrences for the capital region of Berlin, German (after Lützenberger et al., 2011a, p. 251).

After the OpenStreetMap map and the provided preconditions and effects have been loaded, the user can choose which infrastructural features should be considered for their simulation scenario. The initial distribution of their selection is then presented on a map. Both, the editor and the simulation engine were implemented without fixed references to specific maps (e.g., of particular cities), thus, simulations for any city of the world can be done (as long as OpenStreetMap provides data for the desired region).

The general principle works fine, although some infrastructural features comprise parameters that can be problematic. As an example consider the capacity of car parks. The capacity usually varies from instance to instance and can not be defined as global constant. OpenStreetMap provides a large amount of additional information (in some cases even for parking capacities), yet, the framework is not all-powerful and for this reason, the editor was designed to present detailed information on the attributes of each single infrastructural feature and to allow for selective manipulations and extensions of those.

Figure D illustrates the editor, showing original car park occurrences for the capital region of Berlin, Germany. Spots with multiple occurrences are represented as colored circles, and labeled with the exact number of contained car parks. Zooming into these spots will cause the circles to collapse into black spots identifying single car parks.

In addition to supporting the configuration of infrastructural features, the editor provides the functionality to extend simulation topologies by regional conditions. The volatile nature of regional conditions disagrees with persistent storage (at least within an OpenStreetMap map), thus, location and scopes can be manually defined through the editor.

Bibliography

American Psychological Association (2010). *Publication Manual of the American Psychological Association*. APA, 6th edition.

Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., and Qin, Y. (2004). An integrated theory of the mind. *Psychological Review*, 111:1036–1060.

Atkinson, R. C. and Shiffring, R. M. (1968). Human memory: A proposed system and its control processes. In Spence, K. W., editor, *The Psychology of Learning and Motivation: Advances in Research and Theory*, pages 89–195. Academic Press, Inc.

Balci, O. (1988). The implementation of four conceptual frameworks for simulation modeling in high-level languages. In *Proceedings of 20th Winter Simulation Conference, San Diego, CA, USA*, pages 287–295. ACM.

Balmer, M., Cetin, N., Nagel, K., and Raney, B. (2004). Towards truly agent-based traffic and mobility simulations. In Jennings, N., Tambe, M., Sierra, C., and Sonenberg, L., editors, *Proceedings of the 3rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2004), New York City, NY, USA*, pages 60–67. IEEE.

Barceló, J., editor (2010a). *Fundamentals of Traffic Simulation*, volume 145 of *International Series in Operations Research and Management Science*. Springer, 1st edition.

Barceló, J. (2010b). Models, traffic models, simulation, and traffic simulation. In Barceló (2010a), pages 1–62.

Bekiaris, E., Amditis, A., and Panou, M. (2003). DRIVABILITY: a new concept for modelling driving performance. *Cognition, Technology & Work*, 5:152–161.

Bellemans, T., Kochan, B., Janssens, D., Wets, G., Arentze, T., and Timmermans, H. (2010). Implementation framework and development trajectory of FEATHERS activity-based simulation platform. *Transportation Research Record: Journal of the Transportation Research Board*, 2175:111–119.

Ben-Akiva, M., Koutsopoulos, H. N., Antoniou, C., and Balakrishna, R. (2010a). Traffic simulation with DynaMIT. In Barceló (2010a), pages 363–398.

Ben-Akiva, M., Koutsopoulos, H. N., Toledo, T., Yang, Q., Choudhury, C. F., Antoniou, C., and Balakrishna, R. (2010b). Traffic simulation with MITSIMLab. In Barceló (2010a), pages 233–268.

Bötticher, A. M. T. and van der Molen, H. H. (1988). Predicting overtaking behaviour on the basis of the hierarchical risk model for traffic participants. In Rothengatter, T. and de Bruin, R., editors, *Road User Behaviour – Theory and Research*, pages 48–65. Van Gorcum.

Cacciabue, C., editor (2007). *Modelling Driver Behaviour in Automotive Environments — Critical Issues in Driver Interactions with Intelligent Transport Systems*. Springer, 1st edition.

Caliper Corporation (2014). Transmodeler overview. `http://www.caliper.com/transmodeler` (accessed May 16, 2014).

Carsten, O. (2007). From driver models to modelling the driver: What do we really need to know about the driver? In Cacciabue (2007), pages 105–120.

Casas, J., Ferrer, J. L., García, D., Perarnau, J., and Torday, A. (2010). Traffic simulation with Aimsun. In Barceló (2010a), pages 173–232.

Cascetta, E. (2001). *Transportation Systems Engineering: Theory and Methods*. Kluwer Academic Publishers.

Christ, R. (2000). GADGET final report: Investigations on influences upon driver behaviour – safety approaches in comparison and combination. Technical report, GADGET Consortium.

Cohen, P. R. and Levesque, H. J. (1990). Intention is choice with commitment. *Artificial Intelligence*, 42(2-3):213–261.

Dennett, D. C. (1989). *The Intentional Stance*. A Bradfort book. MIT Press, 1st edition.

Dijkstra, E. W. (1959). A note on two problems in connection with graphs. *Numerische Mathematik*, 1:269–271.

Dons, E., Poppel, M. V., Kochan, B., Wets, G., and Panis, L. I. (2014). Implementation and validation of a modeling framework to assess personal exposure to black carbon. *Environment International*, 62(0):64–71.

Edie, L. C. and Foote, R. S. (1960). Effect of shock waves on tunnel traffic flow. In *Proceedings of Highway Research Record, HRB, National Research Record Council, Washington, D.C., USA*, volume 39. Port of New York Authority.

Ehmanns, D. (2001). Simulationsmodell des menschlichen spurwechselverhaltens – Simulation model of human lane change behaviour. In *VDI/SAE/JSAE Gemeinschaftstagung, Der Fahrer im 21.Jahrhundert, Berlin, Germany*. VDI-Verlag.

Engström, J. and Hollnagel, E. (2007). A general conceptual framework for modelling behavioural effects of driver support functions. In Cacciabue (2007), pages 61–84.

Federal Ministry of Transport, Building and Urban Development (2010). *Mobilität in Deutschland 2008*. Bonn and Berlin, Germany: Federal Ministry of Transport, Building and Urban Development.

Fellendorf, M. and Vortisch, P. (2010). Microscopic traffic flow simulator VISSIM. In Barceló (2010a), pages 63–94.

Gazis, D. C. (2002). *Traffic Theory*. Kluwer Academic Publishers.

Gazis, D. C., Herman, R., and Potts, R. B. (1959). Car-following theory of steady-state traffic flow. *Operations Research*, 7(4):499–505.

Gerlough, D. L. (1955). *Simulation of freeway traffic on a general-purpose discrete variable computer*. Doctoral dissertation, University of California, Los Angeles, CA, USA.

Gerlough, D. L. and Huber, M. J. (1975). Traffic flow theory – a monograph, special report 165. Technical report, Transportation Research Board, National Research Council, Washington, D.C., USA.

Gibson, J. J. and Crooks, L. E. (1938). A theoretical field-analysis of automobile-driving. *The American Journal of Psychology*, 51(3):453–471.

Gipps, P. G. (1981). A behavioural car-following model for computer simulation. *Transportation Research Part B: Methodological*, 15(2):105–111.

Hale, A. R., Stoop, J., and Hommels, J. (1990). Human error models as predictors of accident scenarios for designers in road transport systems. *Ergonomics*, 33(10–11):1377–1387.

Hatakka, M., Keskinen, E., Katila, E., and Laapotti, S. (1997). Do psychologists have something to offer in driver training, driver improvement and selection? In Risser, R., editor, *Assessing the driver: contributions to a Workshop on Driver Diagnostic and Selection, March 17, 1997, Basle (Switzerland)*, number 41 in Faktor Mensch im Verkehr. Rot-Gelb-Grün Braunschweig, Deutschland.

Hatzopoulou, M., Hao, J. Y., and Miller, E. J. (2011). Simulating the impacts of household travel on greenhouse gas emissions, urban air quality, and population exposure. *Transportation*, 38:871–887.

Herman, R., Montroll, E. W., Potts, R. B., and Rothery, R. W. (1959). Traffic dynamics: Analysis of stability in car following. *Operations Research*, 7(1):86–106.

Hidas, P. (1998). A car following model for urban traffic simulation. *Traffic Engineering Control*, 39(5):300–305.

Hilliges, M. (1995). *Ein phänomenologisches Modell des dynamischen Verkehrsflusses in Schnellstraßennetzen.* Doctoral dissertation, Universität Stuttgart.

Hoch, N., Werther, B., Bensler, H.-P., Masuch, N., Lützenberger, M., Heßler, A., Albayrak, S., and Siegwart, R. Y. (2011). A user-centric approach for efficient daily mobility planning in e-vehicle infrastructure networks. In Meyer, G. and Valldorf, J., editors, *Advanced Microsystems*

for Automotive Applications 2011 – Smart Systems for Electric, Safe and Networked Mobility, VDI-Buch, pages 185–198. Springer.

Hollnagel, E. (1993). *Human Reliability Analysis: Context and Control*. Computers and Peoples Series. Academic Press, Inc.

Hollnagel, E. and Woods, D. D. (2005). *Joint Cognitive Systems: Foundations of Cognitive Systems Engineering*. CRC Press.

Illenberger, J., Flötteröd, G., and Nagel, K. (2007). Enhancing MATSim with capabilities of within-day re-planning. In *Proceedings of the IEEE Intelligent Transportation Systems Conference, Seattle, WA, USA*, pages 94–99. IEEE.

INRO (2014). Emme website. `http://www.inro.ca/en/products/emme/index.php` (accessed May 16, 2014).

Janssens, D., Yasar, A.-U.-H., and Knapen, L., editors (2014). *Data Science and Simulation in Transportation Research*. IGI Global.

Jennings, N. R. (2001). An agent-based approach for building complex software systems. *Communications of the ACM*, 44(4).

Jennings, N. R. and Wooldridge, M. (2000). Agent-oriented software engineering. *Artificial Intelligence*, 117:277–296.

Kassin, S. (2003). *Psychology*. Prentice Hall, 4th edition.

Keiser, J., Glass, J., Masuch, N., Lützenberger, M., and Albayrak, S. (2011). A distributed multi-operator W2V2G management approach. In *Proceedings of the 2nd IEEE International Conference on Smart Grid Communications (SmartGridComm), Brussels, Belgium*, pages 291–296. IEEE.

Kerner, B. S. and Konhäuser, P. (1993). Cluster effect in initially homogeneous traffic flow. *Physical Review E*, 48:R2335–R2338.

Keskinen, E. (1996). Why do young drivers have more accidents? *Junge Fahrer und Fahrerinnen*, Heft M 52:42–53.

Keskinen, E., Hatakka, M., Laapotti, S., Katila, A., and Peräaho, M. (2004). Driver behaviour as a hierarchical system. In Rothengatter, T. and Huguenin, R. D., editors, *Traffic & Transport Psychology: Theory and Application*, pages 9–23. Elsevier, 1st edition.

Krajzewicz, D. (2010). Traffic simulation with SUMO – Simulation of Urban MObility. In Barceló (2010a), pages 269–294.

Krajzewicz, D., Hertkorn, G., Wagner, P., and Rössel, C. (2002). SUMO (Simulation of Urban MObility) – an open-source traffic simulation. In *Proceedings of the 4th Middle Eastern Simulation and Modelling Conference (MESM 2002), Sharjah, UAE*, pages 183–187.

Krajzewicz, D. and Wagner, P. (2002). ACME (A Common Mental Environment)-driver – a cognitive car driver model. In Amborski, K. and Meuth, H., editors, *Proceedings of the 16th European Simulation Multiconference on Modelling and Simulation*, pages 689–693. SCS Europe.

Krauß, S. (1998). *Microscopic Modeling of Traffic Flow: Investigation of Collision Free Vehicle Dynamics*. Doctoral dissertation, Deutsches Zentrum für Luft- und Raumfahrt Hauptabteilung Mobilität und Systemtechnik, Köln.

Kuwahara, M., Horiguchi, R., and Hanabusa, H. (2010). Traffic simulation with AVENUE. In Barceló (2010a), pages 95–130.

Lee, W. D., Joh, C.-H., Cho, S., and Kochan, B. (2014). Issues in feathers application in the Seoul metropolitan area. In Janssens et al. (2014), pages 71–85.

Lieberman, E. and Rathi, A. K. (2005). Traffic simulation. In Gartner, N. H., Messer, C. J., and Rathi, A. K., editors, *Revised Monograph on Traffic Flow Theory: A State-of-the-Art Report*, pages 10–1 – 10–23. Turner-Fairbank Highway Research Center, Federal Highway Administration, U.S. Dept. of Transportation. To be published as a Special Report by the Transportation Research Board of the National Research Council.

Liu, R. (2010). Traffic simulation with DRACULA. In Barceló (2010a), pages 295–322.

Liu, R., van Vliet, D., and Watling, D. (2006). Microsimulation models incorporating both demand and supply dynamics. *Transportation Research Part A: Policy and Practice*, 40:125–150.

Lückemeyer, G. (2007). *A Traffic Simulation System Increasing the Efficiency of Schedule Design for Public Transport Systems Based on Scarce Data*. Doctoral dissertation, Universität zu Köln.

Lützenberger, M. (2014). A driver's mind – psychology runs simulation. In Janssens et al. (2014), pages 182–205.

Lützenberger, M., Ahrndt, S., Hirsch, B., Masuch, N., Heßler, A., and Albayrak, S. (2011a). Strategic behaviour in a living environment. In Jain, S., Creasey, R., Himmelspach, J., White, K., and Fu, M., editors, *Proceedings of the 2011 Winter Simulation Conference (WSC'11), Phoenix, AZ, USA*, pages 246–258. IEEE.

Lützenberger, M., Ahrndt, S., Hirsch, B., Masuch, N., Heßler, A., and Albayrak, S. (2012a). Reconsider your strategy – an agent-based conceptualisation of compensatory driver behaviour. In *Proceedings of the 15th Intelligent Transportation Systems Conference (ITSC 2012), Anchorage, AK, USA*, pages 340–346. IEEE.

Lützenberger, M. and Albayrak, S. (2013). Can you simulate traffic psychology? an analysis. In Pasupathy, R., Kim, S.-H., Tolk, A., Hill, R., and Kuhl, E., editors, *Proceedings of the 2013 Winter Simulation Conference (WSC'13), Washington D.C., USA*, pages 1539–1550. IEEE.

Lützenberger, M. and Albayrak, S. (2014). Current frontiers in reproducing human driver behavior. In *Proceedings of the 46th Summer Computer Simulation Conference (SCSC 2014), Monterey, CA, USA*, pages 514–521.

Lützenberger, M., Keiser, J., Masuch, N., and Albayrak, S. (2012b). Agent based assistance for electric vehicles – an evaluation. In Huang, R., Ghorbani, A. A., Pasi, G., Yamaguchi, T., Yen, N. Y., and Jin, B., editors, *Active Media Technology, 8th International Conference, AMT 2012, Macau, China, December 2012, Proceedings*, volume 7669 of *Lecture Notes in Computer Science*, pages 145–154. Springer.

Lützenberger, M., Küster, T., Konnerth, T., Thiele, A., Masuch, N., Heßler, A., Keiser, J., Burkhardt, M., Kaiser, S., Tonn, J., Kaisers, M., and Albayrak, S. (2013). A multi-agent approach to professional software engineering. In Cossentino, M., Seghrouchni, A. E. F., and Winikoff, M.,

editors, *Engineering Multi-Agent Systems – First International Workshop, EMAS 2013, St. Paul, MN, USA, May 6–7, 2013, Revised Selected Papers*, volume 8245 of *Lecture Notes in Artificial Intelligence*, pages 158–177. Springer.

Lützenberger, M., Masuch, N., Hirsch, B., Ahrndt, S., and Albayrak, S. (2011b). Strategic behaviour in dynamic cities. In Weed, D., editor, *Proceedings of the 43rd Summer Computer Simulation Conference (SCSC 2011), The Hague, The Netherlands*, pages 148–155.

Lützenberger, M., Masuch, N., Hirsch, B., Ahrndt, S., Heßler, A., and Albayrak, S. (2011c). The BDI driver in a service city (extended abstract). In Tumer, K., Yolum, P., Sonenberg, L., and Stone, P., editors, *Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2011), Taipei, Taiwan*, pages 1257–1258. IFAAMAS.

Lützenberger, M., Masuch, N., Hirsch, B., Heßler, A., and Albayrak, S. (2011d). Predicting future(e-)traffic. In Balsamo, S. and Marin, A., editors, *Proceedings of the 9th Industrial Simulation Conference (ISC'2011), Venice, Italy*, pages 169–176. EUROSIS-ITI.

MacKenzie, C. M., Laskey, K., McCabe, F., Brown, P. F., Metz, R., and Hamilton, B. A. (2006). Reference model for service oriented architecture 1.0. `http://docs.oasis-open.org/soa-rm/v1.0/soa-rm.pdf` (accessed May 16th, 2014).

Mahut, M. and Florian, M. (2010). Traffic simulation with Dynameq. In Barceló (2010a), pages 323–362.

May, A. (1990). *Traffic Flow Fundamentals*. Prentice Hall.

Michon, J. A. (1976). The mutual impacts of transportation and human behaviour. In Stringer, P. and Wenzel, H., editors, *Transportation planning for a better environment*, pages 221–236. Plenum Press.

Michon, J. A. (1985). A critical view of driver behaviour models: What do we know, what should we do? In Evans, L. and Schwing, R. C., editors, *Human Behavior and Traffic Safety*, pages 487–525. Plenum Press.

Nationale Plattform Elektromobilität (2011). Zweiter bericht der nationalen plattform elektromobilität. Technical report, Gemeinsame Geschäftsstelle Elektromobilität der Bundesregierung.

Neisser, U. (1976). *Cognition and Reality: Principles and Implications of Cognitive Psychology.* W. H. Freeman & Co Ltd.

Newell, G. F. (1961). Nonlinear effects in the dynamics of car following. *Operations Research*, 9:209–229.

Panou, M., Bekiaris, E., and Papakostopoulos, V. (2007). Modelling driver behaviour in European Union and international projects. In Cacciabue (2007), pages 3–25.

Parker, M. T. (1996). The effect of heavy goods vehicles and follower behavior on capacity at motorway roadwork sites. *Traffic Engineering Control*, 37(9):524–531.

Peters, B. and Nilsson, L. (2007). Modelling the driver in control. In Cacciabue (2007), pages 85–104.

Pipes, L. A. (1953). An operational analysis of traffic dynamics. *Journal of Applied Physics*, 24:274–281.

Ramm, F., Topf, J., and Chilton, S. (2010). *OpenStreetMap: Using and Enhancing the Free Map of the World.* UIT Cambridge Ltd., 1st edition.

Raney, B. and Nagel, K. (2004). An improved framework for large-scale multi-agent simulations of travel behavior. In *Proceedings of the 4th Swiss Transport Research Conference (STRC 2004).*

Ranney, T. A. (1994). Models of driving behavior: A review of their evolution. *Accident Analysis & Prevention*, 26(6):733–750.

Ranney, T. A. (1999). Psychological factors that influence car-following and car-following model development. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2(4):213–219.

Rao, A. S. and Georgeff, M. P. (1995). BDI agents: From theory to practice. In Lesser, V. and Gasser, L., editors, *Proceedings of the 1st International Conference on Multiagent Systems, San Francisco, CA, USA*, pages 312–319.

Rasmussen, J. (1986). *Information Processing and Human-Machine Interaction: An Approach to Cognitive Engineering*, volume 12 of *North-Holland Series in System Science and Engineering*. Elsevier Science Ltd.

Rechenberg, I. (1973). *Evolutionsstrategie: Optimierung technischer Systeme nach Prinzipien der biologischen Evolution*, volume 15 of *Problemata*. Frommann-Holzboog, Stuttgart-Bad Cannstatt.

Reuschel, A. (1950a). Vehicle movements in a platoon. *Zeitschrift des Österreichischen Ingenieur und Architekten Vereines*, 4:193–215.

Reuschel, A. (1950b). Vehicle movements in a platoon with uniform acceleration or deceleration of the lead vehicle. *Zeitschrift des Österreichischen Ingenieur und Architekten Vereines*, 95:59–62, 73–77.

Russel, S. and Norvig, P. (2003). *Artificial Intelligence: A Modern Approach*. Artificial Intelligence. Prentice Hall, 2nd edition.

Salvucci, D. D. (2006). Modeling driver behavior in a cognitive architecture. *Human Factors*, 48(2):362–380.

Salvucci, D. D., Boer, E. R., and Liu, A. (2001). Toward an integrated model of driver behavior in a cognitive architecture. *Transportation Research Record*, 1779:9–16.

Shvetsov, V. I. (2003). Mathematical modeling of traffic flows. *Automation and Remote Control*, 64(11):1651–1689.

Steuer, F., Keiser, J., Geithner, T., Masuch, N., Lützenberger, M., and Ahrndt, S. (2013). Vehicle 2 grid – intelligentes laden und entladen verteilter energiespeicher. In Krems, J. F., Weinmann, O., Weber, J., Westermann, D., and Albayrak, S., editors, *Elektromobilität in Metropolregionen: Die Feldstudie MINI E Berlin powered by Vattenfall*, number 766 in Reihe 12: Verkehrstechnik/Fahrzeugtechnik, pages 114–135. VDI Verlag GmbH.

Summala, H. (1996). Accident risk and driver behaviour. *Safety Science*, 22(1–3):103–117.

Summala, H. (1997). Hierarchical model of behavioural adaptation and traffic accidents. In Rothengatter, T. and Vaya, E., editors, *Traffic &*

Transport Psychology: Theory and Application, pages 41–52. Pergamon, Elsevier Science, U.K.

Sycara, K. P. (1998). Multiagent systems. *AI Magazine*, 19(2):79–92.

Sykes, P. (2010). Traffic simulation with paramics. In Barceló (2010a), pages 131–172.

TRL Software (2014). The strategic transport model. `https://www.trlsoftware.co.uk/products/economic_appraisal/stm`.

Tulving, E. (1972). Episodic and semantic memory. In Tulving, E. and Donaldson, W., editors, *Organization of Memory*, chapter Episodic and Semantic Memory, pages 381–403. Academic Press, Inc.

Vaa, T. (2001). Cognition and emotion in driver behaviour models: Some critical viewpoints. In *Proceedings of the 14th ICTCT Workshop, Caserta, Italy*, pages 48–59.

van der Molen, H. H. and Bötticher, A. M. T. (1988). A hierarchical risk model for traffic participants. *Ergonomics*, 31(4):537–555.

Vattenfall Europe Innovation GmbH, Bayerische Motoren Werke Aktiengesellschaft, Technische Universität Berlin, Technische Universität Chemnitz, and Technische Universität Illmenau (2011). Gesteuertes Laden V2.0, Gemeinsamer Abschlussbericht.

Wang, J., Liu, R., and Montgomery, F. (2005). Car-following model for motorway traffic. *Transportation Research Record: Journal of the Transportation Research Board*, 1934:33–42.

Wooldridge, M. (2002). Intelligent agents: The key concepts. In Mařík, V., Štěpánková, O., Krautwurmová, H., and Luck, M., editors, *Multi-Agent Systems and Applications II*, volume 2322 of *Lecture Notes in Computer Science*, pages 3–43. Springer.

Wooldridge, M. and Jennings, N. R. (1995). Intelligent agents: Theory and practice. *Knowledge Engineering Review*, 10(2):115–152.

Index