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**SIMULATION OF
SPATIAL LEARNING MECHANISMS**

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ABSTRACT

The evolution of information technology brings an entirely new perspective to old issues of transportation and the problem of overloaded road traffic networks. At the forefront of progress in the field of information technology is the opportunity for the driver to acquire knowledge through media.

The present study is aimed at investigating effects of spatial orientation in typical situations. To this end, it starts out from the following exemplary scenario: Traffic in the Zurich metropolitan area is congested. Vehicles often move at walking pace. Traffic demand leads to an average volume of 118 vehicles per kilometer. Every driver has planned his itinerary with the help of an off-the-shelf navigation device and sticks to his shortest route. In view of this situation, the question investigated in this study is: How much will the traffic situation improve if part of the drivers use real-time navigation information (such as may be available via smartphone)? The research to answer this question proceeds on the assumption that a driver behaves either in a “conventional” or in a “progressive” manner. The conventional drivers move along on the route they perceived as the shortest one when they planned it before starting on their trip. The progressive drivers are informed about the current traffic situation and head for their destination dynamically by choosing the currently most advantageous link at each traffic node on their trip.

The decision processes of the informed drivers will be mapped in a simplified form and microscopically simulated using the MATSim software. A model postulated for the route choice describes the behavior of drivers guided by real-time navigation information, but not obstinately following it; their experience regarding the reliability of the traffic information also influences their route choice. The model analyzes how differing knowledge levels and modes of behavior of the drivers affect the state of the traffic system in the real-world setting of the Zurich metropolitan area.

The results of the experiments testify to the existence of great differences in respect of the load on the road network, the mean daily travel times and the consequential

properties of a trip up to the driver's arrival time at his destination. – A key result is that all drivers benefit even when only part of them navigate by using current traffic information. Further results show in detail the time savings that each of the two classes of drivers achieves, and also how the entirety of drivers benefits from certain shares of informed drivers. Especially interesting for the analyst is the finding that the effect of descriptive and normative behavior in respect of route choice varies significantly. The scenario's estimated mean saving potential of about 25 percent can be fully exploited if the informed drivers behave in a disciplined manner and follow the recommended links.

When 30 percent of the drivers in the Zurich metropolitan area are guided by real-time navigation system information and comply exactly with it, the traffic density will be reduced from 118 vehicles to 56 vehicles per kilometer, and traffic speed will increase from four to 22 kilometers per hour. Starting from a share of 50 percent of informed drivers, traffic density will diminish to just above 30 vehicles per kilometer, and a driver will reach his destination at an average speed of little more than 50 kilometers per hour. The better distribution of the traffic may triple the distance of an informed driver, it is true; and yet it amounts to an 84 percent time saving for all drivers. – However, if more than 70 percent of the drivers go by real-time navigation system information, the traffic situation will again deteriorate to as many as 43 vehicles per kilometer moving at a speed of 34 kilometers per hour.

This (probably unexpected) deterioration of the traffic situation at a high share of drivers being guided by real-time navigation system information asks for more research. Further analyses are required. Most likely they will show that to prevent this unwanted effect, the quality of the information must be improved. The hypothesis that suggests itself is that navigation system guidance must be based on marginal cost, which in turn requires that the traffic densities and the time-flow-capacity curves of the links are measured exactly, and that this information is made available in real time.

Notes: (1) The mentioned traffic data is self-consistent and serves the purpose of comprehensively expressing the relations within the system. (2) Every model of a real socio-economic system is inaccurate, on the one hand, due to irregularly occurring effects (stochastic effects) and, on the other hand, because not all system-related influences can be taken into account. The results of the simulation of concrete scenarios can also vary because they are differently configured and calibrated. (3) The purpose of the model is to demonstrate the interaction between the microscopic level (that of the driver's decision) and the macroscopic level (the state of the traffic).

KURZFASSUNG

Die Entwicklung der Informationstechnologie rückt alte Fragen des Transports rund um das Problem der Überlastung von Verkehrsnetzen in ein neues Licht. Im Mittelpunkt dieses Fortschritts steht der mediale Wissenserwerb von Autofahrern. Die neue Art der räumlichen Orientierung wird an typischen Situationen untersucht. Die Arbeit geht aus von folgendem Beispielszenarium: Der Verkehrsraum Zürich ist überlastet. Die Fahrzeuge bewegen sich im Schrittempo. Die Verkehrsnachfrage erzeugt ein mittleres Volumen von 118 Fahrzeugen pro Kilometer. Jeder Fahrer hat seinen Weg mit Hilfe eines im Handel üblichen Routenplaners festgelegt und bleibt auf seiner kürzesten Route.

Die Fragestellung, der die Studie auf den Grund geht, lautet: Wie stark verbessert sich die Verkehrslage, wenn ein Teil der Fahrer eine (z. B. über Smart-Phones verfügbare) Echtzeitnavigation nutzt? Es gilt die Annahme, dass sich ein Fahrer entweder in „konventioneller“ Weise verhält oder „fortschrittlich“ agiert. Die konventionellen Fahrer bewegen sich auf den vor der Reise festgelegten kürzesten Routen. Die fortschrittlichen Fahrer sind über die Verkehrslage informiert und steuern ihre Ziele dynamisch an, indem sie an jedem Verkehrsknoten ihrer Reise die aktuell günstigste Verbindung wählen.

Die Entscheidungsprozesse der informierten Fahrer werden in vereinfachter Form abgebildet und mit der Software MATSim mikroskopisch simuliert. Ein für die Routenwahl postuliertes Modell beschreibt das Verhalten von Fahrern, die navigiert sind, aber der Information nicht immer stur folgen; ihre Erfahrung bezüglich der Zuverlässigkeit der Verkehrsinformation spielt bei der Wahl der Routen eine Rolle. Am realen Fall des Verkehrsbereichs Zürich analysiert das Modell die Wirkung unterschiedlicher Wissensstufen und Verhaltensweisen der Fahrer auf den Zustand des Verkehrssystems.

Die Ergebnisse der Versuche belegen große Unterschiede bezüglich der Belastung des Verkehrsnetzes, der mittleren täglichen Reisezeiten und der damit verbundenen Merkmalen einer Fahrt bis hin zur Ankunftszeit des Fahrers an seinem Ziel. – Ein

Schlüsselergebnis ist darin zu sehen, dass alle Fahrer profitieren, selbst wenn nur ein Teil davon navigiert ist. Weitere Ergebnisse zeigen detailliert auf, welche Zeitersparnisse die beiden Klassen von Fahrern jeweils für sich verbuchen; ferner, wie die Gesamtheit der Fahrer von gewissen Anteilen informierter Fahrer profitiert. Selbst die Wirkung von deskriptivem und normativem Verhalten bei der Wahl der Routen variiert signifikant. Diese Einsicht ist besonders für den Analytiker interessant. Das Ersparnispotenzial des Szenariums kann ausgeschöpft werden, wenn sich die dynamisch informierten Fahrer diszipliniert verhalten und den empfohlenen Verbindungen folgen.

Wenn 30 Prozent der Fahrer im Großraum Zürich navigiert sind und sich genau an die Information halten, reduziert sich das Verkehrsaufkommen von 118 Fahrzeugen auf 56 Fahrzeuge pro Kilometer, und das Tempo steigt von vier auf 22 Kilometer pro Stunde an. Ab einem Anteil von 50 Prozent informierter Fahrer sinkt die Dichte des Verkehrs auf knapp über 30 Fahrzeuge pro Kilometer, und ein Fahrer kommt durchschnittlich mit etwas mehr als Tempo 50 an sein Ziel. Die bessere Verteilung des Verkehrs mag die Wegstrecke eines informierten Fahrers verdreifachen, sie bringt jedoch eine Zeitersparnis von 84 Prozent für alle Fahrer. – Sind mehr als 70 Prozent der Fahrer navigiert, verschlechtert sich die Verkehrslage erneut auf bis zu 43 Fahrzeuge pro Kilometer bei einer Geschwindigkeit von 34 Kilometer pro Stunde.

Die (wohl unerwartete) Verschlechterung der Verkehrslage bei einem hohen Anteil navigierter Fahrer erfordert eine Klärung. Weitere Analysen sind nötig. Sie werden vermutlich ergeben, dass die Qualität der Information erhöht werden muss, um diese unerwünschte Wirkung verhindern zu können. Es liegt die Hypothese nahe, dass die Navigation auf der Basis von Grenzkosten erfolgen muss, was eine genaue Messung der Verkehrsdichten und der Leistungskurven der Verbindungen sowie die Verfügbarkeit dieser Information in Echtzeit voraussetzt.



Anmerkungen: (1) Die genannten Verkehrsdaten sind selbst-konsistent und dienen dem Zweck, die Beziehungen innerhalb des Systems verständlich auszudrücken. (2)

Jedes Modell eines realen, sozioökonomischen Systems ist ungenau, einesteils durch unregelmäßig auftretende Einflüsse (stochastische Effekte) und anderenteils, weil nicht alle systematisch bedingten Einflüsse berücksichtigt werden können. Die Ergebnisse der Simulation konkreter Szenarien können auch dadurch variieren, dass sie unterschiedlich konfiguriert und kalibriert sind. (3) Der Zweck des Modells ist, die Wechselwirkung zwischen der mikroskopischen Ebene (der Entscheidung des Fahrers) und der makroskopischen Ebene (dem Zustand des Verkehrs) aufzeigen zu können.

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Note: To facilitate reading, only the masculine form is used in this dissertation; all references to the male gender also refer to and mean the female gender if applicable in the context.

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ABBREVIATIONS

ATIS.....	Advanced Traveler Information Systems
BPR.....	U.S. Bureau of Public Roads
EU	Expected Utility
EV	Expected Value (or expectation value)
GPS	Global Positioning System
MATSim	Multi Agent Transport Simulation
MDT.....	Mean Daily Travel time
MDTS....	Mean Daily Travel time Savings
MD	Mean Vehicular Traffic Density
MF.....	Mean Vehicular Traffic Flow
MS.....	Mean Vehicle Speed
RU	Random Utility
SO	System Optimum
SUE.....	Stochastic User Equilibrium
TMC.....	Traffic Message Channel
UE	User Equilibrium
VRU	Value-Risk Utility (or μ - σ -rule)
WBR.....	Weighted Best Route

Chapter 1

INTRODUCTION

1.1 Research prospect

The research project *Simulation of Spatial Learning Mechanisms* began in the year 2000. In December of 2012, the results of the experiments were fully available. Now, in May of 2013, the work has been accomplished. – The research question concerns *learning mechanisms and choice behavior of drivers when choosing their routes*. The first Section reflects on the developments that have taken place in transport and traffic within the timeframe of the project, insofar as required by the formulation of the problem and the objective of the work.

In retrospective, the study has progressed just about how Eco (1998) described it in his book ‘How to Create a Thesis’: “Imagine you are planning a trip by car. You want it to be a journey of about 1,000 kilometers and you have one week available for it.” Nobody would aimlessly drive across the country, thinks Eco, and continues: “Perhaps you are contemplating going from Milan to Naples (on the Autostrada del Sole) with one or the other side trip, maybe to Florence, Siena, Arezzo, a somewhat longer stay in Rome and a sightseeing tour of Montecassino. When you then realize in the course of the trip that Siena has taken more time than intended, or that it really was worth combining Siena with a visit to San Gimignano, you may decide to drop Montecassino. Once in Arezzo, it might even occur to you to turn east and get to know Urbino, Perugia, Assisi and Gubbio. That means you have changed – for very sensible reasons – your itinerary half-way through your trip. Yet it was this route that you changed, *not just any*.”

The story can be continued in the style of Eco: The trip led over mountain passes, not all of which ended in ravines or dead-ends. When you happened to run out of fuel, other drivers passed and told you about this or that point helpful for further orientation or not worth stopping for. At the end of the long, sometimes tortuous tour lay a plateau opening up to interesting views of the landscape of transportation – looked at from the spot resulting from the course of the trip, *not just any*.

Between the inception and the end of this study has been progress in the field of information technology that has fundamentally changed the conditions of public and private passenger and freight traffic. An article by Ashley (Scientific American, 2001-10) about the state of telematics documents the critical evaluation of its possibilities existing in the year 2001. The emphasis is on negative aspects, especially the danger of distraction at the wheel while operating some device. Wochinger and Boehm-Davis (1995) report from the U.S.A. that the choice between text navigation and a road map in about two of three cases is decided in favor of the map. Back then, most drivers set their route before starting their trip. The distances of the road network links were known to the driver. Today he can have at his disposal information describing the current state of the traffic network or the probable change of the conditions so that the driver can adjust his route to the existing conditions at any time. Dynamic routing influences not just his own routing but that of other drivers as well. The traffic load on the roads is the product of the mass of all road users.

In the meantime, digital media have changed the markets and also the behavior of consumers, including that of road users. Telematics, in particular, has created innovations such as, in the area of vehicle navigation, as a component of the driver assistant system. With respect to the year 2003, Zuurbier (2010) stated concerning the application and dissemination of navigation devices in vehicles: “Only seven years later, in Europe 25% and in North America 20% of the vehicle fleet already have some sort of navigation device and growth in Europe is projected to 40% according to market research. In addition the route guidance service itself is also continuously changing due to innovation. As a result, there is a shift toward navigation on smartphones as an online service.”

The possibilities provided by information technology have not yet led to an improved allocation of traffic demand and a balancing of the load on the road traffic networks. Current reports in the trade magazines confirm the daily experience of road users: “Within one year, every driver has spent eight working days in grueling deadlock on the roads. [...] The more the experts of [the largest German automobile club] ADAC refine their traffic congestion analyses and the more information they collect, the more they become aware of the true scope of the

daily delays” (ADAC Motorwelt, 2013-2). ADAC Motorwelt further reports that about one-half of congestion results from overburdening of the road links when the capacity limit (around 1,800 vehicles per hour and lane) is reached, and in that context it talks about lacking collective intelligence: “Everybody is primarily concerned with his individual aims. That causes unrest among the crowd. The denser the traffic, the more disruptive is the impact of selfishness and asociality.” ADAC Motorwelt underlines its statements by means of a congestion analysis on the basis of the traffic simulator presented by Treiber and Kesting (2010).

It is logical to assume that road traffic is passing through the inception of an evolution which will gradually exploit the potential offered by information technology. The impact of information emanates from the microscopic level. The drivers’ knowledge and mode of behavior will determine their route choices. The choice of the routes determines the traffic flow. Under which conditions a traffic network can be more efficient and how much time the drivers can save as a result are questions that can be answered by means of traffic simulation.

A dissertation in the field of transportation and engineering science shall provide theoretical and practical impetus to researchers and planners implying potential utility to the public. To achieve this superordinate research objective, the analysis of the spatial learning mechanisms had to be adapted to real world conditions. Questions and issues concerned with visual imprinting and spatial orientation of the users, such as about cognitive maps (Lynch, 1960) or about cognitive processes of route choice (Benshoof, 1970, Reichenbach, 1979, Stern and Leiser, 1988, Bovy and Stern, 1990) are brought face to face with questions and issues of medial learning and temporal orientation. Within the framework of activity research, Axhausen (1988), based on Reichenbach (1979), puts the degree of awareness of decision spaces in relation to their frequency of being visited; the orientation stages of the agents are considered to be the individual space, the activity field, the knowledge field, the information field, and the expectation field.

As this example shows, the classical orientation fields of the drivers will be in their entirety condensed by the ubiquitously available traffic information until traffic

may possibly have become a cybernetic system with drivers moving through an information space that fully envelops the real traffic space.

Conclusion

Looking at the evolution of information technology changes the concept of spatial orientation of the driver. Countless physiological properties of the traffic space are superimposed by a few quantitative properties, such as the travel times on the routes acquiring great importance in the driver's decision space when it comes to choosing his route. *Spatial learning means for the driver to be oriented towards the information space; he learns taking advantage of traffic information* (on the assumption that a driver thinks economically, that he decides rationally, and that he continually wants to have up-to-the-minute information about the consequences of his decision).

1.2 State of the Art

The abundance of studies regarding the possible influences of a traffic environment on individual knowledge and behavior is presented in general terms in Bell et al. (2001) and with respect to spatial-physiological-oriented route choice in the literature survey by Ramming (2002). Widely discussed are the economically oriented approaches of information-oriented traffic modeling, such as in respect of route choice in Levinson (2003). A general survey of the literature is offered by Chorus et al. (2006). Both aspects, the spatial physiological one and the temporal informational economical one, are also associated with each other, such as in the report by Wochinger and Boehm-Davis (1995), or in the work by Karl (2003): "It was found that commuter drivers enter a learning curve affected by previous experience and immediate need in which learning to access and utilize appropriate travel information is a dynamic process. Drivers learn about using traveler information, they learn about the types of traveler information available and they also learn whether to trust the information provider."

Among the studies analyzing the potential and the effect of traffic information under new realities are the contributions by Busch et al. (2012a, b) and Madir (2012). Also closely related to the present work are the study by Zuurbier (2010) and the Greenway project, which was awarded a prize and is being supported by the

Microsoft Corporation – a real-time navigation first tested as an app on Windows smartphones in the Munich area, now also offered as a cloud service in the Nunav Traffic Management by the startup company Graphmasters. The idea of Greenway goes back to three students of Bielefeld and Hannover universities, among them Brüggemann. Greenway is still in the trial phase. A scientifically usable analysis or documentation of the Greenway project is not yet available, only simulations for comparison with the Braess network provided by Hagstrom and Abrams (2001), which Brüggemann has attached to his fall 2012 correspondence.

Because the Greenway project represents a real experiment in traffic management and, like the here developed model, is aimed at finding out the effect of continuously updated traffic information for the purpose of dynamic routing, the features of Greenway shall be outlined here. The online versions of the magazine *Der Spiegel* (Stockburger, 2012) and of the *Technology Review* (Metz, 2012) reported in this respect: The volume of traffic on a certain route is being analyzed in real time. A maximum capacity is specified for each road. If the system detects that too many vehicles are simultaneously approaching a road, part of them are redirected to another route to prevent a traffic jam. Greenway indicates to the user the shortest route, provided the capacity of its links is not already used to the full, otherwise the second-shortest, and so on. If the driver chooses the Greenway route, the app reports its GPS data every 30 seconds to find out whether the current route is still the best one. For this to be determined, both the current speed of the user vehicle and the current position of other Greenway users are taken into account. That means, the vehicles are constantly being guided so that a route is never used at 100 percent. If, nevertheless, any congestion, which Greenway can detect from the falling speed, is being noticed, drivers will be rerouted. According to Brüggemann, the software can currently simulate up to 50,000 vehicles. First estimates show that on average the Greenway route gets drivers twice as fast to their destination – with a fuel saving of up to 20 percent. Greenway will, of course, be made good use of only when as many drivers as possible use the technology. Brüggemann estimates that about ten percent of the vehicles in a town or city must use the app for the system to function optimally. The team wants to get there faster by entering into partnerships with taxi companies.

Previous State

Dobler, Axhausen and Weinmann (2013) have reported on the development and the previous state of the science in the field of Advanced Traveler Information Systems (ATIS): “Literature covers various aspects of road users’ behavior and the role of information. Investigations on Advanced Traveler Information Systems (ATIS) suggest that changing mode, departure time or route are the most common responses to congestion information (Ziegelmeier et al., 2008). One class of studies primarily analyses the effects of behavioral changes based on modal choices like shifts between private car and public transport (e.g. Reed and Levine, 1997, Gärling and Axhausen, 2004, Klöckner and Blöbaum, 2010). Departure time changes are mainly discussed in the context of route choice (e.g. Abdel-Aty et al., 1995, Noland and Small, 1995, Hensher, 1997, Cohen and Southworth, 1999). The mainstream of research on ATIS reflects the potential of information provision (e.g. Emmerink et al., 1995a, b, Chorus et al., 2006) and potential effects of changing routes when drivers’ decisions are simulated initially (pre trip) or dynamically (en-route). The value of ATIS for route choice is described by numerous authors; Levinson (2003) concludes from previous research (e.g. Khattak et al., 1994, Al-Deek et al., 1998) that ATIS not only reduces the drivers travel time and vehicle operating costs, but also affects other users’ travel time. Levinson (2003) specifies that dynamic route guidance provides maximum opportunities to save time when traffic flow is at 95% of capacity and that ATIS does provide travel time benefits to users (although it may increase the time for certain non-informed travelers).”

Changes

Nöcker, Mezger and Kerner (2005) report on the development of Anticipatory Advanced Driver Assistance Systems: The communication between vehicle and infrastructure creates a telematic horizon that provides information about current traffic conditions and dangers and enables road users to react in time to critical traffic situations. The vehicle becomes part of an interconnected cooperative system that gathers and diffuses information, harmonizes technical on-the-road behavior, and helps to optimally distribute the traffic load. Popiv (2011) adds: “Both with solely visual HMI [Human-Machine Interface] and coupled with AGP [Active Gas Pedal] feedback, help drivers to increase safety: in the potentially critical situation

of highway jams eight collisions occur during unassisted drives. In the assisted drives they are prevented, and resulting minimal decelerations are significantly milder – the driven speed is reduced in advance due to the preceding coasting phases before the braking sequence is initiated.”

The trend shows that information technology influences traffic more and more. Assistance systems connecting sensors to board computers, interconnecting their information, and connecting the vehicle to the GPS, are able to transform an ordinary driver into an ideal driver, i.e. a driver who behaves ideally from both a technical and an economic point of view. Driver assistance systems, on the one hand, offer help in steering the vehicle, such as in switching traffic lanes without interfering with traffic flow. Or they help adjusting the optimal distance from the vehicle in front to the current speed so that the capacity of the road section does not decrease below the calculated technical norm (see Sections 2.1 and 2.3). Furthermore, to help the driver take the best possible itinerary towards his destination, the assistance system will inform him about the current travel times on his routes. Changing conditions on the alternative links are detected at ever shorter intervals. The dynamically informed driver can re-plan his route at every intersection.

Review

The preceding overview of the present state of research and technology underscores the central thought put forward in the first Section: Information technology has changed the concept of learning in road traffic and behavior of the road users. As a consequence, new questions emerge. Considering the example of Greenway (above): Starting from which share of informed drivers does Greenway become useful? Brüggemann estimates that about ten percent of the vehicles circulating in a city would have to use the app [the navigation] for the system to function optimally [and for mean travel times to be cut in half] (cf. Stockburger, 2012, Metz, 2012). More general questions in this connection are: What role do drivers play who possess more knowledge than the majority of the other drivers? Does a higher level of information imply for the driver that he is perceived as a competitor by the other drivers or does he, as a result, unconsciously cooperate with them? Into what state of traffic does full information available to all drivers lead? Does the potentially

ubiquitously available information about the current traffic state bring about a paradigm shift in driver behavior? – To clear up these questions in general, information must be examined as an economic parameter in traffic systems.

Conclusion

For the following statement of the problem and objectives this means in summary: The state of science and technology corroborates the assumptions made in Section 1.1. The driver does no longer learn primarily from his experience on the traffic network; he learns from his experience on the traffic information network; the driver learns how to deal with information, i.e. to evaluate traffic information to gain the maximum utility from it. The questions “How or through what kind of perceptions does a road user acquire his knowledge and how does he arrive at his decisions?” have turned into the questions “What does a road user know about the system and how can he benefit from it subject to which condition?” The learning mechanisms, i.e. how drivers acquire their knowledge in detail, have lost their significance in favor of the question what significance does the acquired knowledge take on for both the individual drivers and for the entire traffic system. The driver’s *learning input* is the information about the most important aspects of his decision. The *learning outcomes* are the microscopic mechanisms emanating from the consequences of his decision. The main question is: *What effect do the decisions made by the informed drivers have on the traffic system?*

1.3 Problem description

Background

The background of the problem is outlined in Dobler, Axhausen and Weinmann (2013): “Transport simulation explores the interaction of traffic flow demand and supply. Both parts – demand and supply – are correlated with the transport network load as an input and an output component at the same time. If the actual capacity of the network turns out to be lower than estimated, the demand is expected to shift to other destinations, modes, times or routes (Ortúzar and Willumsen, 2001). Research on traffic flow describes aspects that look similar in physical systems (Lighthill and Whitham, 1955, Richards, 1956). Although the dynamic of traffic flows has macroscopic features, vehicle densities and travel times are hard to predict, due to

different microscopic sources of uncertainty. For example, the studies of Nagel and Schreckenberg (1992) and Lübeck et al. (1997) show that the phenomena of traffic flow cannot be explained solely by physical mechanisms. In addition, drivers' stochastic effects must be taken into account. To describe traffic dynamics in a realistic way, models that simulate interplay of drivers at the microscopic level are needed. For measuring the effects of different knowledge levels and choice behavior, models like cellular automata or simulation toolkits like MATSim are indispensable. Information on the driver's decision and condition of the traffic network is very significant. What exact effect differently informed drivers have on certain traffic network situations has not yet been determined. Even if drivers are informed regularly about current conditions in the network, it is not clear that such information can aid in distributing traffic over the whole network and reducing congestion levels (Ziegelmeier et al., 2008). Some previous research shows that public information about traffic jams can cause a welfare-decreasing adjustment and may lead to an unforeseeable outcome (Ben-Akiva et al., 1991, Arnott et al., 1999), caused by overreaction, e.g., that is if too many drivers receive traffic information and all respond to the information. Such effects underline the importance of microscopic models which simulate choice behavior under different levels of knowledge.”

About ten years ago, a driver may have benefited from being able to get an idea as detailed as possible about his traffic environment and to take the less frequented links during rush hours. Today, if a driver wants to gain an edge over the other drivers, knowledge about the periodical traffic load trends is not sufficient anymore. The generally available level of information has grown. More and more drivers are able to take their cue from current, or – as in the case of Greenway – from currently forecast traffic conditions.

Foreground

The question is whether the available means, such as driver assistant systems and the ubiquitously available traffic information can substantially contribute to maintaining traffic systems under high traffic demand in regular condition (without them having to be regulated)? Or formulated differently: What do the microscopic mechanisms look like that offer an as high as possible general utility – how much

information does a driver need, and how much freedom of decision may he be afforded when he chooses his routes? This leads to further questions: What benefits can a road user derive from the potential of the traffic world changed by information technology? What effects do the users' differing levels of knowledge and differing degrees of freedom have on the traffic system? How can individual knowledge about current traffic network conditions be micro-economically and macro-economically evaluated?

Basic interactions

The task of moving persons or goods from their places of origin to their destinations within certain time limits requires systematic planning of the available resources (such as time, money, or energy). Under ideal conditions, a traffic network would behave according to the rules of physics, and the traffic flows could be dealt with as macroscopic variables. An ideal driver would as a result of his marginal contribution change the flow of traffic in a way consistent with the laws of flow. Transport, however, requires a socio-technical and a socio-economic system. Between the macroscopic changes of the state of the system and the microscopic changes exists a continuous direct interaction. From a microscopic point of view, the interaction of human being, technology, information and economic behavior brings into play three essential instances of uncertainty:

1. The driver's motoric capability
2. The driver's knowledge about the traffic situation
3. The driver's decision owing to his knowledge.

The first uncertainty relates to the technical control of the vehicle. Traffic demand for being controllable requires that each road user behaves in a technically conformant manner. The emergence of a single driver moving his vehicle far apart from the norm can unpredictably disturb traffic flow. A predictable (system-conformant) way of driving must be taken for granted to a certain degree for analyzing the two other uncertainties: the knowledge level and the rational decision making behavior of the drivers on their trip. The informationally economical issues of navigation of the vehicle constitute the core theme of this dissertation.

Model inaccuracy

Between system and model there is always some inaccuracy. How much the model deviates from the system depends on the type of influences and the number of their properties. The inaccuracy of a model is caused by two types of shortcomings: uncertainty and limitedness. Properties that are not measurable because they occur irregularly cause random errors in the model. The uncertainty arising in a decision process is a typical example of a stochastically caused inaccuracy affecting the result of the decision (see Sections 2.1, 2.4 and 3.1). An inaccuracy in the model can also result from incomplete data. The following examples describe systemic influences that, even though their properties are basically calculable (rather than random), cannot be individually taken into account in practice because of the diversity of the influences (and, therefore, fall into the twilight zone between the purely stochastic and the system-related influences).

Example 1: Technically caused limitedness

The complexity of just the technical factors is demonstrated by the test of tire condition and braking performance conducted by Germany's largest automobile club ADAC (Motorwelt, 2013-4). The discrepancies between a very good and a bad tire are enormous. With respect to the vehicle with the best tires having come to a full stop, braking tests conducted at speed 80 [k.p.h.] demonstrated residual speeds of up to 49 [k.p.h.], corresponding to a more than 18 meters longer brake distance as compared to a vehicle with tires in optimum condition.

Note (in addition to the example above): The EU tire label provides for rating tires in seven categories according to a tire type's fuel efficiency (rolling resistance), braking ability on wet roads, and external noise level.

This first example shows that data can be collected on almost countless technical influences and taken into account in a model. By analogy, there are almost countless economic or ecological factors potentially influencing the drivers' behavior (as shown in the second example). Yet many technical and economic properties influencing traffic on the microscopic level cannot be taken into account in a model aimed at, for example, calculating traffic flows.

Example 2: Economically caused limitedness

The changes that have taken place within the past decade do not only concern the technological side of traffic. Road user behavior is also influenced by secondary factors, such as the economic weighting of the resources time, money, and energy. Since the year 2000, energy prices (and fuel prices alike) have risen by more than 60 percent in Europe, whereas real income has increased by only about six percent, and energy consumption decreased by about ten percent as a result of better energy efficiency and other savings. (cf. Statistisches Bundesamt Deutschland, 2012, Statistica, 2013).

The second example indicates that the financial resources of consumers have diminished since 2000. That could cause drivers to behave more economically and to adapt their way of driving and the choice of their route to normative conditions. For that to happen requires that a driver is early and reliably informed about the consequences of his decisions; only this way can he judge the benefits of his economical behavior and perceive it as an individual incentive.

Conclusion

For the following setting of the objective and scope of this study this means in summary: The effect of traffic information shall be microscopically analyzed in respect of differing knowledge and behavior of the drivers within a certain scenario. The technical conditions of, and the economic influences upon, road traffic shall be condensed to the essentials (structurally) in the model. Drivers shall be assumed to have the following traits: a system-conformant way of driving, an economic way of thinking, and a rational mode of behavior. To be able to find out the effects of descriptive and normative decisions, the drivers shall be allowed differing degrees of freedom in the choice of their route. *The objective will be finding economic principles for the valuation of the routes, a rational criterion for the choice of the route, and a standard measure that relates the decisions of the informed drivers to the states of traffic flow.*

1.4 Objective and Scope

Assumptions

Drivers want to reach their destination fast; most of them ask for the route offering the shortest travel time. Under which conditions a driver can reach his destination with minimum expenditure of time – and every other driver too – is one of the most important issues of traffic planning. The more current and reliable the information is, the better the driver should be able to make the best of the traffic situation. That presumption suggests itself. But does it apply to every informed driver regardless of whether all drivers are informed or only part of them? – This question is of practical importance because it describes scenarios which may take place as follows: Part of the drivers use simple routers that know only the shortest roads on a load-free traffic network. The other part have at their disposal a navigation system that knows the shortest travel times on the real, load-bearing traffic network and communicates them to the driver before every intersection. A dynamically informed driver then can take either the recommended shorter route or an alternative route – subject to a certain degree of freedom.

Objective

This dissertation has the objective to research the effect of differently informed drivers in relation to a real-world traffic scenario. This effect will be measured in terms of utility, utility to the driver on the microscopic level and aggregate utility to the entirety of drivers on the macroscopic level. – The aim is to find the answers to the following four questions:

- What are the effects of there being different shares of informed and non-informed drivers?
- What are the effects of different levels of compliance with the instructions provided by a navigation system?
- What constellation of different levels of knowledge and modes of behavior yields the largest saving potential (as compared to a norm)?
- What generally useful recommendation to the traffic planners can be deduced from the results of the experiments?

The objective includes fundamental tasks of general significance (I) and four main tasks of specific importance (II).

The general, fundamental tasks of the research to be undertaken are:

I.1 To provide an explanation and concise presentation of the concepts and relations of traffic and the fundamentals of economic behavior (Chapter 1 and Chapter 2);

I.2 To select a software for the simulation and a scenario so that the models and methods relating to the specific main tasks can be readily incorporated and the simulation leads to results that are relevant for the transport planner (Sections 4.1 and 4.2).

The specific main tasks of the research to be undertaken are:

II.1 To provide an analysis of the decisions made by the drivers in respect of the choice of their route (Sections 2.4 and 3.1), to construct a learning mechanism for the stochastic mapping of the confidence in the information about the travel time on the routes (Section 3.2);

II.2 To conceive of and model relevant levels of knowledge and classes of behavior on the part of the drivers (Sections 3.3 and 3.4);

II.3 To simulate the traffic in a real scenario (Section 4.1) and with characteristic constellations of drivers (Section 4.2);

II.4 To evaluate statistically, present, judge, and recapitulate the results of the experiments (Section 4.4 and Chapter 5).

Scope

The simulation of a certain traffic demand will be limited to the decision as regards the route choice, depending on the drivers' level of knowledge and his mode of behavior. The agents' activities, modes of transport, and departure times will not change; keeping these influencing factors constant will yield a clear picture of the results of the decision processes regarding the choice of the routes. Further aspects, such as ecological criteria, will also be left out of account in regard to the decisions

by the drivers even though methodologically they can be included in utility-oriented planning. Ecological criteria can be transformed into economic parameters. For example, the extent of the damage to the environment that is systematically caused by traffic could be rendered quantifiable in monetary units and included as a weight in the optimization function of utility maximization (*even swap trade-off*).

1.5 Methodology

Frame

Processes in road traffic are stochastic. That is an important finding of traffic analysis. Using microscopic, discrete decision models, the traffic planner wants to simulate processes resembling those taking place in the real world. The probability of an event, to be sure, does not apply to the singular instance, but considered statistically, spanning all decisions, stochastic experiments yield a similitude of reality. Using simulation as an instrument for microscopic analysis of real traffic systems is legitimized by the regularity of stochastics.

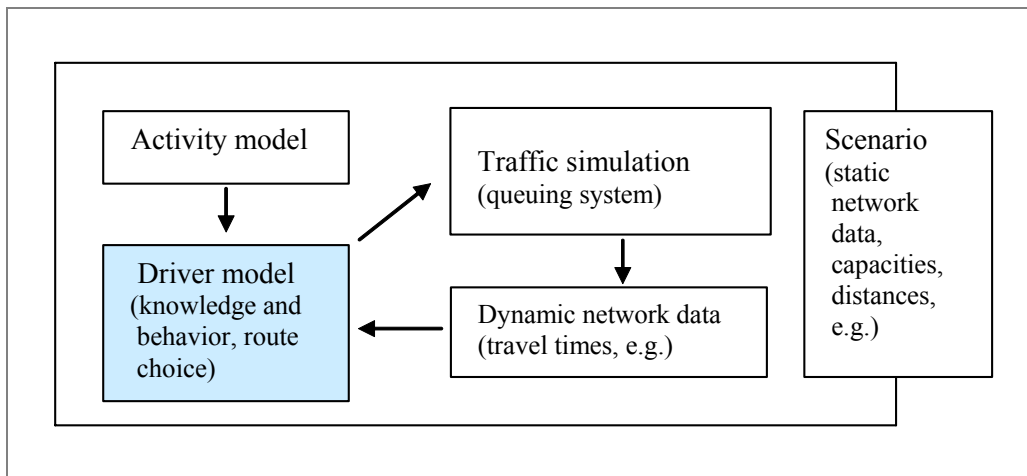
In simple terms the simulation of a socio-economic system means that the researcher selects a group of persons who generate a certain demand within a scenario; he lets these persons act and observes the results. The actions follow from decisions made on the basis of certain criteria, according to certain rules and patterns of behavior. The observations concentrate on the characteristic properties of the alternatives associated with the driver's objective.

The simulation comprises the following subject areas.

- The rules of the system (see Chapter 2)
- The nature of the scenario (see Section 4.1)
- The constellation of the statistical population (see Sections 3.3, 3.4, and 4.2)
- The analysis of the decision made by the driver (see Sections 2.4, 3.1, and 3.2)
- The appropriate variables for measuring the effects of the decisions (see Sections 3.1 and 4.2)

The formal rules of the system correspond to the standard of the microscopic model named MATSim. MATSim has been developed and used for simulations in transport planning (see Section 4.1) since 1998. Also given is a scenario tested for its suitability by a circle of researchers. Considered will be a real section of the traffic in the Zurich metropolitan area (see Section 4.1). Within that scenario, the behavior of drivers can be mapped by MATSim on the basis of agents; they constitute the core of the microscopic level of the transport system (Figures 1.1 and 1.2). Their mechanisms of action shall be easy to understand and shall be rendered by means of simple decision models. Stochastic influences shall be mapped by as few parameters as possible. Typical patterns of behavior will be represented at differing levels of knowledge by classes of drivers. The knowledge of the drivers concentrates on features that are essential with regard to the decision criterion.

Figure 1.1: Microscopic model of the transport simulation

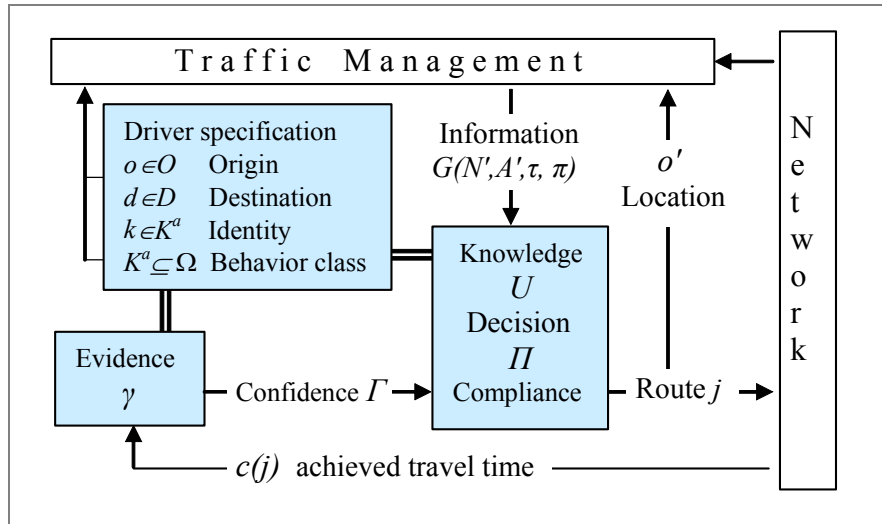


Decision process

The microscopic part of the traffic simulation will proceed according to the following concept: For each experiment, the population of the drivers will be subdivided into two classes, in a class with static knowledge and deterministic behavior, and in a class with dynamic knowledge and stochastic behavior (see Section 3.4). A driver belonging to the dynamic class will decide in favor of a route on the basis of its utility. The utility will be derived from the properties of a route (see Section 3.1). At every traffic node, a dynamic class driver goes through a process comprising the following steps: before getting to the node, the driver will be dynamically informed about the travel times on the routes and the best routes

will be recommended to him; the driver decides in favor of a route and proceeds towards his destination; after every traffic node, the driver checks whether there has been a divergence between the expected and the actual travel time and evaluates it on the basis of his tolerance (see Sections 3.2 and 4.2).

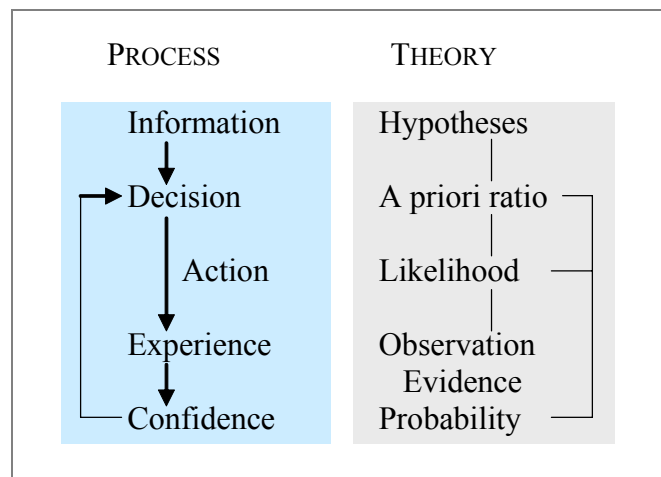
Figure 1.2: Driver model – microscopic core of the transport simulation



Spatial learning

During the trip, the driver evaluates the traffic information on the basis of a Bernoulli experiment. He compares the expected travel time with the actual travel time spent on a given link. As a result of the statistical learning mechanism, the confidence in the information will be marginally adjusted after each decision by the driver and will be incorporated into the next choice of his route (Figure 1.3).

Figure 1.3: Concept of probabilistic spatial learning



Utility maximization

The decision model will be oriented according to the economic principle of action, i.e. utility maximization. The approaches in the literature will be compared, and the one most suitable for the route choice by means of the simulation with MATSim will be chosen (see Sections 2.4 and 3.1). The utility of a route is decisive for it to be chosen. The utility is made up of the expected travel time, the driver's confidence in the traffic information, and a driver's typical attitude towards the risk of the consequence of his decision. The confidence can be firmly specified so as to be able to measure also the effect of constant level of compliance (see Sections 3.2, 3.4 and 4.2).

The effect of traffic information will be measured with respect to the mean daily travel times for (a) the entirety of drivers, (b) the class of the non-informed drivers, and (c) the class of the dynamically informed drivers. The reference value used will be the mean daily travel time that will result if the entire demand is met by way of the shortest routes on the load-free travel network, i.e. if every driver sticks to his (statically) shortest route (see Section 4.2).

Summary

The tasks associated with the research question of the work (see Section 1.4) will be handled within the scope and by using the concepts and methods set out below:

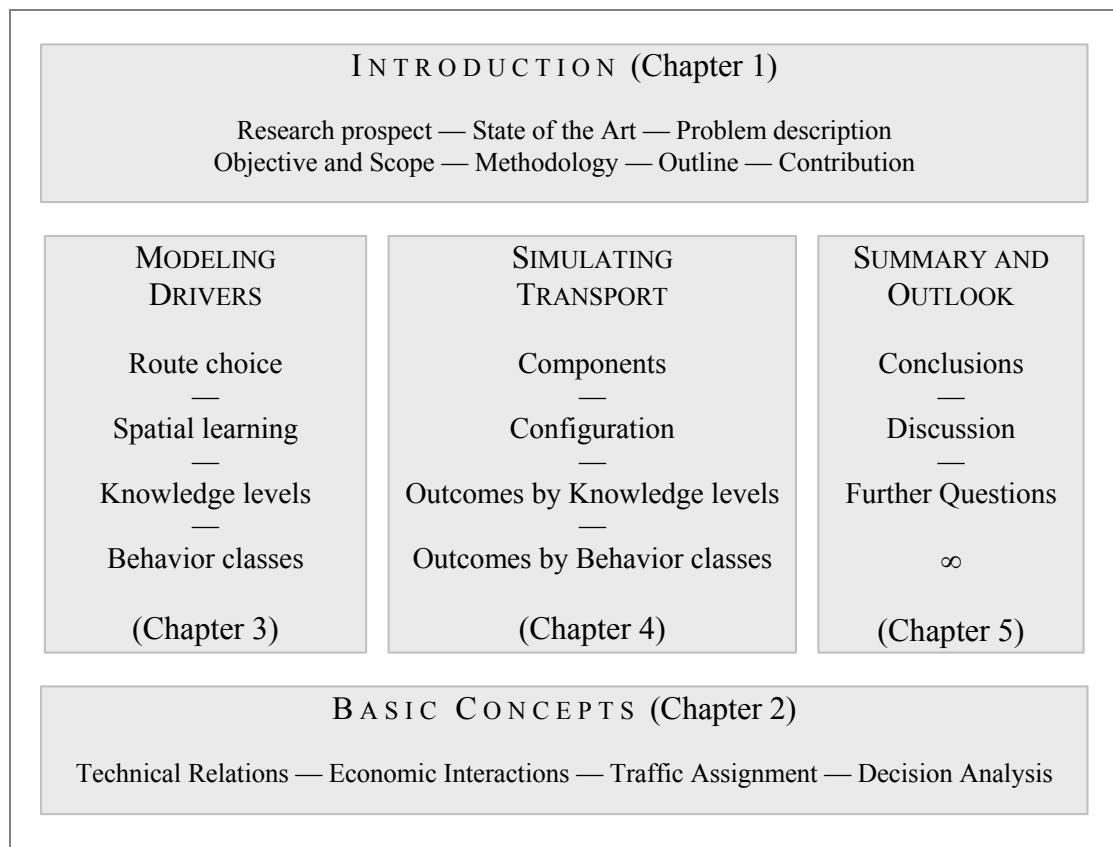
1. The scope of the traffic simulation will consist of the standard software MATSim and the proven traffic scenario of the Zurich metropolitan area. Consequently, the traffic network and all traffic data associated with the agents' demand are given.
2. The effect of traffic information will be determined microscopically by the agents' choice of routes. The decision criterion will be maximization of utility. The pertinent properties of utility will be the *travel time on the route* and the *confidence in the information about the traffic time*. The assessment of the confidence in the information will proceed through a statistical learning process that evaluates the results of the decisions. The drivers will be subdivided into two classes on the basis of their knowledge and their behavior. The effect of traffic information will be measured by the mean daily travel time of the drivers. The reference measure will

be the mean daily travel time when all demand is met by way of the shortest routes available on the load-free network.

1.6 Outline

The dissertation is divided into five chapters. The relation between the topics and their assignment to the Sections is shown in Figure 1.4.

Figure 1.4: Topics and Sections of the dissertation



Chapter 1 describes the background of the research project and reports about the development of the research landscape. The subject of the research – the simulation of spatial learning mechanisms – is placed in the context of the technical progress within the research period.

Chapter 2 will be devoted to the discussion of the fundamental concepts and relations required for understanding the main part. The technical and economic relations, as well as the macroscopic and microscopic relations in transport and traffic will be presented and discussed. The last Section (2.4) of that Chapter will

provide the technical basis for the core of the topic: the decision made by the driver based on the utility to him, his level of information, and his characteristic mode of behavior.

Chapter 3 will discuss the most important characteristics of the route choice and will derive a model for the decision behavior of the drivers. The statistical driver population will be subdivided into behavioral classes on the basis of levels of knowledge. The degree of confidence in the traffic information will be mapped by a stochastic learning model from which the driver's inclination to follow the information will be deduced (Figure 1.3). The components of the driver model and the flows of information of the simulation environment are depicted in Figure 1.2.

Chapter 4 will describe the scope of the traffic simulation (Figure 1.1): the software MATSim and the scenario of the Zurich metropolitan area. Characteristic conditions for the scenario will be configured and tested. The driver model integrated into the MATSim software (Figure 1.2) will be varied and simulated within the scope of the configuration. The results of the tests will be analyzed, described, evaluated, and discussed.

Chapter 5 will consolidate the results of the experiments and draw the important conclusions. The effect of the route choice in the eyes of the user and from the point of view of the traffic planner will be considered as a whole in the context of the descriptive and normative analysis of decisions. The work will conclude with a consideration of future issues and tasks following from the findings of this study.

◇

Note: In case a reader is interested in – beyond the technical context – the general structure of a scientific study, Chapter 1 will not provide him with a model in this respect. The survey of the evolution of the research landscape (Section 1.1) can be omitted (according to taste). The State of the Art (Section 1.2) does not (normally) precede the Problem description (Section 1.3).

1.7 Contribution

The theoretical contribution of this work is the decision analysis as can be expected from a microscopic model for traffic simulation. Sections 2.4, 3.1 and 3.2 place the decision process of the driver on a scientific basis. The discussion of the qualitative and quantitative properties yields three essential criteria for the evaluation of the routes: 1) the travel time; 2) the reliability of the information; and 3) the driver's inclination in case of doubt to choose the faster route. These three criteria determine the utility and the choice of the route. The random utility maximization with Gumbel distributed residuals and exponential utility function makes up the class of the logit decision models. This branch has spread in the literature on transport planning more than almost all the other ones. Rarely are alternative models set against the logit model and even more rarely are logit models substituted by alternative probability models. – With regard to further studies making it possible to explicitly introduce the probable deviation (the risk) of the information about the travel time into the driver's decision, the approaches offered in Sections 2.4 to 3.2 will provide impetus for using alternative methods of choice.

The practical, directly applicable utility of this work emanates from the results of the simulation of the chosen traffic scenario (Section 4.1). Owing to the simple concept of subdividing all drivers in two classes, i.e. the class of those having static knowledge and behaving in a deterministic mode, and the class of the dynamically informed and stochastically behaving drivers, the results of the route choice and, consequently, the effect of information on the system remain very transparent to and easy to understand for the transport planner.

The software MATSim developed for scientific purposes in the field of transport planning, and the likewise proven scenario of a real segment of the Zurich traffic area will constitute the basis for the following analytical experiments; the questions formulated in the Sections 1.2 to 1.4 can be schematically answered on the basis of their outcomes. The results recapitulated in the sections 4.4 and 5.1 confirm the hypothetical potential of traffic information, and they show how much of this potential can be exploited under what conditions. The study provides impetus to planners for increasing the utility in terms of time and money on the individual

level and the social utility of the traffic system in general. Moreover, specific task fields in transport, such as itinerary planning (cf. Barthels and Weinmann, 2006) can draw on the results of this study.

BASIC CONCEPTS

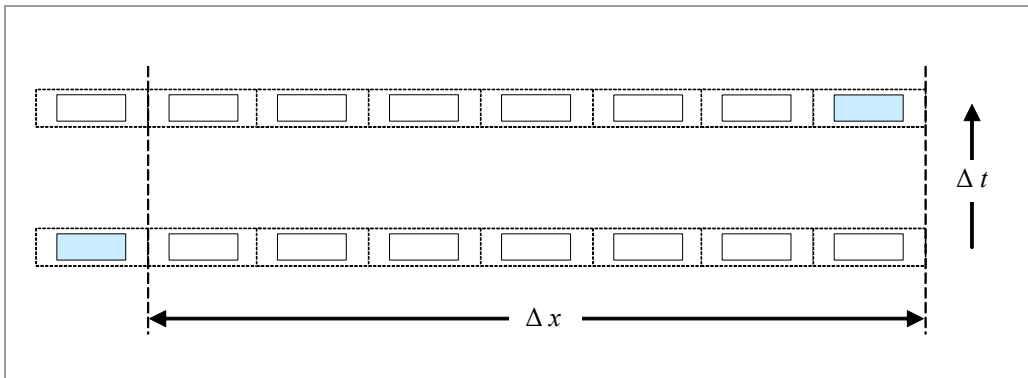
2.1 Technical relations

A vehicle stream is moving on a section of traffic network; its volume is the product of mean traffic density and mean vehicle speed.

$$flow = density \cdot speed \quad \left[\frac{veh}{hour} = \frac{veh}{km} \cdot \frac{km}{hour} \right] \quad (2.1.1)$$

The three fundamental variables (2.1.1) are measured in the following units: The traffic flow (*flow*) in [vehicles per hour], the traffic density (*density*) in [vehicles per kilometer], and the traffic speed (*speed*) in [kilometers per hour].

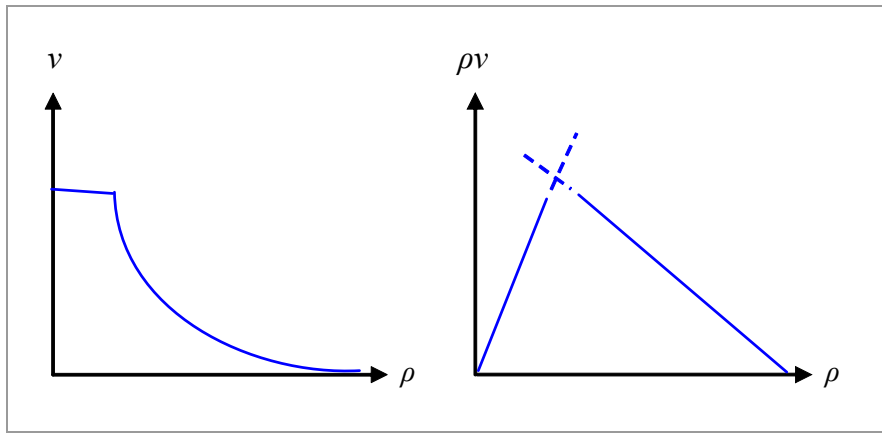
Figure 2.1: Marginal flow-density-speed relation in a one-lane section



The diagram depicting two states of one (and the same) vehicle lane shows the movement of a vehicle (marked in blue, Figure 2.1). It covers the distance Δx in the time Δt . Its mean speed is $\Delta x \div \Delta t$ kilometers per hour. The traffic flow amounts to $(1 \div \Delta x) \cdot (\Delta x \div \Delta t) = 1 \div \Delta t$ vehicles per hour. For example, over a distance of 200 meters and a time period of 10 seconds, the traffic density amounts to 5 vehicles per kilometer, the speed to 72 kilometers per hour, and the traffic flow to 360 vehicles per hour.

The changes in the traffic state on a certain road section are the result of interaction between flow, density and speed of the vehicles. The two diagrams in Figure 2.2 show the dynamic relations between the traffic speed $v(x, t)$ and the traffic density $\rho(x, t)$, as well as between the traffic flow $\rho(x, t) \cdot v(x, t)$ and the traffic density $\rho(x, t)$. Traffic on a road link is changing from a free flow state ($\rho = 0$) to a congested state. From a critical traffic density onward, the traffic speed (Figure 2.2, left part) and the traffic flow density (Figure 2.2, right part) clearly decrease until traffic is at a standstill ($v = 0$).

Figure 2.2: Speed-density and flow-density relations on a road link



The theory of the fundamental relation between traffic density and traffic flow was developed by Lighthill and Whitham (1955) and Richards (1956). On a closed road section (where no vehicle enters or exits) the following macroscopic relation applies (2.1.2).

$$\frac{\partial \rho}{\partial t} + \frac{\partial(\rho v)}{\partial x} = 0 \quad (2.1.2)$$

The continuity equation (2.1.2) says that the change of density $\partial \rho$ and the change of flow $\partial(\rho v)$ on the section ∂x cancel each other out. If both changes form an equilibrium, the flow or the speed can be determined from the density. The equilibrium relation (2.1.3) implies that any change of density $\partial \rho$ is coupled with the equilibrium speed $v_e(\rho)$. The density profile $\rho(x, t)$ results from the density at time $t = 0$ and the density-dependent shift $v_e(\rho) \cdot t$. For vehicle streams $dv \div d\rho < 0$

applies; thus $v_e(\rho) < v(\rho)$ results from (2.13); i.e. the kinematic density wave propagates against the traffic direction because it is slower than the vehicle stream.

$$v_e(\rho) = \frac{d(\rho v)}{d\rho} = v + \rho \frac{dv}{d\rho} \quad (2.1.3)$$

From the relations (2.1.2) and (2.1.3) follows the Lighthill-Whitham-Richards equation (LWR equation) named after its founders, which forms the core of macroscopic calculation of traffic states (2.1.4).

$$\frac{\partial \rho(x,t)}{\partial t} + v_e(\rho) \frac{\partial \rho(x,t)}{\partial x} = 0 \quad (2.1.4)$$

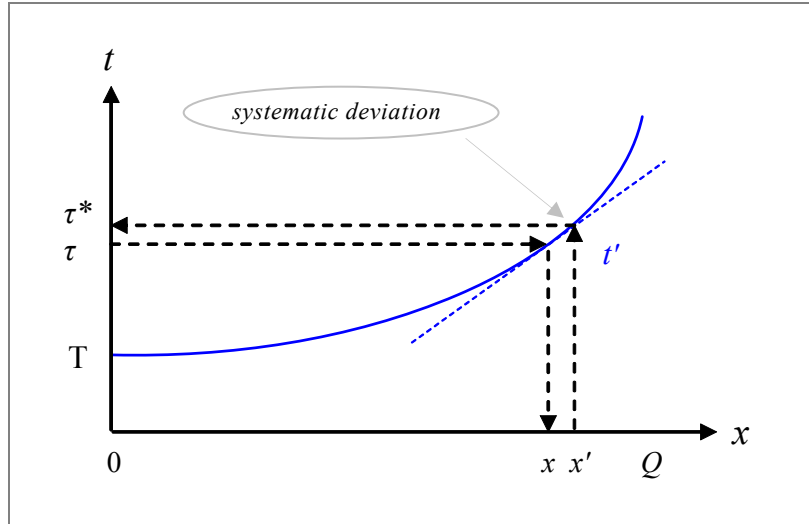
Discussion

The macroscopic analysis of traffic dynamics records the movement of vehicles as continuous traffic streams. Microscopic simulation models map the movement of individual vehicles with the advantage of obtaining a more realistic picture of traffic state changes. Here emerges an analogy to physics. Peters (1967) writes: “One might naively believe that physics at the microscopic level is but a scaled-down version of macrophysics. [...] This perception is wrong. The most notable new characteristic from the realm of microphysics is the quantization of energy. However there is not something like a uniform smallest size of energy, something comparable to the smallest monetary coin, but rather this coin furthermore depends on the frequency given by the temporal process; if this frequency is f , one quantum, according to the theory formulated by Max Planck (1900), contains the energy $h \cdot f$ with the Planck constant of action h .”

The solution of the time-flow relation (Figure 2.3) renders the transition from the macroscopic to the microscopic analysis visible. The theoretical (or determined) travel time t on some road link is proportional to the current traffic flow $x = \rho \cdot v$ and to that link’s flow capacity Q . In order to predict the travel time on a certain road link, it is first necessary to make an observation allowing to determine one of the two variables, x or t . Assuming that speed is determined by way of sensors or

the Global Positioning System (GPS) and that the mean travel time τ on that link is determined from the result. How exact will the forecast be if the control system passes on information τ to the drivers unchanged?

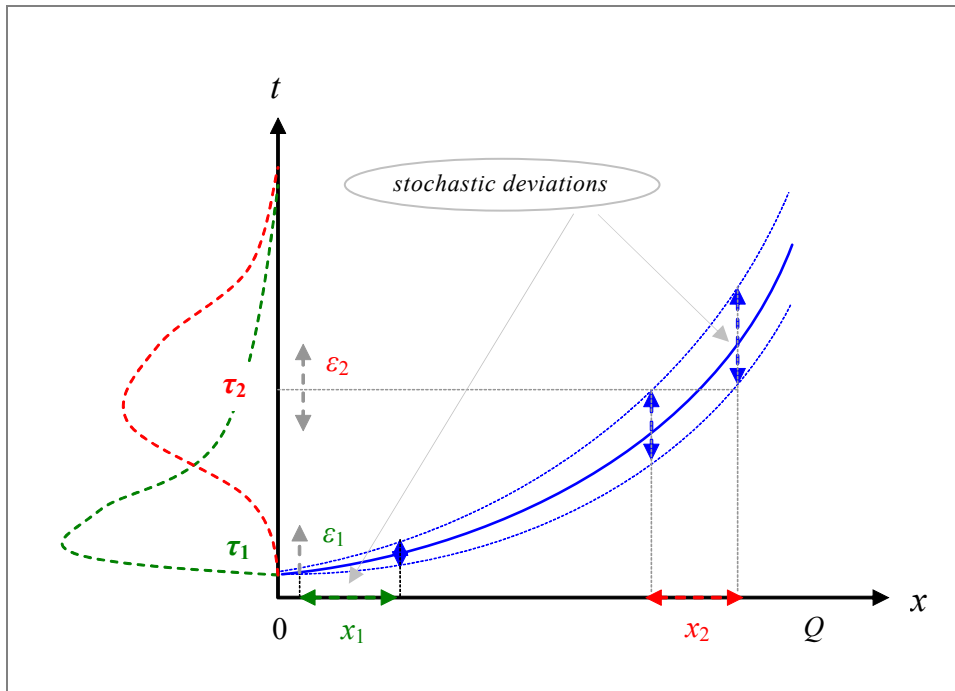
Figure 2.3: Time-flow-relation on a link and its marginal change



The traffic state change brought about by a single vehicle is called marginal (situated at the margin). The marginal expenditure is system-dependent, i.e. it is determined by the driver's decision and constitutes an analytic variable of the time-flow-relation. Because every observation is blurred due to random disturbance, the values of time-flow-relation are stochastic. Even though, in consequence, the marginal time expenditure is also stochastic, its system-dependent part must not be treated as a random value; its value must be analytically determined and added to the measured travel time τ . The calculation of an anticipatory information τ^* about travel time takes the marginal expenditure into account in an analytical stochastic manner by deriving the time function $t(x)$ on the basis of the estimates for x and Q (see Sections 2.2, 2.3, and 2.4).

The stochastic part ε represents the unsystematic deviations of all properties of a link. In the simplest case, if only time is valued as a property of the link, ε is the error of the travel time information τ on a link. The error has at least two sources: the inaccuracy of time-flow relation of a link and the uncertainty of the load period that corresponds to the information τ about the travel time (Figure 2.4).

Figure 2.4: Time-flow-relation and stochastic deviations of τ at two states



Each information τ corresponds to a situation with a specific error density. A low load period has an extreme-value distribution in which ε is small and varies on one half side. Most probability models (probit or logit) assume that the residuals ε are Gaussian or Gumbel distributed with an expectation value of 0 (see Section 2.4). A fundamental problem exists when the marginal expenditures of time are attached to the residual ε . In this case, the expectation value of the distribution of ε would be greater than zero, and the requirement that the errors over all observations statistically cancel each other out would not hold true.

In the context of the theory of measurement errors, Kreyszig (1979) stresses the difference between types of error: Deviations distorting the results of all measurements in the same manner are called regular or systematic errors. These errors interest us just as little as the gross errors, because both types of errors have nothing to do with the theory of probability. What remains are errors caused by a multitude of small disturbances distorting the measurement in an uncontrollable and changing way. These errors are called random or statistical errors; their theoretical treatment was initiated by Gauss and Laplace.

Model types

What exactly is meant by a macroscopic, a microscopic, or (possibly) a mixed traffic model can be clarified with the help of the above-cited analogy to physics (Peters, 1967): Energy measured in quanta is microscopic treatment. Energy treated in continuous form corresponds to the macroscopic view. In between there is nothing (that would correspond to the designation “mesoscopic“). – When (symbolically viewed) *macroscopic* (∂ , \int) and (discrete) *microscopic* (Δ , Σ) operations occur mixed in one model, *hybrid model* is an adequate designation. This type occurs, for example, where a microscopic model analytically calculates the marginal cost of travel time on a road link (Figure 2.3) by means of an aggregated function like, for example, the BPR time-flow-capacity curve (see Section 2.3) or where the state of the traffic system is described by means of kinematic-statistical equations with the position and speed of the vehicles being microscopically mapped (e.g. Bellomo, 2002).

The Nagel and Schreckenberg model (1992) counts among the first complex traffic models conceived according to the microscopic approach of cellular automata. Because computing time plays an important role in simulation, researchers and planners frequently use models that connect traffic nodes to each other by waiting queues. For example, Gawron (1998) developed an efficient model on the basis of waiting queues, which is implemented in similar form in the MATSim software and will be used in this study for microscopic simulation (see Section 4.1).

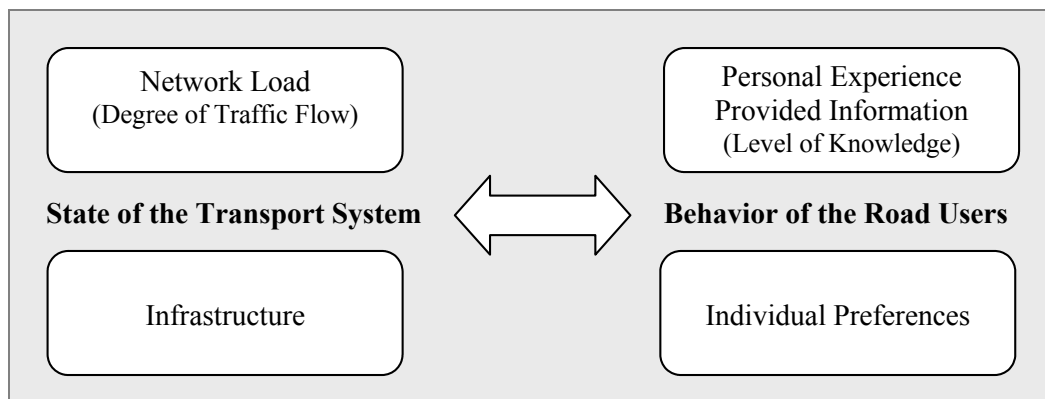
The technical relations in transport are described in a detailed and advancing manner in the literature: the foundations of macroscopic analyses of traffic flows for instance in Fowkes and Mahony (1994), Smulders (1989); more generally, for example in Helbig (2005, 1997), or in specific studies such as Bogenberger et al. (2006), Kerner (2004), Schick (2003), Schadschneider (1999) or Schreckenberg et al. (1996), etc.

2.2 Economic interactions

Connected to technical relations are economic interactions. If the number of vehicles per time unit increases, the travel time will increase, and increasing travel times will lower demand and reduce traffic flow. From the market point of view, transportation consists of barter deals of transportation products, on the one side, and time or money, on the other. A transportation product consists in the change of place of a person or good, brought about by public or private means of transport.

The interaction of demand and supply in terms of the network load and the effect of road user behavior on the network are shown in Figure 2.5 borrowed from Dobler, Axhausen and Weinmann (2012).

Figure 2.5: Relation of the Transport System State and the Behavior of Road Users



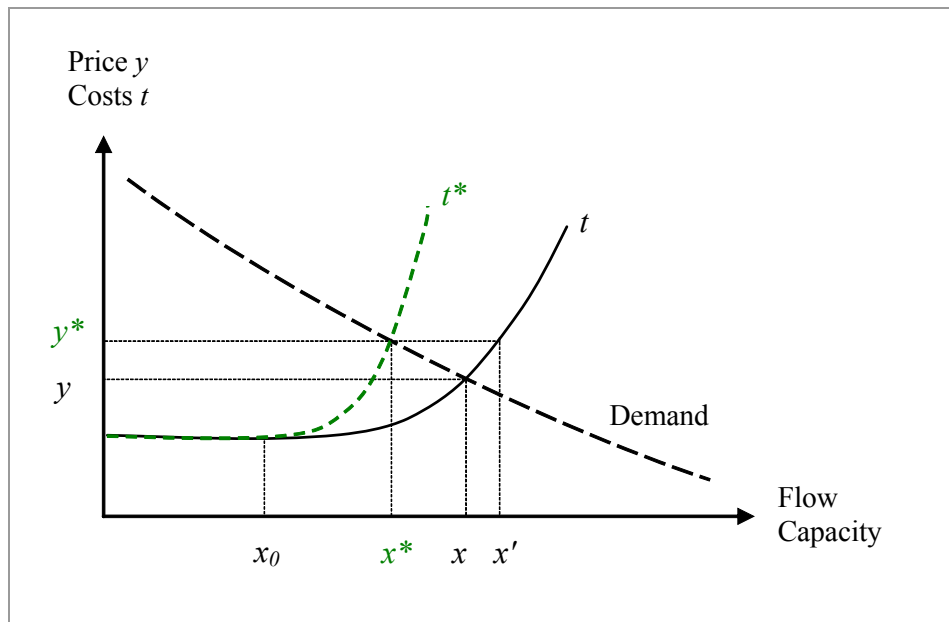
Source: Dobler, Axhausen and Weinmann (2012)

The transport business causes traffic. The higher the demand, the higher the price. If the price expended in road traffic is considered to be the actually needed travel time on a route, prices will, unlike on ordinary markets, be known only after the product is consumed. How large the margin between the expected price and the actual price is for the driver depends mainly on the accuracy of the information about the travel time. Measuring the prices and costs of the demand (load) in relation to the capacities of the road sections (the offer) and providing information about the prices for their use are the primary tasks of economic traffic analysis. Optimum utilization of the traffic network can be achieved by means of a resource-optimal collection and communication of the travel times so that the sum of all travel times expended is reduced to a minimum (see Section 2.3).

The travel times on a given link are principally dependent on the traffic flows on the entire network: In the case of short links flowing well into each other (like, for example, traffic circle nodes in urban areas), a separate analysis is less called for than in the case of separable links that are longer and depend to a relatively minor extent on the type of their intersection nodes (Ortúzar and Willumsen, 2001).

Figure 2.6 schematizes the time-flow-capacity curve of a certain link (see Section 2.3) describing the change in travel time in relation to the vehicular traffic flow on the link. The marginal cost t^* consists of the cost of time t and the marginal cost of time Δt on a link.

Figure 2.6: Cost and price in relation to flow and capacity

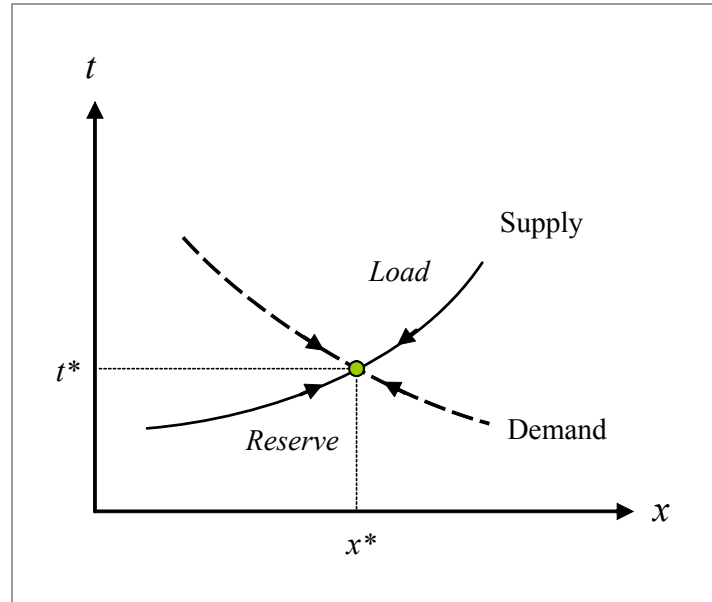


In the free capacity area ($x \leq x_0$), the cost of time t of the traffic volume x and the marginal cost t^* are about the same ($t^* - t \approx 0$). In the area under load ($x > x_0$), the marginal cost exceeds the cost ($t^* > t$). The price difference $\Delta y = y^* - y$ reflects the marginal cost of time $\Delta t = t^* - t$ being caused by the additional user (Pigou, 1960).

The interaction of travel time t and traffic flow x is self-consistent. Like in the case of a classical offer-demand relation, it is possible to calculate a certain market equilibrium in respect of price and quantity of a product (e.g. Samuelson and Nordhaus, 2010). The equilibrium of a traffic segment is determined by the choice

of the routes. Any change in behavior of the drivers means a shift of the demand curve and the equilibrium (Figure 2.7).

Figure 2.7: Supply and demand equilibrium point



(Macroeconomic) market equilibrium results from the behavior of the consumers. The microscopic analysis of the consumers considers among other things the price of a product in relation to the capacity-dependent cost of its production. – The same characteristic relation is found in traffic systems: The Wardrop principles express the relations between the (global) state of the system and (local) maximization of utility (see Section 2.3).

Unlike in purely physical systems, in socio-technical and socio-economic systems there are additional mechanisms that are not as easily recognizable and are more difficult to measure than natural forces. Where the behavior of persons plays a decisive role, the principle of maximization of individual expected utility has proven to be the most important factor for statistically mapping causal relationships in the field of uncertainty of decisions (see Section 2.4).

2.3 Traffic assignment

Within a traffic network $G = (N, A)$ with a set of traffic nodes N , a set of links (arcs) $A \subseteq N \times N$, a set of origin nodes $O \subset N$, and a set of destination nodes $D \subset N$ exist demands which cause f_{od} vehicles to move on a set of routes R_{od} from $o \in O$ to $d \in D$. A route $j \in R_{od}$ consists of an ordered set (a tuple) of links $i \in A$.

A certain traffic demand can arise from a time-independent distribution of the vehicles (*static assignment*), or it can take into account the points in time of the events leading to a change of traffic states (*dynamic assignment*). For a given demand f_{od} between a departure node $o \in O$ and a destination node $d \in D$, the volume of traffic $O \times D \rightarrow (x, t)$ can be determined according to the following procedure:

1. Determine the set of routes R_{od}
2. Determine the travel time t_j on each route $j \in R_{od}$
3. Distribute the demand f_{od} among the routes $j \in R_{od}$
4. Calculate the traffic flow x_i of each link $i \in A$.

Steps (2) to (4) are repeated until the traffic flows or the travel times do no longer significantly change. The travel times can be initialized using the shortest routes in the load-free network (without taking into account the capacities of the links) (*all-or-nothing assignment*).

Note: The shortest routes between a pair of nodes can be found efficiently ($O(|N|^2)$) by means of the Dijkstra Algorithm (1959). The algorithm of Roy (1959), Floyd (1962), and Warshall (1962) calculates the shortest routes of all pairs of nodes of a demand with complexity $O(|N|^3)$, e.g. Rosen (2000).

A traffic assignment must meet the following basic conditions for each demand f_{od} : The demand must be completely met (2.3.1), and the vehicles must be duly allocated to the routes in the process (2.3.2).

$$\sum_{j \in R_{od}} f_j = f_{od} \quad (2.3.1)$$

$$f_j \geq 0 \quad \forall j \in R_{od} \quad (2.3.2)$$

The traffic flow x_i of a link results from the flows f_j of the routes leading over the link (2.3.3), where $\delta_{i,j} = 1$ will be true if the link $i \in A$ belongs to the route $j \in R_{od}$, otherwise $\delta_{i,j} = 0$ will be true.

$$x_i = \sum_{i \in A} \sum_{j \in R_{od}} \delta_{i,j} \cdot f_j \quad (2.3.3)$$

$$0 \leq x_i \leq q_i \quad \forall i \in A \quad (2.3.4)$$

The relation (2.3.3) means that the traffic flow on a link equals the sum of the traffic flows of all routes using this link. The relation (2.3.4) requires that the traffic flow x_i must not be negative and must not exceed the capacity q_i .

The crux of the allocation problem is the determination of the travel times on the routes depending on the changing states of the traffic flows on their links. The travel time t determined by the flow is a theoretical variable, which by observation (measurement) and by its communication becomes a stochastic information τ about the travel time (see Section 2.1).

The assignment of a demand can take place according to the first principle of Wardrop (1952) by way of determined travel times (costs) t : Under equilibrium conditions, traffic arranges itself in congested networks such that all used routes between an origin-destination pair have equal and minimum costs while all unused routes have greater or equal costs.

$$f_j \cdot \left(t_j - \min_{r \in R_{od}} t_r \right) = 0 \quad \forall j \in R_{od} \quad (2.3.5)$$

When traffic reaches the state of Wardrop's first principle, the result is a user equilibrium. The traffic arranges itself. Equilibrium among the drivers is reached when the demand f_{od} is met by routes that have minimal (determined) travel times t .

In real traffic, the drivers do not know the determined travel times t_j . The condition (2.3.5) is not suitable for the simulation of real scenarios. To be able to use travel time as decision criterion for the following microscopic analysis (see Sections 2.4, 3.1 and 3.4), τ_{jk} will stand for the travel time on route j that is known to a driver $k \in K^a$ of class $K^a \subseteq \Omega$ (2.3.6).

$$f_j \cdot \left(\tau_{jk} - \min_{r \in R_{od}} \tau_{rk} \right) = 0 \quad \forall j \in R_{od} \quad k \in K^a, \cap K^a = \emptyset, \cup K^a = \Omega \quad (2.3.6)$$

Ω denotes the statistical population of the drivers; the classes K^a constitute a partition of Ω . When each driver believes that he cannot further shorten his trip by deviating from his route, the stochastic user equilibrium has been reached. Accordingly, Wardrop's first principle applied to real traffic reads: Under equilibrium conditions traffic arranges itself in congested networks in such a way that no individual trip maker can reduce his path costs by switching routes.

Wardrop's first principle (2.3.6) corresponds to descriptive models whose decision criterion is the maximization of (subjective) utility. It suits questions and issues regarding the current state of traffic and the actual behavior of the drivers, such as traffic forecasts. In the theory of games, the behavior of the users leads to a Nash equilibrium, which corresponds to the user equilibrium of the drivers; this is true for the normal case where the players compete with each other and (necessarily) do not cooperate with each other. Typical user behavior implies that the Nash equilibrium is the only stable self-arranging state. The extent to which the equilibrium deviates in each case from the optimum state of the traffic system is determined by the level of information and the behavior of the drivers (see Section 4.4 and Chapter 5).

Wardrop's second principle reads: Under social equilibrium conditions, traffic should be arranged in such a way that the average or total travel cost is minimized.

The optimum state involving all drivers is reached when the total cost of transport is at a minimum (2.3.7).

$$\min \sum_{j \in R_{od}} f_j \cdot t_j \Rightarrow \min \sum_{i \in A} x_i \cdot t_i(x_i) \quad (2.3.7)$$

The state where the sum of all travel times (or the mean travel time) is at a minimum is referred to as the system optimum. Decision models oriented towards the system optimum are normative (or *prescriptive*). They require cooperative behavior on the part of all users in order to achieve a state of welfare which establishes a social equilibrium among the drivers. The condition (2.3.7) corresponds to the vision of the traffic planner; it suits questions regarding the should-be state of traffic and the systemic behavior of the drivers, such as the analysis of the potential of predictive traffic information. In the theory of games, cooperative behavior on the part of the users is only theoretically relevant, because each competing player is consistently looking for his own advantage and only (unconsciously) cooperates if he (consciously) interprets this as an incentive implying added value for him. The optimum among all players can be reached if each player is fully informed about the consequence of his decision and if all players (must) cooperate.

Optimum traffic flows can also be achieved via user equilibrium without external pressure on the drivers. If the travel time t on a link is increased by the marginal travel time $x \cdot (dt \div dx)$ (2.3.8) and a program for calculation of user equilibrium is used, condition (2.3.5) will result in a solution with system-optimal flows (cf. for example, Gawron, 1998, Bekhor, 1999, Mandir, 2012). If travel time t is replaced by the marginal cost $t^* = t + x \cdot t'$, the system becomes optimal by arranging itself. Since full information corresponding to condition (2.3.5) cannot be provided, this condition is not tenable in real systems. Nevertheless, the theoretical transition from user equilibrium to system optimum is relevant for practical application because it describes the ideal process of a traffic system which is technologically approximable.

$$t^* = t + x \frac{dt}{dx} \quad (2.3.8)$$

A generalized analysis of the relationship between user equilibrium and system optimum, as well as an overview of the research in this subject area is presented by Yang and Huang (2004). They assume that the travel time $t(x)$ on a link is a differentiable, monotone and convex function of the traffic flow x and show that as a result of surcharges on the links, system-optimal flows can arise from the user equilibrium model – irrespective of whether the prices expended on the links appear in the form of time or money values.

The functional relation between travel time, traffic flow, and the capacity of a link is expressed by an array of widespread models (Ortúzar and Willumsen, 2001). Frequently used is the BPR function of the U.S. Bureau of Public Roads (1964: The relative load $x_i \div Q_i$ resulting from the traffic flow x_i and the capacity Q_i yields the travel time t_i on the link i .

$$t_i = T_i \cdot \left(1 + \alpha \cdot \left(\frac{x_i}{Q_i} \right)^\beta \right) \quad (2.3.9)$$

where:

t_i the travel time on link i

T_i the travel time on link i on the traffic-free network

x_i the traffic flow on link i

Q_i the traffic flow capacity of link i

α the calibration parameter (standard $\alpha = 0.15$)

β the calibration parameter (standard $\beta = 4$)

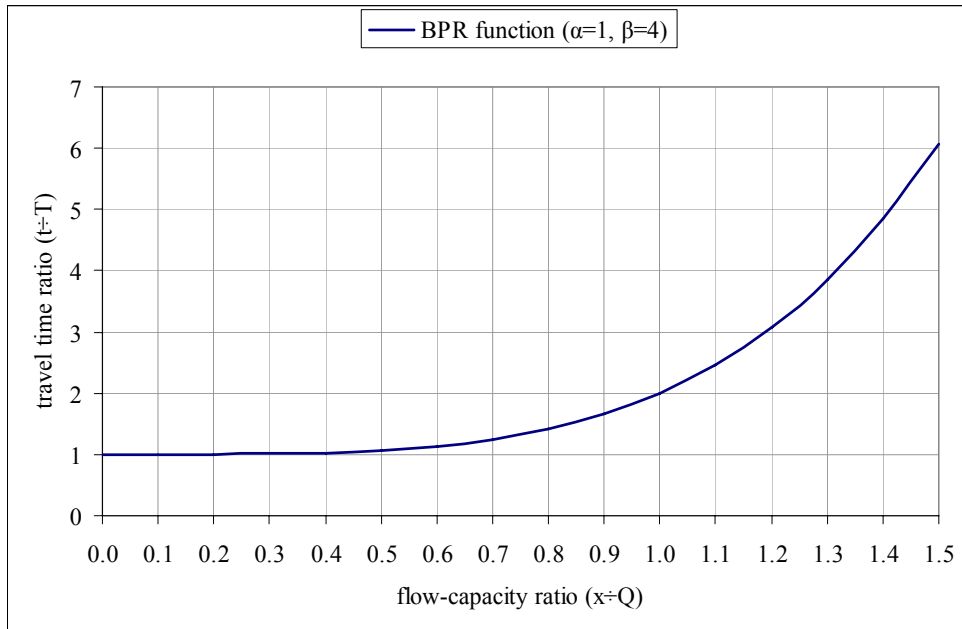
For $Q_i = q_i$, the BPR function (2.3.9) does not meet the capacity restriction (2.3.4). In the model of Davidson (1966), $x_i \div Q_i$ is replaced by $x_i \div (Q_i - x_i)$, which results in the capacity restriction being met. The BPR function with marginal travel time

cost (2.3.10) was introduced by Spiess (1990). The relations (2.3.8) and (2.3.9) yield a full travel time t^* on a link containing the marginal cost of time of the BPR function (2.3.10).

$$t_i^* = T_i \cdot \left(1 + \alpha \cdot (\beta + 1) \cdot \left(\frac{x_i}{Q_i} \right)^\beta \right) \quad (2.3.10)$$

The time-flow-capacity relation of the BPR function (2.3.9) is mapped by the time quotient $\tau \div T$ dependent on the flow quotient $x \div Q$ in Figure 2.8.

Figure 2.8: Time-flow-capacity function (BPR: $\alpha=1, \beta=4$)



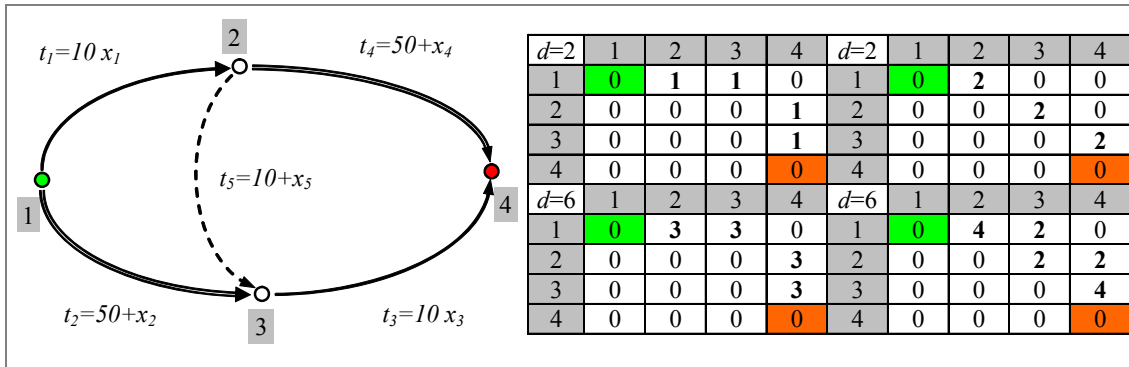
Braess network

The example provided by Braess (1968) shows how the capacities and the costs of the road links affect the allocation of a given demand: Already the change of the cost of just one link changes travel time for every driver. The traffic network is symmetrically designed from four nodes $N = \{1, 2, 3, 4\}$ in such a way that optimal allocation of the demand f_{14} to the two routes $r_1 = (1, 2, 4)$ and $r_2 = (1, 3, 4)$ generates identical traffic flows $f_{(1, 2, 4)} = f_{(1, 3, 4)} = \frac{1}{2} \cdot f_{14}$; the system optimum equals the user equilibrium. An additional link from traffic node 2 to node 3 opens

to the drivers the alternative route $r_3 = (1, 2, 3, 4)$ via the link $a_5 = (2, 3)$ which is independent of the two main routes r_1 and r_2 .

For $G_{\text{Braess}} = G(N, A) = G(\{1, 2, 3, 4\}, \{(1, 2), (1, 3), (2, 3), (2, 4), (3, 4)\})$, $O = \{1\}$, $D = \{4\}$, the traffic flows $x_1 = x_3 = \frac{1}{2} \cdot (f_{14} + x_5)$ and $x_2 = x_4 = \frac{1}{2} \cdot (f_{14} - x_5)$ are on the links $a_1 = (1, 2)$, $a_2 = (1, 3)$, $a_3 = (3, 4)$, $a_4 = (2, 4)$ of the two main routes dependent on flow x_5 on link $a_5 = (2, 3)$. The travel times on the links are given by the linear functions $t_1 = 10 \cdot x_1$, $t_2 = 50 + x_2$, $t_3 = 10 \cdot x_3$, $t_4 = 50 + x_4$ and $t_5 = 10 + x_5$ (Figure 2.9). The travel time is $t(r_3) = 10 + 20 \cdot \frac{1}{2} \cdot (f_{14} + x_5) + x_5$ on the secondary route r_3 , and $t(r_1) = t(r_2) = 50 + \frac{1}{2} \cdot (f_{14} - x_5) + 10 \cdot \frac{1}{2} \cdot (f_{14} + x_5)$ on the main routes r_1 and r_2 .

Figure 2.9: Braess network, different flows x of demands d depending on link (2,3)



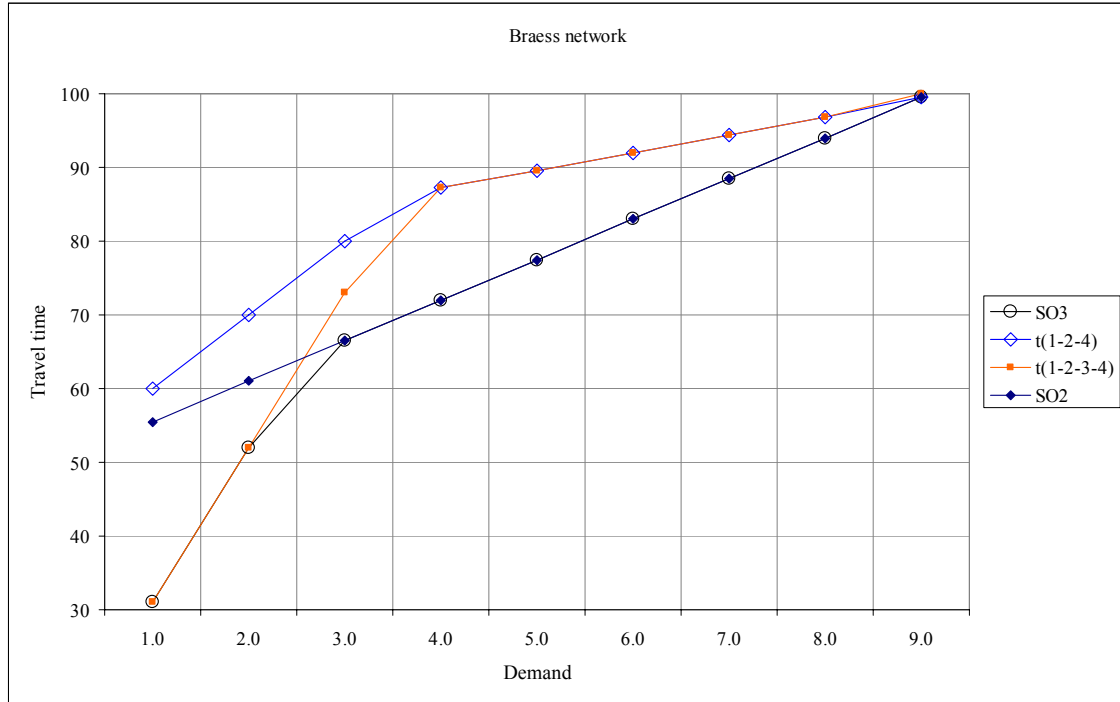
Taking the example of the three routes r_j of the Braess network, Wardrop's principles read $t(r_1) = t(r_2) = t(r_3)$ according to the user equilibrium (2.3.5), $\tau(r_1) = \tau(r_2) = \tau(r_3)$ according to the stochastic user equilibrium (2.3.6), and $f_1 \cdot t(r_1) + f_2 \cdot t(r_2) + f_3 \cdot t(r_3) = \min$ or $x_1 \cdot t_1 + x_2 \cdot t_2 + x_3 \cdot t_3 + x_4 \cdot t_4 + x_5 \cdot t_5 = \min$ according to the system optimum (2.3.7).

Given a demand of $d = 6$, the drivers need for their trip from 1 to 4 without the link (2, 3) an average of 83 minutes. With the link (2, 3) added, the average travel time on the traffic network increases to 92 minutes. This unexpected effect of the enlargement of the traffic network leading to a worse state is called Braess's paradox (Figure 2.10).

The time curves in Figure 2.10 show: In the case of a demand f_{14} in the range between about 2.6 and 8.9 units, the travel times at user equilibrium on the enlarged

network are higher than on the plain network without the additional link (2, 3); in the case of demands $f_{14} \geq 9$ units, the traffic flow on the additional link amounts to 0 (Table 2.1).

Figure 2.10: Braess network travel times in the states of SO and UE



SO3 and SO2 denote the travel times of the system optima on the enlarged network and on the plain network without the link (2, 3). The travel times on the routes $r_1 = (1, 2, 4)$, $r_2 = (1, 3, 4)$, and $r_3 = (1, 2, 3, 4)$ are denoted $t(1, 2, 4) = t(1, 3, 4)$ and $t(1, 2, 3, 4)$ in user equilibrium. The user equilibrium flows result from the demand f_{14} and the equilibrium flow x_5 (Table 2.1). Demand $f_{14} = 4$, for example, generates the flows $f_3 = x_5 = 3.38$, and $f_1 = f_2 = x_2 = x_4 = \frac{1}{2} \cdot (f_{14} - x_5) = 0.31$, as well as $x_1 = x_3 = \frac{1}{2} \cdot (f_{14} + x_5) = 3.69$.

Table 2.1: Braess network user equilibrium flow on additional link (2,3)

Link flow	Demand f_{14}								
	1	2	3	4	5	6	7	8	9
$x_5=(2,3)$	1	2	3	3.38	2.69	2	1.31	0.62	0

Note: Many characteristic properties for complex networks can be derived from the example of the Braess network. Upon closer consideration, the Braess network is

not as simple as it appears at first sight. The analyses are multifaceted: Gawron (1998) presents a dynamic variant of the Braess network under the aspect of different link capacities. Roughgarden (2005) calculates for different classes of link-cost functions (*latency functions*) bounds for the “worst-case ratio between the total latency of a Nash equilibrium and that of the best coordinated outcome – of a flow minimizing the total latency”. Chmura (2005) considers the simplest form of the Braess network from the viewpoint of the theory of games and describes experiments (*minority games*) with users in the context of route choice. Witthaut and Timme (2012) quantify effects of Braess’s paradox in a complex network (UK power grid) based on critical links, dependent on their load level.

2.4 Decision analysis

Knowledge and Behavior

If the effect of information does not emanate from calculators or computers, but rather is put into practice by individuals, behavioral research will be part of the analysis of decision-making. Behaviorism (Watson, 1913) abstracts learning processes according to the following point of view: Decisive is *what* is learned and not *how* the knowledge has been acquired. The physiological processes of learning are not considered. Behaviorism objectivizes knowledge acquired through learning on the basis of the results of the actions following from it. An individual’s decision-making behavior is evidence of his knowledge. The behaviorist view fits a type of driver who expresses his knowledge by choosing that route which promises him maximum utility. His decision is based on rational behavior and on the information he obtains during his trip (see Sections 1.3, 3.1, 3.2, and 4.2).

The behavioral models of traffic planning assume a rational driver who proceeds according to certain rules so as to reach his destination. Whether a rational driver possesses no knowledge, or whether an irrational driver possesses complete knowledge is irrelevant with respect to the effect because both cases can only be treated stochastically as all changes of state resulting from ignorance or from arbitrariness can occur with the same probability (Figure 2.11). Viewing the borderline cases of stochastic decision processes in relation to the effect of the level

of information in the case of rational behavior will enhance the understanding of the mathematical description of uncertain decisions.

The concepts of *rational* and *utility* are closely associated with Wardrop's principles (see Section 2.3). The user equilibrium results from individual rational decisions based on the principle of utility maximization. Individual utility reaches its maximum when the choice of his route lets the driver achieve inner equilibrium. In a similar way, a fair deal is achieved by way of exchanging objects, such as money against merchandise, merchandise against service, or time against money; the valuation of the utility in the process takes place by weighting the properties of the objects until an equivalent is reached in respect to which the decision maker is indifferent.

Utility maximization

Decision analysis is at the core of microscopic modeling and simulation of traffic systems. Its objective is to analyze the behavior of individuals who are acting in an (economical) rational manner. An individual decides rationally when he chooses that alternative from which he expects to gain the highest utility, i.e. faced with two alternatives A and B his choice meets the utility preference relations:

$$u(A) > u(B) \Leftrightarrow A \succ B,$$

$$u(A) = u(B) \Leftrightarrow A \sim B.$$

An individual prefers alternative A over alternative B when the utility $u(A)$ of alternative A is greater than the utility $u(B)$ of alternative B . He is indifferent about the two alternatives, when the utilities of both are equal. Rational decision models are based on the assumption that any individual, in any situation, is able to assign to any alternative that utility which corresponds to his inclination towards, and his knowledge about, the properties of the alternatives. A rational decision does not require general objective knowledge (*subjective* does not mean *arbitrary* and *rational* does not have to mean *objective*). Preference calculus of utility maximization relates to individual knowledge about the decision criteria and about their subjective evaluation. A product's utility expresses the subjective appreciation

and weighting of different components (such as time, money, pleasure, or risk) in a given situation (for instance, time and monetary leeways, pleasurable sensation, or inclination to take risks). In traffic, travel time has emerged as the simplest and at the same time most important target variable. The reasons for this will be dealt with in more detail on the following pages in the context of the decision criteria.

Utility quantification

The individual utility $u(A)$ of an alternative A is considered as a subjective quantum consisting of k different properties t_k with different weights θ_k . The weighted properties $\theta_k \cdot t_k$ are supposed to map an individual's state of inner equilibrium as a result of a fair exchange between the unequal properties of the alternatives (such as time, money, energy, etc.).

An individual's decision behavior cannot be predicted, but it can be observed. Statistical properties and behavioral patterns for the conception of stochastic decision models can be gained from a series of experiments confronting a class of individuals in characteristic situations with the need to make decisions.

From the observation that an individual prefers object A over object B , it is possible to determine the (subjective) hierarchy of the two objects. Closer observations about the valuation of the objects are necessary for being able to map the qualitative preference relation on a quantitative scale. For example, in order to obtain the information about the difference of two utilities $u(A) - u(B)$, the individual would have to be placed in different situations and then observed. Many processes about which a model is expected to provide a proposition cannot be closely observed. When a process cannot be directly observed, the statistical property can be indirectly determined, and theory can be developed on the basis of the indirectly gained observations. This corresponds to the stochastic approach. The concept for determining the preference calculus according to von Neumann and Morgenstern (1943) can be described using two examples.

Example 1: Utility distance

Assume an individual preferring the consumption of a beverage tea (B) over that of coffee (A) and that of coffee to milk (C): $\hat{u}(B) > \hat{u}(A)$, $\hat{u}(A) > \hat{u}(C)$. To find out

whether the subjective utility \hat{u} of A is closer to B or closer to C , it suffices to let the individual decide whether to prefer the coffee to a glass that with a probability of 50 percent contains either milk or tea, respectively. – Observing the choice yields the additional information that, $\hat{u}(A)$ is closer to $\hat{u}(B)$ than to $\hat{u}(C)$ if the individual prefers the coffee (A) to the combination (of B and C).

Example 2: Utility units ratio

Assume an individual has to decide between the opportunity to participate for sure in an event A , or to be given the chance to participate in A two times, with the probability α , or not at all, with the probability $1 - \alpha$. From observing the choice, we gain the additional information about the relation q of the utility that one unit of A has over two units of A . If the individual prefers to be certain of participating in the event A , then $\alpha < q$, in the other cases $\alpha > q$ or $\alpha = q$.

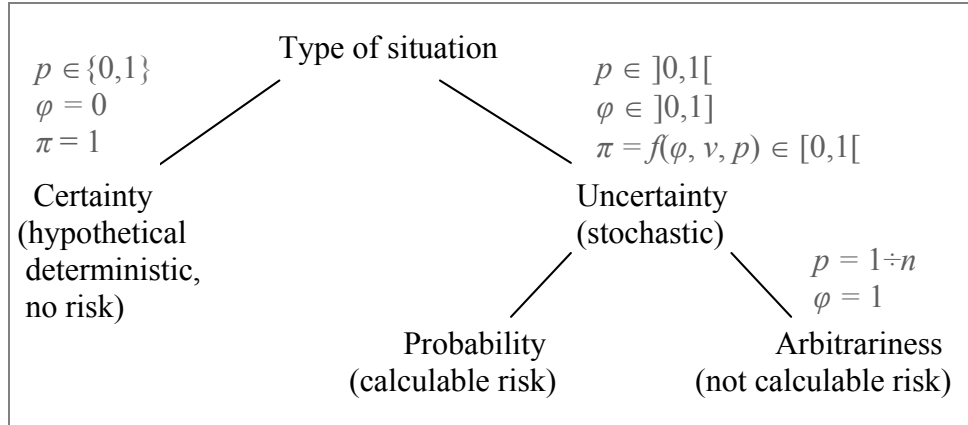
The two examples show that with the help of probabilities it is possible to determine the numerical utility as perceived by an individual. Similar experiments were performed by Kahneman and Tversky (1979), within the context of behavioral psychology, and later by Tversky and Kahneman (1992) and formulated as a descriptive theory of cumulative prospects. The axioms of preference calculations and the determination of normative (prescriptive) utility models are described in the literature on decision theory (e.g. Eisenführ and Weber, 2010, Laux et al., 2012).

Road users in particular may be assumed to base their choices on the relation of their resources (such as time or money values). A driver makes his choice based on simple, natural questions: How much time and money are available to me at this moment? What does the time at stake mean to me in a given decision situation? What can I do with a potential gain of time? How much do I dread the loss of time or money resulting from the detour caused by the choice of an alternative route? All these questions and also the observation that rising consumption of a product always leads to some saturation (decreasing marginal utility, Gossen, 1954) confirm the experience that individual decisions depend on the subjective weighting of the properties of an alternative.

Measuring the consequences of a decision

Rational decisions can be made based on the hypothesis of the infallible evaluation of the result of a decision (certainty), or on the assumption that the evaluation of the consequences is prone to error (uncertainty), see Figure 2.11.

Figure 2.11: Types of situations for decision problems and terms of uncertainty



In the real world, decision processes are uncertain regarding the valuation of their potential results. Actually, when looked at more closely, everything is imprecise: A sure result certainly is exact, but not realistic. An unsure result is realistic, but it is not exact. Whether the outcome of an uncertain decision is calculable or not depends on the decision-maker's level of information. Figure 2.11 sets out the principal situations in respect of the evaluation of an alternative in view of the decision for one of the alternatives. An alternative A_j is evaluated under a horizon S by means of its stochastic information $L_j = (v_j(s), p_j(s)); s \in S$; L stands intuitively for lottery. The function $p(s)$ denotes the probability of the situation s in which the alternative's property is assigned the value $v(s)$. The extreme values are $p(s) = 0$: situation s and value $v(s)$ will certainly not occur; $p(s) = 1$: situation s and value $v(s)$ will certainly occur (alone); $p(s) = 1 \div n$: all n situations and values will occur with the same probability. The variables φ and π are specified in the Sections 3.1 and 3.2; their values schematize a decision-maker's degree of uncertainty; the extreme values mean $\varphi = 0$: certainty, absolute information; $\varphi = 1$: uncertainty and arbitrariness, no information; and for the probability of an alternative being chosen $\pi_j = 1$: the j th alternative will certainly be chosen, otherwise (for $\varphi > 0$) with the probability $\pi_j = f(\varphi, v_j, p_j)$.

A decision in the face of uncertainty can be resolved by different approaches, like, for example, by means of fuzzy decision methods, which maximize the *fuzzy utility* of alternatives (Rommelfanger, 1988). Discrete decisions like, for example, the choice of a route, are most easily resolved by means of the *random utility* method (2.4.9 to 2.4.14) because it requires a lesser amount of information for maximizing utility than the initially described methods of decision theory: *value-risk utility* (2.4.3 to 2.4.5) and *expected utility* (2.4.6 and 2.4.7).

The expected gain (or loss) of an alternative can be determined by its lottery. The value function $v(s)$ and its probability $p(s)$ can be given in discrete or in continuous form. The independent variable $s \in S$ represents a certain situation (or state). The *expectation value* (also called *expected value*) of an alternative is given by (2.4.1) for discrete, and by (2.4.2) for continuous $v(s)$, $p(s)$ and s .

$$EV_j = \sum_{s \in S} v_j(s) p_j(s) \quad (2.4.1)$$

$$EV_j = \int v_j(s) p_j(s) ds \quad (2.4.2)$$

Value-Risk Utility

Besides the expected value $\mu_j = EV_j$, the statistical value-risk utility (called the μ - σ -rule in the literature) evaluates an alternative A_j , using its scattering σ_j as a risk measure of the disbursement according to its lottery L_j . The value-risk utility of an alternative is given by (2.4.1), (2.4.3), (2.4.4) for discrete and (2.4.2), (2.4.5) for continuous $v(s)$, $p(s)$ and s .

$$VR_j = U(\mu_j, \sigma_j) \quad (2.4.3)$$

$$\sigma_j^2 = \sum_{s \in S} (v_j(s) - \mu_j)^2 p_j(s) \quad (2.4.4)$$

$$\sigma_j^2 = \int (v_j(s) - \mu_j)^2 p_j(s) ds \quad (2.4.5)$$

Taking a discrete model as an example, the choice of one of two alternative routes (for simplicity on the assumption that each of the routes consists of one link only)

shall be decided by way of a balance between the expected value μ and the risk σ . Given shall be the travel time information τ_1 and τ_2 on the two routes r_1 and r_2 , in the states s_1 and s_2 . The probability that an information τ_i is true within the confidence interval $[t^-, t^+]$ shall be p_i . Outside the confidence interval are the estimated values τ_{i-} and τ_{i+} of the travel times, which (in the case of a Gaussian distribution) shall be true with the probability $(1 - p_i) \div 2$; hence, the information about a route is provided by their lottery $L = (\tau_{i-}, p_{i-}; \tau_i, p_i; \tau_{i+}, p_{i+})$.

The typical choice behavior of a driver to whom the information L_j about route r_j is available, will be illustrated with respect to the following example: A driver can choose between the routes r_1 and r_2 . Known about r_1 be that $L_1 = (25, 0.1; 30, 0.8; 40, 0.1)$, and about r_2 that $L_2 = (20, 0.1; 25, 0.8; 60, 0.1)$. The expected time values of the lotteries are $\mu_1 = 30.5$ and $\mu_2 = 28$. The expected time values of the lotteries show scattering with $\sigma_1 = 3.5$ and $\sigma_2 = 10.8$.

The example demonstrates well how the driver determines his utility U (and is striving to achieve inner equilibrium as a result of his decision) by weighing the expected value μ against the risk σ (*value-risk trade-off*, $\partial U \div \partial \sigma$).

1. $U(\mu_2, \sigma_2) > U(\mu_1, \sigma_1) \Leftrightarrow r_2 \succ r_1$, if the possible reduction of travel time weighs heavier than the probable loss of time (*risk seeking*, $\partial U \div \partial \sigma > 0$, e.g. $U = -\mu + \sigma$)
2. $U(\mu_1, \sigma_1) > U(\mu_2, \sigma_2) \Leftrightarrow r_1 \succ r_2$, if the probable loss of travel time weighs heavier than the possible reduction of time (*risk averse*, $\partial U \div \partial \sigma < 0$, e.g. $U = -\mu - \sigma$)
3. $U(\mu_1, \sigma_1) = U(\mu_2, \sigma_2) \Leftrightarrow r_1 \sim r_2$, if the probable loss of travel time and the possible reduction of travel time offset each other so that the driver is indifferent about the two alternatives r_1 and r_2 (*value-risk neutral*, $\partial U \div \partial \sigma = 0$, e.g. $U = -\mu$).

If the driver makes his decision based on the expected value $\tau = \mu$, he fulfills the preference relation $r_2 \succ r_1$ and prefers route r_2 with the lower loss of time. If the driver factors into his decision the scattering σ of the time value τ as a risk factor, he will choose r_2 , if he is a risk seeker, and r_1 , if he is a risk averter; the driver's preference can be numerically expressed by the value-risk utility (2.4.3).

Expected Utility

The Expected Utility Theory founded by von Neumann and Morgenstern (1943, 1953) is in its expanded form, for example as formulated by Savage (1954), generally applied with respect to decisions in the face of uncertainty. Expected utility (known as the Bernoulli's Principle after Daniel Bernoulli) requires that probabilities for the occurrence of situations are known.

For a utility function $u(v)$ of a value $v(s)$ in the state s , which is monotone in each of the ranges $v \leq 0$ or $v \geq 0$, expected utility of A_j results from (2.4.6) and (2.4.7).

$$EU_j = \sum_{s \in S} u(v_j(s)) p_j(s) \quad (2.4.6)$$

$$EU_j = \int u(v_j(s)) p_j(s) ds \quad (2.4.7)$$

Maximization of the expected utility ascribes to the consumers a monotone utility function $u(v)$ with respect to gains or losses $v(s)$. Descriptive analyses regarding risk behavior (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) show that the behavior of most consumers is described by utility functions that prefer risk in the case of losses whereas in the case of gains they avert risk. For a utility function with $du \div dv = u' \neq 0$, the Arrow-Pratt absolute measure of attitude towards risk (2.4.8), named after Arrow (1963) and Pratt (1964), in relation to a utility function $u(v)$, which maps the loss v as a negative value, yields in general: risk aversion for $\lambda > 0$, risk preference for $\lambda < 0$, and risk neutrality for $\lambda = 0$. In the case of a positive notation of loss v the algebraic sign of λ will change.

$$\lambda = -\frac{u''}{u'} \quad (2.4.8)$$

The cited experiments by Kahneman and Tversky refer to monetary losses. Newer experiments by Kroll (2010) point out that time losses and monetary losses are evaluated the same way. The power utility ascertained by Tversky and Kahneman (1992) (see Section 3.1) would in the given example (above) prefer the more risky alternative r_2 over r_1 , because the difference of the time values $\mu_1 - \mu_2 = 2.5$ (the

possibly smaller loss of time) weighs more than the lower risk (with the difference $\sigma_2 - \sigma_1 = 7.3$) involved in choosing r_1 instead of r_2 .

Sample analysis

A driver again is faced with the choice between two alternative routes r_1 and r_2 . The two routes differ with respect to their total capacities (but are homogenous with respect to the capacity of their individual links). The shorter route r_1 in a no-load condition becomes the longer route in the traffic marginal state, and vice versa, the longer route r_2 in the no-load condition becomes the shorter one in the fully loaded condition. Here, two other lotteries are given with $L_1 = (3, 0.2; 5, 0.6; 7, 0.2)$ and $L_2 = (4, 0.1; 5, 0.8; 6, 0.1)$.

The analysis of the consequences for the lotteries L_j (Table 2.2) yields the following picture: The expectation values of the travel times are for both links $\mu_1 = \mu_2 = 5$, corresponding to the information $\tau_i = 5$ which is assumed to apply to route r_1 with $p_1 = 60\%$ and to route r_2 with $p_2 = 80\%$ probability. Drivers oriented only towards the expected value μ are indifferent about the two routes r_1 and r_2 .

Table 2.2: Analysis of decision regarding two routes r_j with information τ_i at situation s_i

	S^-	S_i	S^+	Expected Utility	Expected Value	Expected Risk	Value-Risk Utility
p_1	0.2	0.6	0.2	EU [%]	μ	σ	(μ, σ)
p_2	0.1	0.8	0.1				
r_1	3	5	7	51.63	5.0	1.26	-3.74
r_2	4	5	6	48.37	5.0	0.45	-4.55

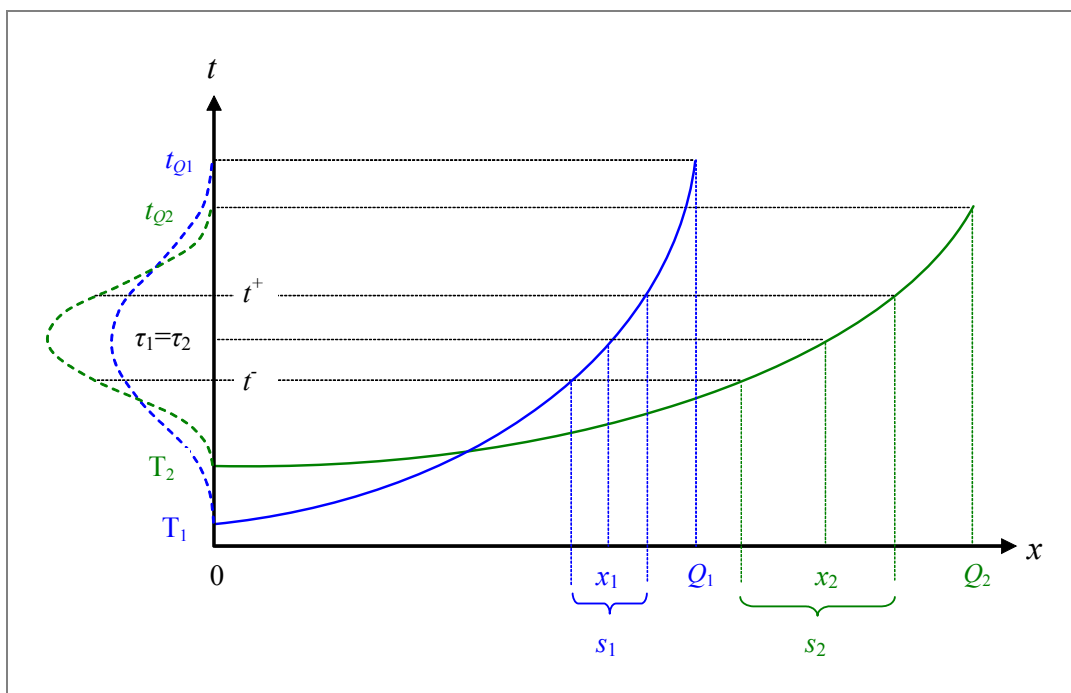
A driver striving to use the chance of a travel time as short as possible will prefer the risky alternative r_1 , even though the information $\tau_1 = \mu_1$ about the travel time on that link bears the higher absolute risk ($\sigma_1 = 1.26$ and the smaller relative chance, coefficient of variation $100 \cdot (1 - \sigma_1 \div \mu_1) \approx 75\%$). A driver having an aversion towards risk would try to minimize the maximum loss of time and to choose route r_2 with the higher capacity and the lower absolute risk ($\sigma_2 = 0.45$ and the larger relative chance, coefficient of variation $100 \cdot (1 - \sigma_2 \div \mu_2) \approx 91\%$).

Whether the decision criterion used is the expected utility or the value-risk utility does not matter when the utility functions are monotone. In each case, the

preference of a road user prepared to take risks in loss situations is $r_1 \succ r_2$. Table 2.2 shows the percentage expected utility calculated from the power utility discussed in the following section (3.1); the value-risk utility results here from the μ - σ -rule $-\mu + \sigma$ (as one of many possibilities).

Figure 2.12 shows the time-flow relation of one link of each of the two routes r_1 and r_2 with different capacities $Q_1 < Q_2$. If the same travel time τ is stated for two routes, the decision will be based on two additional traffic data: the distribution of the probabilities $p(s)$ of the information $\tau(s)$ in state s , and the time-flow relation $t(x)$. From this it ensues for the driver that he needs more information than merely that about the travel time τ on a route, to be able to make the best possible decision. The risk of the probable deviation from the travel time information τ and the attitude towards risk of a typical driver are to be integrated into the decision model (see Section 3.1).

Figure 2.12: Travel time information τ about two links with different time-flow-relations



Random Utility Maximization

The theory of random utility maximization forms the basis for the most frequently applied decision model in transport planning. It factors the risk only globally into the choice of a route (or a means of transportation) by way of residuals ε of a

certain distribution $f(\varepsilon)$. As opposed to the expected utility and the value-risk utility, the random utility requires less information about the properties of the alternatives for making a decision.

The probability of the choice of an alternative can be with ease determined by means of its random utility. The utility $U_j = V_j + \varepsilon_j$ of an alternative A_j is postulated to be the sum of the measurable value V_j and the unobserved deviation ε_j . The stochastic part ε_j of the utility of the alternative A_j also comprises the user's individual measures of value. The residuals $\varepsilon = (\varepsilon_1, \dots, \varepsilon_m)$ of all m alternatives are assumed to have a distribution $f(\varepsilon)$ with has the expectation value 0.

Assume that a user evaluates an alternative A_j at its random utility (2.4.9 and 2.4.10).

$$U_j = V_j + \varepsilon_j \quad (2.4.9)$$

$$V_j = \sum_k \theta_k \cdot t_{jk} \quad (2.4.10)$$

where:

U_j the utility of alternative A_j

V_j the value of alternative A_j (observed, hypothetically deterministic)

ε_j the random value of alternative A_j (unobserved, stochastic)

t_{jk} the value of k th attribute of alternative A_j

θ_k the weight of the k th attribute of alternative A_j (Standard: $\theta_k = 1$)

The value V and the parameter θ are defined differently (2.4.10); depending on the application, θ for example, can be varied in relation to the alternatives (e.g., Ortúzar and Willumsen, 2001). A user may choose the alternative A_j on the condition that A_j has the highest utility among all the alternatives (2.4.11).

$$U_j \geq \max_{i \neq j} (U_i) \quad (2.4.11)$$

$$\pi_j = P(\varepsilon_i - \varepsilon_j \leq V_j - V_i), \quad \forall i \neq j \quad (2.4.12)$$

The user chooses alternative A_j with the probability of (2.4.12). If $f(\varepsilon)$ is assumed to have a Gaussian distribution, this will result in decision models of the probit class; Gumbel distributed residuals ε result in logit decision models (Train, 2003). The properties of the most important variants of the logit model, such as the multinomial logit model (McFadden, 1973), the C-logit model of Cascetta et al. (1996), or the Path-Size logit model of Ben-Akiva and Bierlaire (1999), are described in a general way, for example in Ortúzar and Willumsen (2001), or Ramming (2002).

Both model types, probit and logit, have been the subject of many discussions since the beginning of the Sixties. The following overview was extracted from McFadden (2000) and Train (2003): The logit model of Luce (1959) was further developed by Marschak (1960), McFadden (1973), Domencich and McFadden (1975). In the context of psychological stimuli, Thurstone (1927) derived the binomial probit model. Marschak (1960) further developed it on the basis of random utility into the multinominal decision model. Hausman and Wise (1978), as well as Daganzo (1979), generalized the probit model on the basis of further characteristics of choice behavior.

In the case of the exponential utility calculation, an individual chooses the alternative A_j exactly then when $U_j \geq U_i, \forall i \neq j$ is true, so that the difference of the deterministic utility is greater or equal to the difference of the stochastic utility deviation: $V_j - V_i \geq \varepsilon_i - \varepsilon_j$. The probability of choosing the alternative A_j is given by $\pi_j = P\{\varepsilon_i \leq \varepsilon_j + (V_j - V_i), \forall i \neq j\}$.

The logistic distribution ascertains the probability π_j of the alternative A_j being chosen (2.4.13) by means of the exponential utility $U_j = \exp(V_j)$.

$$\pi_j = \frac{U_j}{\sum_{i=1}^m U_i} = \frac{e^{V_j}}{\sum_{i=1}^m e^{V_i}} \quad (2.4.13)$$

Brilon and Dette (2002) mention other sources for random utility approaches, such as Abraham and Coquand (1961), Beilner and Jacobs (1972), and LeClerk (1975).

They postulate the utility $U_j = V_j \cdot \zeta_j$ of an alternative A_j as the product of its deterministic utility part V_j and its stochastic deviation factor ζ_j , and they base the deviation ζ_j on a distribution that has the expectation value 1. On the assumption that the deviation ζ_j of the utility is Weibull distributed and the deterministic utility portion $V_j = \lambda + \sum \theta_k \cdot t_{jk}$ corresponds to a linear combination with a value constant λ and the attributes t_j weighted by the parameters θ_k , Brilon and Dette (2002) deduced the probability π_j of the alternative A_j being chosen (2.4.14).

$$\pi_j = \frac{U_j}{\sum_{i=1}^m U_i} = \left\{ \sum_{i=1}^m \left(\frac{V_j}{V_i} \right)^\alpha \right\}^{-1}. \quad (2.4.14)$$

Note: The parameter α corresponds to the scattering of the error factor ζ_j . Brilon and Dette (2002) express the deterministic utility portion V_j of A_j as a negative number.

In the case of power utility calculation, an individual will choose alternative A_j precisely when $U_j \geq U_i, \forall i \neq j$ is true, so that the relation of the deterministic utilities is greater than or equal to the relation of the stochastic utility deviations: $V_j \div V_i \geq \zeta_i \div \zeta_j$. The probability of alternative A_j being chosen is given by: $\pi_j = P\{\zeta_i \leq \zeta_j \cdot (V_j \div V_i), \forall i \neq j\}$. For the binary decision case (with two alternatives A_1 and A_2) the resulting probabilities for the choice of the alternatives are $\pi_1 = V_2^\alpha \div (V_1^\alpha + V_2^\alpha)$ and $\pi_2 = V_1^\alpha \div (V_1^\alpha + V_2^\alpha) = 1 - \pi_1$.

Conclusion

The evaluation of alternatives by means of the expected utility (the Bernoulli principle) or by means of the value-risk utility (the μ - σ -rule) requires, in addition to the value function v , the probability distribution p . Because most of the time only the current travel time on a route can be made available and the probability of its occurrence is not known and can be only be hypothetically (by way of an extreme distribution) used, the two decision models are rarely being discussed and applied. Consequently, for the route choice, a variant of the random utility method will be specified in the following Section 3.1.

MODELLING DRIVERS

3.1 Route choice

In Section 2.4, the theoretical basis of the analysis of rational choices has been presented. The main criterion for the choice of a route is its utility. Random utility maximization is generally applicable; it is deductively derived (2.4.9). The essential element of utility, the time required for the trip, has been intuitively shifted to the center. The driver is assumed to perceive the utility of a route as the higher for him the shorter he expects the travel time on it to be. Before getting into the issue of the choice of a route, it is appropriate to take a closer look at time as a property of utility and choice criterion. The question as to whether additional properties are to be taken into account when it comes to choosing a route will also be considered.

Route utility properties

Travel time is generally mentioned as the most important attribute with respect to the evaluation of routes (e.g. Ortúzar and Willumsen, 2001, Bezuidenhout and Zealand, 2002, Wardman, 2004). There are a number of rational reasons for considering the saving of time as the most important property of utility when it comes to choosing a route:

- Travel time on a traffic-free road is proportional to its distance; i.e. the time required to travel is a transformed measure of the distance of a route – even though both variables, length of time and distance, are perceived differently.
- In calculating the monetary cost of using a busy road, travel time carries the most weight (generally, i.e. if the variable costs weigh more than the fixed costs).
- As opposed to monetary cost, length of time has the decisive advantage that the results of the decisions are generally comparable and transparent.
- Time is the simplest, universal measure, available to every individual to a limited extent; the marginal utility of time varies substantially less than the individual marginal utility of practically unlimited resources like money or energy.

If the driver is indifferent when it comes to evaluating two routes, he is inclined, *unless further information is available to him*, to choose the shorter route, even if the chance of achieving the expected travel time is smaller in the case of the shorter distance than in the case of the detour. Drivers who in the period from 1974 to 1998 traveled from the German city of Memmingen to Stuttgart (and vice versa) by car will confirm this phenomenon. The empirical data of the two routes, (r_1), the bypass on the highway, and (r_2), the shorter route (in terms of distance) leading through the city of Ulm, are presented in Table 3.1.

Table 3.1: Empirical analysis of choice between road through Ulm downtown and bypass

Route	Expected duration	Estimated distance	Average duration	Average deviation	Observed preference	Observed preference
	Δt [Min.]	Δx [Km]	μ [Min.]	σ [Min.]	1974-1998	2008-2013
Bypass (r_1)	14	30	15	1	2.	1.
Town centre (r_2)	14	21	19	5	1.	2.

Even though travel time on the city route (r_2) varies about fivefold as compared to that on the bypass (r_1), and therefore has a lesser time-risk-utility, the majority of the drivers preferred the shorter route (in terms of distance) for transit (without making use of any other feature of the city route, like, for example, its closeness to downtown). This trend was ascertained by the author through observations or polls conducted in the time from 1974 to 1998. A series of newer observations from 2008 until today has yielded the opposite trend of the bypass being used more frequently than the city route. This may be due to a better level of information together with the circumstance of travel time on the city route varying even more than before (Table 3.1) due to its rehabilitation having lasted for several years (and still going on).

Note: This reversal also reflects to some extent the reorientation of the drivers from the physical into the cybernetic space as described in Section 1.1.

A further criterion for the choice of route decision is the mean deviation from travel time as a measure of the risk of not being able to achieve the informed-about travel time. Based on random utility (2.4.9), Liu et al. (2004) investigated the *value of travel time*, the *value of travel-time reliability*, and the *degree of risk aversion*.

They found out that “the estimated median value of travel-time reliability is substantially greater than that of travel time, and the median value of degree of risk aversion is significantly greater than 1, indicating that travelers value more highly a reduction in variability than in the travel time saving for that journey.” The results obtained by Liu et al. (2004) confirm in principle that the reliability of information is an attribute of utility for the driver –, even though it might be doubted that the scattering of travel time should be valued higher than travel time itself.

The arguments mentioned suggest using travel time of a trip as the first and foremost criterion for a driver’s decision in choosing his route. The second criterion for the decision concerns the reliability of the information about travel time. The third criterion, the drivers attitude towards the risk attached to his choice, is speculative, on the one hand, and, on the other, the analysis by Kroll (2010) cited in Section 2.4 also confirms the general inclination of users to favor the alternative with the lowest loss of time (even when the mean deviation from the expected travel time is relatively large).

All in all, there are three essential properties relevant for the evaluation of the utility of a route and for the choice of a route oriented towards maximization of utility: the travel time, the reliability of the information, and the user’s attitude towards the risk attached to the information:

- (P1) the value of travel time saving,
- (P2) the value of travel time information reliability,
- (P3) the ‘value-risk trade-off property’ as the attitude towards risk tendency.

The properties P1 to P3 shall be taken into account regarding the driver’s decision. The current travel time τ will be provided within the framework of the traffic simulation with MATSim (Section 4.1). The second property (P2), the risk σ (2.4.4) attendant to the information is not directly available (it will be needed in the model in Section 3.2). For this reason, the reliability (in the sense of accuracy) of a forecast must be determined experimentally. From the driver’s point of view, the quality of some information can be assessed as follows: In addition to the informed-

about travel time τ , c shall stand for the actually achieved travel time on the chosen route. The deviation $c - \tau$, ascertained by a driver on his trip, is a suitable measure for the reliability of that information. With n experiments, the accuracy of the information can be defined by the mean relative deviation (3.1.1).

$$\delta = \frac{1}{n} \sum_{k=1}^n \frac{|c_k - \tau_k|}{\tau_k} \quad (3.1.1)$$

Hardly a driver would take a stop watch along on his trip and use it for determining on every route or even on every road link the time differences $c - \tau$ so that in the end the exact value δ would result. A rough measure, containing the essential property of the second criterion, can be gained on the basis of a relative tolerance threshold that can be assumed for a certain class of drivers. It suffices for the driver to participate in the following experiment by means of the relation (3.1.2): Assuming E to be the event “Driver accepts the deviation according to his tolerance threshold w ” (3.1.2), and assuming X to be the random variable registering the number of times of E coming true: $P(X = 1) = P(E)$.

$$|c_k - \tau_k| \leq w \cdot \tau_k \quad (3.1.2)$$

The associated probabilities are $P(X = 1) = \alpha$, and $P(X = 0) = 1 - \alpha$. For the event $X = x$, n experiments yield x times the value α and $n - x$ times the value $1 - \alpha$, with a total of n over x different arrangements. On the assumption that the experiments are independent of each other, the probability (3.1.3) for $X = x$ is obtained.

$$P(X = x) = \binom{n}{x} \alpha^x (1 - \alpha)^{n-x} \quad (3.1.3)$$

Assuming that the individual experiments for determining the acceptance of the travel information are independent from each other, and assuming further that the sensitivity of the measurement does not vary, so that the probability of acceptance of a certain information has the value α , then this is a Bernoulli experiment, and the

results of the experiments are binomially distributed (3.1.3). Now, the question is whether the relative frequency of a series of experiments is a good estimate for the value α . The unknown probability α shall be estimated with the help of the maximum-likelihood method (e.g. Kreyszig, 1979).

Assuming E to have come true k times in the course of n experiments. Being sought is an estimator $\tilde{\alpha}$ for the probability $\alpha = P(X = k)$ on the assumption that the probabilities of event E are binomially distributed. The presumptive likelihood function then is

$$L = \alpha^k (1 - \alpha)^{n-k}.$$

The natural logarithm of the likelihood function is

$$\ln L = k \ln \alpha + (n - k) \ln(1 - \alpha).$$

The natural logarithm is monotone, which means that $\ln(L)$ and L have their maximum in the same place. From the relation

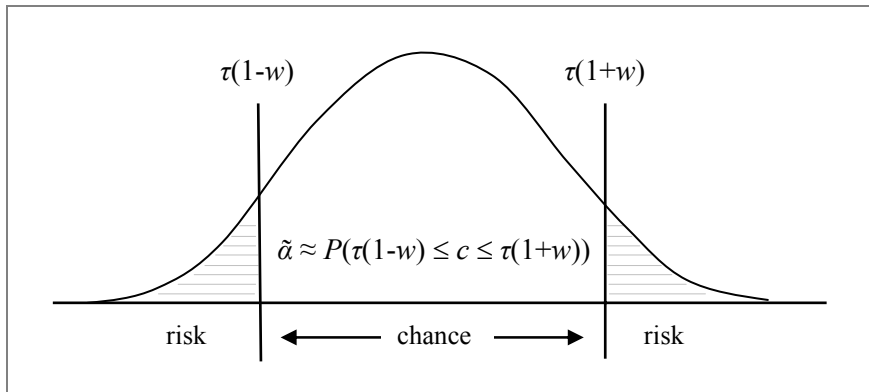
$$\frac{\partial \ln L}{\partial \alpha} = \frac{k}{\alpha} - \frac{n-k}{1-\alpha} = 0$$

follows the maximum of the likelihood function as the relative frequency of E :

$$\tilde{\alpha} = \frac{k}{n}. \tag{3.1.4}$$

The relative frequency (3.1.4) indicates the accuracy of the traffic information. Consequently, the second property (P2), the quality of the information, can be taken into account for evaluating the utility of a route. The estimator $\tilde{\alpha}$ can be taken into account in the driver's decision as an acceptance or confidence factor; $\tilde{\alpha}$ stands for the chance of the information τ coming true within the tolerance bounds, or the probability of the achieved travel time c being contained within the confidence interval $[\tau(1 - w), \tau(1 + w)]$ (Figure 3.1).

Figure 3.1: Chance of achieving the expected travel time τ



The third property (P3), the driver's attitude towards risk when he makes his decision, follows from the weighting of the two main properties (P1 and P2) as the further analysis in this Section will show.

Basic Assumptions

Like every decision, the choice of a route also leads to an uncertain result. Drivers will accept detours if there is a chance of gaining time, or if the risk of losing time on their habitual route seems to be too high. Initially, the probability of choosing a route shall take into account only the utility of time, as well as the general inclination of the user wanting to avoid time losses by means of risk-seeking behavior (properties P1 and P3). A utility function that maps the behavior of a class of rational drivers shall, in the framework of this study, fulfill the following postulates:

- The utility of a route diminishes with increasing expenditure of time.
- Drivers want to reach their destinations as quickly as possible. To avoid time losses they are prepared to take risks as shown in the descriptive analyses of Kahneman and Tversky (1979), as well as Kroll (2010).
- The principle of diminishing marginal utility shall be taken into account, so that it matters whether the difference of the utility of two routes relates to a small or to a large sum of times expended. (For example, the difference of the utilities in the case of saving 100 and 110 units shall be smaller than the difference of utilities in the case of saving 10 and 20 units.)
- The probability of a route being chosen shall be proportional to its utility. (For example, it shall not matter whether the expenditures of time on two routes amount to 10 and 20 units, or 50 and 100 units.)

Intuitive Route Choice

In searching for a function that maps the behavior of the driver, it is possible to go by intuition in the first approach. An action is based on decisions which are determined by the utility of the action according to the information about the possible consequences. Assuming a driver can on his way to his destination choose between two routes A and B . The expected time expenditures are $v(A)$ and $v(B)$. To reach a decision, a driver will engage in his utility considerations.

Let the assumption be that the driver usually takes route B . After he learns that the time expenditures of the routes amount to $v(A) = 3$ and $v(B) = 4$ units, he does not want to stick to his habit, but rather make a choice based on his rational behavior. How can the driver come to a reasonable decision?

A natural operation that maps the utility $\hat{u}(A)$ of the consequence of the decision for alternative A constitutes the only reciprocal relation to the expenditure $v(A)$ of the alternative. This way, the expenditures $v(A) = 3$ and $v(B) = 4$ yield the utilities $\hat{u}(A) = 1 \div 3$ and $\hat{u}(B) = 1 \div 4$; for two values in general:

$$\hat{u}(A) = \frac{1}{v(A)}, \quad \hat{u}(B) = \frac{1}{v(B)}, \quad v(A), v(B) \neq 0.$$

Determining the probabilities $\pi(A)$ and $\pi(B)$ of the choice of one of the two routes can just as easily be accomplished via the relation of their respective utility to the total utility ($\hat{u}(A) + \hat{u}(B)$). The respective utilities $\hat{u}(A) = 1 \div 3$ and $\hat{u}(B) = 1 \div 4$ yield the probabilities $\pi(A) = 4 \div 7$ and $\pi(B) = 3 \div 7$; for two utilities in general:

$$\pi(A) = \frac{\hat{u}(A)}{\hat{u}(A) + \hat{u}(B)}, \quad \pi(B) = \frac{\hat{u}(B)}{\hat{u}(A) + \hat{u}(B)}, \quad \hat{u}(A) + \hat{u}(B) > 0.$$

The probability of choosing alternative A_j out of m alternatives amounts to:

$$\pi_j = \frac{\hat{u}_j}{\sum_{k=1}^m \hat{u}_k}, \quad \hat{u}_j \geq 0.$$

For each probability, $\pi_j \geq 0$ is true and their sum total is:

$$\sum_{j=1}^m \pi_j = \sum_{j=1}^m \frac{\hat{u}_j}{\sum_{k=1}^m \hat{u}_k} = \frac{\sum_{j=1}^m \hat{u}_j}{\sum_{k=1}^m \hat{u}_k} = 1.$$

The formal conditions for the operation with probabilities are fulfilled. Replacing eventually the expenditure v by the informed travel time τ yields the probability of the j th route being chosen out of m alternatives:

$$\pi_j = \frac{(\tau_j)^{-1}}{\sum_{k=1}^m (\tau_k)^{-1}} = \frac{1}{1 + \tau_j \left(\frac{1}{\tau_1} + \dots + \frac{1}{\tau_{j-1}} + \frac{1}{\tau_{j+1}} + \dots + \frac{1}{\tau_m} \right)}, \quad \tau_k \geq 1 \quad \forall k. \quad (3.1.5)$$

The distribution (3.1.5) resembles Kirchhoff's first law for electrical currents. Considering, according to (2.4.14), the probability π in turn as a function of the utility $\pi(u)$ yields for $u(\tau)$ the simplest form of the odd power function (3.1.6).

$$\hat{u}_j = \tau_j^{-1}, \quad \tau_j \geq 1 \quad \forall j. \quad (3.1.6)$$

Before developing any further the intuitive utility (3.1.6) and the probability (3.1.5) of a route, there shall be a comparison with the random utility decision models that were deductively determined in Section 2.4.

Discussion

The logistic distribution of the random utility $U = V + \varepsilon$ according to (2.4.12) yields for the route r_j with the travel time τ_j and $V_j = \beta \cdot \tau_j$ the probability of being chosen (3.1.7) in the simplest form of the multinomial logit model.

$$\pi_j = \frac{e^{\beta \tau_j}}{\sum_{k=1}^m e^{\beta \tau_k}}, \quad \tau_j \geq 1, \beta < 0. \quad (3.1.7)$$

The distribution of the random utility $U = V \cdot \zeta$ according to (2.4.14) yields for route r_j with the travel time τ_j and $V_j = \tau_j$ the probability of being chosen (3.1.8) as the simplest form of the power utility.

$$\pi_j = \frac{\tau_j^\alpha}{\sum_{k=1}^m \tau_k^\alpha}, \quad \tau_j \geq 1, \alpha < 0. \quad (3.1.8)$$

The two models (3.1.7) and (3.1.8) differ in respect of the evaluation of the utility of the travel time. They will be compared to each other on the basis of the above-defined four postulates for the route choice (see Figures 3.2 and 3.3).

- The utility of a route diminishes with increasing time expenditure, i.e.

$$\tau_1 > \tau_2 \Rightarrow u(\tau_1) < u(\tau_2) \Rightarrow \frac{du}{d\tau} = u' < 0. \quad (3.1.9)$$

For $u(\tau) = e^{\beta\tau}$, that condition is fulfilled: $\frac{d}{d\tau} e^{\beta\tau} = \beta e^{\beta\tau} < 0, \quad \beta < 0$.

For $u(\tau) = \tau^\alpha$, that condition is fulfilled: $\frac{d}{d\tau} \tau^\alpha = \alpha \tau^{\alpha-1} < 0, \quad \alpha < 0$.

- The drivers behave in a risk-seeking manner towards time losses, i.e.

$$\frac{du'}{d\tau} \cdot \frac{d\tau}{du} = \frac{u''}{u'} < 0 \quad (3.1.10)$$

For $u(\tau) = e^{\beta\tau}$, that condition is fulfilled: $\frac{du'}{du} = \beta < 0, \quad \beta < 0$.

For $u(\tau) = \tau^\alpha$, that condition is fulfilled: $\frac{du'}{du} = \frac{\alpha-1}{\tau} < 0, \quad \alpha < 0, \tau \geq 1$.

The following example illustrates the attitude towards risk underlying the two utility functions. A user shall decide between the alternatives A and B . The two

lotteries are $L_A = (3, \frac{1}{2}; 5, \frac{1}{2})$, and $L_B = (4, 1)$. Both lotteries have the same expected value (2.4.1) $EV_A = EV_B = 4$. The alternative A will be chosen if the user is risk-seeking and prefers the possible time gain of one unit over the certain time loss on the alternative B . A risk-averse user chooses B , and a risk-neutral user would be indifferent ($A \sim B$). The power utility $u(\tau) = \tau^{-1}$ leads to the expected utility (2.4.6) $EU_A > \frac{1}{4}$ and $EU_B = \frac{1}{4}$, so that the alternative A is preferred over B . This simple case shows the attitude towards risk underlying the power utility τ^α in the case of positively denoted time losses τ with $\alpha < 0$. For $\beta < 0$ the exponential utility $e^{\beta\tau}$ has the same risk characteristic as the power utility function.

- The principle of diminishing marginal utility shall be taken into account and the probability of a route being chosen shall be proportional to its utility, i.e.

$$\frac{\pi_A}{\pi_B} = \frac{u_A}{u_B}. \quad (3.1.11)$$

For $u(\tau) = e^{\beta\tau}$, neither of the two conditions is fulfilled: $\frac{e^{\beta\tau_A}}{e^{\beta\tau_B}} = e^{\beta(\tau_A - \tau_B)}$.

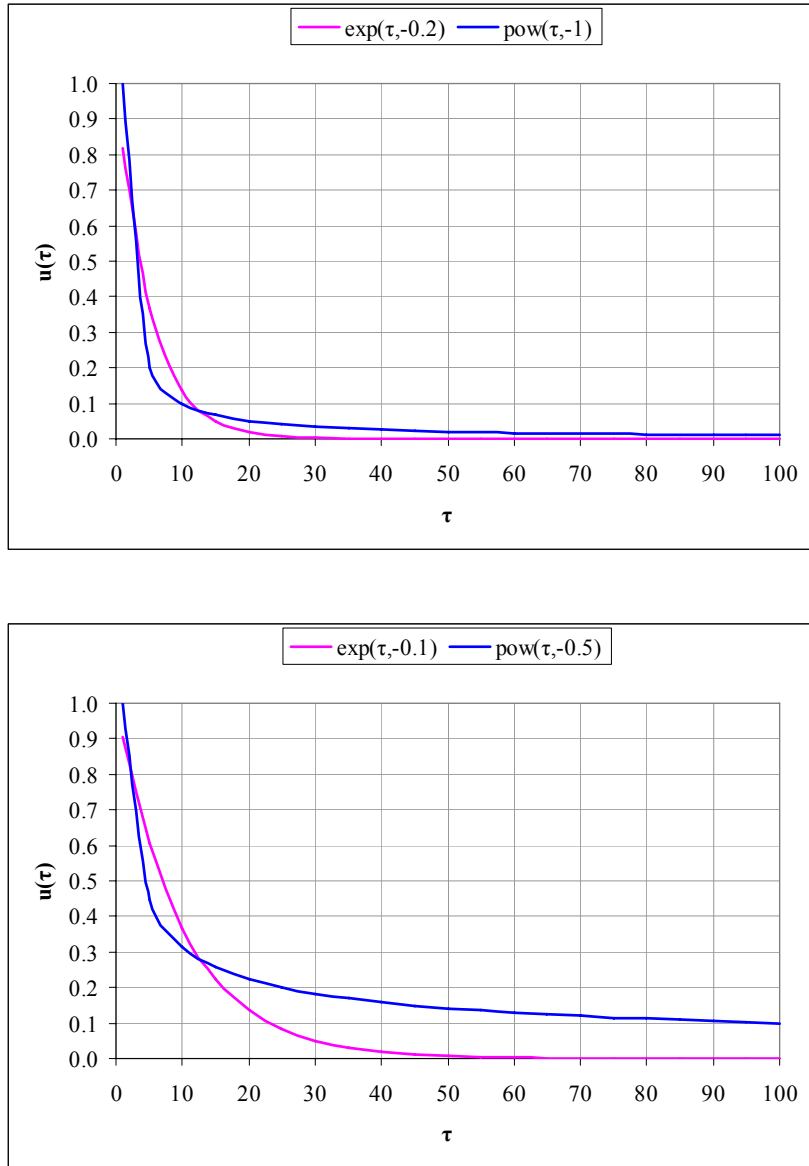
For $u(\tau) = \tau^\alpha$, both conditions are fulfilled: $\frac{\tau_A^\alpha}{\tau_B^\alpha} = \left(\frac{\tau_A}{\tau_B}\right)^\alpha$.

The exponential utility $e^{\beta\tau}$ does not fulfill the condition that the relation of the probabilities of two routes is equal to the relation of their utility. For the exponential utility function $e^{\beta\tau}$, the relation of two utilities is dependent on the difference of their values; in the case of the power utility function τ^α , the relation of two utilities is dependent on the quotient of their values.

The utility function $e^{\beta\tau}$ does not, for example, distinguish between whether route A requires 10 minutes and route B 20 minutes, or route A 100 minutes and route B 110 minutes. Just as problematic is in the case of utility $e^{\beta\tau}$ that when route A requires 5 minutes and route B 10 minutes, there will be a completely different probability than if route A requires 50 minutes and route B 100 minutes (Figure 3.2). This disadvantage of time being measured in seconds instead of minutes, for example,

must be compensated by calibrating the parameters β . In the case of the logit model (3.1.7), any change of the scaling requires an adjustment of the parameter β . Use of the multinomial logit model makes the comparability of simulations of different scenarios more difficult (since from $e^{\beta\tau} = \tau^\alpha$ follows $\beta = \alpha \cdot \ln(\tau) \div \tau$).

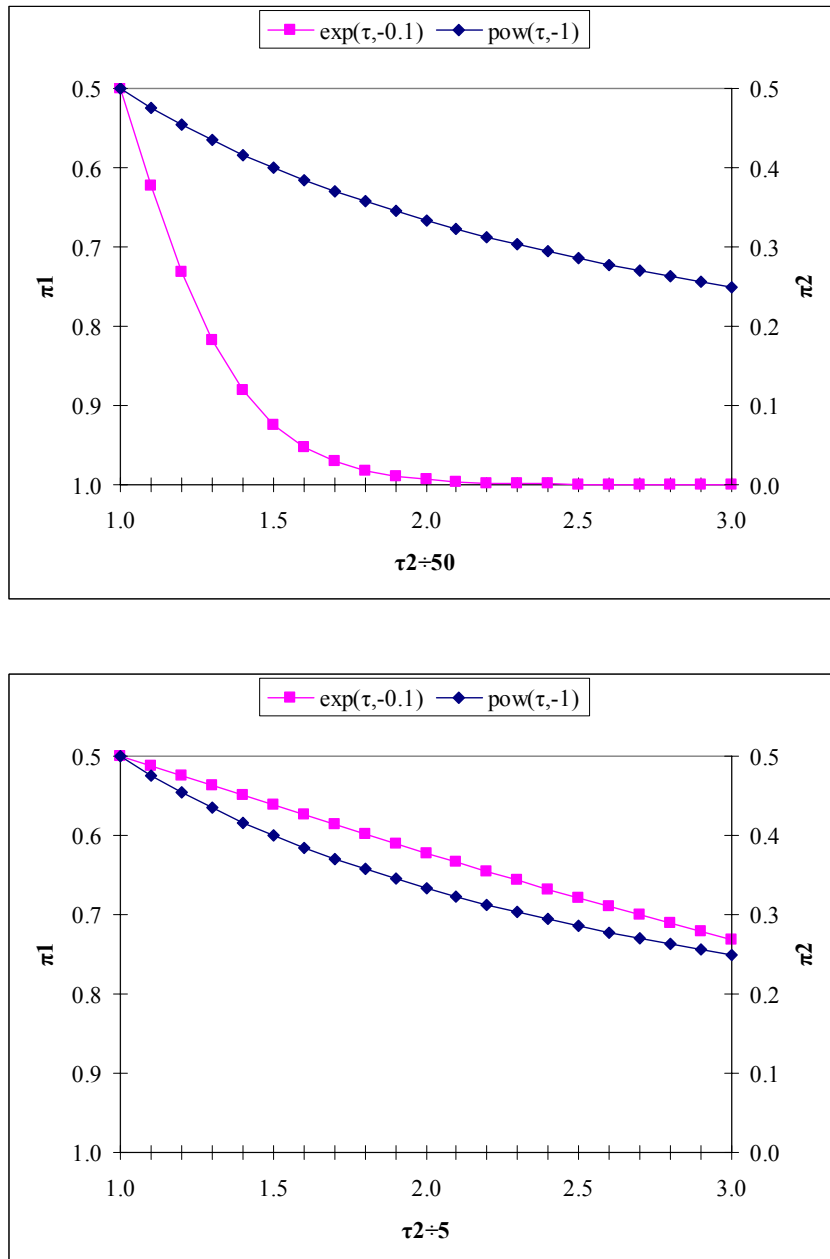
Figure 3.2: Exponential utility $exp(\tau) = e^{\beta\tau}$ and power utility $pow(\tau) = \tau^\alpha$ of travel time τ



By reference to the travel times $\tau = 1$ to 100, Figure 3.2 compares the exponential utility $u(\tau) = exp(\tau) = e^{\beta\tau}$ with the power utility $u(\tau) = pow(\tau) = \tau^\alpha$ for the parameters $\beta = -0.1$, $\alpha = -0.5$ (lower graph) and $\beta = -0.2$, $\alpha = -1$ (upper graph). Depending on the choice of either β and α , the curves of the exponential and the power utility are located more or less closely to each other.

Figure 3.3 shows the difference between the decision models (3.1.7) and (3.1.8) in respect of the probabilities in the case of the choice between two routes with different scaling of the travel time τ (here with factor 10): While the probabilities determined by the power utility are the same, different probabilities result in the case of the exponential utility.

Figure 3.3: Choice probabilities π_1 and π_2 of two routes with travel time ratio $\tau_2 \div \tau_1$



Additional properties can be included in the comparison of the two utility functions, such as the elasticity as exists in economic models between price and cost, or price

of and demand for a product (cf. Samuelson, 2010). Elasticity e refers to the percentage change in the dependent variable divided by the percentage change of the independent variable:

$$e = \frac{\Delta u}{u} \div \frac{\Delta \tau}{\tau} \approx \tau \frac{u'}{u}. \quad (3.1.12)$$

The elasticity for $u(\tau) = e^{\beta\tau}$ falls relative to τ : $\tau \frac{u'}{u} = \tau \frac{\beta e^{\beta\tau}}{e^{\beta\tau}} = \beta\tau$, $\beta < 0$.

The elasticity for $u(\tau) = \tau^\alpha$ is constantly falling: $\tau \frac{u'}{u} = \tau \frac{\alpha \tau^{\alpha-1}}{\tau^\alpha} = \alpha$, $\alpha < 0$.

In connection with discrete decision models of route choice, the IIA (Independence of Irrelevant Alternatives) property is discussed (e.g. Daganzo and Sheffi, 1977, Ben-Akiva and Lerman, 1985, Maier and Weiss, 1990). The IIA property means that the relation of the choice probabilities of two alternatives is independent of the availability of other alternatives. This refers to the impossibility of taking common sections among the alternative routes adequately into account. Neither of the two decision models discussed here takes into account the commonalties of the alternative routes. The IIA property will not be paid further attention to in the following descriptive decision model because the choice of the route is made by way of a situational decision at each intersection (leave link re-planning) on the basis of current information; this dynamic approach accomplishes a corrective effect so that the IIA property does not have here the same effect as in static (initial) routing (see Sections 3.3 and 3.4).

Conclusion

The logit family, widely used and discussed, is the standard type for discrete choice problems in transport planning (as referred to in Section 2.4). The probability function (3.1.8), structured according to Kirchhoff's law known from electrical physics, also discussed by Bovy (1984), is applied to discrete route choice models, for example by Fellendorf and Vortisch (2000), Erath (2004) or Chen et al. (2008). For the following simulation, the dynamic drivers will be assumed to act according to a probability function conceived on the basis of the power utility.

Power utility and Choice probability

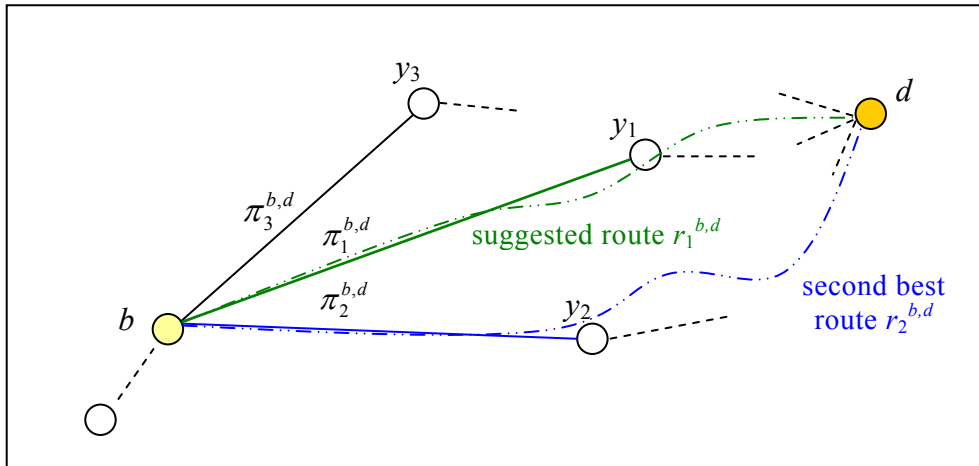
Let τ_j be the driver's perceived travel time on route $r_j^{b,d}$ which leads from node b to the destination d , and m the number of leaving links at node b (Figure 3.4). The driver's rational choice at node b will be the route $r_j^{b,d}$ via link (b, y_j) with the probability (3.1.13).

$$\pi_j^{b,d} = \frac{(\tau_j^{b,d})^\alpha}{\sum_{k=1}^m (\tau_k^{b,d})^\alpha}, \quad \alpha \equiv -1, \quad \tau_j^{b,d} \geq 1 \quad \forall j \in [1..m]. \quad (3.1.13)$$

Weighted best route choice

By using navigation information, a driver behaves economically according to the value of time, and his decision will most of the time result in the choice of the suggested route. On the other hand, even if a driver has navigation information at his disposal, his choice will probably also depend on some preferences, mainly his confidence (or degree of belief) in the quality of the information provided by the navigation system.

Figure 3.4: Probability π of choosing routes in ascending order of the travel time cost



The ‘weighted best route’ (WBR) decision model is postulated to simulate the behavior of drivers who get directions from a navigation system, but sometimes also choose alternative links based on their experience with the traffic information. To take the confidence in the information of the navigation system into account, the

cost term τ is combined linearly with a weight parameter as follows: In ascending order of the travel time cost, let τ_1 be the perceived travel time of the least cost route $r_1^{b,d}$ leading from node b to the destination d via y_1 , m the number of leaving links at node b , φ the factor which raises the probability of taking the least cost route by weighting its cost, and τ_j the travel time cost of an alternative route $r_j^{b,d}$ to d via y_j . The probability π_1 of switching to the suggested route $r_1^{b,d}$ via link (b, y_1) is given by (3.1.14).

$$\pi_1^{b,d} = \frac{(\varphi \tau_1^{b,d})^{-1}}{(\varphi \tau_1^{b,d})^{-1} + \sum_{k=2}^m (\tau_k^{b,d})^{-1}}, \quad 0 < \varphi \leq 1, 1 \leq \tau_1^{x,b} \leq \tau_j^{x,b} \quad (3.1.14)$$

An alternative route $r_j^{b,d}$, $j > 1$ has the chance (3.1.15).

$$\pi_j^{b,d} = \frac{(\tau_j^{b,d})^{-1}}{(\varphi \tau_1^{b,d})^{-1} + \sum_{k=2}^m (\tau_k^{b,d})^{-1}}, \quad 0 < \varphi \leq 1, 1 \leq \tau_1^{x,b} \leq \tau_j^{x,b} \quad (3.1.15)$$

The weight φ is related to the driver's confidence in the advice of the navigation system (3.1.16). Confidence can be viewed as an endogenous component of the driver's knowledge model which reflects his (short-term or long-term) experience with the accuracy of the guidance information. Two different types of confidence are applied in the decision processes: First, the experiential confidence γ which is postulated as the driver's probability of acceptance and second, a fixed level of confidence Γ in order to prescribe the driver's level of compliance (see Section 3.2).

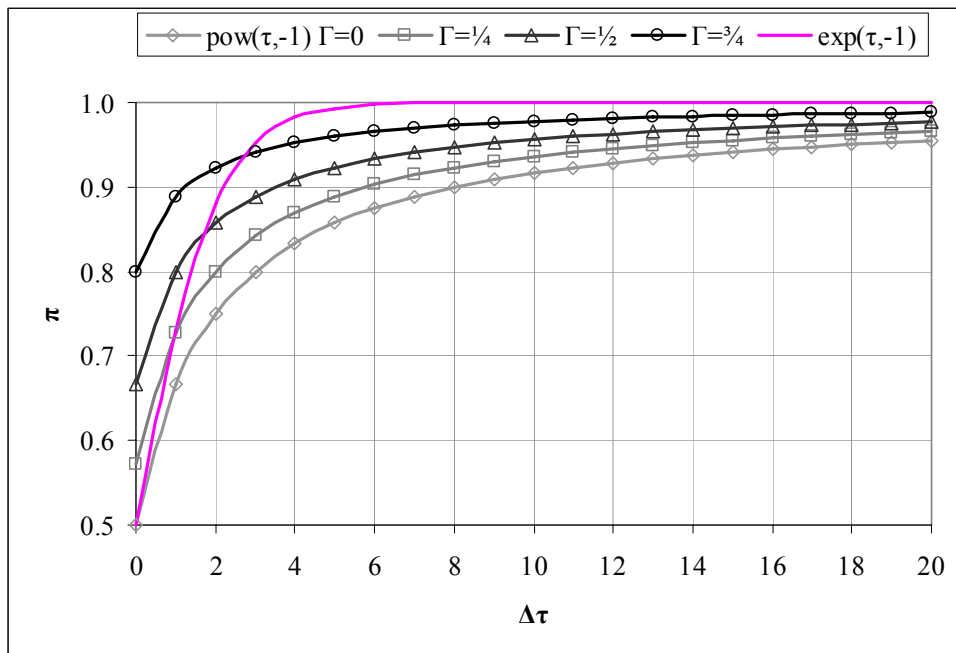
$$\varphi = \begin{cases} 1 - \gamma, & 0 \leq \gamma \leq 1 \quad (\text{descriptive approach}) \\ 1 - \Gamma, & 0 \leq \Gamma \leq 1 \quad (\text{normativ approach}) \end{cases} \quad (3.1.16)$$

Since the driver's confidence correlates negatively with the weight φ , it can be used for the relative cost term $\varphi\tau_1$. As the confidence increases, the weighted cost of the cheapest route gets smaller. If a driver shows the greatest deal of trust, the weighted cost $\varphi\tau_1$ of the recommended route shrinks to zero; when Γ is set to 1, he agrees totally with the suggested direction and takes the route via y_I without fail (3.1.17).

$$\varphi = 0: \quad \pi_1^{b,d} = 1, \quad \pi_j^{b,d} = 0, \quad j > 1 \quad (3.1.17)$$

The curves in Figure 3.5 show the probabilities of the WBR model choosing the recommended (shortest) route depending on the time difference $\Delta\tau$ relative to the alternative route according to different levels of compliance depending on the four characteristic degrees of confidence $\Gamma = 0, \Gamma = 1/4, \Gamma = 1/2$ and $\Gamma = 3/4$.

Figure 3.5: Probability of choosing the suggested route based on travel time differences



The choice probability of the WBR model places instead of on $\Delta\tau = 0$ (in the case of indifference between alternatives) the weight on the route recommended by the navigation system. The WBR model thus fulfills the intended purpose of expressing different levels of compliance (depending on certain degrees of confidence Γ).

The pink curve shows the course of the probability of the MNL model (3.1.7) for the parameter $\beta = -1$; the MNL degree of freedom (to deviate from the suggested route) reaches here about six time units, whereas the WBR model for $\Gamma = \frac{3}{4}$ allows also an about 3 to 1 percent chance to the detours involving six time units and more (Figure 3.5).

Figure 3.6: Choice probabilities π_1 and π_2 with time ratio $\tau_2 \div \tau_1$ at different levels of Γ

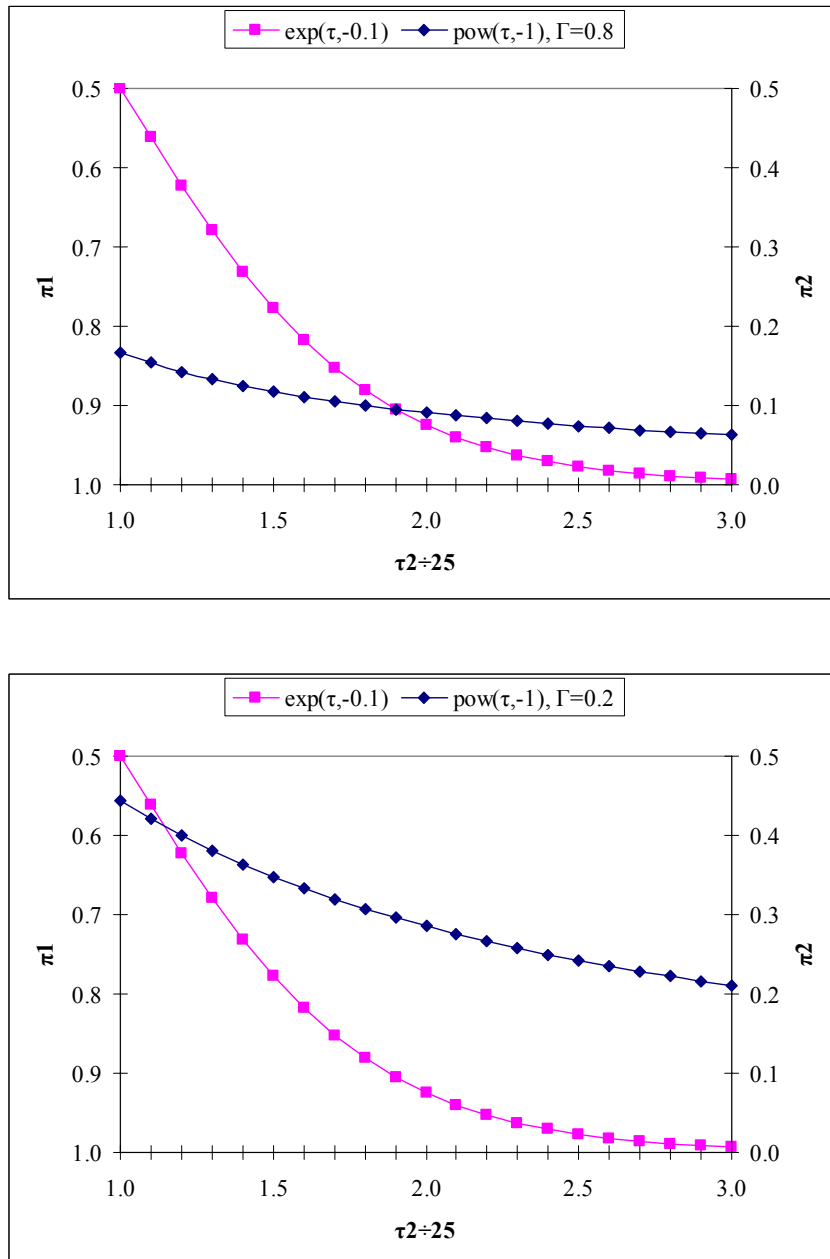


Figure 3.6 shows the probabilities in the case of choice between two routes according to the levels of compliance subject to $\Gamma = 0.2$ and $\Gamma = 0.8$, respectively,

of the WBR model. The pink curve shows the course of the probability of the MNL model for $\beta = -0.1$ (under uniform scaling of travel time τ).

3.2 Spatial learning

Empirical evidence

A driver's willingness to deviate from his chosen route depends on both structural conditions and dynamic factors, such as the physical condition of the roads, the relative length of the detour, or the reliability of the traffic information. Within the framework of his analysis of route choice, Schlaich (2009) provides an overview of the results of the empirical studies by some authors according to which it is appropriate to proceed from the following properties: The acceptance of traffic news is influenced by past experience in dealing with traffic news (Jansen and van der Horst, 1992). The probability of acceptance of an alternative route is higher the smaller the detour connected with it and if the alternative route belongs to the same road category as the original road (Emmerink et al., 1996). Road users are able to differentiate in their judgment about traffic news in relation to both the cause of the tie-up or disruption and the spatial extent and duration of traffic jam (Kim and Chon, 2005). Regarding the degree (the relative frequency) of compliance with the traffic instructions, there are only rough indications according to which the rate of compliance generally is between 10 percent and 70 percent (Everts, 1978, Kayser and Krause, 1986, Knoll et al., 1972) and the values vary between 10 percent and 20 percent in cases where the detour amounts to more than 50 percent of the length of the original route, otherwise between 30 percent and 40 percent (FGSV 2007, in Trapp and Feldges, 2009). Schlaich (2009) recapitulates that in the case of dynamic information, the degree of compliance increases to 90 percent, with higher degrees of compliance in the case of reports of massive delays on the main route.

From the results of the studies cited above it is to be expected that drivers learn from their dealing with traffic news and that their experience influences their decisions. The Bernouilli experiment discussed in Section 3.1 and the maximum likelihood relation (3.1.4) are suitable for experimentally determining the accuracy of traffic information. The level of compliance subject to the degree of confidence (3.1.16) and the probability of the choice of a route (3.1.14 to 3.1.17) derive from

the following model (3.2.1 to 3.2.5) of confidence on the basis of acceptance of the traffic information.

Acceptance, Confidence and Compliance

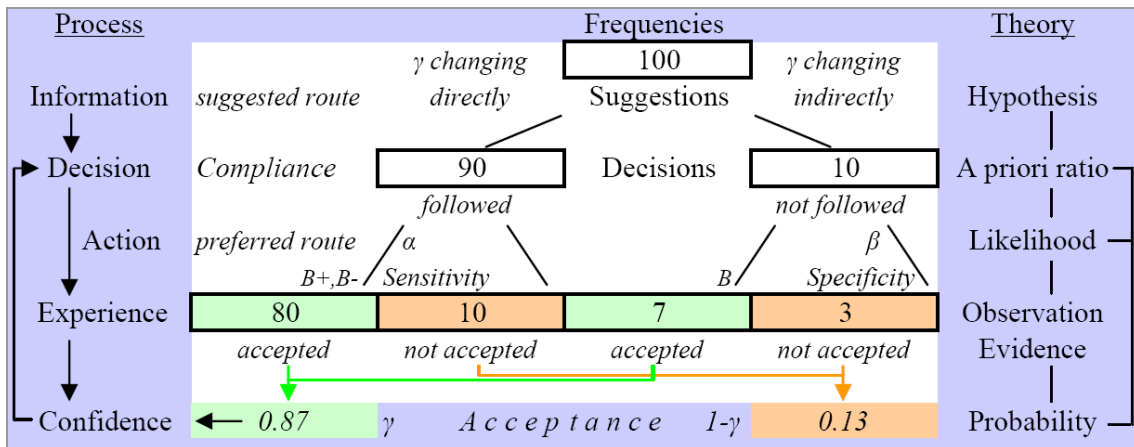
Random utility maximization simplifies the route choice in that the reliability of the traffic information does not explicitly come up in the decision model. The expanded WBR route choice model (3.1.14 to 3.1.17) needs the property of reliability as a measure of the confidence, or more precisely, of the probability of acceptance of the information. As a result, it is possible to map the driver's inclination to follow the recommendations of the navigation system.

A driver choosing a route according to the WBR model will compare the expected travel time τ to the actual travel time c and thus find out whether his expectation has been fulfilled within the boundaries of his acceptance range $[B^+, B^-]$ (3.1.2). The available information is deemed to be accurate when $\tau = c$ is true. The driver will also accept the information of the navigation system if the relative error $\hat{e} = (c - \tau) \div \tau$ does not exceed his tolerance threshold B^+ ($\hat{e} \leq B^+$) and does not fall short of his tolerance threshold B^- ($\hat{e} \geq B^-$).

This microscopic model takes into account the simple but very important consideration that in socio-economic systems the effect of information does not just depend on the information τ (the hypothetical travel time) and the finding $c - \tau$ (the quality of the information), but also on the valuation of the finding \hat{e} by the driver (see Section 3.1). The extent to which the state of the system is influenced by the drivers' confidence in the information can be found out by varying the three tolerance thresholds $[B^+, B^-, B]$.

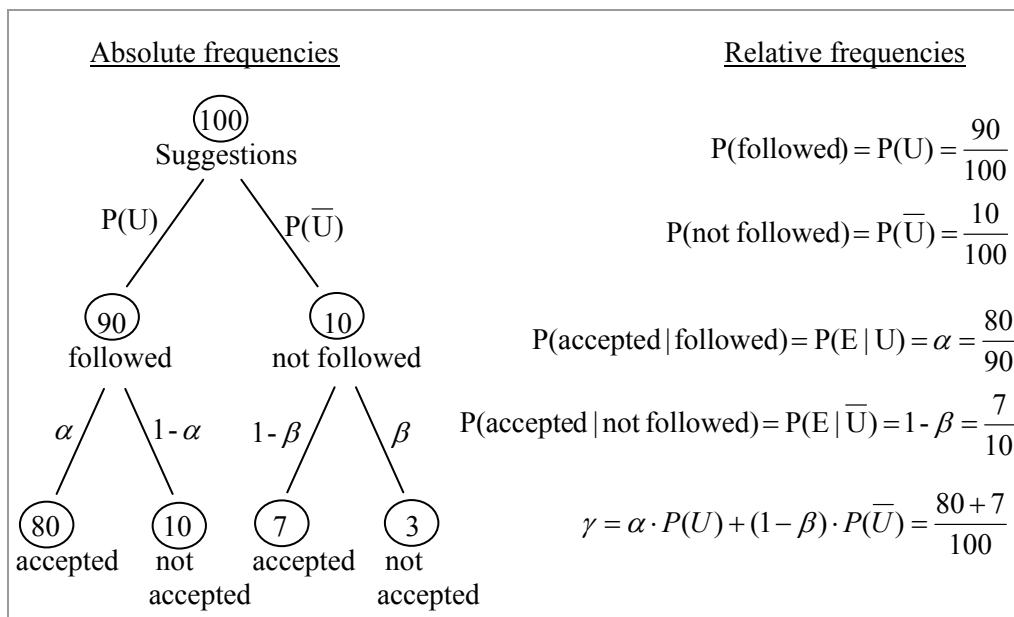
The learning mechanism depicted in Figure 3.7 brings about a marginal adjustment of the driver's acceptance after every choice of a route. The degree of confidence in the traffic information that the driver has at the moment of his decision results from a statistical learning process based on the driver's experience in relation to the expected travel time τ and the actually needed travel time c . The confidence resulting from the decision consists of two components: the direct part $P(\text{accepted} | \text{followed})$ and the indirect part $P(\text{accepted} | \text{not followed})$.

Figure 3.7: Sample decision process and probabilistic spatial learning mechanism



The theory of the learning mechanism is explained by the numerical example in Figure 3.8. In it, U stands for the event “driver follows information”, \bar{U} for the event “driver does not follow information”, E for the event “driver accepts information”, $P(U)$ for the *a priori* probability, and $P(E|U)$ and $P(E|\bar{U})$ for the conditional presumed likelihoods.

Figure 3.8: Probabilistic confidence – absolute and relative frequencies



If the choice is between two routes r_1 and r_2 , with $\tau_1 \leq \tau_2$, the hypothesis is: The recommended route r_1 (and information τ_1) will be accepted by the driver (within the limits of his tolerance thresholds). This hypothesis will be confirmed, when the driver follows r_1 and conditions $\tau_1(1 - B^-) \leq c \leq \tau_1(1 + B^+)$ are fulfilled or when he

decides in favor of alternative r_2 and condition $c > \tau_1(1 + B)$ is true (see below); the probabilities are $P(\tau_1(1 - B^-) \leq c \leq \tau_1(1 + B^+)) = \alpha$ and $P(c \leq \tau_1(1 + B)) = \beta$.

The probability of the acceptance results from the products of the *a priori* probabilities and the likelihoods in accordance with the statement of total probability (e.g. Ross, 2000):

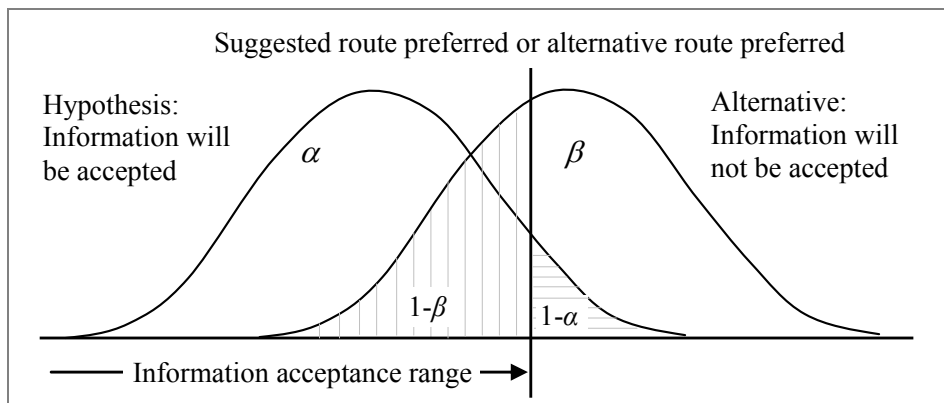
$$P(E) = P(U) \cdot P(E | U) + P(\bar{U}) \cdot P(E | \bar{U}). \quad (3.2.1)$$

If the confidence in the information is defined as the probability of its acceptance $\gamma := P(E)$ and the likelihoods are denoted with $\alpha = P(E|U)$ and $\beta = 1 - P(E|\bar{U})$, the result is:

$$\gamma = \alpha \cdot P(U) + (1 - \beta) \cdot P(\bar{U}). \quad (3.2.2)$$

The likelihoods α and $1 - \beta$ express the two situations where a driver rightly trusts or wrongly mistrusts the navigation system. The direct part α of his confidence results from the used links being part of the shortest routes, i.e. from the frequency of the instances of accepted information relative to the total number of used links being part of the shortest routes. The indirect part $1 - \beta$ of the confidence results from the used links varying from the shortest routes, i.e. from the frequency of the instances of accepted information relative to the total number of used links being on alternative routes (Figure 3.9).

Figure 3.9: Densities of hypothesis evidence and alternative evidence



Where $A(E|U)$, $A(U)$, $A(E|\bar{U})$ and $A(\bar{U})$ denote the absolute frequencies of the events $E|U$, U , $E|\bar{U}$ and \bar{U} , the direct part α and the indirect part $1 - \beta$ of confidence γ will be obtained in conformity with (3.1.4) by means of the maximum likelihoods (3.2.3).

$$\alpha = \frac{A(E|U)}{A(U)}, \quad 1 - \beta = \frac{A(E|\bar{U})}{A(\bar{U})} \quad (3.2.3)$$

According to (3.1.4), α or β will change after each observation made by the driver at the end of a link to check whether or not his expectation has been fulfilled within the tolerance bounds (see Section 3.1). A driver following the information of the navigation system will accept it only if the difference between the actual travel time c and the expected travel time τ does not exceed the relative tolerance values B^+ and B^- (3.2.4).

$$E|U := \begin{cases} c - \tau \leq \tau B^+ & \text{if } c \geq \tau \\ \tau - c \leq \tau B^- & \text{if } c < \tau \end{cases} \quad (3.2.4)$$

A direct loss of confidence can occur in two ways: The driver notices for his link a delay ($c > \tau$) that he does not tolerate ($c > \tau(1 + B^+)$). As a consequence, he will be left with a bad impression of that information provided by the navigation system so that his trust in further information will diminish. Yet a loss of confidence will result even if the driver notices that the actual travel time c on his link is too far ($c < \tau(1 - B^-)$) below the expected travel time τ , i.e. ($c < \tau$).

The two cases (3.2.4) shall be illustrated by means of a numeral example: The driver follows the recommended route $r_1^{x,b}$. The expected travel time on the link (x, y_1) is assumed to be $\tau(x, y_1) = 50$, the actual travel time is assumed to be $c(x, y_1) = 55$. The driver tolerates the expected travel time being exceeded by maximally $B^+ = 15\%$; he accepts the information he got because the link (x, y_1) takes less than $\tau(x, y_1)(1 + B^+) = 57\frac{1}{2}$ time units. If the actual travel time were $c(x, y_1) = 40$, and the driver would also tolerate the actual travel time falling short

of the expected travel by maximally $B^- = 15\%$, then the driver would not accept the information because the route section (x, y_1) took less than $\tau(x, y_1)(1 - B^-) = 42\frac{1}{2}$ time units. The example shows that the direct confidence part α grows when c does not exceed $\tau(1 + B^+)$ and drops when c is shorter than $\tau(1 - B^-)$.

When a driver does not follow the information provided by the navigation system, the indirect confidence part $1 - \beta$ changes. In this case the following assumptions shall apply: first, because the expected subjective travel time $\hat{c}_2 = \hat{c}(\tau_2)$ on the alternative route $r_2^{x,b}$ must not exceed the expected travel time on the route ($\hat{c}_2 \leq \tau_1$) recommended by the navigation system, it shall be (by definition) equal to it, i.e. ($\hat{c}_2 = \tau_1$); second, the subjective travel time $\hat{c}(x, y_2)$ on the alternative link (x, y_2) is proportional to the subjective travel time \hat{c}_2 on the alternative route. The driver will accept his choice if the difference between the actual travel time c and the expected subjective travel time \hat{c} does not exceed the relative tolerance value $\hat{c}B$ (3.2.5).

$$E | \bar{U} := c - \hat{c} > \hat{c} B \quad (3.2.5)$$

The case (3.2.5) shall be illustrated by means of a numeral example: The informed travel time on the recommended route $r_1^{x,b}$ is assumed to be $\tau_1 = 100$, and the informed travel time on the alternative route $r_2^{x,b}$ is assumed to be $\tau_2 = 110$. The driver chooses the alternative route expecting that it does not take more time than the recommended route, i.e., that it would take the same number of subjective time units ($\hat{c}_2 = \tau_1 = 100$). The informed travel time on the alternative link (x, y_2) is assumed to be $\tau(x, y_2) = 50$, so that the subjectively expected travel time $\hat{c}(x, y_2) = 50 \cdot 100 \div 110 = 45\frac{1}{2}$. Assuming a relative tolerance value $B = 10\%$, the driver, according to (3.2.5), would not accept the information, if the actual travel time $c(x, y_2)$ of section (x, y_2) were to take not more than 50 time units. In this case, the driver would be content with his choice of the alternative route and his confidence in the traffic information would diminish. For $c(x, y_2) > 50$ units (and in case of $B < 10\%$ and $c(x, y_2) \leq 50$), the driver would consider the alternative link (x, y_2) (chosen despite the information) as disadvantageous, and his confidence in the information provided by the navigation system would (indirectly) increase.

The significance of stochastic values increases with the number of experiments; therefore, the expectation values of previous series of experiments, for instance experiments conducted on the previous day, are an advantage. If (*a priori*) no points of reference for α and β are available, both factors will, according to the principle of indifference, be initialized with $\frac{1}{2}$.

Note: The *a posteriori* probability $P(U|E)$ according to the Bayes rule indicates by means of the relation $A(E|U) \div (A(E|U) + A(E|\bar{U}))$ the probability with which an accepted information is the result of a complied-with information (the probability with which the driver is satisfied after he has followed the recommended route).

Summary

The confidence in the information provided by the navigation system is taken into account when a route is chosen. The confidence is the probability of acceptance of the information resulting from the learning mechanism as deduced in section 3.1 by means of a Bernoulli experiment. The acceptance of the information depends on three tolerance thresholds [B^+ , B^- , B] on the part of the driver. The change of the confidence and the theoretical relations involved in estimating such confidence are illustrated by means of numeral examples (Figures 3.7 and 3.8).

With the probability model (3.1.4 to 3.1.17) and the learning mechanism (3.2.2 to 3.2.5), the two most important criteria for the driver's decision are mapped: The objective utility of the traffic information is linked to the subjective assessment of the quality of the information. The two components of the driver model in Figure 1.2 of Section 1.5 are mapped in such a way that the questions posed in the objective as stated in Section 1.4 can be investigated in a differentiated mode.

How different degrees of confidence affect the average travel times can be determined by varying the share of the informed drivers while keeping confidence constant, e.g. at $\Gamma = \frac{3}{4}$ (three of four instructions are accepted), and by varying the degrees of confidence while keeping the share of informed drivers constant (see Sections 3.4 and 4.2).

3.3 Knowledge levels

First to be considered shall be those agents who hypothetically know almost nothing about the traffic network and choose their routes prior to the trip (*pre-trip route choice*). In contrast with them there will be agents who are informed about current travel times on the routes and who re-plan their routes according to various strategies. These knowledge levels have been modeled and described by Dobler, Axhausen and Weinmann (2013) as follows:

„The implemented model is based on the idea that the agents are able to re-plan their routes at any time during the simulated day. This allows a person to choose a route using dynamic information about the current transport system condition – mainly link travel times based on current traffic flows.

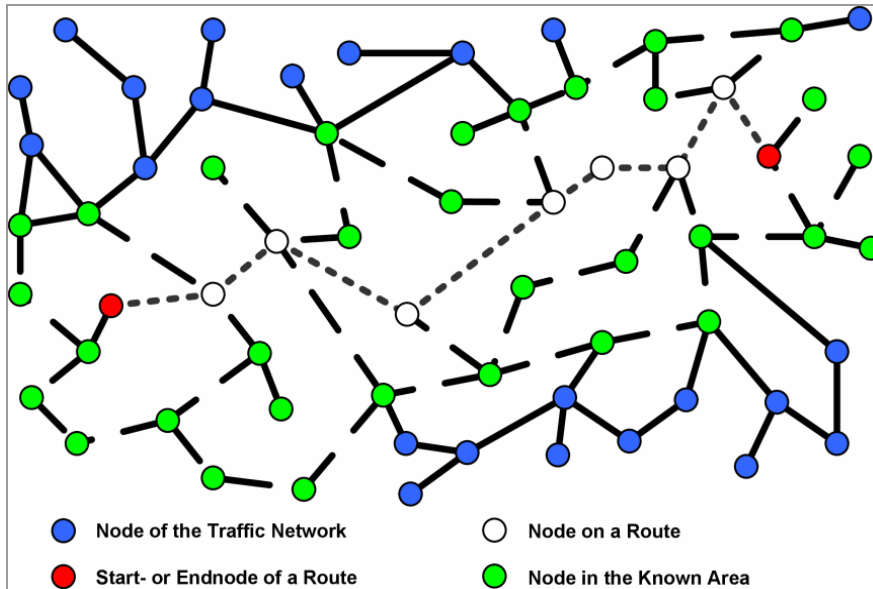
An agent’s static knowledge concerns the road network infrastructure. For example, a person living and working in Zurich will know the roads there – and in the surrounding areas – but not single roads in a different city like Basel or Bern. Therefore, a person will use only known streets when planning a route. To take this fact into account, each person is provided with spatial knowledge describing those road network parts known by the person. By varying the size of this area, different levels of spatial knowledge can be simulated.

For the experiments presented in this paper, a person’s spatial knowledge is created using an approach based on a least cost path algorithm. In a first step, the least cost path from point A to point B is created, resulting in a route with cost C . To create the known area, cost C is multiplied with a factor $F \geq 1$. All routes from A to B with costs less than or equal to $C \cdot F$ are contained in the spatial knowledge. In this context, F can also be understood as the threshold factor below which drivers would accept deviations from the least cost path. An example of a network with a least cost path and known area within that network is shown in Figure 3.10. A detailed description of the algorithm which defines a person’s known area is given in the Appendix III.

The authors are aware of the fact that this approach to defining a person’s spatial knowledge is very simple and limited. Therefore we expect to extend it with

additional features, such as a factor defining the probability that a link is known by an agent as a function of the link type (the factor will be higher for highways than for minor roads) and the distance to locations where the person performs activities.

Figure 3.10: Example traffic network with least cost route and known area



Source: Dobler, Axhausen and Weinmann (2012)

When people create routes from one location to another, the term $C \cdot F$ determines the degree of flexibility of their route choice behavior (the larger a person's spatial knowledge, the more routes for a trip are available). In the following, some behavioral strategies are described and their interactions with the underlying knowledge are characterized.

- Random Router: At each node of the network, the router randomly chooses the next link. Because the router has no memory, it is possible to turn or to create loops.
- Tabu Router: The Tabu Router is an extended version of the Random Router. It also chooses the next link randomly, but it knows the previous node in the route and will only return directly to it if there is no link available leading to another node.
- Compass Router: This router uses a compass to generate routes. At each crossing, the router chooses that link whose direction is closest to the destination of the route. Depending on the origin and destination of the route and the traffic network, it is possible that the router gets stuck in a dead end and will not find a valid route.

- **Random Compass Router:** As its name says, this router is a combination of a Random and a Compass Router. Based on a probability factor, the router chooses the next link of a route based on a Random or a Compass Router. This should eliminate the possibility that the router gets stuck in a dead end.
- **Least Cost Router:** There are several implementations of Least Cost Routers available. Commonly used variants implement the Dijkstra algorithm (Dijkstra, 1959). This router uses a cost calculator to determine links' costs within a road network. Based on the type of cost calculator, different attributes like travel time and distance are taken into account. Unlike other described routers, a Least Cost Router can also take the actual load of a traffic network into account when creating a route.

To analyze the influence of re-planning the routes during a day (called *within-day re-planning*), three different timing strategies are used. Each timing strategy defines one or multiple points in time, when an agent can replan.

- The first strategy is based on an Initial Creation of routes before the simulation starts, so that an empty network is used for calculation of travel times and costs. Therefore, it is assumed that each link can be passed in free speed travel time. This strategy uses only structural network information and does not take actual network load – as the real, dynamic factor – into account. Hence, re-planning during a simulation will not produce a different route and is therefore not used.
- The Activity End Re-planning strategy creates a new route when a person has ended an activity and starts traveling to the next scheduled activity. When doing so, the actual traffic load of the network's known parts can be interpreted.
- The Leave Link Re-planning strategy allows re-planning a route every time the end of a link is reached; meaning that the next link of a route is chosen just before it is entered – a highly dynamic way of re-planning. Again, the load of the known parts of the network can be taken into account. Axhausen (1988) describes a comparable approach, but with the condition that all agents have total information.

Table 3.2: Combinations of Knowledge levels and Timing strategies

Timing strategy	Knowledge level of Router				
	Random	Tabu	Compass	Random compass	Least cost
Initial creation	x	x	x	x	x
Activity end re-planning	-	-	-	-	x
Leave link re-planning	-	-	-	-	x

Due to the different function of the described routers, not every combination of router and timing strategy is reasonable. For example, a Random Router does not take the network load into account. Creating an initial route would result in the same route as using a within-day re-planning strategy. On the other hand, a Least Cost Router must be run using within-day re-planning to take the network load into account. The practical combinations used in this study are listed in Table 3.2.”

3.4 Behavior classes

The technology of communication has been developed during the past decade into a system in which ubiquitous information on the state of a traffic network is available in real time. This is a reason to assume that a driver’s decision is likely to depend more on the level of service provided by a traffic information system than on his individual knowledge of the network.

The more current and reliable the information is, the better a driver should be able to use the current traffic conditions to his advantage. This presumption suggests itself. But does it apply to every informed driver regardless of whether all drivers are informed or only a part of them? – This question is significant from a theoretical and from a practical point of view because it describes scenarios which could occur in the following way (cf. Section 1.4): Part of the drivers use simple navigation devices which know only the shortest distances on the load-free traffic network. The other part of the drivers have at their disposal a navigation system which knows the shortest travel times on the traffic-loaded network and informs the driver about them at every intersection. Subject to a certain degree of freedom, the dynamically informed drivers take either the recommended shortest route or an alternative route.

There are basically three classes of drivers K^0 , K^I , or K^M to be analyzed.

Class K^0

Static knowledge model and deterministic behavior model. Known to the drivers in this class are the time-wise shortest routes on the load-free traffic network. They behave in a determined way by not deviating from their route.

Class K^I

Dynamic knowledge model and stochastic behavior model. Known to the drivers in this class are the current (time-wise and load-wise) travel times on the links. These drivers behave stochastically by choosing within the limits of a firm or (acquired by experience during the trip) dynamic degree of freedom the routes recommended by a navigation system.

Class K^M

Dynamic knowledge model and deterministic behavior model. Known to the drivers in this class is the marginal cost of the travel times on the links. The drivers behave determinedly by using the system-optimal route. The additional utility arising from the information about the marginal cost of time consists in the minimization of the risk of not being able to achieve the expected travel time or directly formulated: The utility of the information about the marginal cost on a certain route consists in the maximization of the chance to achieve the expected travel time (see Section 5.3).

Note: Class K^M cannot be simulated with MATSim within the time frame of this study. The marginal cost of current travel times is currently not available.

For the purpose of the following simulation, the population of the drivers Ω shall be subdivided into two classes: a class K^0 with static knowledge and deterministic behavior, and a class K^I with dynamic knowledge and stochastic behavior. A driver with static knowledge knows the shortest routes on the load-free traffic network. He plans the route prior to the trip without knowing the traffic volume on the links. From a practical point of view, a class K^0 driver has a navigation device that calculates the shortest route between two traffic nodes prior to a trip. He sticks to this route during the entire trip. A class K^I driver has available to him a navigation system that knows the current speeds on the links so that at every intersection the driver gets informed about the currently fastest of several possible routes. He then chooses either the fastest route or one of the alternatives in descending order, i.e., with the greatest probability he chooses the fastest link, with the second-greatest probability the second-fastest link, etc (see Appendix IV). When he reaches the end of a link, he compares the expected travel time with the time it actually took him on

that route and he decides on whether or not he accepts (*a posteriori*) the instruction provided by the navigation system. In this way, his confidence in the traffic information and the probability of following the next instruction increase or decrease. The change of behavior in choosing the route arises from a learning process (Bernoulli experiment), which statistically evaluates the acceptance of the decisions on the basis of tolerance thresholds (see Sections 3.1 and 3.2).

In the case of a class $K^{l,\varphi}$ driver, the factor φ corresponds to the degree at which the driver is inclined to deviate from the recommended route (with the greatest utility). For this reason, φ can also be understood as degree of freedom or degree of uncertainty. In the case of $\varphi = 1 - \gamma$, the level of compliance of a class $K^{l,\varphi}$ driver corresponds to the driver's experiential confidence in the traffic information, or in the case of $\varphi = 1 - \Gamma$, to a firmly held degree of confidence (see Section 3.2).

Table 3.3: Behavior classes and objects of a driver's decision

Class	Type of attributes of a driver's decision			
	Knowledge	Behavior	Criterion	Rule
K^0	static	deterministic	travel time $\tau(0)$	$\min \tau(0)_j$
$K^{l,1}$	dynamic	stochastic	utility $u(\tau)$	$\max u(\tau_j)$
$K^{l,\varphi}$	dynamic	stochastic	weighed $u(\tau,\varphi)$	$\max u(\tau_j,\varphi)$

The properties of the behavior classes K^0 and K^l (especially $K^{l,\varphi}$) are summed up in Table 3.3. Class $K^{l,\varphi}$ drivers choose their routes according to a mixed strategy based on the information about the current state of traffic (the expected travel times on the links) and the subjective assessment of the quality of information (the confidence in the instruction provided by the navigation system).

The probability of choosing the fastest link increases with the degree of confidence. When the (experimental) confidence is at its minimum ($\gamma = 0$, $\varphi(0) = 1$), the driver has a maximum degree of freedom to deviate from the currently fastest route. When the confidence is at its maximum ($\gamma = 1$, $\varphi(1) = 0$), the recommended fastest link will be chosen for sure, i.e. at $\varphi = 0$, all class $K^{l,0}$ drivers will stick to the currently fastest links (See Sections 3.2 and 3.3, as well as Least Cost Router, Leave Link Re-planning Strategy, in Dobler, Axhausen and Weinmann, 2013).

SIMULATING TRANSPORT

4.1 Components

Microscopic mechanisms

The learning mechanisms and behavioral patterns of the drivers choosing their routes are at the core of the microscopic simulation of the transport system. Therefore, the structures derived in Section 2.4 and Chapter 3 will be recapitulated here.

Central to the simulation is the class of the dynamically informed drivers K^I . Each class K^I driver is presumed to think economically, to decide rationally, and to always want up-to-the-minute information about the consequences of his decision, i.e. a class K^I driver chooses his route according to the principle of maximizing the utility he expects by his decision.

Among the decision models discussed in Section 2.4, the random utility method is best suitable for simulation with the MATSim standard software (see below). The random utility method associates a route's measurable property with a stochastic value that stands for the non-measurable part of the utility. According to the analysis in section 3.1, the expected travel time τ (as the property) and the power utility τ^α (as the criterion) are best suitable for calculating the probability π_j of the route r_j being chosen. The driver's confidence γ in the quality of the traffic information τ modelled in section 3.2 is included as weight $\varphi = 1 - \gamma$ in the utility evaluation and, consequently, also into the driver's decision.

The decision process of a class K^I driver is associated with an individual learning process as follows: On his way towards his destination the driver is approaching an intersection. With probability π_1 , he decides, on the strength of the utility $(\varphi\tau_1)^{-1}$, to take the recommended (i.e. at the time most favorable) route (and with probability $1 - \pi_1$, one alternative route). Having reached the end of the chosen route section, the driver determines, by comparing the actually needed travel time c to the expected travel time τ_e , whether, given his tolerance range $\tau_e w$, the choice paid off

for him (in retrospective), i.e. whether $(c - \tau_e) \leq \tau_e w$ came true. The outcome of the experiment leads to an adjustment of his confidence γ in the information τ , which changes the assessment φ of the utility of the information and, consequently, the probability of choosing the recommended route next time.

The impact of the drivers' microscopic learning mechanisms and behavioral patterns on road traffic will be measured below using the MATSim simulation environment.

MATSim

MATSim (Multi-Agent Transport Simulation) is an open source software for the microscopic simulation of transport systems. The MATSim Toolkit (MATSim-T) is a software suite counting among the standard simulation tools of transport planning. It has been developed by research groups at the TU Berlin and ETH Zurich universities since 1998.

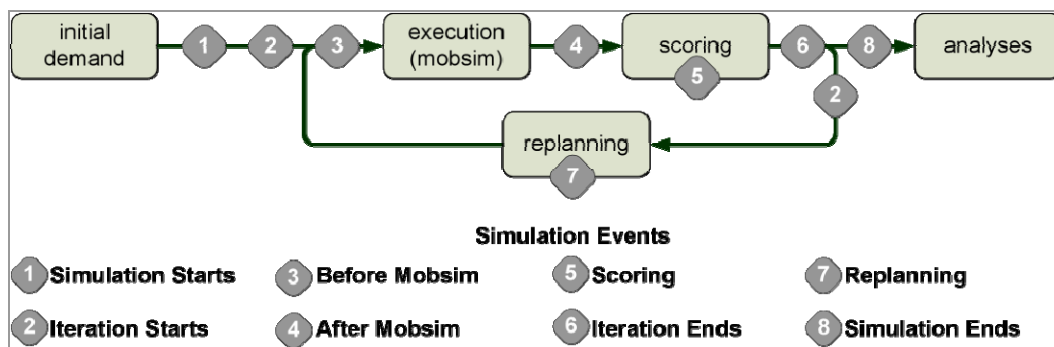
The MATSim components model microscopically a traffic scenario on the basis of agents. Every agent can possess individual properties. By using MATSim, it is possible to simulate certain sections of real traffic networks with real demand situations, so that travel times, traffic flows, and distribution of demand together form a dynamic self-consistent system. The documentation of the MATSim software suite, as well as publications about MATSim traffic analyses are available on the MATSim portal and on the pages of the research groups, see in particular Balmer (2007), Balmer et al. (2008), Balmer et al. (2010), and Dobler et al. (2012). The most important features of MATSim are described in Dobler, Axhausen and Weinmann (2013) as follows: "To analyze road users' behavior, the knowledge models described are implemented in the iterative, agent-based micro-simulation framework MATSim [...]."

In MATSim's agent-based approach, each person in a transport system is modeled as an individual agent in the simulated scenario. Each of these agents has personal attributes like age, gender, available transport types and scheduled activities per day. Klügl (2001), Eymann (2003) and Ferber (1999) give a detailed overview on multi-agent-systems and simulations.

The framework consists of several modules that can be used independently or as part of the framework. It is also possible to extend a module or replace it with alternative implementation. Some examples of modules are: mobility simulation (mobsim), the router, scoring and replanning strategies. While a simple implementation of the mobility simulation only simulates private cars, a more complex version also supports public transport and non-motorized travel modes.

The modular structure of the MATSim framework also allows addition of further attributes to the agents. A new attribute could, for example, define which kind of timing strategy an agent uses. Another attribute could describe whether an agent knows only the road network, or also has information about the traffic load. A third attribute could specify that an agent knows only certain areas of the road network and thus does not create route outside those areas. By adding such attributes, the previously described knowledge models are implemented in the MATSim framework.

Figure 4.1: MATSim structure



Source: Dobler, Axhausen and Weinmann (2012), matsim.org (2008-07-20)

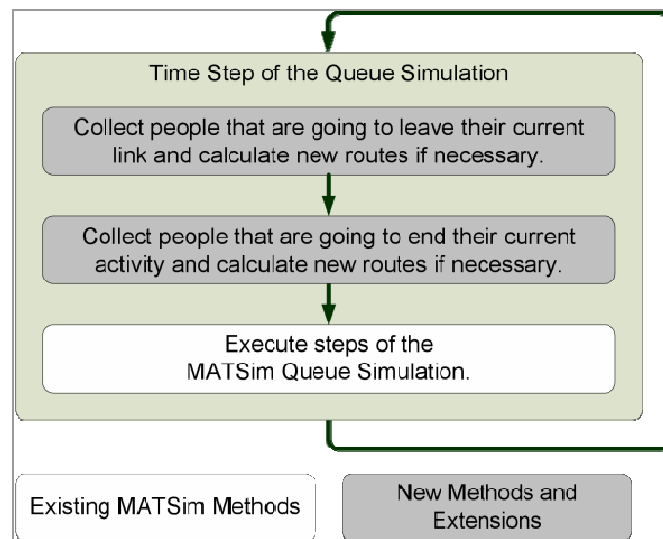
Figure 4.1 shows the structure of a typical MATSim simulation run. After the creation of initial demand, agents' plans are modified and optimized in an iterative process. When the optimization process cannot improve the quality of the agents' plans any further, a Stochastic User Equilibrium (Nagel and Flötteröd, 2009) is reached and the iterative process ends. Finally, results of the simulation are analyzed.

The loop shown in Figure 4.1 contains the elements execution (mobsim), scoring and replanning. The mobility simulation executes the agents' plans. MATSim's

default mobility simulation (called Queue Simulation) is based on a queue model, uses a time-step size of one second and produces deterministic outcomes (Balmer, 2007). Then, a utility function is used to calculate the executed plans' quality (scoring). Based on this, agents' plans are replanned, e.g. by varying start times and durations of activities, as well as routes and modes used to travel from one activity to another.

Due to the fact that agents are able to change their routes depending on the current load in the traffic system, MATSim's structure was slightly changed. By extending the Queue Simulation, every agent can now decide in each simulated time-step if re-planning is necessary. Re-planning means, in this context, that a route used to travel from one activity to another is planned again. Changing the duration of an activity or its scheduled start and end times must be still done before the queue simulation runs. In Figure 4.2, extensions of the Queue Simulation are illustrated.

Figure 4.2: Extensions of the MATSim queue simulation



Source: Dobler, Axhausen and Weinmann (2012)

By extending routing modules, agents are able to analyze their knowledge of the traffic system. The routers will take a link into account only if the re-planning agent knows the link – otherwise it is ignored. The link's travel time is estimated by averaging the travel times of all vehicles that have passed that link within the last 15 minutes. Agents that are creating new routes will try to avoid links with high travel times.”

Scenario

Meister et al. (2010) presents the application of MATSim to a large scale scenario of Switzerland (over six million agents simulated on a high resolution network with one million links) as described in Dobler, Axhausen and Weinmann (2013):

„For the simulation runs, a square section of Zurich with an edge length of 100 km is used. As a constraint, a person is considered in the simulation only if all scheduled activities take place within the simulated area. To keep the computational effort reasonable, only 10% of the population within this area is simulated. As a result, an agent basically represents 10 people. The capacities of the road network and the activity locations are scaled accordingly. The simulation model includes about 87,600 people and 64,380 facilities (a facility is a place where activities can be performed). The used road network is based on the Swiss National Traffic Network (Vrtic et al., 2003). The focus of this case lies on individual transport; public transport is not simulated. This scenario contains a large amount of traffic, which increases differences in the mean travel times between the different timing strategies, depending on the quality of the created routes.

The underlying daily plans of the population result from an earlier simulation run with 150 iterations, for which the Charypar-Nagel-Scoring Function (see Formula 4.1.1; Charypar and Nagel, 2005) was used, creating a realistic distribution of scheduled activities over the simulated time period. The plans of its last iteration are used as input plans for simulations with different timing strategies and knowledge levels. The routes in those plans are ignored because they are replaced when the agents do their re-planning.

$$U_{total, default} = \sum_{i=1}^n U_{act}(type_i, start_i, dur_i) + \sum_{i=1}^{n-1} U_{trav}(dur_i, dist_i) \quad (4.1.1)$$

For further simulations, start and end times, as well as activities' durations, are fixed because only the quality of created routes matters in the experiments conducted (not an optimal distribution of activities and traffic during the day). Thus, the only parts of an agent's plan that can be changed are the routes.

As mentioned before, simple routers (random, compass and random compass routing) do not use any traffic load-related information. Random number generators used by these routers are re-initialized for each simulation run, resulting in deterministic sequences of drawn random numbers. Since the Queue Simulation also produces deterministic results, re-running the simulation multiple times will always produce the same results. Thus, only one single iteration must be conducted. As part of future work, further experiments will be conducted where random number generator seeds are varied, producing different outcomes. The simulations will be re-run multiple times to determine the resulting variance.

The least-cost router-based strategy is used only in combination with within-day re-planning. There, link travel times, used by the router, are collected within each iteration from scratch. A link's travel time is calculated by averaging the travel times of all vehicles that have left the link within the past 15 minutes. If a link becomes jammed, the time frame is enlarged. When the traffic jam has dissolved, the length of the considered period is reduced to 15 minutes again.

To render simulation results more comparable, a scoring function is used that accounts solely for travel time of the executed daily plans (Formulas 4.1.2 and 4.1.3), although the default scoring function includes factors like type, start time and duration of executed activities, as well as travel time and travel distance (Formula 4.1.1). Quality of the routes is measured and compared by the different trip durations. This adaption is also passed on to the router, which can then calculate the costs of a link also based only on travel time; Thus, behavior of agents is also altered.

$$U_{total, simplified} = \sum_{i=1}^{n-1} U_{trav}(dur_i) \quad (4.1.2)$$

$$U_{trav,i} = -dur_i \quad (4.1.3)$$

As reference value for route quality created by implemented timing strategies and knowledge levels, an additional series of iterative simulations is run using the traditional MATSim optimization strategy *without* the added within-day re-planning

modules. The agents are able to optimize their routes within their known areas of the network, using the travel time-based scoring function, but are not allowed to change duration or start and end times of their activities. The mean travel times per person and day of the relaxed system that depend on size of the known areas are taken as comparative values for other simulation runs (called *Stochastic User Equilibrium* in the analysis).

As a second reference value, a simulation is run where every agent creates its routes on an empty network using a least-cost path algorithm with a time-based scoring function (called *Initial Creation* in the analysis). This simulates a scenario where every driver uses a typical navigation system that knows the entire network, but has no information about traffic load.“

As described by Dobler, Axhausen and Weinmann (2013) above, the knowledge and behavior models developed in Chapter 3 are applied to the traffic scenario of the Zurich metropolitan area. The choice of the routes takes place according to the knowledge levels explained in Section 3.3 (Random Router, Tabu Router, Compass Router, Random Compass Router and Least Cost Router) and timing strategies (initial creation, activity end re-planning, and leave link re-planning), as well as the behavior classes K^0 and K^I discussed in Section 3.4.

The degree of utilization of the Zurich traffic scenario network capacity is 96% at the Stochastic User Equilibrium (see Section 4.4, *Network analysis*). This condition is applied for the simulation of the behavior classes in the Zurich scenario, which is configured and presented in the following Sections 4.2 and 4.4.

Note: Compared to the given traffic conditions of the applied Zurich scenario, the knowledge levels described in Section 4.1 are simulated at a lower average degree of utilization of the network capacity (see Appendix VI) so that the Stochastic User Equilibrium obtained with the standard assignment method of MATSim on the basis of a logit model results in about 28.9 minutes of Mean Daily Travel Time (MDT).

4.2 Configuration

Applying the learning mechanisms and choice behavior of the driver (Chapter 3), MATSim simulates the Zurich traffic scenario (Section 4.1) in accordance with the configuration of the driver population Ω chosen in this section. The shares of the non-informed drivers K^0 and the informed drivers K^I , as well as the levels of compliance with navigation information are varied in a systematic manner so as to be able to answer the questions formulated in Section 1.4. The parameters of the partition of the drivers and the results are described in the Tables 4.1, 4.2 and 4.3.

Partition

A partition $\Omega^{q,\varphi}$ of the driver population (4.2.1) varies the classes K^0 and $K^{I,\varphi}$ (see Section 3.4) in two ways: first, by way of different shares q of informed drivers K^I and $(100 - q)$ non-informed drivers K^0 , and, second, by way of different degrees of freedom φ .

$$\Omega^{q,\varphi} = K^0 \cup K^{I,\varphi}, \quad K^0 \cap K^{I,\varphi} = \emptyset \quad (4.2.1)$$

$K^{I,\varphi}$ means that a class K^I driver complies with his traffic information subject to a degree of freedom φ (see Sections 3.1 and 3.2). The factor φ is specified by one of the two parameters γ or Γ (Table 4.1).

Table 4.1: Parameters of behavior class $K^{I,\varphi}$

Parameter	Relation	Meaning
φ	$\varphi = 1-\gamma, \varphi = 1-\Gamma$	Degree of uncertainty or degree of freedom
γ	$\gamma = g(B) \in [0..1]$	Experienced degree of confidence or probability of acceptance
Γ	$\Gamma \in [0..1]$	Fixed degree of confidence

$K^{I,\gamma}$ means that a class K^I driver complies with his traffic information subject to the experientially gained confidence factor γ with its initial value f . $K^{I,\Gamma f}$ means that a K^I driver complies with his traffic information subject to the fixed confidence factor $\Gamma = f$. In the extreme case, $\Gamma = 1$ is so that $K^{I,\Gamma f}$ denotes all drivers who fully comply with the navigation instructions. The properties of the various classes are set out in Table 4.2.

Table 4.2: Behavior classes, objects of a driver's decision, and levels of compliance

Class	Type of attributes of a driver's decision				
	Knowledge	Behavior	Criterion	Rule	Compliance
K^0	static	deterministic	travel time $\tau(0)$	$\min \tau(0)_j$	total
$K^{l,1}$	dynamic	stochastic	utility $u(\tau)$	$\max u(\tau_j)$	partial
$K^{l,\gamma}$	dynamic	stochastic	weighted $u(\tau,\gamma)$	$\max u(\tau_j,\gamma)$	threshold B accepted γ
$K^{l,\Gamma}$	dynamic	stochastic	weighted $u(\tau,\Gamma)$	$\max u(\tau_j,\Gamma)$	fixed level subject to Γ

Values

The variants are compared on the basis of the mean daily travel times (MDT). The result $M^{q,\varphi}$ of the simulation of a partition $\Omega^{q,\varphi}$ means the MDT of all drivers $\Omega = K^0 \cup K^l$ in the case of $q\%$ of informed drivers $K^{l,\varphi}$. The result $M^{q,\gamma f}$ of the specific partition $\Omega^{q,\gamma f}$ denotes the MDT of all drivers Ω in the case of a share of $q\%$ informed drivers $K^{l,\gamma f}$ with a variable confidence factor γ and an initial value f . The result of the specific partition $\Omega^{q,\Gamma f}$ denotes the MDT of all drivers Ω in the case of a share of $q\%$ informed drivers $K^{l,\Gamma f}$ with a constant confidence factor $\Gamma = f$.

If the mean daily travel time refers to only one of the two classes, $M0$ stands for the class K^0 and MI for the class K^l , i.e. $M0$ is the mean daily travel time for the class K^0 drivers, and MI is the mean daily travel time for the class K^l drivers (Table 4.3).

Table 4.3: Types of partitions $\Omega^{q,\varphi}$ and terms of outcomes of the driver sets Ω , K^0 and K^l

Partition	Outcome	Meaning	[MDT = Mean Daily Travel time]
Ω^0	M^0	MDT of all drivers $K^0 = \Omega$	
$\Omega^{q,\gamma f} = K^0 \cup K^{l,\gamma f}$ Experiential confidence	$M^{q,\gamma f}$	MDT of all drivers Ω when $q\%$ belong to class $K^{l,\gamma f}$	
	$M0^{q,\gamma f}$	drivers K^0 when $q\%$ belong to class $K^{l,\gamma f}$	
	$MI^{q,\gamma f}$	drivers K^l when $q\%$ belong to class $K^{l,\gamma f}$	
$\Omega^{q,\Gamma f} = K^0 \cup K^{l,\Gamma f}$ Fixed confidence	$M^{q,\Gamma f}$	MDT of all drivers Ω when $q\%$ belong to class $K^{l,\Gamma f}$	
	$M0^{q,\Gamma f}$	drivers K^0 when $q\%$ belong to class $K^{l,\Gamma f}$	
	$MI^{q,\Gamma f}$	drivers K^l when $q\%$ belong to class $K^{l,\Gamma f}$	

In addition to the mean daily travel times M , $M0$, and MI , there are three further parameters by way of which the simulation of a partition $\Omega^{q,\varphi}$ will be evaluated: the percentage time savings (MDTS) S , $S0$, SI , for each of the entire driver population Ω , the class K^0 drivers, and the class K^l drivers (Table 4.4). All values are related to the benchmark M^0 (the mean daily travel time of the basis partition Ω^0 , see below, as well as Table 4.3 and Table 4.6).

Table 4.4: Pattern of simulation outcomes MI , $M0$, M and SI , $S0$, S of partitions $\Omega^{q,\varphi}$

Share of drivers $K^{l,\varphi}$	Partitions Ω^{q,γ^f} and Ω^{q,Γ^f} of driver classes K^0 and $K^{l,\varphi}$					
	MI^{q,γ^f}	MI^{q,Γ^f}	$M0^{q,\gamma^f}$	$M0^{q,\Gamma^f}$	M^{q,γ^f}	M^{q,Γ^f}
q [%]	MDT [min]	MDT [min]	MDT [min]	MDT [min]	MDT [min]	MDT [min]
	SI^{q,γ^f}	SI^{q,Γ^f}	$S0^{q,\gamma^f}$	$S0^{q,\Gamma^f}$	S^{q,γ^f}	S^{q,Γ^f}
q [%]	MDTS [%]	MDTS [%]	MDTS [%]	MDTS [%]	MDTS [%]	MDTS [%]

The MDTS (4.2.2) refers to the norm time M^0 (Table 4.3 and Table 4.6).

$$S = \frac{(M^0 - M)}{M^0} \cdot 100 \quad (4.2.2)$$

The effect of traffic information is measured in relation to mean daily travel times M and compared to the mean daily travel time M^0 . M^0 is the value of the *all-or-nothing assignment*, here called $\tau(0)$ assignment, resulting from the partition Ω^0 ($K^0 = \Omega$); i.e. all drivers stick to the routes of the load-free traffic network. Taking the mean daily travel time M^0 of the $\tau(0)$ assignment as the benchmark is reasonable for the following points:

- From a theoretical point of view: M^0 is the result of the information level of class K^0 , which in the case of unhindered travel (on the load-free network), is optimal.
- From a practical point of view: M^0 is a standard value which fairly corresponds (at least in traffic segments) to real conditions because every vehicle can be equipped with an ordinary router and the device is easy to operate.
- From an empirical point of view: M^0 is the result of a typical behavior which views every deviation from the shortest route (on a load-free traffic network) as a detour, the time loss of which the driver does not like to put up with (see Sections 2.4 and 3.1).
- From a methodological point of view: The benchmark M^0 also corresponds to the results of two characteristic partitions, $\Omega^{50,\Gamma^{1/2}}$ and $\Omega^{100,\gamma^{1/2}}$. The value $MI^{50,\Gamma^{1/2}}$ results for the class K^l drivers when one-half of all drivers have traffic information at their disposal, and choose the recommended routes with the fixed confidence factor $\Gamma = 1/2$. The value $MI^{100,\gamma^{1/2}} = M^{100,\gamma^{1/2}}$ will result, if all drivers are informed about the current travel times and follow a recommendation with a variable factor γ , which *a priori* is $\gamma = 1/2$ (see *Threshold analysis*, Table 4.6; and Section 4.4, Figure 4.11; Section 5.1, Table 5.3; Appendix V, Figure A.2).

M^S denotes the mean daily travel time at the theoretical state of the capacity of all links being arbitrarily high and all drivers belonging to class K^0 . Arbitrarily high capacities mean arbitrarily small obstruction on the links so that in the presence of any traffic demand the load-free network travel times will apply, and no class K^0 driver could fare any better by deviating from his statically shortest route (Wardrop's first principle). Because under these conditions the marginal travel time cost on all links is equal to 0, M^S is a lower bound not only for the user equilibrium, but also for the system optimum (Wardrop's second principle).

Tolerance threshold analysis

First of all, there is the question: Which tolerance thresholds $[B^+, B^-, B]$ shall basically determine the experiment-based confidence of a class $K^{L,ff}$ driver (the measure of the acceptance γ of the traffic information)?

Appropriate tolerance thresholds shall be determined by means of an experimental analysis. The selection of tolerance thresholds is limited by the ranges $B^+ \in [10\%, 25\%]$, $B^- \in [25\%, 40\%]$, and $B \in [0\%, 10\%]$. Out of this B^+ , B^- , and B will be combined, tested by simulation, and ranked. The characteristic results are expected to come from the two combinations located at the interval margins: $B^+ = 25\%$, $B^- = 40\%$, and $B = 0\%$ (much tolerance in the evaluation, and high acceptance of the information), and $B^+ = 10\%$, $B^- = 25\%$, and $B = 10\%$ (little tolerance, and low acceptance) (Table 4.5).

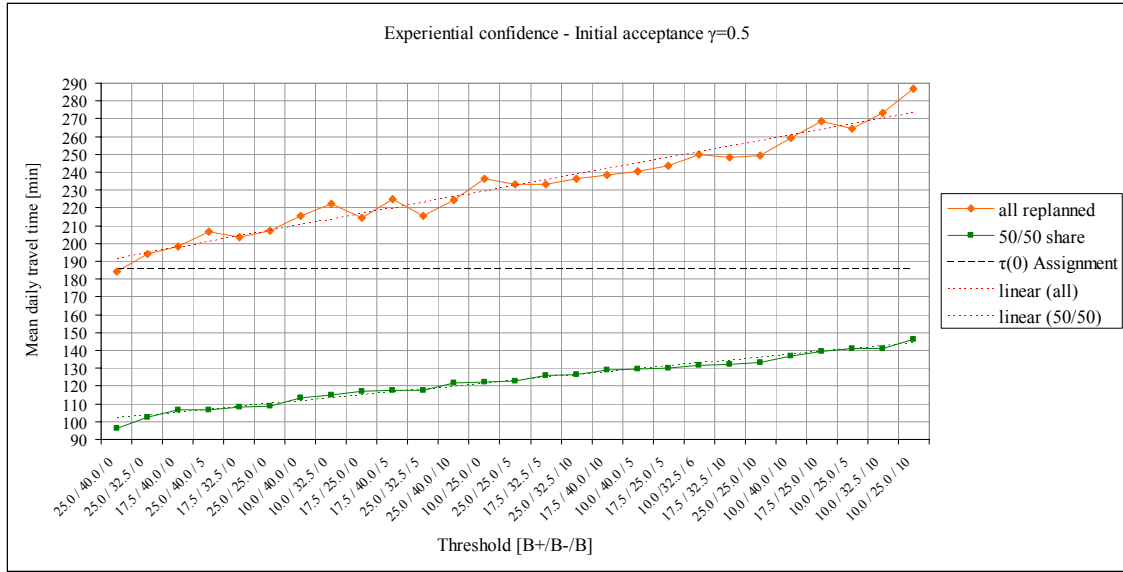
Table 4.5: Variations of different thresholds B^+ , B^- , B of the drivers' tolerance

Threshold	Tolerance of travel time deviation (c – achieved, τ – expected on r_1 , $\hat{c}(\tau)$ – expected on r_i)		
	low [%]	medium [%]	high [%]
$c > \tau$: B^+	10	17 ½	25
$c < \tau$: B^-	25	32 ½	40
$c > \hat{c}(\tau)$: B	0	5	10

Reminder: The tolerance threshold $B^+ = 25\%$ for example means that the driver accepts a traffic information provided the actual travel time c on the recommended link is not more than 25 percent longer than the expected travel time τ (see Section 3.2).

As expected, the ranking of 27 different tolerance combinations (Figure 4.3) of partition $\Omega^{100,\gamma^{1/2}}$ (all re-planned, red line) and $\Omega^{50,\gamma^{1/2}}$ (50/50 share, green line) leads to the results $M^{100,\gamma^{1/2}}$ and $M^{50,\gamma^{1/2}}$ (Table 4.6), at which the two marginal combinations $B^+ = 25\%$, $B^- = 40\%$, and $B = 0\%$ (which means high acceptance), as well as $B^+ = 10\%$, $B^- = 25\%$, and $B = 10\%$ (low acceptance) lead to extreme results.

Figure 4.3: Mean daily travel time according to different thresholds of $\Omega^{100,\gamma^{1/2}}$ and $\Omega^{50,\gamma^{1/2}}$



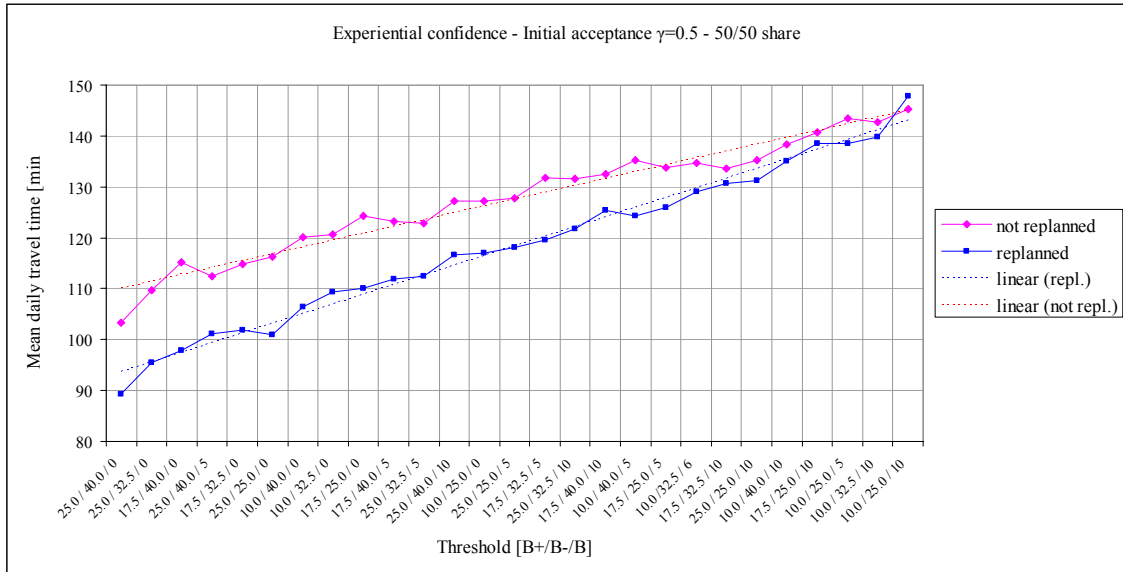
In the case of fully dynamic planning on the part of the partition $\Omega^{100,\gamma^{1/2}}$ (with all drivers knowing the current travel times on the links, i.e. $K^l = \Omega$, and dynamically following the information with initial confidence $\gamma = 1/2$), only one of the 27 different combinations of tolerance thresholds falls short of the norm time M^0 : the variant $B^0 = [B^+ = 25\%, B^- = 40\%, B = 0\%]$ for the valuation of the travel time differences which means the highest information acceptance.

Table 4.6: Mean daily travel times M according to different thresholds of acceptance B

Thresholds [B^+, B^-, B]	$\Omega^{100,\gamma^{1/2}}, \Omega^{50,\gamma^{1/2}}$ (experiential confidence – initial acceptance $\gamma=1/2$)		
	$M^{100,\gamma^{1/2}}$ (all informed)	$M^{50,\gamma^{1/2}}$ (50/50 share)	M^0
[25,40,0]	184	96	186
[25,25,5]	233	123	
[10,25,10]	287	146	

All in all, a clear trend emerges: a negative correlation between tolerance and travel time, i.e. the higher the drivers' tolerance, the shorter the mean travel time.

Figure 4.4: Mean daily travel time according to different thresholds, $\gamma = 0.5$, 50/50 share



There are considerable differences between full dynamic planning and partial dynamic planning. In the case of partial re-planning (50/50 share), the mean travel time is about one-half as high than in the case of full re-planning (all drivers re-planning). That means, if only every second driver can change to the currently shortest routes, whereas the others stay on the statically shortest routes, the travel time of all drivers will be cut by an average of about 50 percent on the basis of a dynamic compliance rate which corresponds to the experience with the instructions provided by the navigation system during the trip (experiential confidence, initial value of acceptance $\gamma = 0.5$).

The green curve in Figure 4.3 depicts the course of the scenario (50/50 share) where every second driver has at his disposal the current travel time on the routes whereas the other one-half of the drivers remain on the statically calculated shortest routes. The mean travel times of the static and dynamic knowledge levels are shown for all 27 different tolerance levels in Figure 4.4.

In the case of partial dynamic planning (with only one-half of the drivers knowing the current travel times on the routes), all MDT of the 27 different tolerance thresholds will be below the norm time M^0 , i.e. all drivers – including the non-informed ones – will benefit from partial dynamic planning.

Except for the extreme variant [$B^+ = 10\%$, $B^- = 25\%$, $B = 10\%$] where the drivers show the lowest information acceptance, the mean travel times of the drivers with dynamic knowledge are below the mean travel times of the drivers with static knowledge, i.e. if one-half of the drivers are informed about the current travel times, the informed ones will benefit more than the non-informed ones, with the biggest time saving being achieved by the first extreme variant B^0 where the drivers have the highest tolerance level ($B^+ = 25\%$, $B^- = 40\%$) among the 27 different tolerance patterns (Table 4.7).

Table 4.7: Mean daily travel time of classes K^0 and K^I according to different thresholds

Thresholds	$\Omega^{50,\gamma/2}$ (50/50 share – experiential confidence – initial acceptance $\gamma=1/2$)		
$[B^+, B^-, B]$	$MI^{50,\gamma/2}$ (informed)	$MO^{50,\gamma/2}$ (non-informed)	M^0
[25,40,0]	89	103	186
[25,25,5]	118	128	
[10,25,10]	148	145	

Both extreme variants, B^0 and [$B^+ = 10\%$, $B^- = 25\%$, $B = 10\%$], have been extensively tested with the Zurich traffic scenario. The results of the experiments where the drivers are assumed to have the tolerance thresholds B^0 will be discussed in Section 4.4 for two reasons: first, because the variant B^0 achieves the norm time M^0 , and, second, because the empirical findings about the willingness of the drivers to deviate from their route, as summarized in Section 3.2, also suggest that the tolerance $B^+ = 25\%$ is suitable.

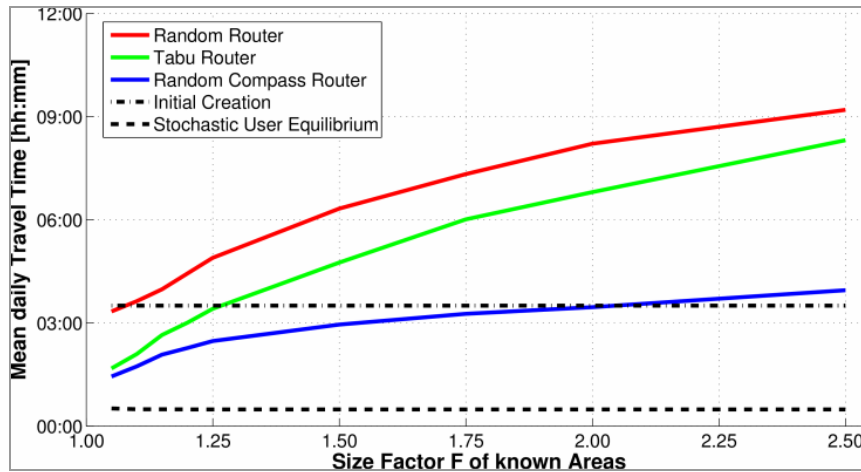
4.3 Outcomes by Knowledge levels

The simulation of the Zurich traffic scenario shows the connection existing between individual route choice and the mean travel times actually achieved. At first, the results of the simulation of the simple knowledge models and timing strategies will be discussed. The experiments of the five knowledge levels described in Section 3.3 lead to the following results (Dobler, Axhausen and Weinmann, 2013):

„In the first set of simulations, routers that do not take the current load of the traffic network into account are used. The agents’ routes are created before the simulation is started. The behavior of the routers is analyzed separately; in each simulated scenario all agents use the same timing strategy. For each strategy, a series of

simulations is run where the spatial region size of the road network that the agents know (and therefore use for their routes) is varied. This allows us to determine whether – and if so, how – the size of the known region influences the routes used by the agents.

Figure 4.5: Outcomes of simple knowledge levels and pre-trip planning



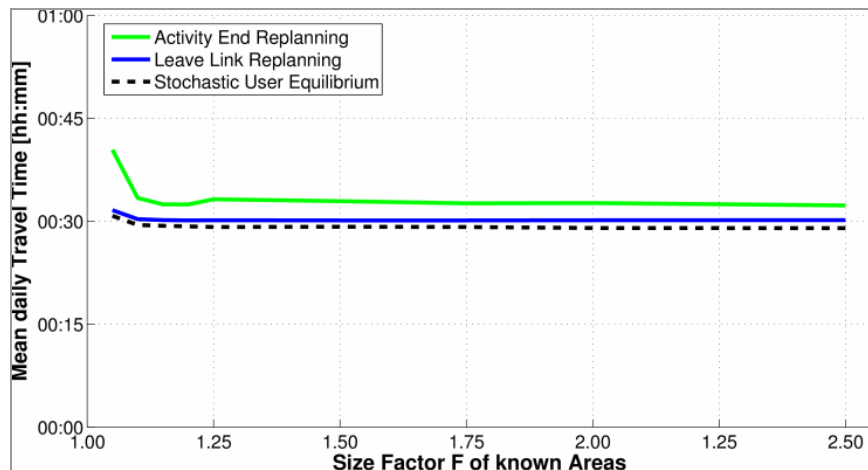
Source: Dobler, Axhausen and Weinmann (2013)

The simulation results are shown in Figure 4.5, which compares different routers' mean travel time. The *Compass Router* results are not shown because almost every agent got stuck. Agents that are still enroute when the simulation is stopped after 96 simulated hours, are declared “stuck”, meaning that they have been unable to finish their planned daily schedule. For comparison, results of the reference simulations are also included in the figures (*Initial Creation* and *Stochastic User Equilibrium*).

These results show that even if travelers can use only very small traffic network sections (e.g. size factor $F < 1.10$), created routes are significantly worse than those in reference simulations. It also can be seen, that mean travel times increase almost linearly. Comparing performance of the three timing strategies shows what one expected: the *Random Compass Router* performs better than the *Tabu Router*, which, in turn, performs better than the *Random Router*. The results also show that the quality of the created routes improves significantly when additional information is provided. Presumably, results of the *Random Compass Router* could be further improved by using an intelligent algorithm for random choice. Currently, a fixed rate defines how often a link is chosen randomly or by using the compass.

However, using random selection is only necessary to prevent the router from being stuck in a loop. Therefore, a logic could be implemented that activates random selection only when a loop is detected. (Computation times increase with the size of the known area and decrease with the information level used by a router, which is reasonable.)

Figure 4.6: Outcomes of within-day timing strategies



Source: Dobler, Axhausen and Weinmann (2013)

The second set of simulation runs analyzes the traffic system when drivers take the current network load into account by using two different timing strategies. People who use the first one can re-plan their routes when they have just ended an activity. Before they enter the network to travel to the next activity location, the route to that activity is re-planned factoring in current traffic load (*Activity End Re-planning*). The second approach allows people to change their routes each time they reach the end of a link. By doing so, they can choose the next link of their route just before they enter that link (*Leave Link Re-planning*). This allows an agent at a traffic intersection to decide "Link A seems to be congested, so I'll take link B instead". In a real world scenario, a timing strategy like this could – for example – be implemented with a traffic management system that communicates with travelers to inform them about the current road network traffic load.

Figure 4.6 again show the mean travel times of a person as a function of the size of the known road network parts. It gives a closer look at both within-day timing strategies and compares them with the relaxed system state.

As expected, results of timing strategies that incorporate travelers' knowledge lie between the reference values. The substantially longer travel times when using an initial timing strategy result from high traffic load causing congestion. People are able to reduce their travel times when the size of the known areas reaches a certain value (size factor F of ~ 1.20 in the simulated scenario). If the size factor increases beyond this value, no further reduction of travel times can be achieved.

The influence of size of the known traffic systems parts depends strongly on the traffic situation. If there is significant traffic or even a traffic jam (as in the scenario used), people familiar with bigger areas are able to find routes that avoid the jammed links that are faster, even if the distance traveled is longer. On the other hand, people do not require that knowledge if they are traveling in an almost empty network, because their travel time is not influenced by other drivers.

Comparing the results of both within-day timing strategies shows that the leave-link strategy performs slightly better. The improvement is relatively small, since the mean trip duration is only about 9 minutes. Within this time, the load of the traffic system usually does not change significantly. Thus, the number of people who change their route while driving is quite low. Interestingly, even if people have only very limited knowledge, they are able to create routes significantly better than those created without knowledge. Using better routes leads to a better balanced traffic load in the network, which – in turn – also reduces travel times.

Comparing computation times of both within-day re-planning strategies shows that *Activity End Re-planning* is approximately three times faster. This is obvious, because the *Leave Link Re-planning* strategy requires multiple least-cost route calculations per trip, whereas *Activity End Re-planning* requires only one. However, the performance of *Leave Link Re-planning* could be improved by checking whether a re-planning is necessary or not (see Axhausen, 1988). This could be, for example, decided based on changes in network load. If link travel times have not changed since the last re-planning, an agent will not find a better route than the one currently selected. Therefore, no re-planning is required.“

4.4 Outcomes by Behavior classes

The demand by drivers of the scenario is allocated in a mixed fashion ($\Omega^{q,\varphi}$), on the one hand, in a deterministic-static fashion by way of a share of $(100 - q)$ class K^0 drivers (*non-informed, no re-planning*) with capacity-independent knowledge, and, on the other hand, in a stochastic-dynamic fashion by way of a share of q class $K^{I,\varphi}$ drivers (*informed, with re-planning*) who have at their disposal current traffic information τ and resort to re-planning $\pi(u(\tau, \varphi))$ at every traffic node (*leave link re-planning*).

The stochastic distribution of the routes takes place according to the functions agreed on in Sections 3.1 and 3.2, i.e. π (route-split at a decision node), u (random utility of τ), τ (information about travel time on a route), φ (weight of the least-cost route).

A partition $\Omega^{q,\varphi}$ varies, on the one hand, due to different shares q of drivers $K^{I,\varphi}$ and, on the other hand, due to different degrees of freedom φ , which depend on the driver's current confidence γ in the traffic information τ or on a normative confidence factor Γ . The experiential confidence γ of a driver is ascertained subject to the tolerance levels $B^0 = [B^+ = 25\%, B^- = 40\%, B = 0\%]$ (as explained in Section 4.2); the following results of the simulations are uniformly based on the tolerance threshold B^0 .

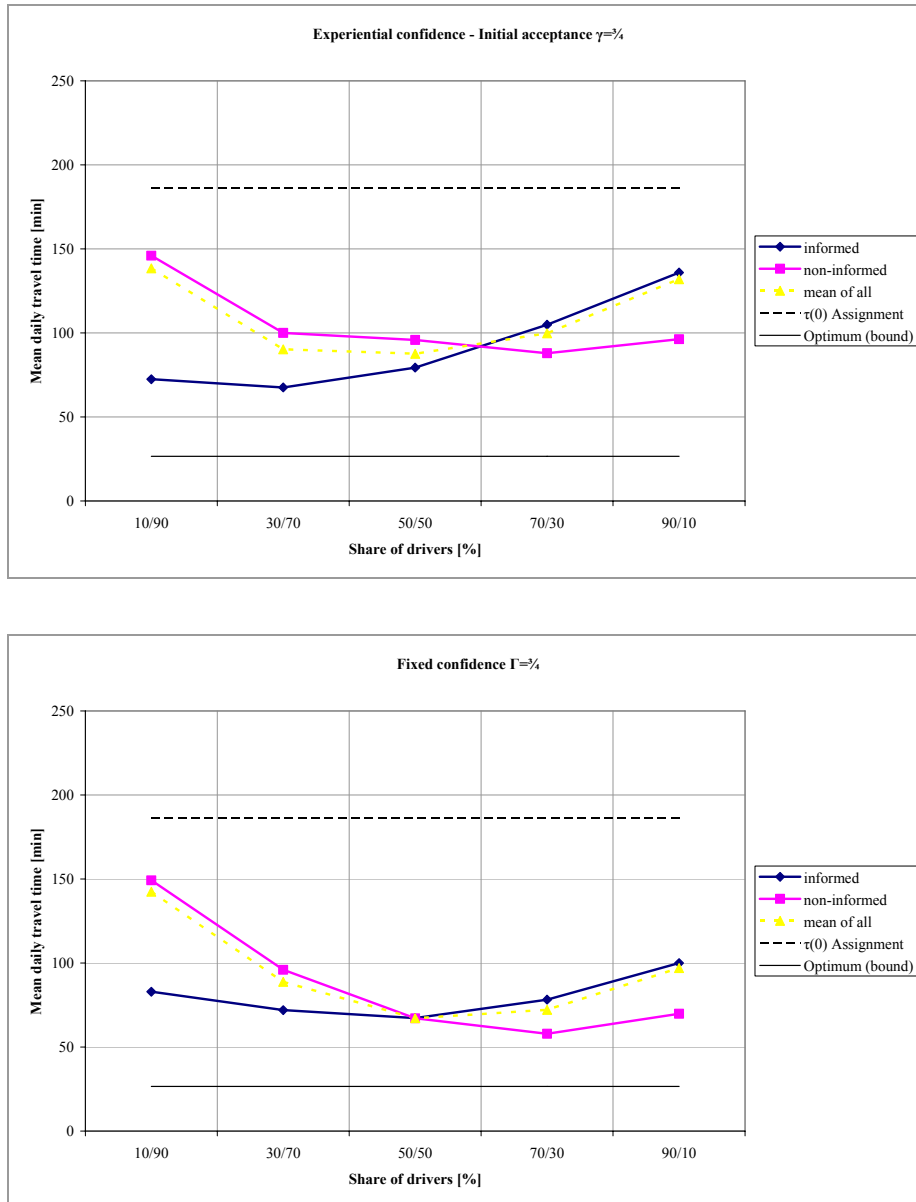
The parameters will be chosen with the following increments: the percentage share value q of class K^I in increments of 10%, the degree of freedom $\varphi = 1 - \gamma$ depending on the experiential confidence γ with initial value $\gamma \in [0..1]$, typically with the values $\gamma \in \{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\}$, the degree of freedom $\varphi = 1 - \Gamma$, which, depending on the invariable factor $\Gamma \in [0..1]$, is simulated in increments of 1÷10 with the results presented below only in $\frac{1}{4}$ increments $\Gamma \in \{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\}$ (Table 4.8).

Table 4.8: Outcome pattern of partitions $\Omega^{q,\gamma}$ and $\Omega^{q,\Gamma}$ at confidence levels $\frac{3}{4}$ and 1

Share of drivers $K^{I,\varphi}$	Partitions Ω^{q,γ^f} and Ω^{q,Γ^f} of driver classes K^0 and $K^{I,\varphi}$					
	$MI^{q,\gamma^{\frac{3}{4}}}$	$MI^{q,\Gamma^{\frac{3}{4}}}$	$MO^{q,\gamma^{\frac{3}{4}}}$	MO^{q,Γ^1}	M^{q,γ^1}	M^{q,Γ^1}
q [%]	MDT [min]	MDT [min]	MDT [min]	MDT [min]	MDT [min]	MDT [min]
	$SI^{q,\gamma^{\frac{3}{4}}}$	$SI^{q,\Gamma^{\frac{3}{4}}}$	$SO^{q,\gamma^{\frac{3}{4}}}$	SO^{q,Γ^1}	S^{q,γ^1}	S^{q,Γ^1}
q [%]	MDTS [%]	MDTS [%]	MDTS [%]	MDTS [%]	MDTS [%]	MDTS [%]

The MDT of different shares q of informed drivers K^I and $(100 - q)$ non-informed drivers K^0 as well as of the entire population of drivers Ω (*mean of all*) are shown in Figure 4.7 and Table 4.9 for experiential confidence starting at $\gamma = \frac{3}{4}$ and fixed confidence $\Gamma = \frac{3}{4}$.

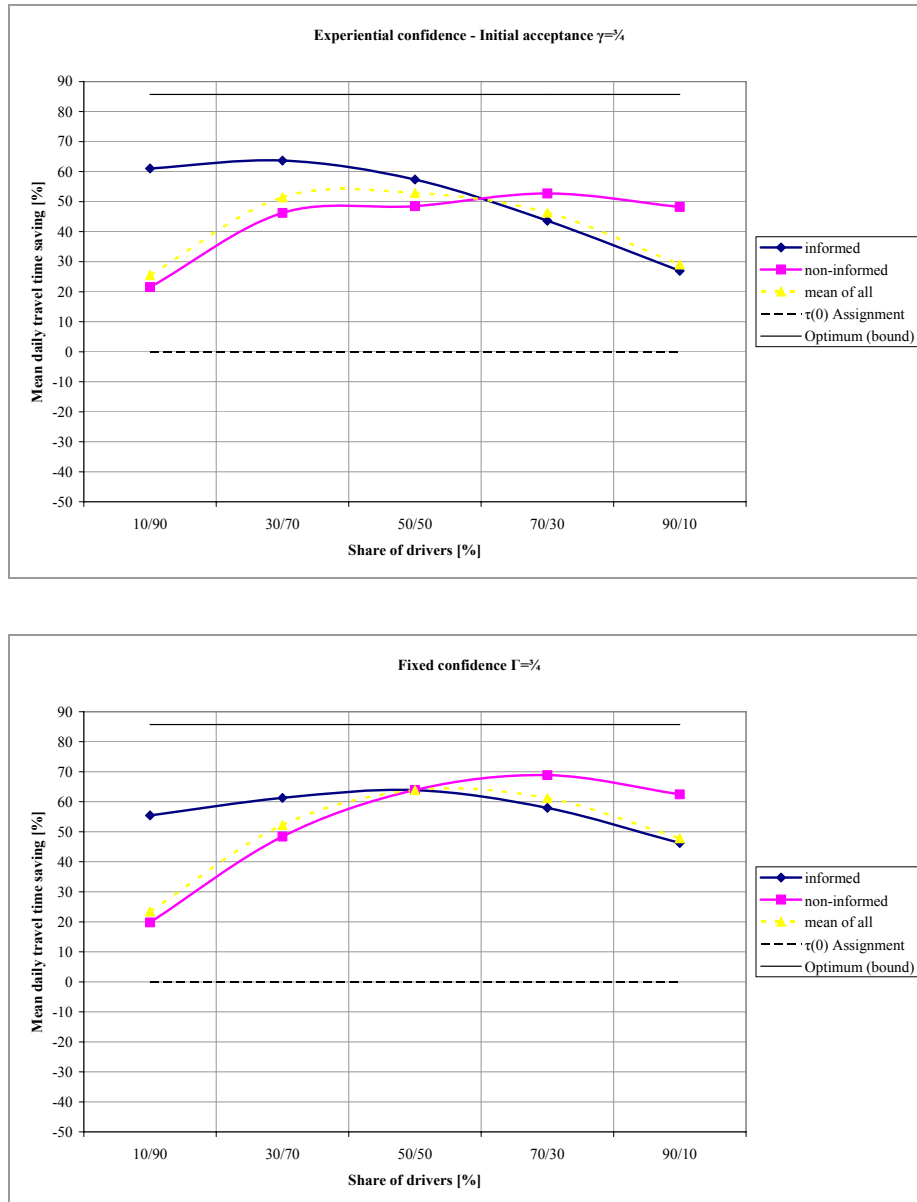
Figure 4.7: MDT according to experiential and fixed confidence $\frac{3}{4}$



In the case of experiential confidence with the initial value $\gamma = \frac{3}{4}$ (Figure 4.7, above) and a share $q = 60\%$ of informed drivers K^I , the MDT (≈ 92) is the same for all drivers. In the case of fixed confidence $\Gamma = \frac{3}{4}$, a share $q = 50\%$ of informed class K^I drivers suffices for all drivers to reach the same MDT (≈ 67 , Table 4.9).

The comparison of the MDTS of different shares q of informed drivers K^I with experiential confidence $\gamma = \frac{3}{4}$ and firm confidence $\Gamma = \frac{3}{4}$ is shown in Figure 4.8 and Table 4.10.

Figure 4.8: MDTS according to experiential and fixed confidence $\frac{3}{4}$



The share q of informed drivers K^I determines whether the time saving SI of the informed drivers K^I is greater than the time saving $S0$ of the non-informed drivers K^0 . In the case of fixed confidence $\Gamma = \frac{3}{4}$, a clear picture results: With $q = 50\%$, the outcome is a social equilibrium with a 64 percent saving as against the norm time M^0 for all drivers (i.e. $S^{50, \Gamma \frac{3}{4}} = S0^{50, \Gamma \frac{3}{4}} = SI^{50, \Gamma \frac{3}{4}}$).

Table 4.9: MDT [min] according to experiential and fixed confidence $\frac{3}{4}$

share q [%]	Partitions $\Omega^{q,\gamma^{\frac{3}{4}}}$ and $\Omega^{q,\Gamma^{\frac{3}{4}}}$ of driver classes K^0 and $K^{L,\varphi}$					
	$MI^{q,\gamma^{\frac{3}{4}}}$	$MI^{q,\Gamma^{\frac{3}{4}}}$	$MO^{q,\gamma^{\frac{3}{4}}}$	$MO^{q,\Gamma^{\frac{3}{4}}}$	$M^q,\gamma^{\frac{3}{4}}$	$M^q,\Gamma^{\frac{3}{4}}$
10	72	83	146	149	138	142
30	68	72	100	96	90	89
50	79	67	96	67	88	67
70	105	78	88	58	100	72
90	136	100	96	70	132	97

In the case of experiential confidence starting at $\gamma = \frac{3}{4}$, the saving of the informed drivers K^I is higher than the saving of the non-informed drivers K^0 , as long as fewer than 60 percent of the drivers are informed (4.4.1). The same applies also in the case of fixed confidence $\Gamma = \frac{3}{4}$, as long as there are fewer than 50 percent informed drivers (4.4.2).

$$SI^{q,\gamma^{\frac{3}{4}}} > SO^{q,\gamma^{\frac{3}{4}}} \quad \text{if } q < 60\% \quad (4.4.1)$$

$$SI^{q,\Gamma^{\frac{3}{4}}} > SO^{q,\Gamma^{\frac{3}{4}}} \quad \text{if } q < 50\% \quad (4.4.2)$$

Table 4.10: MDTS [%] according to experiential and fixed confidence $\frac{3}{4}$

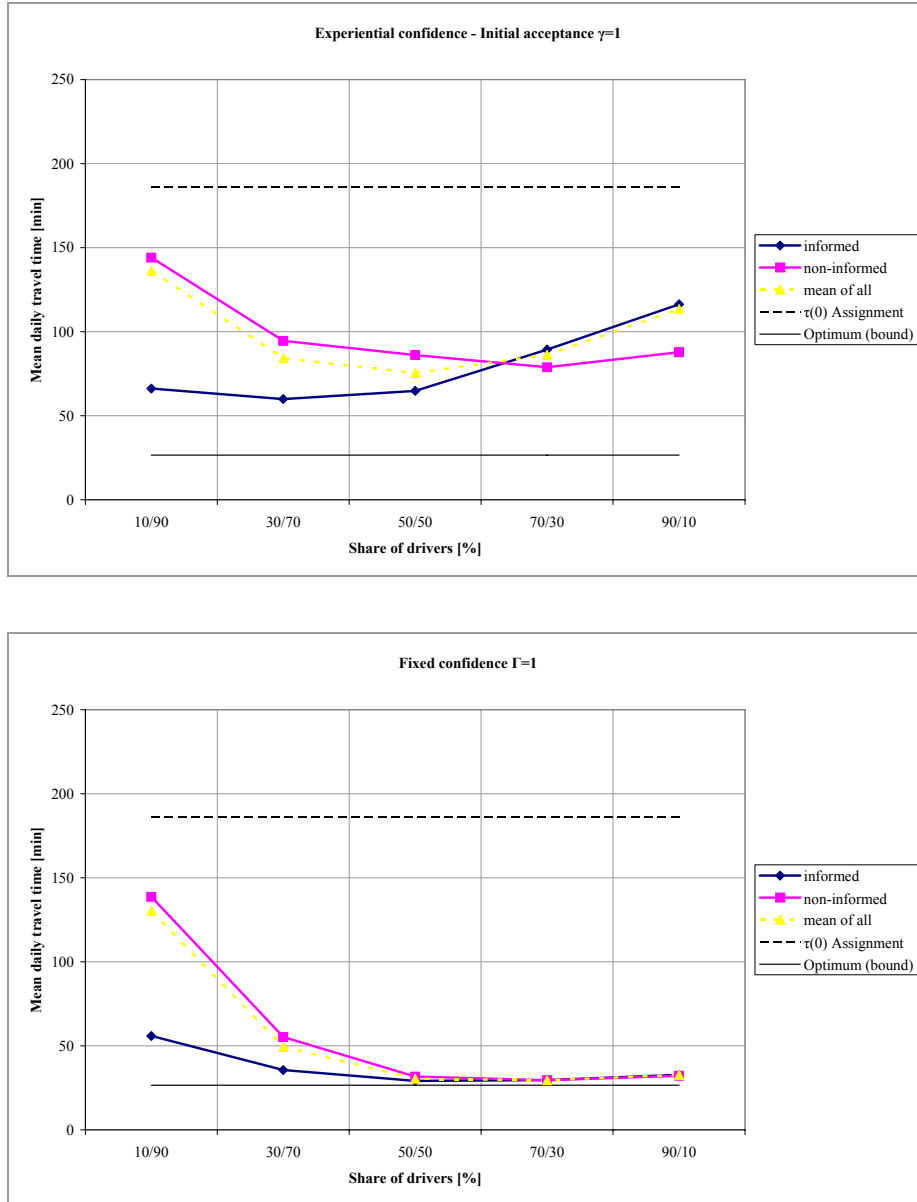
share q [%]	Partitions $\Omega^{q,\gamma^{\frac{3}{4}}}$ and $\Omega^{q,\Gamma^{\frac{3}{4}}}$ of driver classes K^0 and $K^{L,\varphi}$					
	$SI^{q,\gamma^{\frac{3}{4}}}$	$SI^{q,\Gamma^{\frac{3}{4}}}$	$SO^{q,\gamma^{\frac{3}{4}}}$	$SO^{q,\Gamma^{\frac{3}{4}}}$	$S^q,\gamma^{\frac{3}{4}}$	$S^q,\Gamma^{\frac{3}{4}}$
10	61	55	22	20	26	23
30	64	61	46	48	51	52
50	57	64	48	64	53	64
70	44	58	53	69	46	61
90	27	46	48	62	29	48

Starting from a share $q > 10\%$ of informed drivers K^I , the normative behavior of class $K^{L,\Gamma^{\frac{3}{4}}}$ brings for all drivers Ω about a higher time saving $S^q,\Gamma^{\frac{3}{4}}$ than the time saving $S^q,\gamma^{\frac{3}{4}}$ by the experiential confidence drivers $K^{L,\gamma^{\frac{3}{4}}}$ (4.4.3) as shown in Table 4.10 and Figure 4.8.

$$S^q,\gamma^{\frac{3}{4}} < S^q,\Gamma^{\frac{3}{4}} \quad \text{if } q > 10\% \quad (4.4.3)$$

The comparison of the MDT of different shares q of informed drivers K^I with experiential confidence $\gamma = 1$ and fixed confidence $\Gamma = 1$, respectively, is depicted in Figure 4.9 and Table 4.11.

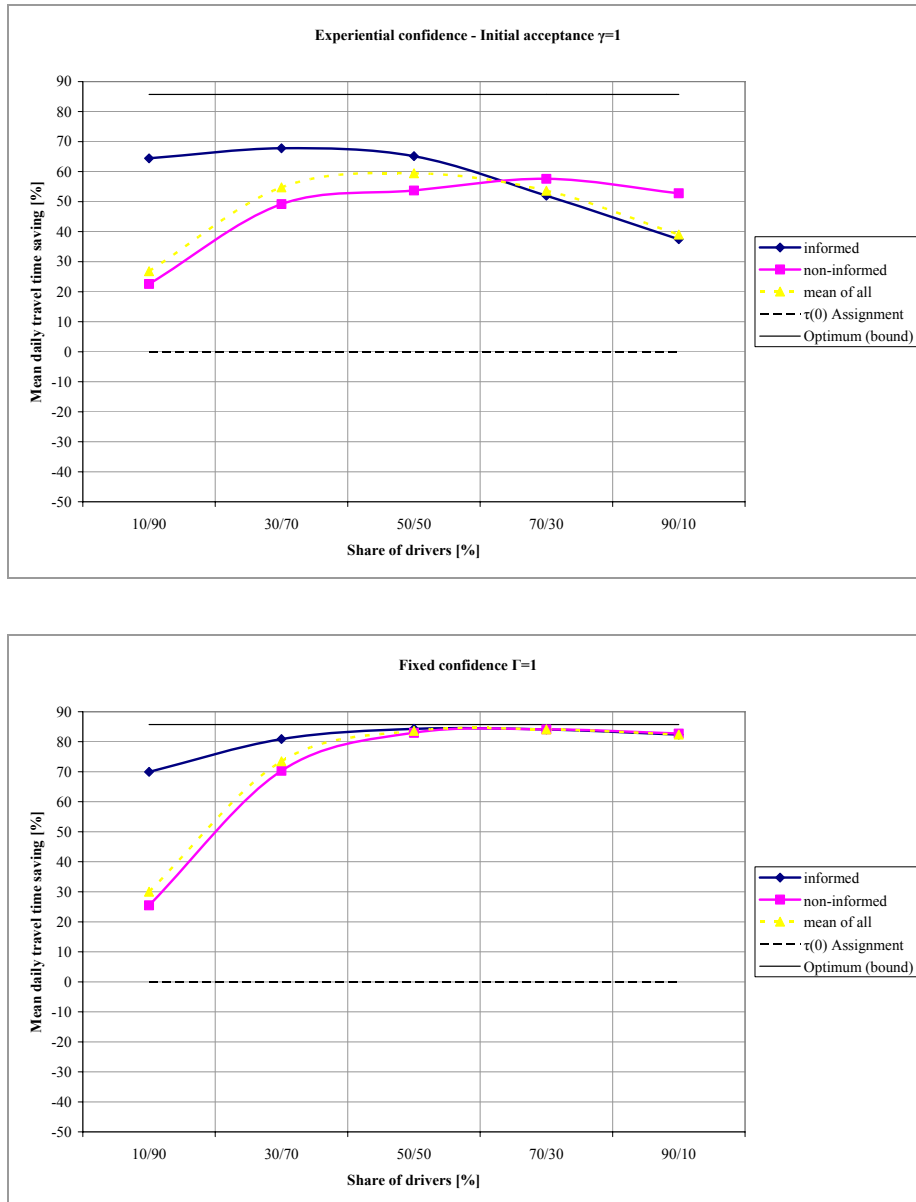
Figure 4.9: MDT according to experiential and fixed confidence 1



In the case of the experiential confidence at initial value $\gamma = 1$ (Figure 4.9, above), and a share $q \approx 63\%$ of informed drivers K^I , the MDT (≈ 81) is the same for all drivers. In the case of fixed confidence $\Gamma = 1$ and a share $q = 70\%$ of informed drivers K^I , the same MDT ($M^U = 29.6$ minutes) is reached by all drivers (Table 4.11). That situation is the state of the stochastic user equilibrium (see Section 2.3).

The comparison of the MDTS of different shares q of informed drivers K^I with experiential confidence $\gamma = 1$ and fixed confidence $\Gamma = 1$ is depicted in Figure 4.10 and Table 4.12.

Figure 4.10: MDTS according to experiential and fixed confidence 1



The large differences in time saving between the normative behavior of class $K^{I,\Gamma 1}$ and the behavior of class $K^{I,\gamma 1}$ are caused by the steadily declining confidence γ and the ensuing higher degrees of freedom φ of the drivers as to deviating from the recommended routes (see Confidence analysis, below).

Table 4.11: MDT [min] according to experiential and fixed confidence 1

share q [%]	Partitions Ω^{q,γ^1} and Ω^{q,Γ^1} of driver classes K^0 and $K^{I,\varphi}$					
	MI^{q,γ^1}	MI^{q,Γ^1}	MO^{q,γ^1}	MO^{q,Γ^1}	M^{q,γ^1}	M^{q,Γ^1}
10	66.0	56.0	144.0	139.0	136.0	130.0
30	60.0	36.0	95.0	55.0	84.0	49.0
50	65.0	29.2	86.0	31.7	75.0	30.5
70	89.0	29.6	79.0	29.6	86.0	29.6
90	116.0	33.0	88.0	32.0	113.0	33.0

In the case of experiential confidence γ , the time saving of the informed drivers K^I is higher than the time saving of the non-informed drivers K^0 , as long as the share of the informed drivers is below $q \approx 63\%$ (4.4.4). In the case of fixed confidence $\Gamma = 1$, the informed drivers K^I do come off better than the non-informed drivers K^0 if the share of the informed drivers is below $q = 70\%$ (4.4.5).

$$SI^{q,\gamma^1} > SO^{q,\gamma^1} \quad \text{if } q < 63\% \quad (4.4.4)$$

$$SI^{q,\Gamma^1} > SO^{q,\Gamma^1} \quad \text{if } q < 70\% \quad (4.4.5)$$

Table 4.12: MDTs [%] according to experiential and fixed confidence 1

share q [%]	Partitions Ω^{q,γ^1} and Ω^{q,Γ^1} of driver classes K^0 and $K^{I,\varphi}$					
	SI^{q,γ^1}	SI^{q,Γ^1}	SO^{q,γ^1}	SO^{q,Γ^1}	S^{q,γ^1}	S^{q,Γ^1}
10	64	70	23	25	27	30
30	68	81	49	70	55	73
50	65	84	54	83	59	84
70	52	84	58	84	54	84
90	37	82	53	83	39	82

From a share $q = 50\%$ and more of informed drivers K^I , the normative behavior of class K^{I,Γ^1} with the highest time saving S^{q,Γ^1} of more than 80 percent as compared to the norm time M^0 , yields a state of welfare for all drivers. For all shares q , the time saving S^{q,γ^1} is below the time saving S^{q,Γ^1} (4.4.6).

$$S^{q,\gamma^1} < S^{q,\Gamma^1} \quad \text{if } q > 0\% \quad (4.4.6)$$

The case $\Gamma = 1$, i.e. the normative route choice of the informed drivers $K^{I,\Gamma 1}$, is beneficial even for the non-informed drivers K^0 . The MDT of the partition $\Omega^{q,\Gamma 1}$ are for the class K^0 : $M0^{10,\Gamma 1} = 139$, $M0^{30,\Gamma 1} = 55$, $M0^{50,\Gamma 1} = 32$, $M0^{70,\Gamma 1} = 30$, $M0^{90,\Gamma 1} = 32$, as compared to the MDT of the entire population of drivers Ω : $M^{10,\Gamma 1} = 130$, $M^{30,\Gamma 1} = 49$, $M^{50,\Gamma 1} = 31$, $M^{70,\Gamma 1} = 30$, $M^{90,\Gamma 1} = 33$ (Table 4.11).

For the Zurich traffic scenario the best conditions are obtained when the share of informed drivers K^I is about 70 percent and all informed drivers strictly follow their traffic information. In the case of the normative route choice $\Gamma = 1$, the mean daily travel times are exactly $MI^{70,\Gamma 1} = MO^{70,\Gamma 1} = M^{70,\Gamma 1} = M^U = 29.6$ minutes. For all drivers together they are about three minutes above the theoretical lowest mark M^S , which is the experimental boundary for the optimum of the scenario (see Section 4.2, *Values*). The mean saving is high as compared to the benchmark M^0 (the $\tau(0)$ assignment): $M^0 - M^{70,\Gamma 1} = 186.1 - 29.6 = 156.5$ minutes. This corresponds to a relative time saving of 84 percent per day for all drivers (Table 4.12).

The results lead to the conclusion that the degrees of freedom of the drivers are beneficial neither for the system nor for the individual driver. In the long run, all fare better when the traffic information is consistently used (4.4.7).

$$SI^{q,\Gamma 1} \cong SO^{q,\Gamma 1} \cong S^{q,\Gamma 1} > 80\% \quad \text{if } q > 40\% \quad (4.4.7)$$

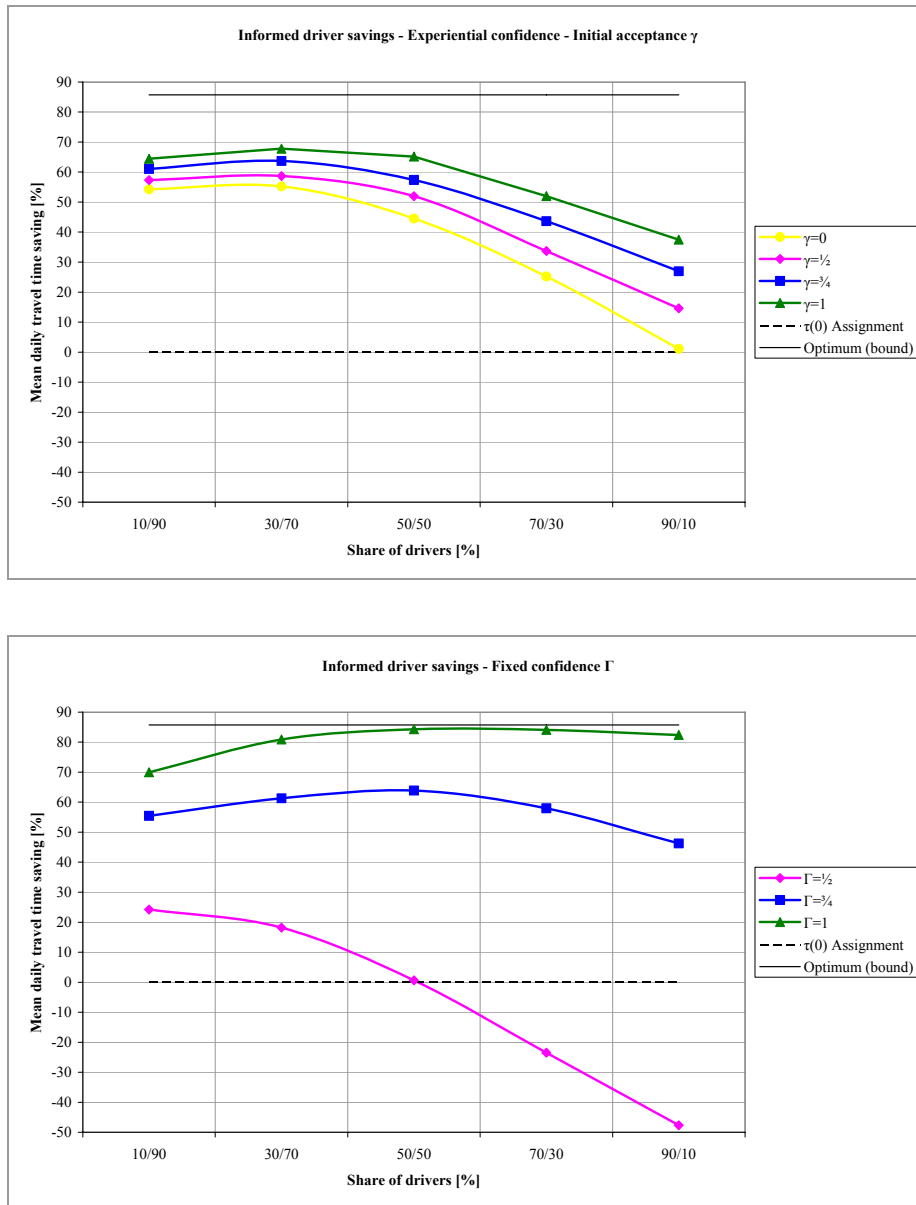
Specific saving aspects

In what follows, the simulations of the partitions $\Omega^{q,\varphi}$ will be considered from the specific point of view of the class K^0 , the class K^I and the population of drivers Ω and schematically compared based on the savings curves for S , SO and SI (Figures 4.11 to 4.16). The absolute travel times M , MO , MI of the partitions $\Omega^{q,\varphi}$ are mapped in the Figures presented in Appendix V.

In the center of the further analysis will be two aspects: (1) The conditions for achieving the saving for the informed drivers K^I , as well as for the non-informed drivers K^0 , respectively; (2) The savings of the partitions $\Omega^{q,3/4}$ of the characteristic confidence factor $3/4$ (see Acceptance analysis, below).

The comparison of the MDTS of different shares q of informed drivers K^I in the case of experiential confidence at initial values $\gamma \in \{0, \frac{1}{2}, \frac{3}{4}, 1\}$, and different degrees of confidence $\Gamma \in \{\frac{1}{2}, \frac{3}{4}, 1\}$, respectively, is depicted in Figure 4.11 from the point of view of the effect on class K^I (*informed drivers*).

Figure 4.11: MDTS of K^I according to their experiential or fixed confidence

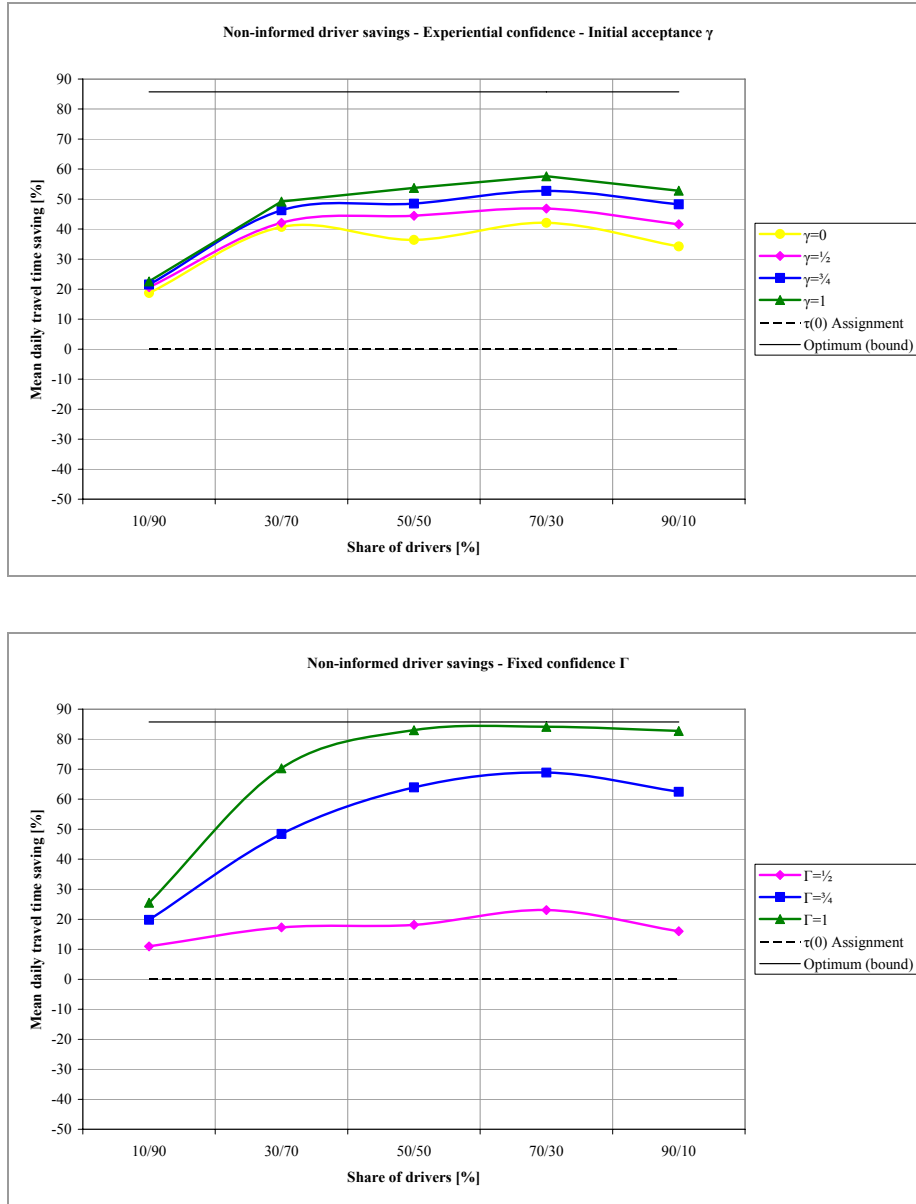


The MDTS of K^I in the case of experiential confidence with an initial value of $\frac{3}{4}$ corresponds roughly to the saving in the case of fixed confidence $\Gamma = \frac{3}{4}$ (4.4.8).

$$SI^{q, \gamma \frac{3}{4}} \approx SI^{q, \Gamma \frac{3}{4}} \quad \text{if } 10\% \leq q \leq 50\% \quad (4.4.8)$$

The comparison of the MDTS of different shares q of informed drivers K^I in the case of experiential confidence at initial values $\gamma \in \{0, \frac{1}{2}, \frac{3}{4}, 1\}$, and different degrees of confidence $\Gamma \in \{\frac{1}{2}, \frac{3}{4}, 1\}$, respectively, is depicted in Figure 4.12 from the point of view of the effect on class K^0 (*non-informed drivers*).

Figure 4.12: MDTS of K^0 according to experiential or fixed confidence of K^I drivers

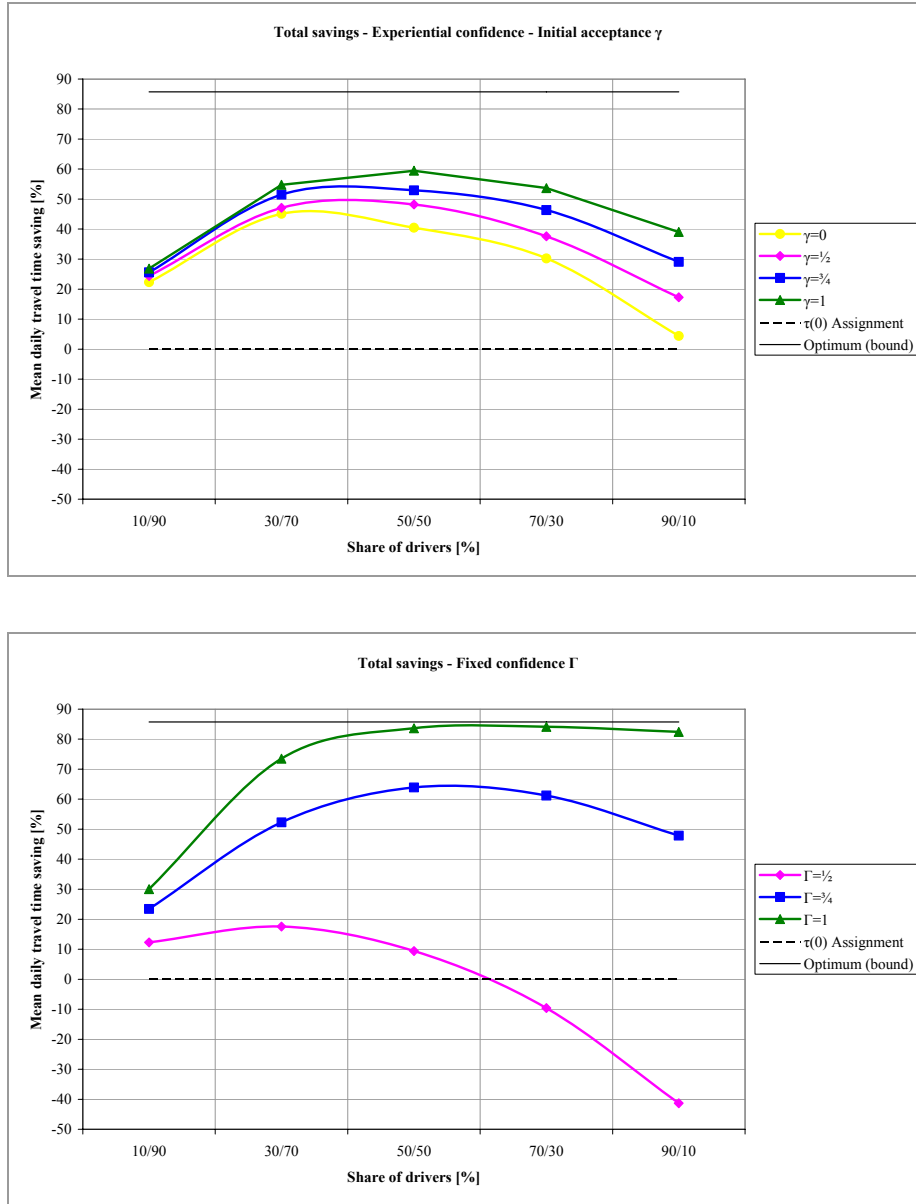


For shares $q > 30$, the MDTS in the case of experiential confidence at an initial value of $\frac{3}{4}$ are below the time savings in the case of fixed confidence $\Gamma = \frac{3}{4}$ (4.4.9).

$$S0^{q,\gamma^{\frac{3}{4}}} \leq S0^{q,\Gamma^{\frac{3}{4}}} \quad \text{if } q > 30\% \quad (4.4.9)$$

The comparison of the MDTS of different shares q of informed drivers K^I in the case of experiential confidence at initial values $\gamma \in \{0, \frac{1}{2}, \frac{3}{4}, 1\}$, and different degrees of confidence $\Gamma \in \{\frac{1}{2}, \frac{3}{4}, 1\}$, respectively, is depicted in Figure 4.13 from the point of view of the population of drivers Ω by way of total mean time saving.

Figure 4.13: MDTS of Ω according to experiential or fixed confidence of K^I drivers

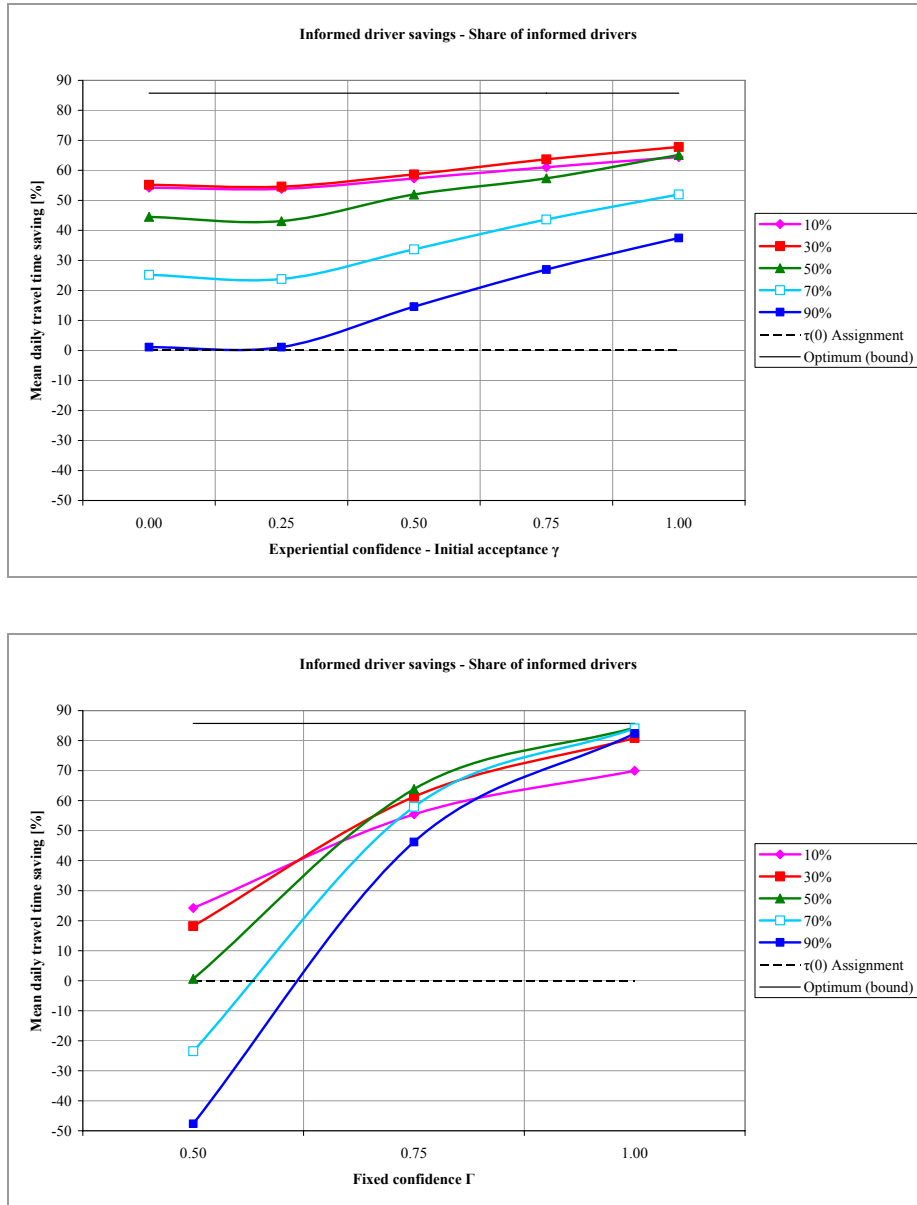


For $q > 30$, the MDTS related to experiential confidence with an initial value of $\frac{3}{4}$ are below the time savings in the case of firm confidence $\Gamma = \frac{3}{4}$ (4.4.10).

$$S^{q, \gamma^{\frac{3}{4}}} \leq S^{q, \Gamma^{\frac{3}{4}}} \quad \text{if } q > 30\% \quad (4.4.10)$$

The comparison between the MDTs in the case of experiential confidence at initial values $\gamma \in \{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\}$, and different degrees of confidence $\Gamma \in \{\frac{1}{2}, \frac{3}{4}, 1\}$, respectively, is depicted in Figure 4.14 for different shares q of informed drivers K^I from the point of view of the effect on class K^I .

Figure 4.14: MDTs of K^I according to different shares of K^I drivers

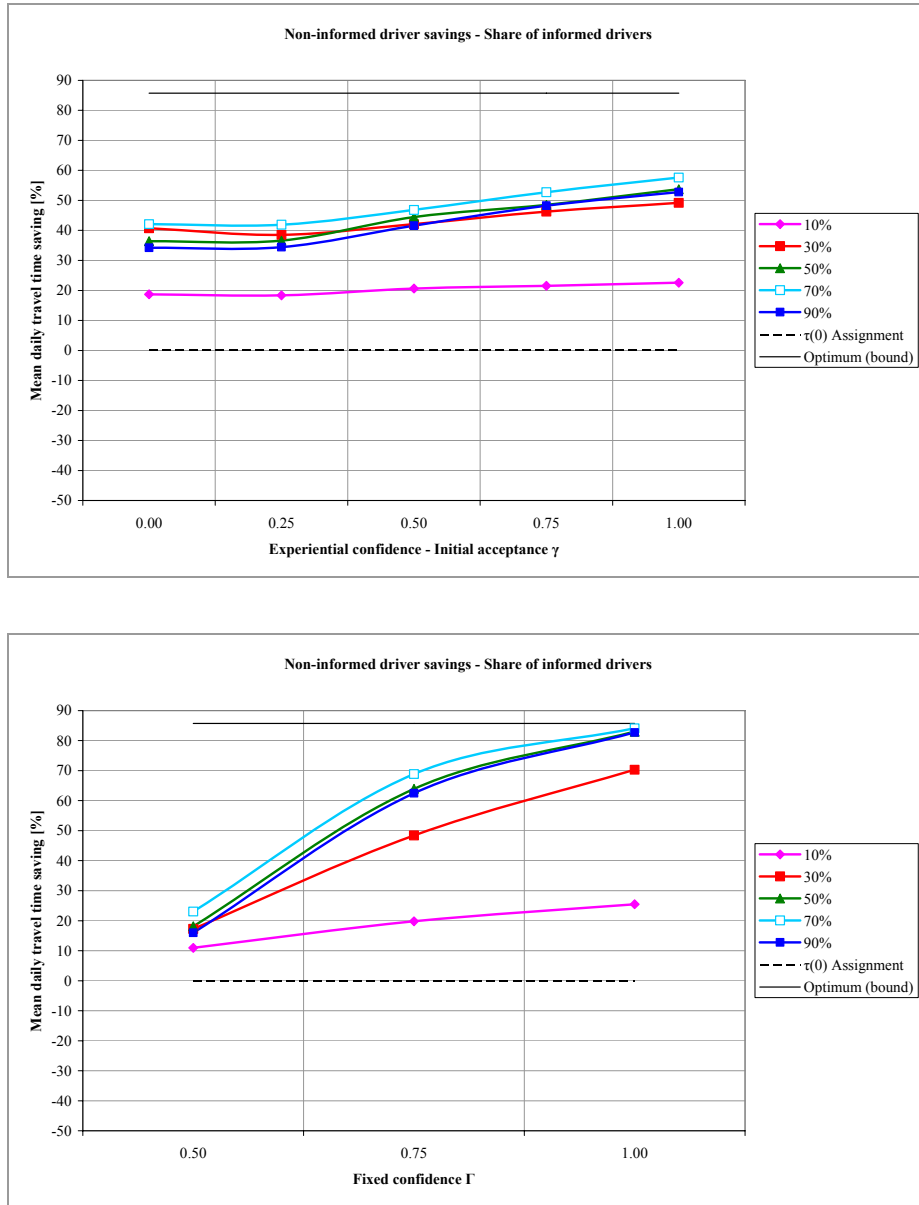


For all shares q of class K^I drivers, the MDTs in the case of experiential confidence are below the time savings in the case of fixed confidence degrees $\Gamma \geq \frac{3}{4}$ (4.4.11).

$$SI^{q,\gamma} \leq SI^{q,\Gamma} \quad \text{if } \Gamma \geq \frac{3}{4} \quad (4.4.11)$$

The comparison between the MDTs in the case of experiential confidence at initial values $\gamma \in \{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\}$, and different degrees of confidence $\Gamma \in \{\frac{1}{2}, \frac{3}{4}, 1\}$, respectively, is depicted in Figure 4.15 for different shares q of informed drivers K^I from the point of view of the effect on class K^0 .

Figure 4.15: MDTs of K^0 according to different shares of K^I drivers

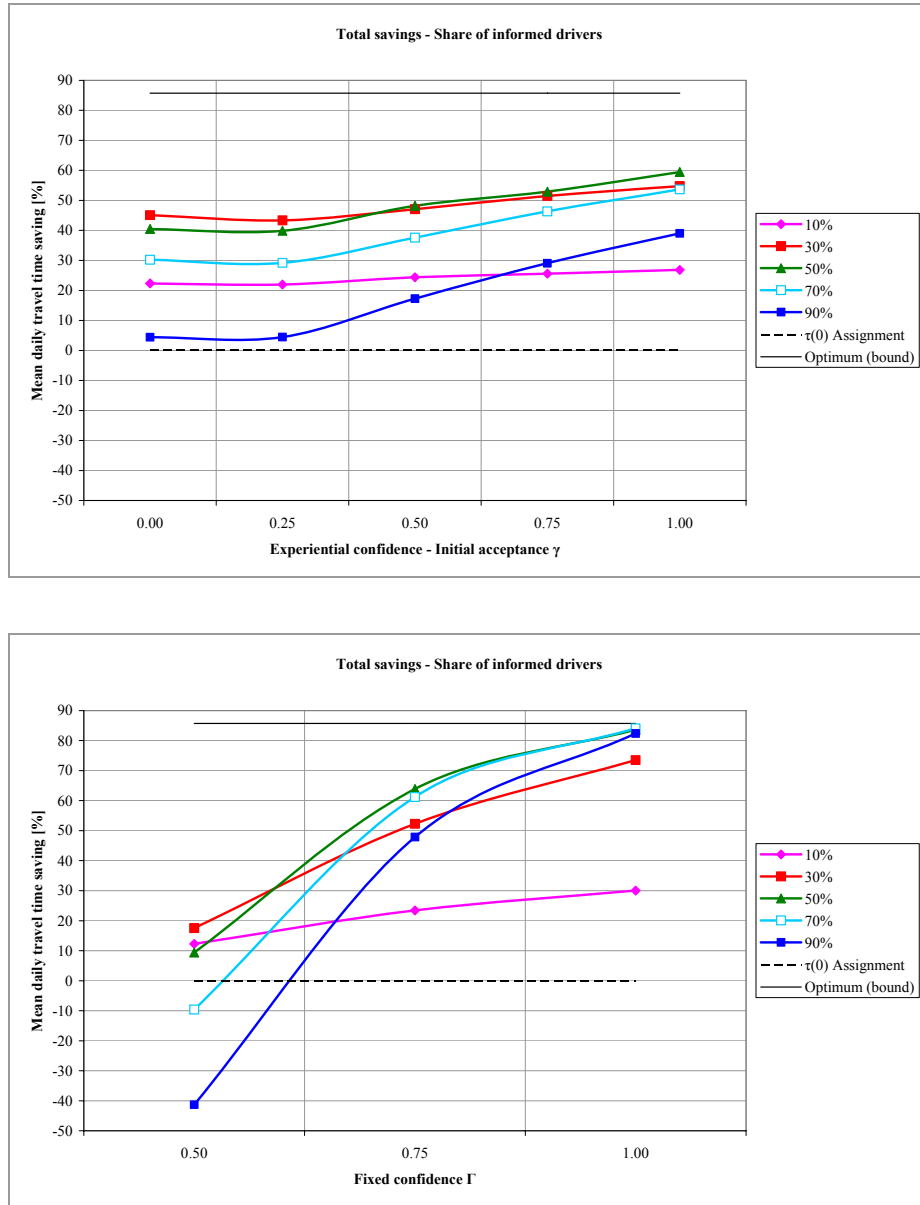


For all shares q of class K^I drivers, the MDTs in the case of experiential confidence are below the time saving in the case of fixed confidence degrees $\Gamma \geq \frac{3}{4}$ (4.4.12).

$$S0^{q,\gamma} \leq S0^{q,\Gamma} \quad \text{if } \Gamma \geq \frac{3}{4} \quad (4.4.12)$$

The comparison between the MDTS in the case of experiential confidence at initial values $\gamma \in \{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\}$, and different degrees of confidence $\Gamma \in \{\frac{1}{2}, \frac{3}{4}, 1\}$, respectively, is depicted in Figure 4.16 for different shares q of informed drivers K^I from the point of view of all drivers Ω by way of total mean time saving.

Figure 4.16: MDTS of Ω related to different shares of K^I drivers



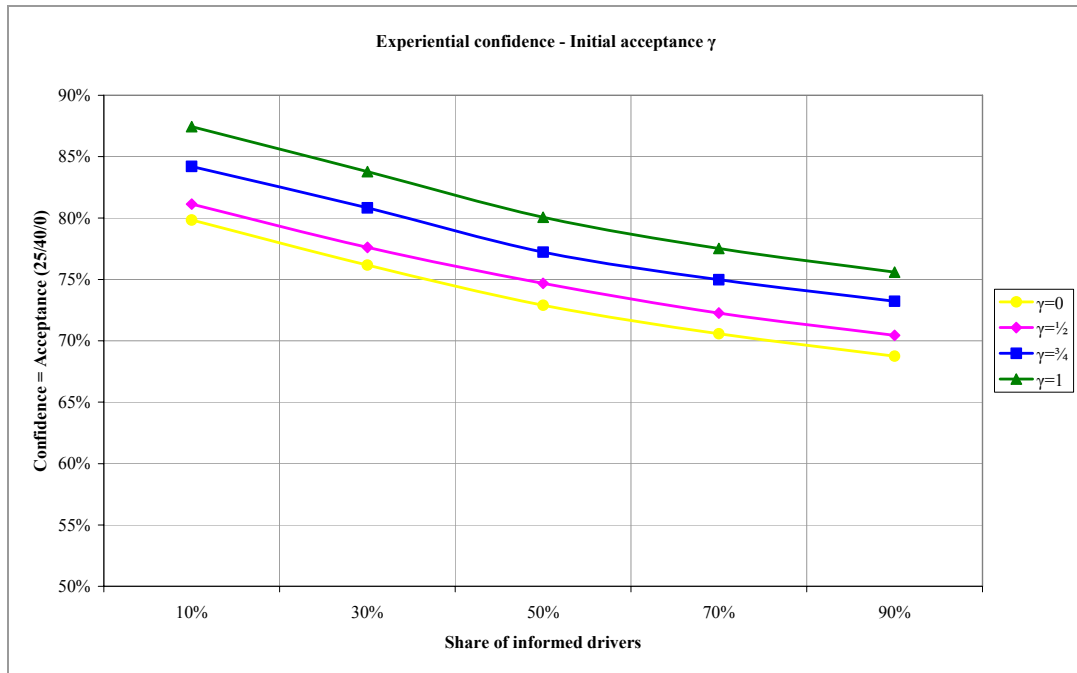
For all shares q of informed K^I drivers, the MDTS related to experimental confidence lies below the time saving for fixed confidence for degrees $\Gamma \geq \frac{3}{4}$ (4.4.13).

$$S^{q,\gamma} \leq S^{q,\Gamma} \quad \text{if } \Gamma \geq \frac{3}{4} \quad (4.4.13)$$

Acceptance analysis

The simulation of the spatial learning model (see Section 3.2) of class K^I ascertains the probability of acceptance γ of the traffic information in the case of experiential confidence at different initial values $\gamma \in \{0, \frac{1}{2}, \frac{3}{4}, 1\}$, and in the case of fixed confidence $\Gamma \in \{0, \frac{1}{2}, \frac{3}{4}, 1\}$. As in the case of all other experiments, it is based on the tolerance thresholds $B^0 = [B^+ = 25\%, B^- = 40\%, B = 0\%]$.

Figure 4.17: Percentage experiential confidence γ related to different initial values



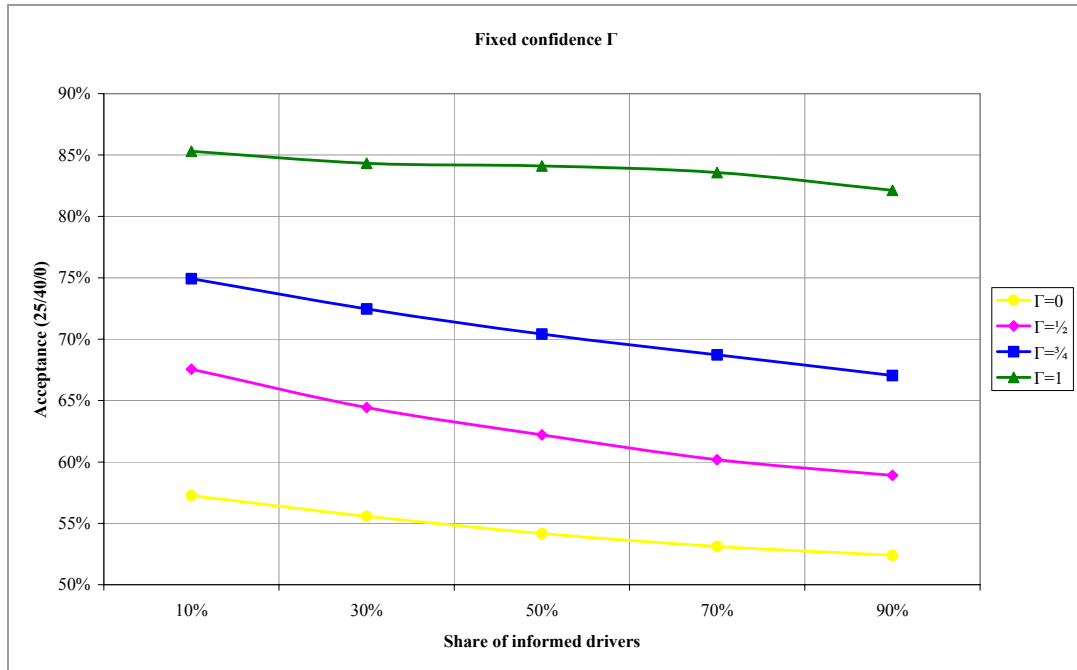
The comparison between the probability of acceptance γ in the case of experiential confidence (Figure 4.17 and Table 4.13) and in the case of fixed confidence (Figure 4.18 and Table 4.14) shows a characteristic property: If the share of informed drivers increases, the probability of accepting traffic information decreases.

Table 4.13: Probability of acceptance γ according to experiential confidence

Initial confidence	Share of informed drivers				
	10%	30%	50%	70%	90%
0	0.80	0.76	0.73	0.71	0.69
$\frac{1}{2}$	0.81	0.78	0.75	0.72	0.70
$\frac{3}{4}$	0.84	0.81	0.77	0.75	0.73
1	0.87	0.84	0.80	0.78	0.76

The optical impression of the acceptance curves (see Figures 4.17 and 4.18) is numerically confirmed by the correlation coefficient ρ (Table 4.15): For $\gamma = \frac{1}{2}$ it is $\rho \approx -0.99$, for $\gamma = 1$ it is $\rho \approx -0.99$, for $\Gamma = \frac{1}{2}$ it is $\rho \approx -0.99$, and for $\Gamma = 1$ it is $\rho \approx -0.96$.

Figure 4.18: Percentage acceptance γ according to a fixed confidence level Γ



The negative correlation of the acceptance probability γ with the growing share of informed drivers K^I can be explained by the mean travel times positively correlating with the share of informed drivers (Table 4.16): For $\gamma = \frac{1}{2}$, $\rho \approx 0.93$, for $\gamma = 1$, $\rho \approx 0.87$, and for $\Gamma = \frac{1}{2}$, $\rho \approx 0.98$.

Table 4.14: Probability of acceptance γ according to fixed confidence levels

Confidence Γ	Share of informed drivers				
	10%	30%	50%	70%	90%
0	0.57	0.56	0.54	0.53	0.52
$\frac{1}{2}$	0.68	0.64	0.62	0.60	0.59
$\frac{3}{4}$	0.75	0.72	0.70	0.69	0.67
1	0.85	0.84	0.84	0.84	0.82

Only in the case of $\Gamma = 1$, which, as their share $q \leq 50\%$ increases, enables the informed drivers K^I to achieve ever shorter travel times ($MI^{10,1} = 56$, $MI^{30,1} = 36$, $MI^{50,1} = 29$, $MI^{70,1} = 30$, $MI^{90,1} = 33$) results a negative correlation ($\rho \approx -0.74$) so that

the acceptance probability γ barely decreases as the share q of informed drivers K^I increases (cf. Figure 4.17 with Figure 4.18 and Table 4.13 with Table 4.14).

Table 4.15: Correlation of acceptance with growing share of K^I drivers

Correlation	Experiential confidence γ and fixed confidence Γ			
	$\gamma = \frac{1}{2}$	$\gamma = 1$	$\Gamma = \frac{1}{2}$	$\Gamma = 1$
ρ	-0.99	-0.99	-0.99	-0.96

Table 4.16: Correlation of mean daily travel time with growing share of K^I drivers

Correlation	Experiential confidence γ and fixed confidence Γ			
	$\gamma = \frac{1}{2}$	$\gamma = 1$	$\Gamma = \frac{1}{2}$	$\Gamma = 1$
ρ	0.93	0.87	0.98	-0.74

The sensitivity of the driver corresponds to the chance α of achieving the travel time on the recommended route within his tolerance range (see Section 3.1, Figure 3.1, as well as Section 3.2, Figures 3.7, 3.8 and 3.9). With the tolerance thresholds $B^0 = [B^+ = 25\%, B^- = 40\%, B = 0\%]$ (see Section 4.2) chosen here, the chance α lies between 80 and 90 percent for the partitions $\Omega^{q,f}$ with $q \leq 50$ and $f \geq \frac{1}{2}$. If the driver decides against the recommendation of the navigation system, the chance β that the achieved travel time on the alternative route meets the driver's expectations lies between 29 and 38 percent. According to the total probability (3.2.1), the confidence γ lies between 75 and 87 percent (4.4.14).

$$\left. \begin{array}{l} 0.80 \leq \alpha \leq 0.90 \\ 0.29 \leq \beta \leq 0.38 \\ 0.75 \leq \gamma \leq 0.87 \end{array} \right\} \text{ if } \Omega^{q,f}, q \leq 50, f \geq \frac{1}{2} \quad (4.4.14)$$

Table 4.17 provides an overview of the experientially determined likelihoods α and β for the partitions $\Omega^{q,f}$ in the case of an *a priori* confidence $\gamma = \frac{1}{2}$ and $\gamma = 1$. In the worst case ($\Omega^{90, \gamma/2}$), the chance α to be able to achieve the travel time on the recommended route is more than 75 percent. The learned confidence γ (probability of the information being accepted) is determined by way of the direct share α and the indirect share $1 - \beta$ according to the model of Section 3.2. The partition $\Omega^{50, \gamma/2}$ marks the ordinary mean value of the experiential confidence $\gamma = \frac{3}{4}$.

Table 4.17: Conditional likelihoods α and β of spatial learning of confidence γ (3.2)

Initial confidence	Experiential frequencies	Share of informed drivers				
		10%	30%	50%	70%	90%
$\frac{1}{2}$	α	0.87	0.84	0.80	0.78	0.76
$\frac{1}{2}$	β	0.36	0.37	0.38	0.39	0.40
$\frac{1}{2}$	γ	0.81	0.78	0.75	0.72	0.70
1	α	0.90	0.87	0.84	0.82	0.80
1	β	0.29	0.32	0.34	0.35	0.36
1	γ	0.87	0.84	0.80	0.78	0.76

Network analysis

The given demand of the Zurich traffic scenario (Section 4.1) leads in the case of the partitions Ω^{q,γ^1} and Ω^{q,Γ^1} to the values listed in Table 4.18. The mean densities at a share of q percent of informed drivers K^I are denoted by the symbols MD^{q,γ^1} and MD^{q,Γ^1} , measured in vehicles per kilometer. The mean speeds are denoted by the symbols MS^{q,γ^1} and MS^{q,Γ^1} , measured in kilometers per hour. The mean traffic flows are denoted by the symbols MF^{q,γ^1} and MF^{q,Γ^1} , measured in vehicles per hour.

Table 4.18: Network states of partitions Ω^{q,γ^1} and Ω^{q,Γ^1} at different shares q of K^I drivers

Share q [%]	Mean outcomes MD (density), MS (speed) and MF (flow)					
	MD^{q,γ^1}	MD^{q,Γ^1}	MS^{q,γ^1}	MS^{q,Γ^1}	MF^{q,γ^1}	MF^{q,Γ^1}
	[veh/km]	[veh/km]	[km/hour]	[km/hour]	[veh/hour]	[veh/hour]
0	118	118	4	4	471	471
10	105	104	6	6	631	643
30	77	56	13	22	996	1266
50	64	33	18	48	1162	1573
70	55	31	24	51	1291	1597
90	56	36	22	42	1267	1530
100	60	43	20	34	1221	1447

Without informed K^I drivers ($q = 0$), i.e. with every driver setting his route in advance and staying on what he perceives as his shortest route, sections of the Zurich metropolitan area traffic network are overloaded. The demand generates a traffic volume $MD^0 = 118$ vehicles per kilometer. The cars are crawling at $MS^0 = 4$ kilometers per hour. The performance of the network translates into a stream of $MF^0 = 471$ vehicles per hour. The mean daily travel time of all drivers amounts to $M^0 = 186$ minutes (see Section 4.2).

The above-mentioned figures serve the purpose of expressing in an easily comprehensible way the relations existing within the system. The results of the simulation of concrete scenarios, such as the given case of the Zurich metropolitan area, can vary for many reasons like, for example, the environment being differently configured or calibrated. The values (Table 4.18) relate to the following technical data: The distance between the vehicles (at a standstill) is specified to be 6.5 meters, and the drivers' reaction time 1.8 seconds. The traffic densities of the two states SUE and SO are $MD^U \approx 31$ and $MD^S \approx 26$ vehicles per kilometer; the speeds of the SUE and SO are about $MS^U \approx 51$ and $MS^S \approx 64$ kilometers per hour; the traffic flows are $MF^U \approx 1597$ and $MF^S \approx 1660$ vehicles per hour; and the mean daily travel times $M^U \approx 30$ and $M^S \approx 27$ minutes.

Here, too, a remarkable difference between descriptive and normative behavior of the drivers in choosing their routes becomes evident. It is the clearest when one-half of the drivers are informed: The average performance of the traffic network is measured by the traffic volume $MF^{50,\gamma^1} = 1162$ and $MF^{50,\Gamma^1} = 1573$, by its average density $MD^{50,\gamma^1} = 64$ and $MD^{50,\Gamma^1} = 33$, by the average speed of the cars $MS^{50,\gamma^1} = 18$ and $MS^{50,\Gamma^1} = 48$ (Table 4.18), as well as by the mean daily travel time $M^{50,\gamma^1} = 75$ and $M^{50,\Gamma^1} = 30\frac{1}{2}$ minutes (Table 4.11), and as opposed to M^0 (Table 4.12) by the mean daily travel time saving $S^{50,\gamma^1} = 59\%$ and $S^{50,\Gamma^1} = 84\%$.

Notes: (1) The estimate of the bound of the scenario's optimum M^S (called *Optimum bound* in the figures of Chapter 4 and Chapter 5) is based on the experimental value 26.6 (as described in Section 4.2, *Values*) and on the theory of traffic assignment (Section 2.3). (2) In the state of SUE (Ω^{70,Γ^1}) the mean detour of all drivers is little more than the double of the mean distance of the shortest routes which amounts to about 12 kilometers. (3) In the state of SUE (Ω^{70,Γ^1}) 30% K^0 drivers move along the shortest routes. If about 30% K^I drivers (i.e. a little less than half of the informed drivers K^I) take also the shortest routes on the load-free traffic network, the mean distance of a K^I driver amounts approximately to the triple of the mean distance of a K^0 driver. (4) Under SUE traffic condition the characteristic speed on the shortest routes is about 25 kilometers per hour, and the mean distance of the K^I drivers is about 36 kilometers at the mean speed of about 75 kilometers per hour.

Résumé

When 30 percent of the drivers in the Zurich metropolitan area are informed and complying exactly with the navigation system information, the traffic density diminishes from 118 vehicles to 56 vehicles per kilometer, and traffic speed increases from four to 22 kilometers per hour. From a share of informed drivers of 50 percent upward, traffic density declines to just above 30 vehicles per kilometer, and a driver reaches his destination at an average speed of little more than 50 kilometers per hour. The better distribution of the traffic doubles the distance of all drivers and triples the distance covered by the dynamic drivers (also results from the values of Table 4.18, and Relation 2.1.1); and yet it amounts to an 84 percent time saving for all drivers. – However, if more than 70 percent of the drivers are dynamically informed, the traffic situation deteriorates again, depending on the level of compliance with the information, to at worst 60 vehicles per kilometer with traffic moving at a mean speed of 20 kilometers per hour.

The deterioration of the traffic situation at a high share of informed drivers ($q > 70$) demands to be looked into. Further analyses are required (see Section 5.3) to prevent this undesirable effect.



Notes: (1) The mentioned traffic data is self-consistent and serves the purpose of comprehensively expressing the relations within the system. (2) Every model of a real socio-economic system is inaccurate, on the one hand, due to irregularly occurring effects (stochastic effects) and, on the other hand, because not all system-related influences can be taken into account. The results of the simulation of concrete scenarios can also vary because they are differently configured and calibrated. (3) The purpose of the model is to demonstrate the interaction between the microscopic level (that of the driver's decision) and the macroscopic level (the state of the traffic). (4) The Zurich szenario marks a mean traffic flow at 96 percent of capacity, according to the ratio of MF^U and MF^S .

SUMMARY AND OUTLOOK

5.1 Conclusions

Methodology review

The driver decision model is the core of the microscopic simulation (see Section 1.5). The criterion for the route choice corresponds to the economic principle of action, that of maximizing utility. Three approaches are being discussed: expected utility, value-risk utility, and random utility. Best suited for the simulation with MATSim is random utility maximization (see Section 2.4). For calculating the probability of a route being chosen, three variants qualify: the probit or the logit model (on the basis of Gauss or Gumbel distributed additive residuals) and the Kirchoff model (based on Weibull distributed multiplicative residuals). Easy, intuitive steps lead to Kirchoff's rule and to power utility. A comparative analysis using the multinomial logit model speaks in favor of the Kirchoff model (see Section 3.1).

The simplest form of power utility is combined with a stochastic component that expresses the driver's confidence in the quality of traffic information. This confidence forms as a result of statistical learning processes on the basis of Bernoulli experiments (see Section 3.1). The route with the shortest travel time is weighted by a factor that corresponds to the degree of confidence in the information (see Section 3.2). The effect of the traffic information on the mean daily travel time is determined by way of knowledge levels and behavior classes (see Sections 3.3 and 3.4, as well as Chapter 4).

The microscopic part of the traffic simulation takes place according to the following concept. In the course of every experiment, the population of the drivers Ω included in the scenario is divided into two classes $K^0 \cup K^I = \Omega$ (see Section 3.4):

1. Class K^0 with static knowledge and deterministic behavior
2. Class K^I with dynamic knowledge and stochastic behavior.

A class K^I driver decides with the probability π based on its random utility (see Section 3.1) in favor of a route. The random utility is calculated on the basis of the power utility (u) that takes into account three properties:

1. The travel time (τ) on the route
2. The confidence (γ or Γ) in the information
3. The risk attitude ($u'' \div u'$) of the class K^I drivers.

At each traffic node a class K^I driver goes through a process consisting of the following four steps (see Section 3.2).

Before a node:

1. Information about the travel times (τ) with suggestion of the best routes (r)
2. Choice of the route (r^*).

After a node:

3. Observation of the deviation ($c - \tau_e$) from the expected travel time (τ_e)
4. Valuation of the deviation ($|c - \tau_e| \leq \tau_e w$) based on the tolerance threshold (w).

The effect of the traffic information is measured in terms of the mean daily travel times M (for the entire population of drivers Ω), M^0 (for the class K^0 drivers) and M^I (for the class K^I drivers) and is compared to the mean daily travel time M^0 . M^0 is the value of the $\tau(0)$ assignment, which is yielded by the simulation of the partition Ω^0 ($K^0 = \Omega$, $K^I = \emptyset$); i.e. every driver sticks to the time-wise shortest route of the load-free traffic network. Taking the mean daily travel time M^0 as the benchmark is reasonable; the reasons for doing so are mentioned in Section 4.2. The analysis for the time savings S (for Ω), S^0 (for K^0), and S^I (for K^I) as compared to M^0 , as well as the analysis of the traffic conditions MD (density), MS (speed) and MF (flow) underline the potential of traffic information.

The various partitions are symbolized by means of $\Omega^{q,\varphi} = K^0 \cup K^{I,\varphi}$, where q is the percentage share of informed drivers K^I , and φ the 1-complement of the confidence factor γ or Γ in the context of the route choice π (see Section 3.1). $\Omega^{10,\Gamma/2}$, for

example, stands for $q = 10\%$ $K^{I,\Gamma^{1/2}}$ drivers with a fixed confidence factor $\Gamma = 1/2$, and 90% non-informed drivers K^0 , or $\Omega^{70,\gamma^{3/4}}$ for $q = 70\%$ informed drivers $K^{I,\gamma^{3/4}}$ with experiential confidence γ in the case of an *a priori* confidence $\gamma = 3/4$, and 30% non-informed drivers K^0 .

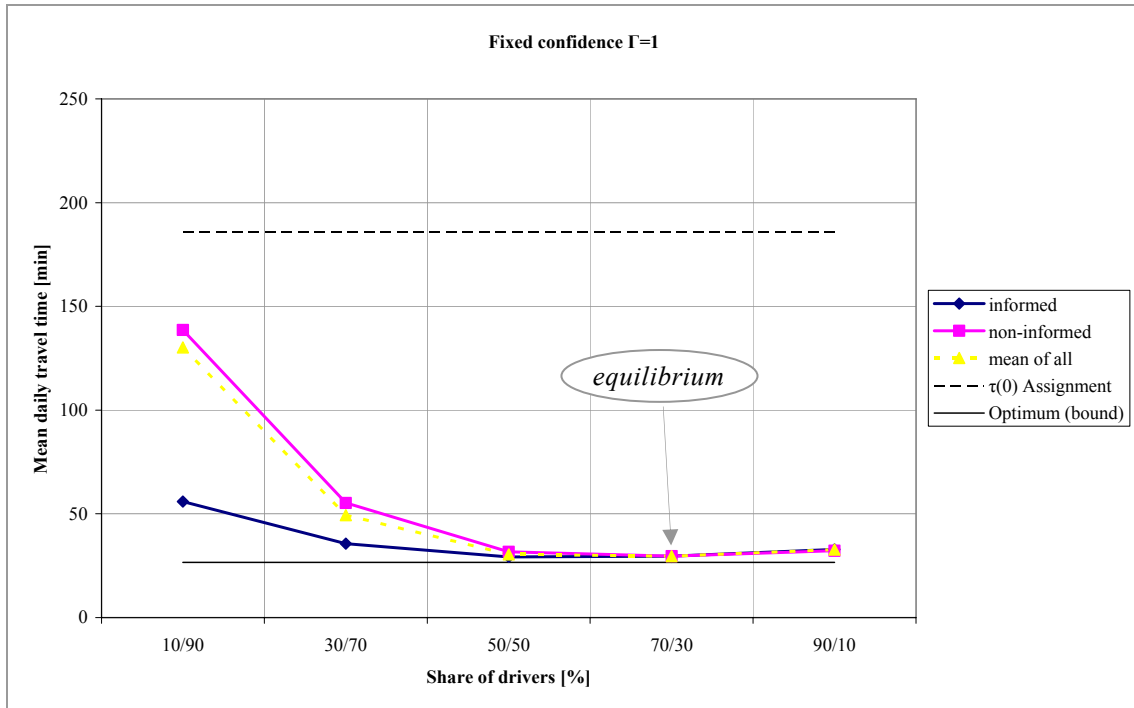
Core results

The simulation of the Zurich scenario (see Section 4.1) shows aside from the results of the tolerance analysis (see Section 4.2), when mean traffic flow at SUE is at 96 percent of capacity (see Section 4.4, *Network analysis*), essentially the following results:

1. The benchmark amounts to $M^0 = 186$ minutes of mean daily travel time (MDT) in the basis partition Ω^0 .
2. The stochastic user equilibrium lies at $M^U = 29.6$ MDT. (It is achieved by the partition $\Omega^{70,\Gamma}$, see item 6.)
3. The lower bound of the optimum lies at $M^S = 26.6$ MDT (achieved for Ω^0 in the load-free traffic network, see Section 4.2, *Values*). The bound M^S lies about three minutes below the stochastic user equilibrium M^U .
4. Of particular interest are the partitions $\Omega^{q,\varphi}$ that reach the benchmark M^0 ; their saving for class K^I , on average, is about 0. M^0 is achieved by the characteristic partition $\Omega^{50,\Gamma^{1/2}}$, i.e. with one-half of the non-informed drivers K^0 and informed drivers $K^{I,\Gamma^{1/2}}$ with fixed confidence factor $\Gamma = 1/2$, $MI^{50,\Gamma^{1/2}} = 185$. Likewise, the travel time for K^I is found to be $MI^{90,\gamma^0} = 186$ based on Ω^{90,γ^0} , i.e. with 90 percent informed drivers K^{I,γ^0} subject to the *a priori* confidence $\gamma < 1/4$. And, finally, there is still $\Omega^{100,\gamma^{1/2}}$ leading to $MI^{100,\gamma^{1/2}} = 184$, i.e. all drivers are informed ($K^I = \Omega$, $K^0 = \emptyset$) and behave according to their experiential confidence γ , which *a priori* is $1/2$.
5. The most important trend results from the partitions Ω^{q,Γ^f} (see the figures in Appendix V): As the class K^I drivers' willingness to follow the traffic information increases ($\Gamma \rightarrow 1$), the mean travel times decrease for all drivers ($M \rightarrow M^S$), and for both classes of drivers ($M^0 \rightarrow M^S$, $MI \rightarrow M^S$) as well.

6. With 70 percent of the drivers being informed and re-planning their route according to current traffic conditions, and 30 percent of the drivers remaining on their statically shortest route, an equilibrium for both classes close to the optimum is achieved: $MI^{70,\Gamma^1} = MO^{70,\Gamma^1} = M^{70,\Gamma^1} < 30$. At this relation (Ω^{70,Γ^1}), the traffic network is least burdened by the total demand, and all drivers equally benefit (Figures 5.1 and 5.2).

Figure 5.1: SUE with 70 percent informed drivers complying absolutely



7. The informed class K^I drivers achieve under Ω^{50,Γ^1} with $MI^{50,\Gamma^1} = 29$ a result which (based on the quality of information available) guarantees the highest saving (subject to the condition that one-half of all drivers have available current traffic information and absolutely follow the navigation system's instructions: $\Gamma = 1$).

8. The discipline of the informed drivers K^I strongly benefits the non-informed drivers K^0 (even though they do not pay any price for this) with $MO^{50,\Gamma^1} = 32$ (Figure 5.1). The non-informed drivers will always benefit from the informed drivers, especially when the levels of confidence are $\Gamma > \frac{1}{2}$ and the shares of informed drivers are between 30 percent and 70 percent (Table 5.1). The reason is that the K^0 drivers have at their disposal a static knowledge that is optimal in a

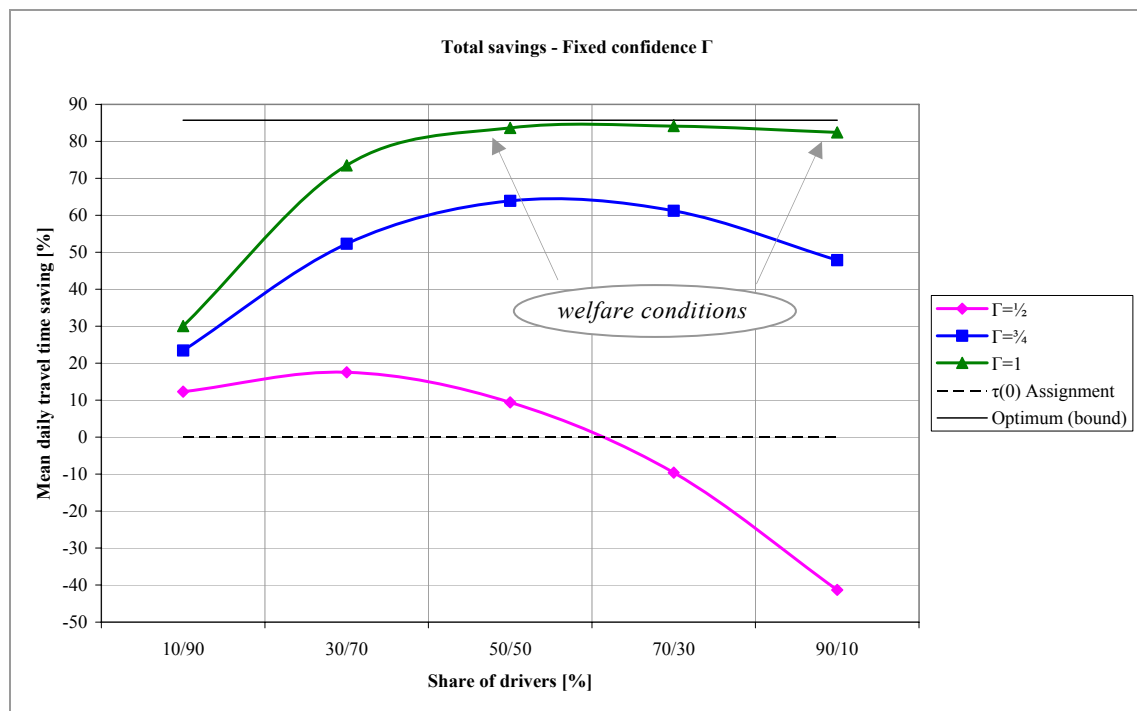
load-free traffic network (because it cannot be further improved on) and the K^I drivers clear the roads for them.

Table 5.1: MDTS $S0$ [%] of K^0 drivers according to fixed confidence $\Omega^{q,\Gamma}$

Confidence Γ	Share q of informed drivers				
	10%	30%	50%	70%	90%
$\frac{1}{2}$	11	17	18	23	16
$\frac{3}{4}$	20	48	64	69	62
1	25	70	83	84	83

9. As the share of informed drivers K^I rises, their willingness to take their clue from traffic information will decrease. The correlation coefficients lie close to -1 (see Section 4.4). The cause for this is that as the share of informed drivers rises, the advantages resulting for the K^I drivers become smaller, the travel times grow and deviations from the expected travel time become more frequent, thus causing a downward spiral of confidence in the traffic information (see Figure 4.17).

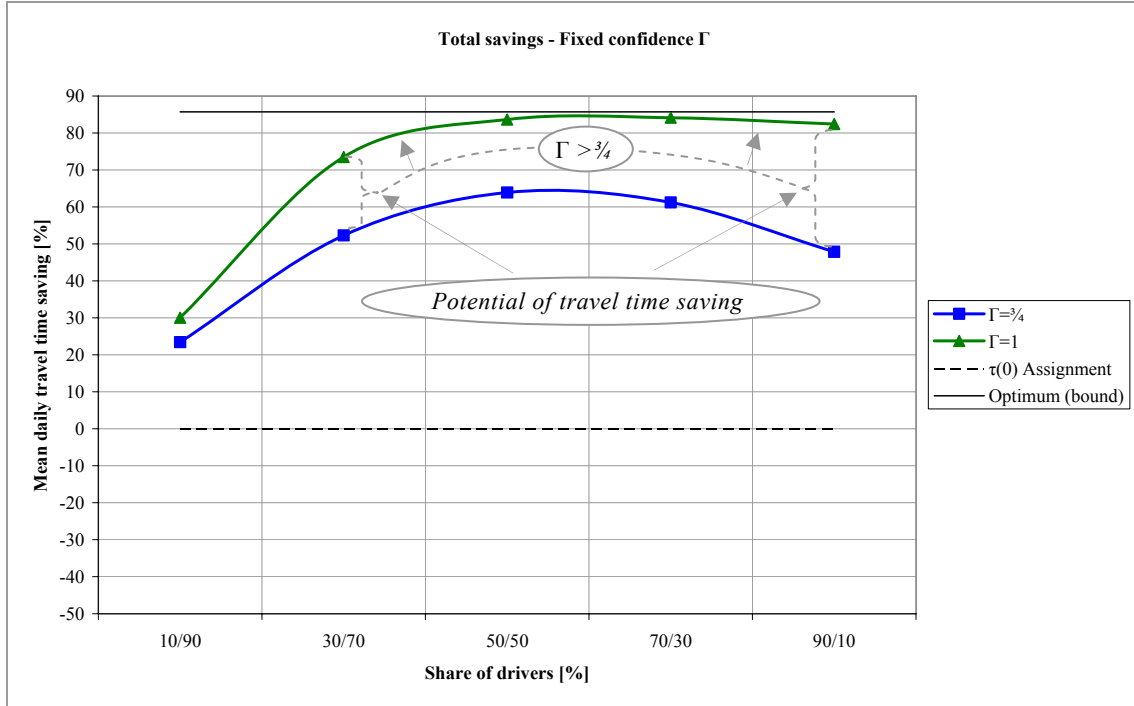
Figure 5.2: MDTS of all drivers Ω at state of welfare with absolute compliance



10. The welfare zone where all users (statistically) equally benefit from the traffic conditions, lies in the zone of between 40 percent and 90 percent of informed and disciplined $K^{I,\Gamma 1}$ drivers. Accordingly, the shares of non-informed drivers K^0 (who

remain on their statically shortest routes) lie between 60 percent and 10 percent (Figure 5.2).

Figure 5.3: MDTS potential $S^{q,\Gamma^1} - S^{q,\Gamma^{3/4}}$ of all drivers Ω



11. With experiential confidence at *a priori* values $\gamma \geq 1/2$, the mean acceptance rate lies in the zone from 70 percent to 80 percent (Table 4.13); the partition $\Omega^{50,\gamma^{1/2}}$ leads to the rate of $\gamma \approx 3/4$ that corresponds with a confidence rate for the normative case of $\Gamma \approx 3/4$. As compared to a 100 percent compliance ($\Gamma = 1$), a share of 30 percent or higher of informed drivers K^I yields a time saving potential of about 25 percent. The saving potential is the difference between S^{q,Γ^1} and $S^{q,\Gamma^{3/4}}$ given a share $q \geq 30\%$ of informed drivers (Figure 5.3).

Table 5.2: MDTS SI [%] of K^I drivers according to fixed confidence Ω^{q,Γ^f}

Confidence Γ	Share q of informed drivers				
	10%	30%	50%	70%	90%
$1/2$	24	18	1	-23	-48
$3/4$	55	61	64	58	46
1	70	81	84	84	82

12. Table 5.2 (as well as Figures 4.11 and 4.14) show that once the share q of informed drivers exceeds 30 percent and they behave in an undisciplined manner

($\Gamma < \frac{3}{4}$), they will hurt themselves (and the entire population of drivers, see also figures in Appendix V). The non-informed drivers will not be entirely spared, but will benefit to some degree even under such circumstances (Table 5.1).

13. The analysis of the traffic network (Section 4.4) shows, first, the difference between the descriptive and the normative behavior of the drivers: Through all percentage shares $q \in \{0, 10, 30, 50, 70, 90, 100\}$ of informed drivers K^I , the partitions Ω^{q,γ^1} and Ω^{q,Γ^1} produce the mean values for the traffic densities $MD^{q,\gamma^1} = 77$ and $MD^{q,\Gamma^1} = 60$, traffic speeds $MS^{q,\gamma^1} = 15$ and $MS^{q,\Gamma^1} = 30$, and traffic flows $MF^{q,\gamma^1} = 1005$ and $MF^{q,\Gamma^1} = 1218$. The network analysis shows, secondly, that even in the case of normative choice of the routes (Ω^{q,Γ^1}) the speed is reduced and the travel time increased when more than 70 percent of the drivers are informed. In relation to, for example, the mean speeds (Table 4.18) that means: $MS^{0,\Gamma^1} = 4$, $MS^{10,\Gamma^1} = 6$, $MS^{30,\Gamma^1} = 22$, $MS^{50,\Gamma^1} = 48$, $MS^{70,\Gamma^1} = 51$, $MS^{90,\Gamma^1} = 42$ and $MS^{100,\Gamma^1} = 34$.

Conclusion

With increasing willingness of informed drivers to follow traffic information, the mean travel times will become shorter for both the entirety of drivers and, each class considered separately, for the informed (dynamic) drivers and the non-informed (static) drivers.

If 70 percent of the drivers are informed and are re-planning their route according to current traffic information strictly, and 30 percent of the drivers remain on their statically shortest route, equilibrium between the two classes close to the optimum will be achieved. With this relation, the entire demand will burden the traffic network the least, and all drivers alike will benefit from the welfare situation (see Sections 4.4 and 5.1); i.e. the non-informed drivers will equally benefit (without deviating from their statically shortest routes) from the discipline of the informed drivers. – The non-informed drivers always benefit from the informed drivers, especially if the confidence rate of the informed drivers exceeds 75 percent and the share of the informed drivers ranges between 30 percent and 70 percent.

From the last mentioned reason follows for the analyst and traffic planner that a normative behavior is useful for the entirety of drivers and that an incentive for

normative behavior must be provided. The studies by Mandir (2012) and Zuurbier (2010) point out that full information amounts to an incentive to the driver.

Expressed in numbers (Table 5.3) that means:

The class of the non-informed drivers K^0 always benefits from the class of the informed drivers K^I , the most so when the share of informed drivers amounts to 70 percent and the least when the share of informed drivers is only 10 percent. The class K^I benefits the most when its share amounts to 30 percent and the least when its share is 90 percent or more. The entirety of the drivers benefits the most when the share of informed drivers amounts to 50 percent in case of descriptive (γ) choice of routes, and, at a significantly higher level of time saving (Figure 4.13), when the share of informed drivers amounts to 60 percent in case of normative (Γ) choice of routes. If the confidence of the drivers erodes, mean travel time will grow.

Table 5.3: Outcomes of characteristic partitions $\Omega^{q,\varphi}$

Partition	MDT [min]	MDTS [%]	[MDT = Mean Daily Travel time, MDTS = MDT savings]
Ω^0	186	0	of all drivers when $K^0=\Omega$ ($K^I=\emptyset$)
$\Omega^{50,\Gamma^{1/2}}$	185	1	of drivers K^I at 50% share $K^{I,\Gamma^{1/2}}$ of Ω
$\Omega^{100,\gamma^{1/2}}$	184	2	of all drivers when $K^I=\Omega$ ($K^0=\emptyset$)
$\Omega^{50,\gamma^{3/4}}$	88	53	of all drivers at 50% share $K^{I,\gamma^{3/4}}$ of Ω
$\Omega^{50,\gamma^{3/4}}$	96	48	of drivers K^0 at 50% share $K^{I,\gamma^{3/4}}$ of Ω
$\Omega^{50,\gamma^{3/4}}$	79	57	of drivers K^I at 50% share $K^{I,\gamma^{3/4}}$ of Ω
Ω^{70,Γ^1}	30	84	of all drivers at 70% share K^{I,Γ^1} of Ω
Ω^{70,Γ^1}	30	84	of drivers K^0 at 70% share K^{I,Γ^1} of Ω
Ω^{30,Γ^1}	29	84	of drivers K^I at 30% share K^{I,Γ^1} of Ω

Class K^I drivers in situations inferior to the partitions $\Omega^{100,\gamma^{1/2}}$, $\Omega^{50,\Gamma^{1/2}}$, and $\Omega^{90,\gamma^{<1/4}}$ will not save any time; that is, the informed drivers K^I will only achieve the norm time M^0 , if all drivers are informed ($K^I = \Omega$, $K^0 = \emptyset$), and the experiential confidence γ of the drivers is *a priori* $\gamma = 1/2$, or if 50 percent of the drivers are informed, but comply with only a level depending on $\Gamma = 1/2$, and, likewise, when 90 percent of the drivers are informed in the case of experiential confidence being at the initial values $\gamma < 1/4$ (see Figure 4.14). The entirety of the drivers Ω and the non-informed drivers K^0 will always save time as soon as there are informed drivers K^I participating in the traffic (see Figures 4.12 and 4.13). As mentioned above, this is due to non-informed drivers possessing a static knowledge that is optimal in the

load-free traffic network, and that their routes are disencumbered owing to the dynamically informed drivers. – Related thereto is the comparison between the ordinary (descriptive) and the normative choice of routes. The scenario's estimated saving potential $S^{q,\Gamma^1} - S^{q,\Gamma^{3/4}}$ of about 25 percent consists of the difference between an ordinary compliance level subject to $\Gamma \approx 3/4$ and fully normative behavior ($\Gamma = 1$) of the informed drivers.

The analysis of the traffic network (see Section 4.4) underlines the essential findings from the study about the knowledge-oriented and behavior-oriented choice of the routes: The states of the traffic depend, firstly, on the level of compliance with the information provided, and, secondly, the share of the informed drivers, because even the normative choice of the routes cannot prevent traffic from slowing down when more than 70 percent of the drivers are informed. That finding would suggest that the state of the traffic also depends on the quality of traffic information (see Sections 5.2 and 5.3).

In summary, the simulation shows two levels for the mean saving of travel time. First, the scenario's estimated mean saving potential $S^{q,\Gamma^1} - S^{q,\Gamma^{3/4}}$ of about 25 percent (the difference of time saving between the experienced compliance level that corresponds to $\Gamma \approx 3/4$ and fully normative behavior $\Gamma = 1$); this finding lead to the conclusion that if the aim is achieving optimal use of the traffic system and letting all drivers alike share in the benefits of this achievement, traffic planners must strive for normative driving behavior. Second, the saving potential $M^U - M^S$ of about three minutes (the difference between the mean daily travel time $M^U \approx 30$ at user equilibrium between the two classes of drivers and the theoretical bound $M^S \approx 27$); it is to expect this saving gap can be closed by providing anticipatory information in the form of marginal travel time costs (see Section 5.2).

The dynamic allocation of traffic demand to the traffic network is very closely connected with the potential of traffic information. To better use the potential of the information, traffic must be understood as a cybernetic space (see Section 1.1). Just making information available is not enough. The driver must be provided with an incentive for normative behavior (see Section 5.3).

Note: The evolution from the physical to the cybernetic room already described at the beginning of this study is preceded by an interesting analogy reported by Axhausen (2006): “What is mostly missing in the current analysis is a framing, which would integrate the short- and long-term dynamics of travelers. While the industrialized world will never again see a similarly dramatic shrinking of its time-space system as it did during the last fifty years, other major changes should force travel behavior analysis to adopt fully dynamic frameworks.” Using as an example the travel-time distances between the traffic nodes in Switzerland in the years 1950 and 2000, respectively, Axhausen and Hurni (2005) show how space in terms of time has shrunk to almost one-half of the time distance within 50 years.

5.2 Discussion

Even though the information about current travel time τ provided in the simulations (Section 4.1) is incomplete in regard of marginal travel time $\Delta\tau$, i.e. the drivers do not have any anticipatory information in the form of marginal cost $\tau^* = \tau + \Delta\tau$, the mean travel times are relatively close to the optimum (in the case of absolute confidence in the information provided by the navigation system corresponding to a normative approach to dynamic route choice). Nonetheless, in the given Zurich scenario there remains a utilizable residual (MDT of three minutes, see Section 5.1) as compared to “full” information with “perfect” behavior (corresponding decision) of the drivers hypothetically.

Note: In a traffic scenario of the Munich metropolitan area, Mandir (2012) ascertained potential time savings, as against a level of information roughly corresponding to τ , of about five to eight percent (distributed throughout the day) achievable by choosing the routes with information about marginal cost τ^* (in units of time, according to formula 2.3.10 in Section 2.3).

Full information and perfect decision

A necessary condition for a perfect decision on the part of the driver is that the forecast travel time can be exactly achieved; a necessary condition for exact traffic information is that it fully takes into account the marginal loss of time caused by the driver himself while on his road link. There are two more reasons speaking in favor of informing the driver about the marginal cost on his route: the separate

treatment of systematic and of stochastic inaccuracies in the model (see Sections 1.3 and 2.1), and the economic aspect of the marginal cost in relation to the user equilibrium, the system optimum, and utility maximization (see Sections 2.2, 2.3 and 2.4). To enable the driver to make a perfect decision, any information about travel time must at least contain the marginal travel cost.

Note: The term “necessary condition” corresponds to the mathematical logic regarding the satisfiability of a statement. Because of the stochastic influences (see Sections 1.3, 2.1 and 2.4) there cannot be a “sufficient condition” for “full information” or for “perfect decision”.

As mentioned before, the marginal addition to the travel time systematically caused by the driver shall (strictly speaking) not be included in the stochastic utility, but rather in the deterministic utility. To analytically improve decision models in this respect, exact information about the time-flow relation and about the traffic load situation on the links will be required. The two necessary conditions for a perfect decision by the driver are, with respect to:

1. Knowledge

Information τ^* about the travel time on a route includes the marginal cost in terms of travel time: $\tau^* = \tau + \Delta\tau = \tau + x \cdot \tau'$.

2. Behavior

A decision $\pi(u)^*$ for a route is made on the basis of utility $u(\tau^*) = u(\tau + \Delta\tau)$.

Notes: (1) The discussion in Section 5.2 is conceived as purely pragmatic in the same way as the judgment about the reliability of the traffic information in the sense of accuracy of a forecast in Section 3.1. Detailed and specific analyses about the assessment of the quality and reliability of traffic information are described in the literature, such as in Wiltschko (2004), as well as in Tu (2008), Lyman and Bertini (2008), Viti (2006) or Van Lint (2004). (2) In general decision theory, the value of an information is discussed as a special case on the assumption that the pay-offs of the alternatives are determined in situations occurring with the same probability, i.e. with respect to all lotteries applies $L_j = (v_j(s), p(s))$ (e.g. Laux, 2012, Saliger, 2003, Hillier and Liebermann, 1997); they cannot be directly applied to the

lottery model discussed in Section 2.4 (because for each property, especially for the travel time on a link, there exists a specific probability distribution $p_j(s)$).

5.3 Further Questions

The deterioration of the traffic situation at a high share of drivers being guided by navigation system information requires clarification. Further analyses will be needed to find out, first, at or above which level of load on the road traffic network this effect occurs and, secondly, whether it can be prevented by improving the quality of information. – The hypothesis that suggests itself is that navigation guidance must be based on marginal cost, which in turn requires that the traffic densities and the time-flow-capacity curves of the road links are measured exactly, and that this information is made available in real time.

The question now is whether under real traffic conditions full information carries additional value for the driver as compared to the kind of traffic information available to him at present; i.e. as far as the travel times are concerned, whether more accurate measurements of the conditions on the roads and calculation of the marginal costs based on their time-flow-capacity curves (see Section 2.3) amount to the hoped-for step towards improvement. The results of the work by Madir (2012) indicate that the answer is Yes (see Section 5.2).

The value of the information about marginal travel time costs, as discussed in Sections 2.1 to 2.3, should be further investigated by way of empirical studies; suitable for this purpose would be the class K^M as defined in Section 3.4: Dynamic knowledge includes the current marginal cost of the travel times on the road links. Deterministic behavior means that every driver consistently uses the system-optimal route (to his personal advantage). Such normative mode of behavior does not violate Wardrop's first principle because the driver decides freely and also maximizes the additional utility $u(\Delta t)$. (The utility $u(\Delta t)$ of the time added Δt consists in maximizing the chance of actually achieving the expected travel time).

Note: Mobility can be fashioned under aspects of social or individual utility. If utility is considered a common good, the collective utility (the system resource) has priority (*welfare state*). Mobility perceived as an individual good emphasizes the

personal utility (*well-being*) of every individual driver. Both aspects are closely intertwined by the maximization of expected utility if individual utility comprises (as an incentive) the probability of actually achieving the expected time or money saving. Knowing the expected utility (the chances or risks of achieving a saving or incurring a loss) means possessing full information about the states of the traffic network and the probable change of these states within the duration of the trip and to act perfectly thanks to such a high level of information. This also corresponds to the idea underlying Greenway: to operate an anticipatory navigation system which by way of a capacity-oriented, microscopic simulation ascertains the probable traffic conditions. – As mentioned, the optimal state can persist in traffic systems if it is accomplished by way of Wardrop's first principle, i.e. when the descriptive (*well-being*) and the normative (*welfare*) approach lead to the same result and the user equilibrium corresponds to the system optimum.



Whether decision models that maximize the driver's expected utility make it possible to move real-world traffic systems in a self-regulating way toward the optimal state that fulfils in practice both of Wardrop's principles is the general question. The next step should try to realize the potential of saving mean travel time through the increase in expected utility. The driver's utility will be increased if the difference between the expected travel time τ_e and the actually needed travel time c is reduced. The risk ($c - \tau_e$) can be diminished by appropriately taking into account, in the information τ , the capacity of a route Q in relation to its load x (cf. Sections 2.1, 2.2 and 2.3). – That should be the (actual) added value of the marginal cost τ^* compared to τ .



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Military service

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Experience

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PUBLICATIONS

Books

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A p p e n d i x I

GLOSSARY

Acceptance	to act according to information with the willingness to tolerate something
Activity	the main business carried out at a location
Compliance	the obedience to a rule or request (or to do what someone wants); especially: to follow information
Confidence	the degree of belief that one can trust or rely on something that is reported; especially: to be confident that information is correct
Cybernetic	controlled by information
Diagram	a drawing or plan that uses simple lines rather than (realistic) details to explain or illustrate principle relations or the structure of a system
Discrete choice	when individuals have to select one of a finite set of alternatives
Expense	the spending of resources, mainly time, money or energy
Flow	Traffic volume (current intensity)
Gain	the outcome of an economic process measured in monetary units
Homo oeconomicus	individuals who act rationally in order to maximize personal utility or to minimize personal expense (in terms of resources measured in units of time, money or energy) subject to a given set of constraints
Individual	a person who belongs to a given homogeneous population; a person of the specified sort
Risk	the calculated uncertainty of the average (absolute or relative) deviation from the expectation value (risk = 1 - chance)
Travel costs	the travel time of a route as the sum of the expected travel times of its links
Marginal travel time costs	the travel time of a route as the sum of the expected marginal travel times of its links
Traffic Message Channel	a digital radio service which transmits traffic hold-ups

Utility a complex value of products or resources as time, money, energy a. s. o. which are weighted by individual preferences in order to select an alternative of a given set. A utility function should respect the trade-off preferences the decision maker will apply in even-swap processes between different values of the given products or resources

Utility Maximization when individuals are postulated to behave like a homo oeconomicus, i. e. the probability of choosing an option is a function that respects socio-economic characteristics and personal measures of utility

Appendix II

NOTATION

G	Directed graph $G(N, A)$ representing a specified traffic network
N	Set of nodes taken to represent the junctions of the traffic network
A	Set of arcs taken to represent the links of the traffic network
O	Set of nodes at which drivers will start their trips
D	Set of nodes at which drivers will end their trips
R_{ik}	Set of paths of the demand $d_{ik} \in O \times D$ taken to represent the routes which a class K of drivers know leading from origin i to destination k
d_{ik}	Travel demand from $i \in O$ to $k \in D$ representing the number of drivers who will travel from their origin i to their destination k
f_r	Flow on path $r \in R_{ik}$ representing the number of cars on the road per time unit
x_a	Flow on link $a = (i, k) \in A$ representing the traffic volume on the link as the number of cars per time unit
δ_{ar}	Indicates if link $a \in A$ is part of path $r \in R_{od}$ ($\delta_{ar}=1$) or not ($\delta_{ar}=0$)
t	Theoretical travel time on a route or link
c	Achieved travel time on a route or link
τ	Perceived travel time on a route or link
Δt	Marginal travel time on a route or link representing the additional travel time inflicted by a single car
t^*	Marginal travel time costs on a route or link
τ^*	Perceived marginal travel time costs on a route or link
T_a	Free flow travel time of link $a \in A$ representing the travel time on a link at which free flow conditions prevail
Q_a	Flow capacity of link $a \in A$ representing the practical limit of flow at which the travel time is (about 15%) higher than its theoretical limit at free flow travel time: $Q_a = \omega \cdot \text{theoretical limit}$, $0.85 \leq \omega \leq 1$)

- Ω Set of all drivers of the given scenario
- $\Omega^{l,\varphi}$ Partition of Ω with (disjoint) classes K^0 and $K^{l,\varphi}$
- φ Parameter representing the class K^l drivers degree of freedom or uncertainty
- γ Parameter representing the class K^l drivers experienced confidence or probability of information acceptance
- Γ Parameter representing the class K^l drivers fixed degree of confidence
- π Probability of choosing an alternative
- p Probability of occurring a specific situation (or value)
- B Parameter representing the class K^l driver's threshold of information acceptance
- K^0 Class of non-informed drivers with static network knowledge and deterministic behavior
- K^l Class of informed drivers with dynamic knowledge and stochastic behavior
- $K^{l,\varphi}$ Class of informed drivers with dynamic knowledge and stochastic behavior with degree φ
- M^0 Mean daily travel time if all drivers Ω belong to class K^0
- M^U Mean daily travel time at the state of stochastic user equilibrium between the two classes of drivers K^0 and K^l
- M^S Optimum bound of the mean daily travel time, i.e. if all drivers Ω belong to class K^0 and the capacity of all links being arbitrarily high
- $M^{q,\Gamma}$ Mean daily travel time of all drivers Ω if $q\%$ belong to class K^l complying with the traffic information subject to a fixed degree of confidence Γ
- $M^{q,\gamma}$ Mean daily travel time of all drivers Ω if $q\%$ belong to class K^l complying with the information subject to their experienced degree of confidence γ
- $M0^{q,\Gamma}$ Mean daily travel time of the non-informed drivers K^0 if $q\%$ of all drivers belong to class K^l complying subject to a fixed degree of confidence Γ
- $M0^{q,\gamma}$ Mean daily travel time of the non-informed drivers K^0 if $q\%$ of all drivers belong to class K^l complying subject to their experienced degree of confidence γ
- $MI^{q,\Gamma}$ Mean daily travel time of the informed drivers K^l if $q\%$ of all drivers belong to class K^l complying subject to a fixed degree of confidence Γ

- MI^{q,γ}** Mean daily travel time of the informed drivers K^I if $q\%$ of all drivers belong to class K^I complying subject to their experienced degree of confidence γ
- S^{q,Γ}** Mean daily travel time saving of all drivers Ω if $q\%$ belong to class K^I complying subject to a fixed degree of confidence Γ
- S^{q,γ}** Mean daily travel time saving of all drivers Ω if $q\%$ belong to class K^I complying subject to their experienced degree of confidence γ
- S0^{q,Γ}** Mean daily travel time saving of the non-informed drivers K^0 if $q\%$ of all drivers belong to class K^I complying subject to a fixed degree of confidence Γ
- S0^{q,γ}** Mean daily travel saving time of the non-informed drivers K^0 if $q\%$ of all drivers belong to class K^I complying subject to their experienced degree of confidence γ
- SI^{q,Γ}** Mean daily travel time saving of the informed drivers K^I if $q\%$ of all drivers belong to class K^I complying subject to a fixed degree of confidence Γ
- SI^{q,γ}** Mean daily travel time saving of the informed drivers K^I if $q\%$ of all drivers belong to class K^I complying subject to their experienced degree of confidence γ
- MD^{q,Γ1}** Mean traffic density at a share of $q\%$ of informed drivers K^I complying totally
- MD^{q,γ1}** Mean traffic density at a share $q\%$ of informed drivers K^I complying subject to their experienced degree of confidence γ by the initial value 1
- MF^{q,Γ1}** Mean traffic flow at a share $q\%$ of informed drivers K^I complying totally
- MF^{q,γ1}** Mean traffic flow at a share $q\%$ of informed drivers K^I complying subject to their experienced degree of confidence γ by the initial value 1
- MS^{q,Γ1}** Mean traffic speed at a share $q\%$ of informed drivers K^I complying totally
- MS^{q,γ1}** Mean traffic speed at a share $q\%$ of informed drivers K^I complying subject to their experienced degree of confidence γ by the initial value 1

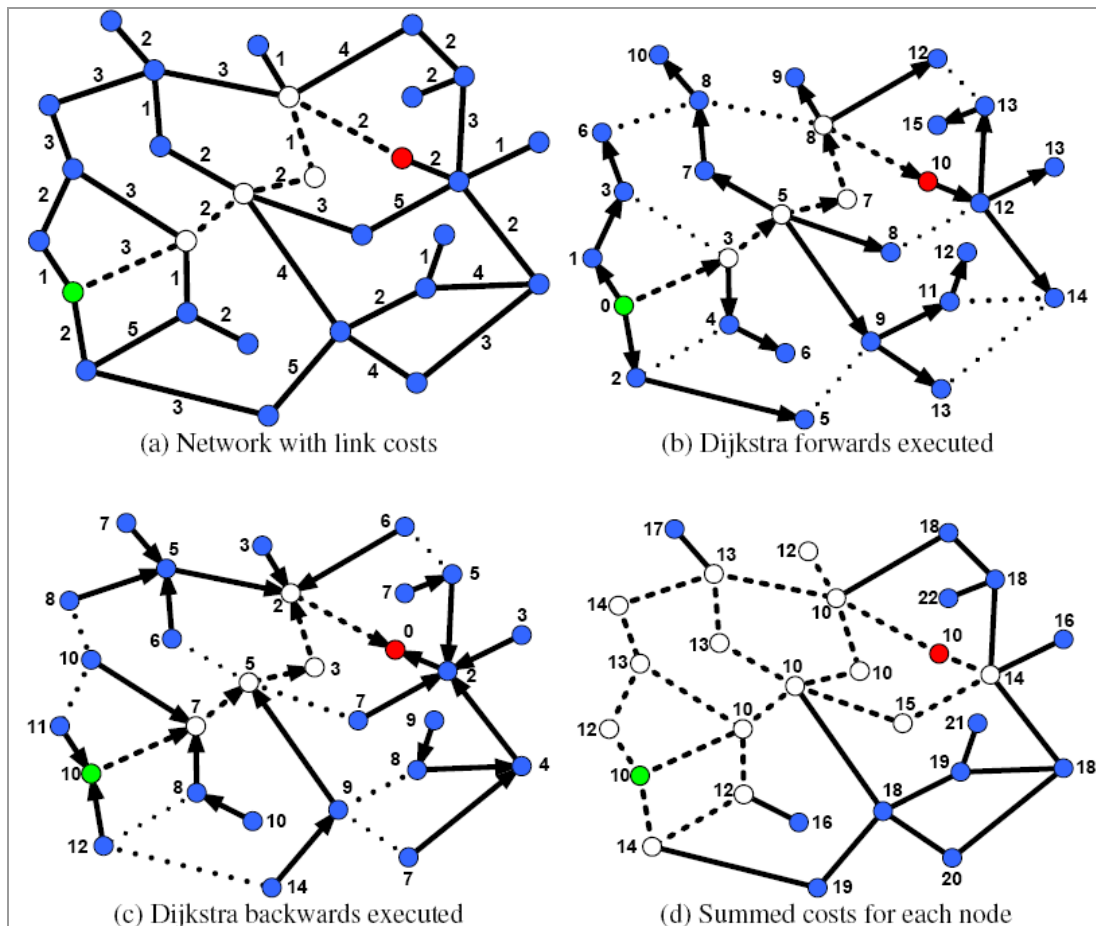
ALGORITHM

Definition of the known areas

As published in Dobler, Axhausen and Weinmann (2012):

“The following algorithm is used to define the known area of an agent. This known area is represented by a list of nodes – if start and end nodes of a link are included in this list, it is assumed that the link is also known. The single steps of the approach are depicted using a sample network as shown in Figure A.1.

Figure A.1: Illustration of the algorithm, numerical example with size factor $F=1.5$



Source: Dobler, Axhausen and Weinmann (2012)

In a first step, travel costs for each link in a network are determined. As simplification for the sample figures, it is assumed that link travel costs are equal in

both directions. Figure A.1a shows the sample network with the costs of each link. Additionally, the least cost path from an origin (green) to a destination (red) is marked (dashed lines).

Subsequently, the next steps are performed for each origin-destination pair contained in an agent's plan. The algorithm creates a set of known nodes for each of these pairs; the agents know the sum of all those nodes.

- Using the origin of the trip as starting point, the least costs to reach all other nodes in the network are calculated using the Dijkstra algorithm (Figure A.1b).
- Next, the costs to reach the trip destination from all other nodes are calculated. However, to do so, the Dijkstra algorithm has to be executed in reverse direction. Typically, costs of the outgoing links are used to calculate the least cost path between two points. When the algorithm is run in reverse mode, the incoming links are used instead. Doing so is necessary for two reasons; on one hand, the costs between two nodes may be different for the incoming and outgoing links. On the other hand, there may be nodes which are only connected in one direction (Figure A.1c).
- Subsequently, the costs calculated by those two Dijkstra executions are summed up. Those nodes, which have costs lower than the defined threshold (minimal costs to travel from origin to destination multiplied with factor F ; the example uses a size factor F of 1.5), are added to the agent's knowledge. The resulting known area is marked with white dots and dashed lines (Figure A.1d).

Using this approach requires that the following assumptions are met:

- The travel costs are not time dependent. Using a time-dependent travel cost function would lead to problems running the Dijkstra in reverse direction because the starting time of the trip would be undefined. Multiple trips between two points using different routes have variable travel times – and therefore multiple arrival times – which would have to be used as starting times for the reverse Dijkstra.
- The network is time invariant. Again, running the Dijkstra algorithm in reverse direction would cause problems if network parameters change over time, because the starting time for the algorithm would be undefined.

For the experiments described in this paper, a cost function was used based on free speed travel times, ignoring costs for driven kilometers. Additionally, the network

was considered to be static; therefore, the requirements described above are met. However, the cost function could be extended to respect additional factors like distance or size of a road. Doing so would, for example, allow creation of known areas, where side roads are included only if they are close to locations the person knows.”

Appendix IV

PROCEDURE

Probabilistic route choice – Leave link replanning

PROBLEM The choice of the next route at traffic junction b (Figure 3.4).

INPUT Decision point: b
Destination node: d
Set of routes R_{bd} via leaving links: $\{(b, y_k)\}, k=1..m$
Probability distribution: $\pi_k, k=1..m$

OUTPUT next route r_j to destination d via link (b, y_j)

SITUATION at time t

The car approaches junction b on the road to destination d . The driver has to decide on the next route according to the route choice probability π_k .

PROCEDURE

```
j = 0;  
x = Random_number_uniform_distributed[0..1];  
z = 0.0;  
REPEAT  
  j = j + 1;  
  z = z +  $\pi[j]$ ;  
WHILE x > z AND j < m;
```

SITUATION at time $t+\Delta$

The driver takes the route r_j via link (b, y_j) .

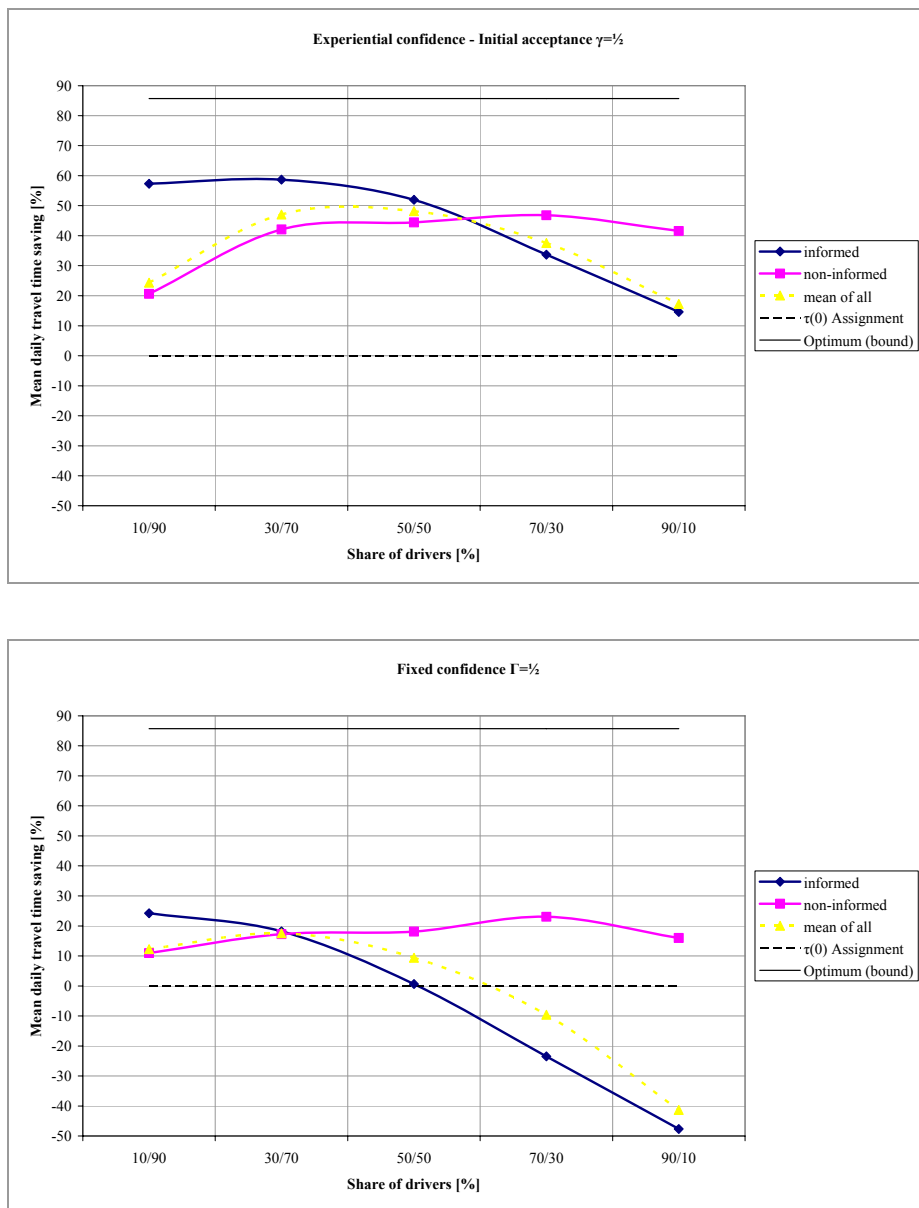
Note: MATSim (Section 4.1) calculates at every traffic junction b for each leaving link (b, y_k) the shortest route to the driver's destination d .

Appendix V

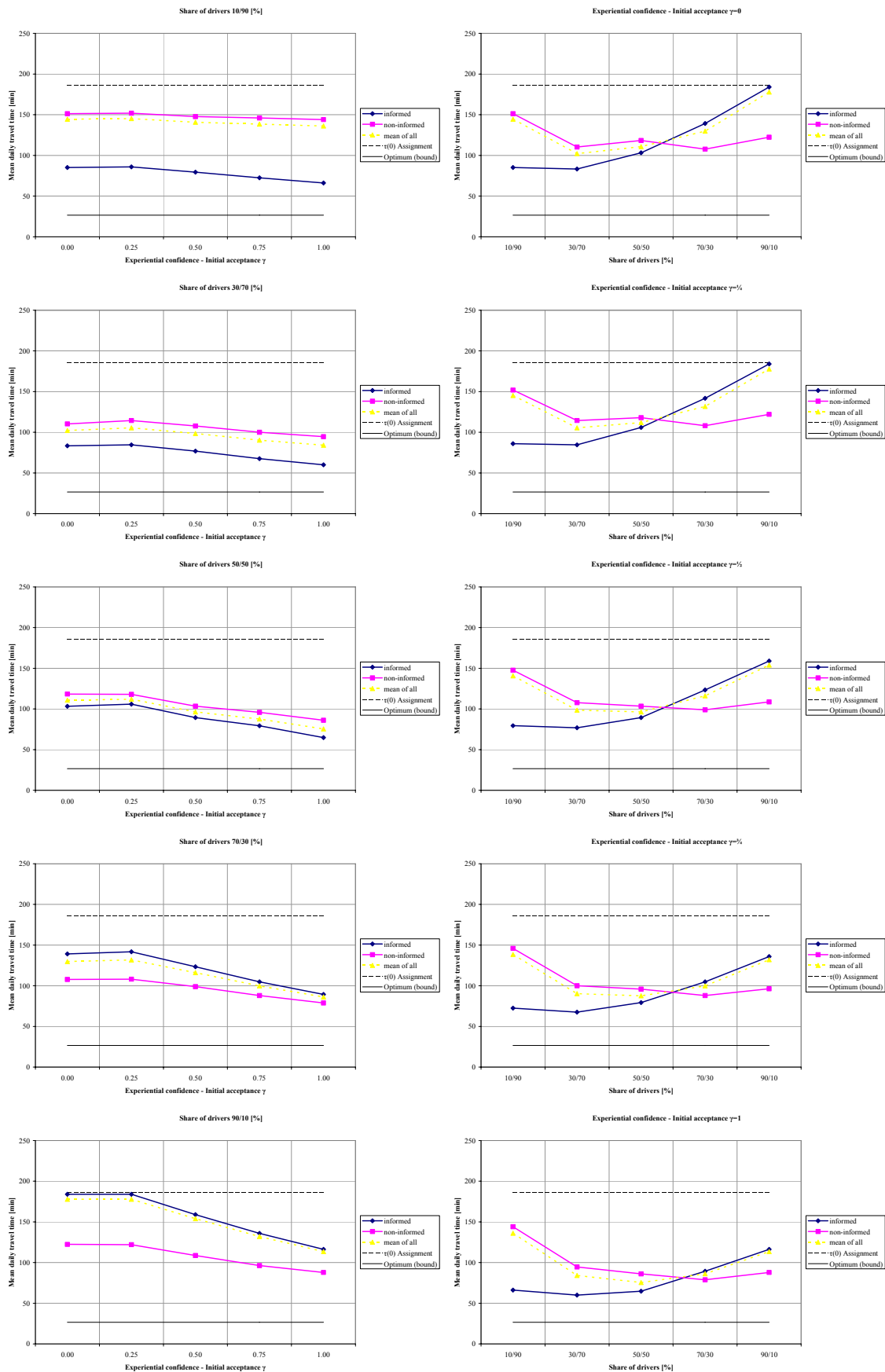
FIGURES

Figure A.2 ($\gamma = \frac{1}{2}$, $\Gamma = \frac{1}{2}$) supplements the Figures 4.10 and 4.11 ($\gamma = \frac{3}{4}$, $\Gamma = \frac{3}{4}$), as well as the Figures 4.12 and 4.13 ($\gamma = 1$, $\Gamma = 1$) of Section 4.4. The Figures A.3 and A.4 compare the results of the modes of behavior (γ , Γ) in the case of different shares of informed drivers.

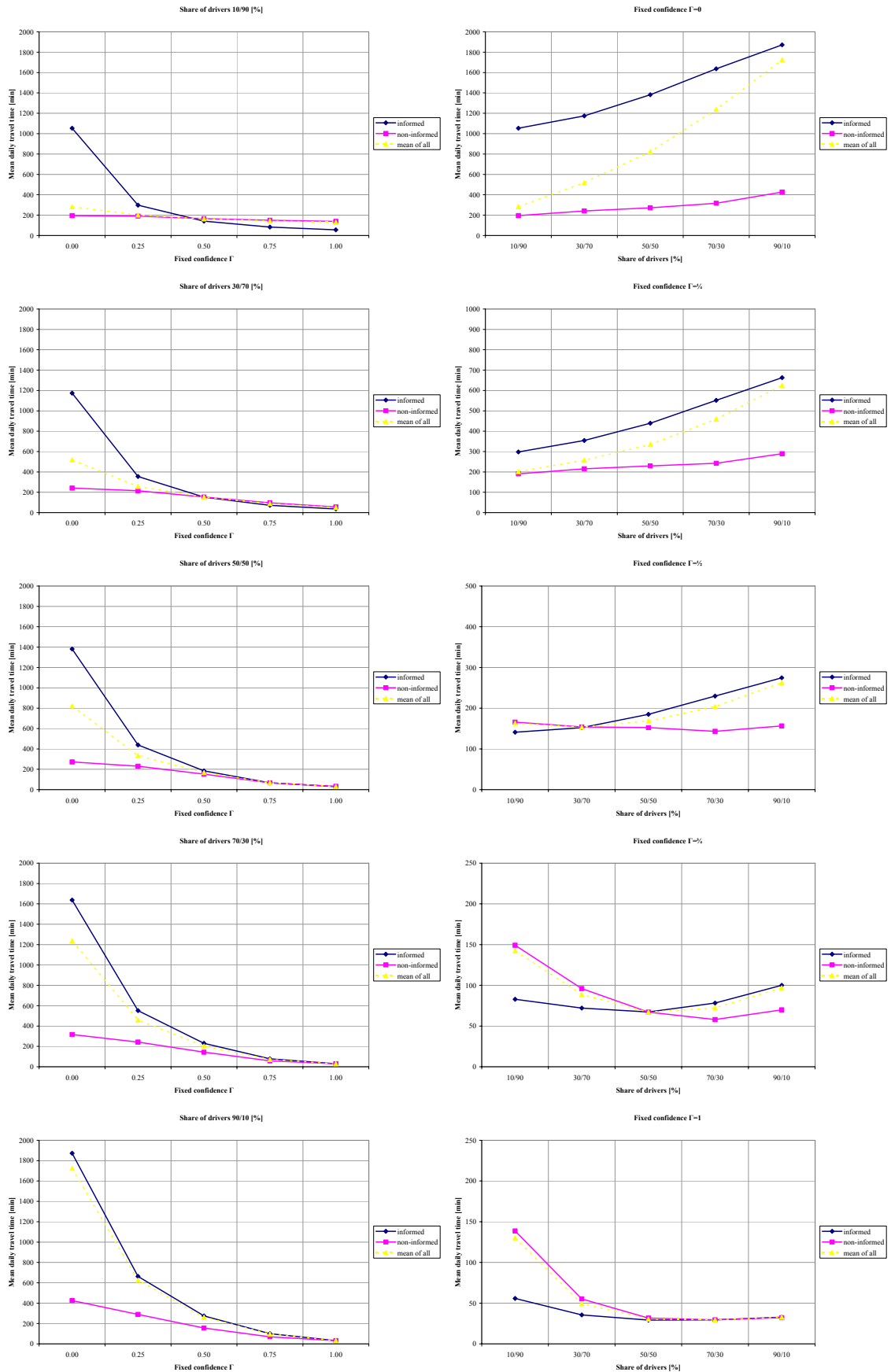
Figure A.2: MDTs according to experiential confidence and fixed confidence $\frac{1}{2}$



Figures A.3: MDT according to experiential confidence and different share of K^I drivers



Figures A.4: MDT according to fixed confidence and different share of K^I drivers



PREVIOUS OUTCOMES

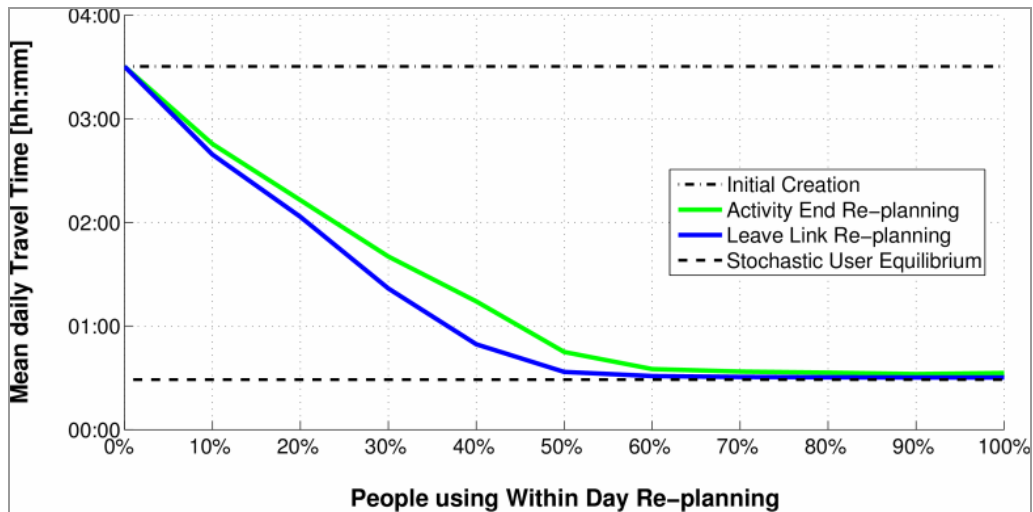
Dobler, Axhausen and Weinmann (2013) present a third set of simulation runs which investigates the influence of knowledge levels among travelers in a traffic system where the load on the network (in proportion to its capacity) is lower than the load on the network of the scenario used in Sections 4.2 and 4.4:

“In the previously mentioned scenario (a traffic management system that informs participants about the network’s state), not everyone would take the opportunity to obtain information from that system. Perhaps they do not have technical equipment, or they just don’t use it because they are afraid that their data could be collected and abused, or they just intuitively know better. So, in reality, usage of such a system could be anywhere between 0% and 100%. The central question is: how is the state of a traffic system affected if the number of people with traffic system knowledge is varied?

To investigate traffic system behavior, simulation runs with varying number of people with knowledge are performed. In each simulated scenario, there are two groups of people. One group employs a timing strategy that incorporates traffic load on the network and the other group does not. Because we are now interested in systems behavior and not in the movement of single persons, we ignore knowledge of network areas (now everyone knows the entire network, equal to a F factor of ∞) and focus on network load knowledge instead. For both within-day timing strategies, a set of simulations is run where the number of people using the router is varied from 0% to 100%.

As the results in Figure A.5 show, it is not necessary for every traveler to use a router that factors in the network load. Even if 40% do not use such a router, the remaining 60% are able to keep the system in a near-optimal state, with no significant change of a person’s daily mean travel time. Again, both within-day re-planning strategies produce comparable results; the *Leave Link Re-planning Router* performs slightly better, as it did previously.

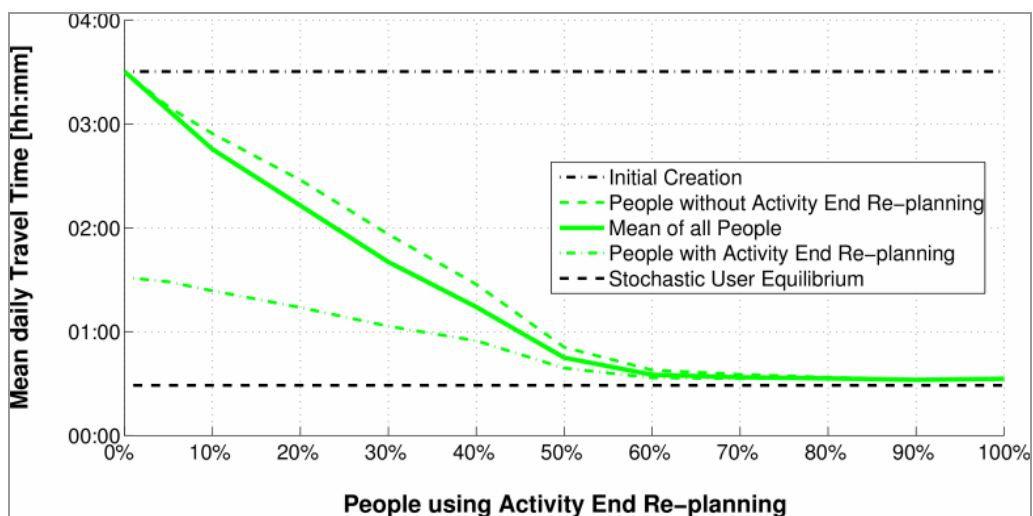
Figure A.5: Activity-end re-planning vs. Leave link re-planning



Source: Dobler, Axhausen and Weinmann (2013)

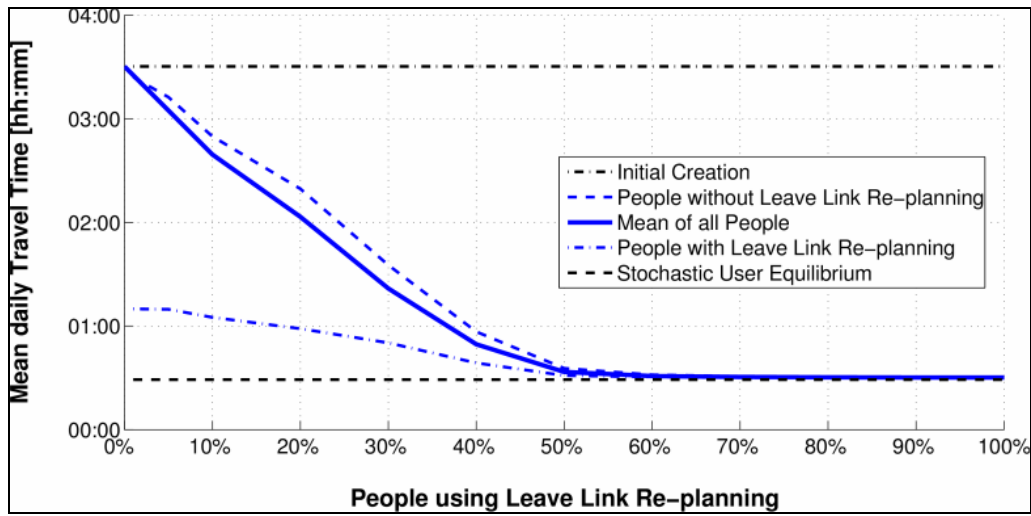
Figures A.6 and A.7 show – in addition to the overall mean daily travel times – agents’ mean travel times with and without a within-day re-planning strategy. If only few agents use within-day re-planning, they are able to reduce their travel times dramatically compared to those without re-planning. However, the more agents use within-day re-planning, the smaller the differences between the mean travel times becomes. If over 60% of the agents re-plan their routes, the mean travel times are almost equal. Therefore, an agent cannot further reduce his travel time by switching from initial creation to within-day re-planning.“

Figure A.6: Outcomes of Activity end re-planning



Source: Dobler, Axhausen and Weinmann (2013)

Figure A.7: Outcomes of Leave link re-planning



Source: Dobler, Axhausen and Weinmann (2013)

Dobler, Axhausen and Weinmann (2013) conclude from the analysis of knowledge levels and timing strategies:

“As one would expect, simulation results indicate that people without a router that takes road network structure into account are unable to find reasonable routes. Mean travel time is reduced significantly if a person has information about the network structure. Even better results can be achieved if information about the load of network links is also available.

We also found that it is not necessary to know the entire network and its state; depending on the network load, even a low degree of flexibility when choosing shortest routes with a small size factor ($F=1.10$) leads to a user equilibrium. This proves that that mean daily travel time cannot be significantly further improved by extending ($F>1.10$) users network knowledge.

An interesting detail for further analysis: in the simulated scenario, use of within-day re-planning strategies incorporating current network load seems to be able to approximate transport system equilibrium. Even if a certain number of people within the system (as shown in Figures A.6 and A.7) use an initial creation strategy – that typically causes more traffic and slower routes – the mean travel time per person stays almost constant. Furthermore, differences in users’ mean travel times with and without re-planning disappear. It was not clear to expect that all drivers

(statistically) make a profit from a router, if only the half use the router to re-plan their routes taking current traffic flows into account, as the results in Figure A.7 clearly show.

Even if more aspects of individual knowledge and choice behavior are considered, modeling and simulation results have great potential value for a planning analyst's understanding of the relationship between knowledge-based route choice and system outcomes.

Several improvements are planned as part of future work. In a first step, the method used to create a person's spatial knowledge will be extended to include factors like type of road or its location. Furthermore, additional simulation runs will be conducted using different seeds for random number generators. This will influence simple routers outcomes and allow us to analyze variance in the results.”

17-12-13 book S. W.