Universität Stuttgart

Institut für Straßen- und Verkehrswesen
Lehrstuhl für Verkehrsplanung und Verkehrsleittechnik
Univ.-Prof. Dr.-Ing. M. Friedrich

Potential of Traffic Information to Optimize Route and Departure Time Choice

Eileen Mandir

Veröffentlichungen aus dem
Institut für Straßen- und Verkehrswesen

Heft 44 (Juli 2012)

ISSN 0932 - 402X
ISBN 978 - 3 - 9810573 - 3 - 1
D 93 (Dissertation der Universität Stuttgart)

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Herausgeber : Institut für Straßen- und Verkehrswesen
Universität Stuttgart

Eigenverlag und Vertrieb : Institut für Straßen- und Verkehrswesen
Universität Stuttgart

Lehrstuhl für Verkehrsplanung und
Verkehrsleittechnik
Pfaffenwaldring 7
70569 Stuttgart

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Von der Fakultät Bau- und Umweltingenieurwissenschaften der Universität Stuttgart zur Erlangung der Würde eines Doktors der Ingenieurwissenschaften (Dr.-Ing.) genehmigte Abhandlung

Vorgelegt von

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aus Stuttgart

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Tag der mündlichen Prüfung: 4. Juli 2012

Institut für Straßen- und Verkehrswesen

Lehrstuhl für Verkehrsplanung und Verkehrsleittechnik

Universität Stuttgart

2012

The Remarkables

This dissertation was written during my time as a research assistant at the Institute of Road and Transportation Science, Department for Transport Planning and Traffic Engineering at the University of Stuttgart.

In the following I want to take the opportunity to notably express my thanks to my advisors, colleagues, students and family.

Professor Markus Friedrich of the University of Stuttgart initiated as well as advised this thesis. Throughout my time at the institute he encouraged me to explore new ideas and supported my research interests. His active participation in my professional development has been an important source of motivation for me. I owe many of the things I learned to his open way of sharing ideas and his kind teaching.

Professor Kay W. Axhausen of the ETH Zurich took on the task of co-advising this thesis. His feedback to my research proposal as well as his helpful responses to my questions gave me the needed advice and guidance throughout my thesis.

Professor Pitu B. Mirchandani of Arizona State University gave me the opportunity to go abroad and join his research team for some weeks. This was a very valuable time for me with many interesting discussions with researchers from different backgrounds.

My colleagues at the University of Stuttgart provided many enriching discussions as well as an always pleasant working atmosphere. Especially, I want to thank Thomas Otterstätter for his patience in helping me speed up algorithmic performance, Juliane Pillat for her collaboration in the project *wiki* and her always wise and timely sharing of intellectual as well as real bits of chocolate, and Alice Lorenz for her assistance in confused moments in front of the library bookshelves.

My students always showed high motivation to participate in ongoing research projects. Especially, I want to thank Maximilian Hartl for our helpful discussions as well as his never ending curiosity.

My family has always supported me in whatever ideas I brought to the kitchen table, by nodding approval combined with a hot cup of tea.

My husband has accompanied me through my entire time at the university and his love is majorly responsible for every single achievement throughout my adult life.

Eileen Mandir

Acknowledgements

This dissertation is partly based on work done on behalf of the German Federal Ministry of Economics and Technology within the project *wiki* (support code 19 P 7048 B).

The responsibility for the content of this dissertation lies solely with the author.

All data sources, data preparation as well as preliminary modelling work provided by project partners (Autobahndirektion Südbayern, BMW Group, PTV AG, Technische Universität Dresden, Technische Universität München, Universität Stuttgart) are explicitly pointed out in the respective chapters. This especially includes work done on preparation of traffic state data by Iris Fiedler at Technische Universität München, model estimation done by Christian Schiller, Frank Zimmermann and Christian Winkler at Technische Universität Dresden, and preparation of GPS data done by Juliane Pillat at Universität Stuttgart.

All figures, tables and pictures are the own illustrations of the author.

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Abstract

Intelligent traffic management has been the means to utilize existing capacities on overloaded road networks for quite some time. In recent years traffic information has become more and more important. The increasing popularity of navigation systems as well as the growing availability of current travel times makes it possible to provide a vast number of car drivers with traffic state information via onboard navigation devices or dynamic roadside traffic signs.

The first part of this work analyses drivers' acceptance of traffic information and compliance with route guidance today on the basis of an empirical study of almost 300 car commuters in the greater Munich area over a period of eight weeks.

An analysis of the collected data reveals that traffic information is not only used for route guidance in case of needing directions but it is also used rather frequently on everyday trips, such as from home to work. Today, the level of drivers' information on potential alternative routes and current travel times is based on incomplete as well as temporally delayed information and thus is greatly dependent on the driver's own knowledge of historical daytime-dependent travel times in the road network.

In the second part of this work econometric choice models are presented based on the collected GPS trajectories as well as questionnaire data using Maximum-Likelihood estimation. These choice models identify the variables influencing route and departure time choice. Special focus is given to the influence of traffic reports received via radio, route guidance via navigation devices or via dynamic roadside traffic signs, traffic state information displayed as Level-of-Service map on navigation devices, and travel time information on dynamic roadside traffic signs.

The analysis of over 16,000 trips shows that survey participants have a strong preference towards their usual main route. Besides the current travel time, traffic information via radio or via Level-of-Service map has the strongest influence on the choice to divert from the main route. The probability of diverting to an alternative route is equal for a 5-minute increase in travel time as for 6 kilometres of congestion or 10 kilometres of minor delays when the information is broadcast over the radio or displayed through the Level-of-Service map.

The evaluation of the questionnaire shows the influence of current travel time information on departure time choice. The results greatly depend on the flexibility of the working hours of the decision maker. For a usual commuting distance of 30 kilometres, persons with flexible working hours show a willingness to change their usual departure time by 15 minutes for a 10-minute travel time reduction, whereas persons with fixed working hours are willing to change their departure time for a 25-minute travel time reduction.

The third part of this work includes modelling concepts to determine the potential of traffic information to reduce the transport time expenditure as well as fuel consumption in the entire survey area. Therefore, a comparison of today's traffic situation with a state with perfect information and a system-optimal state from the transport planning perspective is performed. The separate models of route and departure time choice are integrated within a macroscopic traffic assignment model.

Optimization of route choice by providing all drivers with perfect information on current travel times reduces the transport time expenditure by 4% in the morning peak hour. A substantially larger reduction of almost 8%, and thus close to a system-optimal state, is achieved by perfect information on the optimal departure time which causes a temporal distribution of the travel demand.

The empirical analysis within this work and the route and departure time choice models based thereon determine impacts of traffic information in the study area of Munich today as well as possibly in the future. The results show the potential of traffic information for the optimization of traffic flows in road networks. Furthermore, this work provides an important contribution to model-based decision guidance for practitioners in optimizing traffic management strategies as well as for politicians deciding on future investments in information infrastructure and technologies.

Zusammenfassung

Verkehrsleitsysteme sind seit geraumer Zeit ein weitverbreitetes Mittel zur Ausnutzung vorhandener Kapazitätsreserven in überlasteten Straßennetzen. In den vergangenen Jahren gewinnt dabei die Verkehrsinformation verstärkt an Bedeutung. Sowohl die zunehmende Verbreitung von Navigationsgeräten, als auch die steigende Verfügbarkeit von aktuellen Reisezeiten ermöglichen die Versorgung einer wachsenden Anzahl von Pkw-Fahrern mit Verkehrslageinformationen durch Navigationsgeräte oder durch straßenseitige dynamische Beschilderung.

Der erste Teil dieser Arbeit analysiert die heutige Nutzung und Akzeptanz von Verkehrsinformation anhand einer empirischen Untersuchung von fast 300 Pkw-Pendlern im Großraum München über einen Zeitraum von acht Wochen.

Die erhobenen Daten zeigen, dass Verkehrsinformation bereits heute nicht nur zur reinen Zielführung bei fehlender Ortskenntnis sondern auch auf alltäglichen Wegen zum Beispiel zum Arbeitsplatz häufig genutzt wird. Die Informiertheit der Autofahrer über potentielle Alternativrouten und aktuelle Reisezeiten basiert heute auf teils lückenhaften und zeitverzögerten Verkehrslageinformationen und ist stark abhängig von der eigenen Kenntnis der historischen tageszeitabhängigen Reisezeiten im Straßennetz.

Im zweiten Teil der Arbeit werden auf Basis erhobener GPS-Trajektorien und durchgeführten Befragungen ökonometrische Entscheidungsmodelle zur Abbildung der Einflussgrößen auf das Routen- und Abfahrtszeitwahlverhalten mittels Log-Likelihood-Methode bestimmt. Untersucht werden mögliche Einflüsse von Verkehrsmeldungen, die über den Verkehrsfunk empfangen werden können, Routenempfehlungen per Navigationsgerät oder über straßenseitige dynamische Beschilderung, Verkehrslagedarstellung als Level-of-Service-Karte im Navigationsgerät und Reisezeitinformation auf dynamischen Anzeigen entlang der Straße.

Die Analyse von über 16.000 Ortsveränderungen zeigt eine starke Präferenz der Probanden zu ihrer üblichen Hauptroute. Den größten Einfluss auf die Änderung der Routenwahl haben, neben der aktuellen Reisezeit, Verkehrsinformationen durch den Verkehrsfunk und die Level-of-Service-Karte. Dabei bewirkt eine Reisezeiterhöhung von 5 Minuten dieselbe Wahrscheinlichkeit zum Verlassen der Hauptroute wie die Meldung von 6 Kilometer Stau bzw. von 10 Kilometer stockendem Verkehr im Verkehrsfunk oder über die Level-of-Service-Karte.

Die Auswertung der Befragung zeigt den Einfluss von Information über aktuelle Reisezeiten auf das Abfahrtszeitwahlverhalten. Die Ergebnisse sind stark abhängig von der Flexibilität des jeweiligen Arbeitszeitverhältnisses der Probanden. Für übliche Pendlerdistanzen von 30 Kilometern zeigen Personen mit flexiblen Arbeitszeiten eine Bereitschaft zum Wechseln ihrer üblichen Abfahrtszeit um 15 Minuten ab einer

Reisezeitersparnis von 10 Minuten. Personen mit festen Arbeitszeiten verschieben hingegen erst ab einer Reisezeitersparnis von 25 Minuten ihre übliche Abfahrtszeit um 15 Minuten.

Der dritte Teil der Arbeit umfasst modelltheoretische Ansätze zur Ermittlung der Potentiale von Verkehrsinformation auf die Reduktion der netzweiten Reisezeiten und Kraftstoffverbräuche im gesamten Untersuchungsraum. Es erfolgt eine Gegenüberstellung der heutigen Situation mit einem Zustand bei perfekter Information und einem verkehrsplanerisch systemoptimalen Zustand. Hierzu werden die Einzelmodelle der Routen- und Abfahrtszeitwahl in einem makroskopischen Verkehrsumlegungsmodell integriert.

Die Optimierung der Routenwahl durch perfekte Information aller Pkw-Fahrer über aktuelle Reisezeiten, ergibt eine Reduktion der netzweiten Reisezeit von 4% in der morgendlichen Spitzenstunde. Eine deutlich größere Reduktion der netzweiten Reisezeit von knapp 8% und damit nahe am theoretisch möglichen Optimum ist durch die perfekte Information über den optimalen Abfahrtszeitpunkt und eine dadurch bedingte zeitliche Verlagerung der Verkehrsnachfrage möglich.

Die empirischen Untersuchungen und darauf basierende Modelle zur Prognose der Routen- und Abfahrtszeitwahl ermitteln die heutigen Wirkungen und zukünftigen Potentiale von Verkehrsinformation im Untersuchungsraum München. Die Ergebnisse machen deutlich, welche Bedeutung Verkehrsinformation für die Optimierung der Verkehrsströme im Straßenverkehr hat. Damit ist eine Basis für modellbasierte Entscheidungshilfen zur Optimierung der Verkehrslenkungsstrategien von Verkehrsleitzentralen als auch zur Investition in zukunftsträchtige Informationstechnologien geschaffen.

1 Introduction

1.1 Motivation

Rising economic costs of congestion and ecological effects of fuel consumption have brought the research discussion on intelligent traffic management systems to political attention. Yet, while it seems clear that new information devices with rising market penetration rates offer promising solutions, the effects of these devices are to some extent still unknown. Furthermore, the role traffic information can play as a traffic control measure in reaching the goal of optimally distributing traffic flows, in order to access the unused capacity of the existing road network, is still unanswered. To what extent can traffic information devices such as the traffic message channel, variable message signs or navigation systems reduce the transport time expenditure or fuel consumption in a road network and what needs to be done to access this potential?

In order to advance state-of-the-art traffic control systems and provide reliable driver information, devising methods for monitoring the current traffic state and creating models for forecasting driver behaviour is crucially important. Therefore, a clear understanding of drivers' route and departure time choice behaviour is needed, especially considering the impact of traffic information on both choices. As route guidance provided by traffic information is not compulsory for drivers, the effects on traffic distribution are highly dependent on driver compliance and thus on the quality of information. To include these effects in the estimation of choice models, it is necessary to establish a sound empirical data basis of observed decisions based on traffic information.

Floating car data has been considered a promising data source for monitoring time-space trajectories of single travellers for some years. The deficits of low market penetration of equipped vehicles and high communication costs could soon be overcome by the success story of smart phones with data flat-rates and the boom in downloadable applications. With increasing amounts of available floating car data, real-time link travel times are becoming more and more reliable and are available not only on network parts equipped with vehicle recognition systems, but on all roads with high traffic volumes. Traffic state detection based on these data sources is the cornerstone for reliable short term forecasts of future behaviour. This work applies GPS data taken from a long-term survey of commuter behaviour in order to identify realistic choice set sizes and suitable choice models for forecasting route and departure time choices for private transport in the Munich metropolitan area.

Intelligent traffic management is widely acknowledged as the promising measure to maintain mobility in metropolitan areas while travel demand is still increasing. Operational management strategies aim to reduce congestion by rerouting traffic around the network's time-dependent bottle necks. Much attention has been invested in models which are designed to forecast the impacts of rerouting traffic to other parts

of the network. Yet current approaches consider a given traffic management scheme with predetermined strategies and advance to modelling route choice. The management strategies, however, are not optimized on a network wide scale, but are mostly scenario-based action plans carried out under the particular constraints of the roadside traffic control infrastructure. In order to explore further arguments for future investment in traffic guidance infrastructure, this research defines specific benchmark states of traffic information and quantifies the potential of traffic information for optimising route and departure time choice in comparison to a theoretical optimum.

This work presents a solution for analyzing route and departure time choice under the influence of traffic information. The extent to which a system optimal traffic distribution can be achieved by means of driver information is a question addressed in this work.

1.2 Research Goals

The underlying question behind this study is: can traffic information devices such as traffic message channels, variable message signs or navigation systems reduce the transport time expenditure and environmental impact of traffic in a road network and what needs to be done to access this potential? In order to answer this question, this research sets out to prove or disprove the following hypotheses:

(I) Traffic information on current delays based on observed section travel times is more reliable than information based on stationary detectors and flow propagation models.

(II) Drivers today are relatively well informed about recurrent traffic conditions and choose sensible routes on their daily commute based on their personal experience.

(III) Better traffic information can reduce drivers‘ travel times substantially in cases of non-recurrent incidents or when travelling to unfamiliar destinations.

(IV) Congested road networks offer a limited number of sensible alternative routes.

(V) A spatial redistribution of selected trips on alternative routes leads to an overall improvement of traffic flow.

(VI) A temporal redistribution of selected trips to other times of the day is far more effective than a spatial redistribution.

(VII) Using route guidance measures to minimize environmental impacts leads to a redistribution of trips to the subordinate road network.

1.3 Outline of Work

This work presents models for analyzing the potential of traffic information for optimizing route and departure time choice in respect to reducing the transport time expenditure as well as the environmental impact of traffic. To understand the components of the models designed, chapter 2 *Fundamentals* gives background information on traffic guidance and information systems, discrete choice models, route search algorithms and traffic assignment methods.

This research is based on a large data basis from the research project *wiki*, which is introduced in chapter 3 *Data Sources*. The different data sources are described and analysed for their volume and quality as well as the relevance for model estimation and calibration.

In chapter 4 *Driver Information*, objectives and conflicts of different players in the traffic information market such as private navigation service companies, political authorities and drivers are discussed. The potentials of route guidance as a traffic management tool are evaluated before the background of today's state of practice. How many of the delays occurring are caused by travel demand? To what extent does information quality affect device acceptance? Does driver compliance with route guidance depend on the contents displayed?

Chapter 5 *Choice Models* addresses the estimation and calibration of driver behaviour models. Route and departure time choice models are estimated using survey data with focus on analyzing the influence of driver information. A joint route and departure time choice model is then integrated into a transport model which is calibrated from traffic data from the case study area of Munich.

In chapter 6 *Optimisation of Traffic Flows*, different states of traffic information are defined in order to assess the potential of traffic information to optimize route and departure time choice. To address this task, approaches to modelling the impact of the quality level of information as well as the information provided by single devices in a transport model with standard assignment methods are introduced.

In chapter 7 *Results for Munich Case Study*, the developed models are applied to the case study of the Munich metropolitan area in order to quantify the potential of traffic information to reduce the total transport expenditure as well as the environmental expenditure.

In chapter 8 *Conclusion*, methodological accomplishments and major findings are summarized, recommendations for decision makers are formulated and prospects for future work are presented.

2 Fundamentals

The fundamentals summarized in the following chapter include background information on traffic guidance and information systems, discrete choice models, route search algorithms, and traffic assignment methods in order to provide the reader with the knowledge needed to understand the analysis and derived models of this research.

2.1 Advanced Traffic Information Systems

This chapter does not aim to provide a complete overview of traffic control systems, but rather focuses on the subclass of advanced traffic information systems (ATIS) which are analysed in this research.

According to FGSV (2000), traffic control systems are defined as systems that dynamically influence travellers to change their driving behaviour, destination, mode, or route choice by means of non-mandatory recommendations or binding regulation. These systems are part of operative traffic management, covering supply management (by dynamic adjustment of road capacities) and demand management (by influencing drivers before or during trips to provoke spatial redistribution of traffic flows or temporal redistribution of travel demand). In general, traffic control systems aim to improve traffic safety and transport performance or to reduce delays and environmental impacts.

FRIEDRICH (2011) classifies traffic control systems according to the following characteristics:

- *Influence on traffic flow:* Dynamic speed controls on motorways and prioritisation of traffic streams at intersections by signal controls enhance the performance of the road network and the safety of travel.
- *Influence on driving manner:* Roadside information on downstream traffic conditions (accidents, congestion, weather conditions such as fog, snow & ice, etc.) help travellers to adjust their driving behaviour.
- *Influence on route choice:* Traffic information via variable message signs, radio traffic message channels or navigation systems enable the driver to choose alternative routes based on current traffic conditions.
- *Influence on departure time:* Pre-trip information on time-dependent travel times for different times of day enable the driver to adapt his or her trip scheduling to avoid temporarily occurring congestion.
- *Influence on mode choice:* Pre-trip information can furthermore provide details on alternative travel possibilities with different means of transport (unimodal or intermodal).

- *Dependency on time of day and traffic:* A static traffic control system is independent of time and the current traffic situation (for example fixed traffic signal programmes). If the state of the system is time-dependent and considers the current traffic situation it is called dynamic. In this case the controls are influenced by measurements of the current traffic volumes (for example ramp metering) or travel times (for example navigation systems).
- *Type of information:* Information can either be provided for individual drivers by navigation systems or for the collective of all drivers by roadside information signs and traffic reports via radio or internet.
- *Binding character:* In contrast to other traffic control systems, ATIS only provides the driver with data on the current traffic state and gives recommendations such as to avoid congestion or construction sites. It is therefore never binding for drivers, unlike, for example, section control by dynamic speed limits.

In the following, an overview of selected ATIS which are of special interest for this research is provided.

Variable message signs

Variable message signs (VMS) communicate all kinds of traffic information to drivers (such as warning messages, advisory messages, and alternative route messages, see DUDEK (2004). In Germany, VMS are also referred to as network control systems and are defined as adjustable roadside signposts which achieve a better distribution of traffic among the existing network capacity by displaying alternative routes to destinations (see BOLTZE ET AL. (2005)). Additive VMS show diversion routes in case of congestion, road works, or incidents. Substitutive VMS are designed like standard destination signposts and change the destinations displayed for the corresponding alternative routes. VMS can be complemented by information on incidents and resulting congestion and are referred to as dynamic signposts with integrated information on traffic jams in Germany (dynamische Wegweiser mit intergrierter Stauinformation, see dWiSta in HARTZ AND SCHMIDT (2004)). Furthermore, VMS in the form of dynamic travel time information signs (TTIS), which provide travel times to downstream motorway junctions or intersections, have become popular in Germany in recent years (dynamische Informationstafel zur Reisezeit-Anzeige, see dIRA in BECKROTH ET AL. (2010)).

Radio reports

Traffic information on motorways, including accidents, motorist driving against to traffic, road works, weather conditions, congestion, and recommended diversion routes, is available via spoken radio reports. These reports are based on information given by other drivers, local policy authorities, or digital messages from the traffic message channel (see below).

Traffic message channel

The traffic message channel (TMC) is a standardised European digital service which was installed nationwide in Germany in 1997 (see EUROPEAN BROADCASTING UNION (1995)). The current traffic conditions occurring on a TMC section (a road section between two consecutive TMC locations) is broadcast via the Radio Data System (RDS). RDS enables receipt of traffic messages via alternative frequencies with automated retuning of the radio receiver independent of the radio station the driver is currently listening to. TMC messages contain event-based information on the length of stagnant flow or congestion and include a decay time. The decay time is given in case the annulment of the original message is not received. In Germany, the Location Code List (LCL) and the Event Code List (ECL) are published by the Bundesanstalt für Straßenwesen (BASt) and assembled by the Federal State Authorities. TMC messages can also be received by navigation systems and are the basis for dynamic routing. In recent years, priced enhancements of TMC (originally named *TMCpro*, or *Navteq Traffic* today) have been developed, which provide more detailed information in terms of location and contents.

Navigation systems

Navigation systems are individual route guidance systems from a starting point to a selected destination. The service of navigation consists of three subtasks:

- Geographical positioning by global navigation satellite systems (GNSS)
- Routing from starting point to destination by calculating the route
- Guidance to destination by audio and/or visual advice

Geographical positioning uses GNSS such as the global positioning system (GPS) and determines the current position with an accuracy of within 10 metres. More advanced services such as the differential GPS (DGPS) achieve an accuracy of within centimetres (see HOFMANN-WELLENHOF ET AL. (2008)).

Routing from the starting point to the selected destination requires a digital map of the road network. Formerly, navigation systems stored map data locally and did not consider current traffic conditions in calculating the optimal route. Today, a driver's routing request is transmitted to a provider's central server and routing is based on current travel times as well as other criteria a driver may select, such as length or exclusion of toll roads etc. In most navigation systems routing is updated if the driver leaves the previously determined route. Actualisation of the road network, such as speed limits etc., can be accessed by downloading new map data from a server. In future, cloud computing trends might lead to the storing of map data as well as the routing application itself on central servers. Besides the vehicle-inbuilt navigation systems, portable devices such as smart phones with navigation applications (App) are becoming more popular.

Another current application of location services is the use of navigation systems not only for route guidance but for information on the traffic conditions in the surroundings of the current location. Traffic conditions are commonly translated to a Level-of-Service (LOS), which is a qualitative interpretation of the performance of an element of infrastructure. The LOS is mostly colour-coded as green, yellow, or red on network links in navigation systems or other devices such as online traffic information platforms or roadside information signs.

Table 1 gives an overview of the characteristics of the ATIS which are of interest for this research.

	Scope of influence				**Dependency on time and traffic**		**Type of information**		**Binding character**	
	traffic flow	driving manner	route choice	mode choice	static	dynamic	collec-tive	indivi-dual	volun-tary	comp-ulsory
VMS	☐	☐	☒	☐	☐	☒	☒	☐	☒	☐
TMC	☐	☒	☒	☒	☐	☒	☒	☐	☒	☐
Navigation system	☐	☒	☒	☒	☒	☒	☐	☒	☒	☐

Table 1: Characteristics of selected ATIS, taken from FRIEDRICH (2011)

2.2 Discrete Choice Models

Discrete choice models are used to describe decisions. Thereby the probability of a decision maker n choosing an alternative j out of a given set of alternatives J is determined. The choice probabilities are determined on the assumption of utility-maximising behaviour under which a decision maker will choose the alternative with the highest utility (or profit), U_{nj}, which is dependent on attributes of the alternative, X_j, as well as the decision maker, S_n. The utility a decision maker obtains from an alternative is defined by a deterministic term, V_{nj}, including all quantifiable attributes (representative utility) and a stochastic term, ε_{nj}, which accounts for non-observable aspects, which can differ for every decision maker or decision situation (see formula 1). Commonly, linear utility functions are specified as a linear combination of the attributes of the alternatives (see formula 2).

$$U_{nj} = V_{nj} + \varepsilon_{nj} \ \forall \ j \tag{1}$$

$$V_{nj} = \alpha_{nj} + \sum_{k \in K} \beta_{nk} \cdot X_{jk} \tag{2}$$

with:	U_{nj}	Utility obtained by decision maker *n* for alternative *j*
	V_{nj}	Representative utility obtained by decision maker *n* for alternative *j*
	ε_{nj}	Random utility obtained by decision maker *n* for alternative *j*
	X_{jk}	Value of attribute *k* of the alternative *j*
	α_{nj}, β_{nk}	Parameters of utility function
	n	Index for decision maker
	j	Index for alternative
	J	Set of all alternatives
	k	Index for attributes of alternative *j*
	K	Set of attributes

The probability that decision maker *n* chooses alternative *i* is given as:

$$\begin{aligned} P_{ni} &= \text{Prob}(U_{ni} > U_{nj}) \ \forall \ j \neq i \\ &= \text{Prob}(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}) \ \forall \ j \neq i \\ &= \text{Prob}(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}) \ \forall \ j \neq i \end{aligned} \tag{3}$$

The probability is a cumulative distribution depending on the density $f(\boldsymbol{\varepsilon}_n)$, where $\boldsymbol{\varepsilon}_n = \{\boldsymbol{\varepsilon}_{n1},\ldots,\boldsymbol{\varepsilon}_{nJ}\}$, of the unobserved portion of utility of each alternative *j*. Different specifications of this density, $f(\boldsymbol{\varepsilon}_n)$, lead to different discrete choice models (see TRAIN (2006)).

Using a Gumbel distribution results in the multinomial Logit (MNL) model, which is by far the most used discrete choice model (see formula 4). A complete derivation of the MNL is given in MCFADDEN (1973). An extensive overview and comparison of existing discrete choice models is given by RAMMING (2001).

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j \in J} e^{V_{nj}}} \tag{4}$$

with:	P_{ni}	Logit probability of decision maker *n* choosing alternative *i*
	V_{ni}	Representative utility obtained by decision maker *n* for alternative *i*
	i, j	Index for alternative
	J	Set of alternatives

The Logit model has certain characteristics relating to the substitution patterns of decision makers. If an alternative *i* becomes more attractive (rise in utility) because attributes change, the probability of choosing alternative *i* increases. This means the probability of at least one other alternative in the choice set decreases. As the ratio of Logit probabilities of two alternatives *i* and *m* depends only on the difference in V_{ni}-V_{nm} (see formula 5), the ratio is independent of irrelevant alternatives (*IIA* property).

$$S_{im} = \frac{P_{ni}}{P_{nm}} = \frac{e^{V_{ni}} / \sum_j e^{V_{nj}}}{e^{V_{nm}} / \sum_j e^{V_{nj}}} = \frac{e^{V_{ni}}}{e^{V_{nm}}} = e^{V_{ni} - V_{nm}} \tag{5}$$

with:	S_{im}	Substitution of alternative *i* by alternative *m*
	P_{ni}	Probability of decision maker *n* choosing alternative *i*
	V_{ni}	Representative utility obtained by decision maker *n* for alternative *i*
	n	Index for decision maker
	i, j, m	Index for alternative

The *IIA* property is realistic for some econometric decisions; however it can be inappropriate if the probability ratio of two alternatives depends on a third alternative. The most prominent example is the red-bus-blue-bus problem in which commuters can initially choose between travelling by red bus or by car (see McFadden (1980)). In this example, the choice probabilities for car and red bus are both 0.5. Introducing a blue bus, which only differs from the red bus in colour (this is assumed to have no effect on the utility of the bus alternatives), will result in Logit probabilities of 0.33 for each of the three alternatives, although it is clear that the substitution pattern of commuters having used the blue bus so far is bound to be different from that of car commuters. Realistic choice probabilities would be $P_{car} = 0.5$ and $P_{redbus} = P_{bluebus} = 0.25$. This property can also be problematic in modelling route choice, where alternatives are not totally independent because two routes may share the same link along their course from origin to destination. The C-Logit model (see Cascetta (2001)) is a model enhancement to address this problem by including the independence of routes in the Logit model (see formulae 6 to 8). Another very common model is the Path Size Logit

model, introduced by BEN-AKIVA AND BIERLAIRE (1999); it uses a path size factor instead of an independence factor.

$$P_{ni} = \frac{e^{V_{ni}} \cdot I_i}{\sum_j e^{V_{nj}}} \tag{6}$$

$$I_i = \frac{1}{\sum_j C_{ij}} = \frac{1}{1 + \sum_{j \forall j \neq i} C_{ij}} \tag{7}$$

$$C_{ij} = \frac{l_{ij}}{\sqrt{l_j} \cdot \sqrt{l_i}} \tag{8}$$

with:	P_{ni}	Probability of decision maker *n* choosing route *i*
	V_{ni}	Representative utility obtained by decision maker *n* for route *i*
	I_i	Independence of route *i*
	C_{ij}	Commonality between route *i* and route *j*
	l_i	Length of route *i*
	l_j	Length of route *j*
	l_{ij}	Length of identical route elements of route i and route *j*
	n	Index for decision maker
	i, j	Index for alternative

Parameter Estimation

The parameters in the utility function are generally unknown and therefore need to be estimated statistically (COSSLETT (1981)). The most prominent of these sampling procedures is the Maximum-Likelihood estimation (see COWAN (2003) and BEN-AKIVA AND LERMAN (1985)). In a Maximum-Likelihood estimation, parameters are optimised such that the choice probability of the given alternatives determined by the model give the best possible match to the actual behaviour in each observed decision situation based on empirical data. Therefore, the utility of each alternative is calculated with the specified utility function, and the choice probability of each alternative is determined with a suitable choice model. The sum of the logarithmic choice probability of each chosen alternative in the data sample gives the Log-likelihood function $L(\alpha_{nj}, \beta_{nk})$, (see formula 9. This function is maximised in the Maximum-Likelihood estimation. If the model has a perfect fit to the observed decision situations, meaning that P_{nj} is 1 if the alternative *j* was chosen by the decision maker and 0 otherwise, the *L* is zero. The poorer the model represents the data sample, the higher the resulting negative value of the *L*.

$$L(\alpha_{nj}, \beta_{nk}) = \sum_n \sum_j y_{nj} \cdot \ln P_{nj} \tag{9}$$

with:	$L(\alpha_{nj}, \beta_{nk})$	Log-likelihood function of parameters of utility function
	P_{nj}	Utility obtained by decision maker *n* for alternative *j*
	y_{nj}	Choice variable, 0 if decision maker *n* chose alternative *j*, 0 otherwise
	n	Index for decision maker
	j	Index for alternative

Goodness of Fit and Hypothesis Testing

To test the goodness of fit, a statistic called ρ^2 (rho squared) is calculated to measure how well the model, including the estimated parameters, performs in comparison to the zero-model in which all parameters are set to zero and thus all alternatives have the same probability (see formula 10). In the best case, a perfect fit between model and observed choice decisions, ρ^2 is equal to 1, as $L_1 = 0$. In the worst case, when $L_1 = L_0$ and therefore the model assumes all alternatives are equally attractive, ρ^2 is equal to 0. Note that the value of ρ^2 has no intuitive interpretation such as the R^2 in linear regression, although both statistics have a similar range (see TRAIN (2006)). A value of ρ^2 between 0.2 and 0.4 is generally regarded as a good model fit (see BACKHAUS ET AL. (2006)) and is comparable to a value of R^2 between 0.44 and 0.72 (see DOMENCICH AND MCFADDEN (1975)). A variation of ρ^2 is the adjusted-ρ^2, which considers the number, *D,* of estimated parameters in L_1 (see formula 11). As *D* is larger than zero, this is a stricter statistic than ρ^2.

$$\rho^2 = 1 - \frac{L_1}{L_0} \tag{10}$$

$$\text{adjusted-}\rho^2 = 1 - \frac{L_1 - D}{L_0} \tag{11}$$

with:	L_1	Log-likelihood of estimated model
	L_0	Log-likelihood of zero-model
	D	Number of estimated parameters

A statistic called the Log-likelihood ratio (LR) tests the goodness of adjustment and determines if the model fit is significantly increased by adding one or more parameters to the utility function (see formula 12).

$$LR = 2 \cdot (L_m - L_0) \tag{12}$$

with: LR Log-likelihood ratio

L_m Log-likelihood of model with *m* estimated parameters

L_0 Log-likelihood of zero-model (or model with less parameters)

The LR is distributed chi-squared and depends on the degrees of freedom (difference in number of estimated parameters in L_m and L_0). A level of significance of 90% means that the null hypothesis, which is the hypothesis of a parameter being zero, meaning the parameter has no influence on the choice probabilities, is disproved with a probability of 90%. Generally, a level of significance of 95% is regarded as significant and a level of significance of 99% as highly significant (see BACKHAUS ET AL. (2006)) in Table 2).

	Level of significance		
Degrees of freedom	**90%**	**95%**	**99%**
1	2.71	3.84	6.63
2	4.61	5.99	9.21
3	6.25	7.81	11.34
4	7.78	9.49	13.28
5	9.24	11.07	15.09
6	10.64	12.59	16.81
7	12.02	14.07	18.48
8	13.36	15.51	20.09
9	14.68	16.92	21.67
10	15.99	18.31	23.21

Table 2: Chi-squared table (taken from BACKHAUS ET AL. (2006), page 818)

The significance of the estimated parameters can be determined by standard t-tests of the null hypothesis for each parameter so that only significant parameters are used in the choice model. For each parameter, β_i, the t-test value, T_i, is given by formula 13.

$$T_i = \frac{\beta_i}{s_{\beta i}} \tag{13}$$

with: T_i T-test value for parameter *i*

β_i Estimated value of parameter *i*

$s_{\beta i}$ Standard error of β_i

For a sufficiently large sample size, the t-test statistic follows the Student's t-distribution. The absolute of T_i should be larger than the values given in Table 3 for different levels of significance, depending on the degrees of freedom (number of observations – number of estimated parameters) in the data sample.

	Level of significance		
Degree of freedom	**90%**	**95%**	**99%**
200	1.653	1.972	2.601
500	1.648	1.965	2.586
1,000	1.646	1.962	2.581
>1,000	1.645	1.960	2.576

Table 3: Student's t-distribution for two-tailed test (from BACKHAUS ET AL. (2006), page 808)

Elasticities

To predict future behaviour in the sense of econometric choices on changed attributes of the alternatives in the choice set, it is important to know how the choice probabilities change if a certain attribute changes. Elasticities describe the percentage change in choice probability related to a one-percent change of an attribute. Formula 14 shows the elasticity in the case where the representative utility, V_{ni}, is linear in respect to parameters α_{nj} and β_{nk}:

$$E_{ni,X_{ki}} = \frac{\partial P_{ni}}{\partial X_{ki}} \frac{X_{ki}}{P_{ni}} = \frac{\partial V_{ni}}{\partial X_{ki}} X_{ki}(1-P_{ni}) \tag{14}$$

with:

$E_{ni,X_{ki}}$	Elasticity of P_{ni} with respect to attribute X_{ki}
P_{ni}	Probability of decision maker *n* choosing alternative *i*
X_{jk}	Values of attribute *k* of the alternative *j*
V_{ni}	Representative utility obtained by decision maker *n* for alternative *i*
n	Index for decision maker
k	Index for attribute
i	Index for alternative

Elasticities are important model results as they are normalised for the attribute values and are comparable for models estimated on different data samples. Therefore, elasticities should be presented together with estimated parameter values.

2.3 Route Search Algorithms

Route search algorithms determine paths from an origin to a destination as a progression of nodes and links in a transport network. These algorithms are needed to determine a set of alternative routes a traveller considers, the so-called choice set, as input for a route choice model. Route search algorithms can generally be classified in shortest path and multipath algorithms.

Shortest path algorithms are mono-criterion algorithms; they include one search criterion. A variety of solutions exists for this problem (see BRAUN (1980), WERMUTH (1994)) which can be classified as follows:

- Adjacency matrix methods (FLOYD (1962))
- Iterative route tree methods of type M (MOORE (1957))
- Non-iterative route tree methods of type D (DIJKSTRA (1959))

Multipath algorithms determine a set of *k* shortest paths through a network based on the following three principles.

Repeated shortest path search

- Link Labelling Approach:
  This deterministic approach determines *k* shortest paths by iterations of a shortest path search based on *k* different criteria such as travel time, length, cost, etc. (see BEN-AKIVA ET AL. (1984)).

- Link Elimination Approach:
  This heuristic approach determines *k* shortest paths by *k* iterations of a shortest path search in which a link of the shortest path, found in the previous iteration, is deleted based on pre-defined rules (see AZEVEDO ET AL. (1993)).

- Link Penalty Approach:
  This heuristic approach determines *k* shortest paths by *k* iterations of a shortest path search in which the cost on all links of the shortest path found in the previous iteration is increased (see DE LA BARRA ET AL. (1993)).

- Simulation Approach:
  This stochastic approach determines *k* shortest paths by *k* iterations of a shortest path search in which the cost on all links in the network is randomly varied after each iteration (see SHEFFI AND POWELL (1982)).

Mathematical multipath search

Mathematical multipath approaches formulate the multicriterion search as a close form sampling problem under certain constraints to generate a set of pareto-optimal paths (see MILLER ET AL. (1994)).

Path Enumeration

- Branch and Bound:
  This algorithm finds exactly *k* shortest paths by an iterative shortest path search on sub-sets of a directed graph of the transport network under certain path constraints (see LAWLER (1976)).

- Branch and Cut:
  This approach enumerates all paths in the network by building up a route tree from origin to destination as a directed graph of the transport network considering constraints for maximum detour factors compared to the respective shortest path (see FRIEDRICH ET AL. (2001), PRATO AND BEKHOR (2006), SCHLAICH (2009), and SCHLAICH ET AL. (2010)). A detailed description of a Branch and Cut algorithm used for choice set generation is given in chapter 5.1.2.3 *Route Generation*.

All of these procedures have been analysed thoroughly for performance as well as quality of results. SWAIT AND BEN-AKIVA (1985) and PRATO AND BEKHOR (2007) show that choice set composition affects choice model estimation as well as the prediction abilities of the resulting model. BEKHOR ET AL. (2006) analyse different choice set generation methods for consistency with observed route choice data and show that Branch and Bound or Branch and Cut techniques produce good results at a higher computational cost. BOVY (2009) discusses various choice set notations and finds that different purposes of route choice sets, such as supply analysis, model estimation, and demand prediction, play a role in choice set modelling. SCHÜSSLER ET AL. (2010) compare performance and results of choice set generation approaches for data from GPS surveys on high-resolution networks.

2.4 Traffic Assignment Methods

Choices of travellers in transport modelling usually include destination, mode, and route choices, all of which can be modelled with discrete choice models. However, when looking at traffic flows in a transport network which result from route choice decisions by many travellers, the situation occurs that the attributes of the alternative routes change according to the decisions of the travellers. This is due to the fact that rising traffic volumes on routes increase saturation and therefore travel times. To address this problem, methods are needed to model the distribution of travel demand

on a transport network as the interaction between many individual travellers. The following overview is adapted from FRIEDRICH (2010).

A traffic assignment consists of the following three sub-tasks:

- Route search: In the first step, a choice set is determined containing all routes a traveller may consider for a trip from an origin to a destination.
- Route choice: In the second step, the choice behaviour of the travellers is modelled by applying a choice model to the choice set.
- Traffic flow: In the last step, the network loading and resulting link travel times are determined using traffic flow models to account for the interaction of travel demand and transport supply.

Traffic assignment methods differ in the kind of route search (static or dynamic), the kind of route choice model (deterministic or stochastic), and the way traffic flows are represented (capacity dependent, macroscopic flow model, microscopic flow model).

- A traffic assignment method is called *static* if the travel demand is distributed on the alternative routes in the transport network without considering time-dependent congestion and departure times. *Dynamic* assignment methods account for time-varying travel demand based on a traffic load curve.

- A traffic assignment method is called *deterministic* if the traffic is allocated on the shortest path of each OD pair according to the highest representative utility. *Stochastic* assignment methods use discrete choice models to allocate traffic with respect to personal preferences according to the obtained utility of each traveller. Thereby, the obtained utilities are randomly varied so that traffic is allocated to the route travellers perceive as the shortest path.

- The simplest way to represent traffic flow is a *capacity-dependent* model in which each link in the network is treated independently. The link travel time is determined from a so-called capacity-restraint or volume-delay function (see SPIESS (1990)) for a given saturation, which is calculated as the ratio of traffic flow and capacity. *Macroscopic flow models* (LIGHTHILL AND WHITHAM (1955), PAYNE (1971), PAPAGEORGIOU (1988), DAGANZO (1994)) consider the interaction of adjacent network links by processing traffic flows through the network based on the concept of 1st and 2nd order models of kinematic waves. These models derive the speed on a link from the density resulting from traffic volume, number of lanes, and link length. The most detailed representation of traffic flow is given by *microscopic flow models* which account for detailed interactions between single vehicles. Most prominent examples of this class of traffic flow model are cellular automata (NAGEL AND SCHRECKENBERG (1992)) and psycho-physical vehicle-following models (WIEDEMANN (1974)).

The classical method of modelling the interactions between travel demand and transport supply in private transport is the equilibrium assignment method, which is based on Wardrop's 1st principle (see WARDROP (1952)):

"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."

In a deterministic case, when all travellers perceive costs in the same way, this is:

"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."

This so-called user equilibrium results in a traffic distribution in which no driver can decrease his or her personal travel time (or more general cost) by switching to an alternative route.

Another equilibrium condition, the so-called system optimum, is based on Wardrop's 2nd principle (see WARDROP (1952)):

"Under equilibrium conditions traffic should be arranged in congested networks in such a way that the total travel cost (for all trips) is minimized."

This equilibrium condition is referred to as a system optimal state in which traffic flows are distributed in such a way that the existing transport supply is used optimally.

Solving deterministic user equilibrium has been the focus of research for the past decades. Starting from all-or-nothing assignments (all drivers from an origin to a destination choose the same shortest path), which fail to model the interdependency of travel demand and route choice, heuristic approximation methods such as incremental assignment (MARTIN AND MANHEIM (1965)) and the learning method (SCHNABEL AND LOHSE (1997)), evolved (see ORTÚZAR AND WILLUMSEN (1944)) for a comprehensive overview). Today there is a variety of different optimisation models based on the following three solution approaches:

- Link-based methods, for example the Method of Successive Averages (MSA) discussed in AHUJA ET AL. (1993) and the Frank-Wolfe-Method (FRANK AND WOLFE (1956))
- Route-based methods, for example by PTV AG (2007)
- Origin-based methods, for example by BAR-GERA (2002) or GENTILE (2009)

The MSA method and the Frank-Wolfe-Method are iterative descent methods. In each iteration step, n, the algorithm calculates an arbitrary solution of traffic flows, y_n, by an all-or-nothing assignment. The solution of traffic flows, x_{n+1}, in the next iteration step,

n+1, is determined by the current solution, x_n, and the arbitrary solution, y_n, (see formula 15).

$$x_{n+1} = x_n + \lambda \cdot (y_n - x_n) \tag{15}$$

with:	x_{n+1}	Solution of traffic flows in next iteration *n+1*
	x_n	Current solution of traffic flows in iteration *n*
	y_n	Arbitrary solution of traffic flows in iteration *n*
	λ	Step size
	n	Index for iteration step

The step size λ is determined by the number of iterations, $\lambda = 1/n$, for MSA and by solving an optimisation problem to identify the steepest descent for Frank-Wolfe.

Route-based equilibrium methods are based on route flows of a feasible starting solution and change route flows by a network balancing procedure until the costs on all routes for each origin destination pair (OD pair) are equal and thus user equilibrium is reached. The network balancing is an iterative procedure over all route pairs of an OD pair, in which travel demand is shifted from one route to another until both have equal costs.

Origin-based methods, in contrast, do not iterate over all route pairs of an OD pair but over all loops (meaning parts of routes) of an origin. For each origin, the traffic flows of the current solution are balanced on all used loops in the network. By balancing loop flows instead of route flows in order to converge to equilibrium, the convergence speed of the assignment is significantly increased. Furthermore, a better distribution of traffic flows is achieved, fulfilling the Proportionality of Routes Criterion which demands that for each loop in the network the share of travel demand along the left-hand route and along the right-hand route is equal for all origins in the network (see BAR-GERA ET AL. (2012)).

3 Data Sources

This research aims at deriving explanatory models of driver behaviour in a wider sense with a special focus on the influence of traffic information and thus requires a sound basis in empirical data. As part of the project *wiki* a large survey was conducted in order to monitor driver behaviour over a long period of time in a variety of different traffic and decision situations. In the following chapter the data sources collected during this survey are described and analysed for their volume and quality as well as relevance for this research.

3.1 Survey Design

The project name *wiki* is an acronym for *Wirkungen individueller und kollektiver Verkehrsinformation auf den Verkehr in Ballungsräumen* and deals with the effects of individual and collective traffic information on traffic in metropolitan areas. Subsidized and supported by the German Federal Ministry of Economics and Technology (*Bundesministerium für Wirtschaft und Technologie, BMWi*) the project started in January 2008 and ended in July 2011.

This research, as part of *wiki*, intends to prove that providing information to drivers can significantly influence their route and departure time choice and can therefore contribute to reducing the transport time expenditure as well as the fuel consumption in private transport. The greater Munich area has a very dense network of motorways, highways and arterial roads north of the city area and thus is an ideal study area for observing route choice. Almost 300 commuters working in the northern part of Munich city and living north of the city in the greater metropolitan area were monitored over a period of eight weeks. The survey data is used as an empirical basis for identifying, estimating and calibrating a route choice model.

The survey was designed as a combination of observing real-life route and departure time choice, so-called Revealed Preference (RP) data, and interviewing drivers on hypothetical choice situations, so-called Stated Preference (SP) data (see TRAIN (2006), KROES AND SHELDON (1988), LOUVIERE ET AL. (2000) and AXHAUSEN (2003)). Both approaches hold methodological benefits and drawbacks which can be utilized or avoided by combining both (LOUVIERE ET AL. (1981), SWAIT ET AL. (1994) and FREJINGER ET AL. (2006)). The RP surveys deliver unbiased observations of real driver behaviour. However, on the one hand there is the problem that only information on the actually chosen alternatives is collected. Information on all non-chosen alternatives is missing later when comparing all possible choice alternatives (chosen and non-chosen) for estimating a route choice model. On the other, hand in real choice situations often some attributes (such as travel time and length of a route etc.) may be correlated, so that the influence of the attributes on the choice taken cannot be analysed separately.

The SP surveys allow the definition of a set of alternatives (choice set) together with the values of all attributes of interest within the framework of a hypothetical choice situation. However, the choice of the interviewed participant is highly dependent on the illustration of alternatives presented to him as well as the values of attributes offered (see BATES (1988)). To help the participant understand and adopt the hypothetical choice situation it is important the interview is designed to be similar to real situations the participant is familiar with.

In part 1 of the survey, the participants had to fill out a questionnaire to state information about socio-demographic, socio-economic and mobility relevant characteristics prior to the field survey in order to include person-specific preferences in the analyses. Further, the participants were asked for the activity locations they commonly frequented, including purpose of activity (leisure, shopping) and the exact address, if possible.

In part 2 – the RP survey – all 278 participants were equipped with a smart phone and GPS sensor. The GPS sensor calculated a position every second. Its latitudinal and longitudinal coordinates, time stamp and speed were transmitted to a server via a phone network every five minutes. The participants recorded all trips they made by car from origin to destination over a period of eight weeks. In contrast to monitoring a large but anonymous basic population of drivers, for example, by Automated Number Plate Recognition cameras (ANPR), on motorway segments, this survey ensures a highly detailed and almost complete detection of the drivers' car trips.

In part 3 of the survey, a personal interview, every participant was requested to state the routes he or she knows from home to work. The routes were clicked link by link on a digital map. Additionally, every participant took part in a SP interview stating his or her preferences for routes and departure time for trips from home to work.

Figure 1 shows an overview of the data collected during the survey. Additional to the surveillance of the driver behaviour described above, continuous detection of the current traffic state and the availability of traffic information took place.

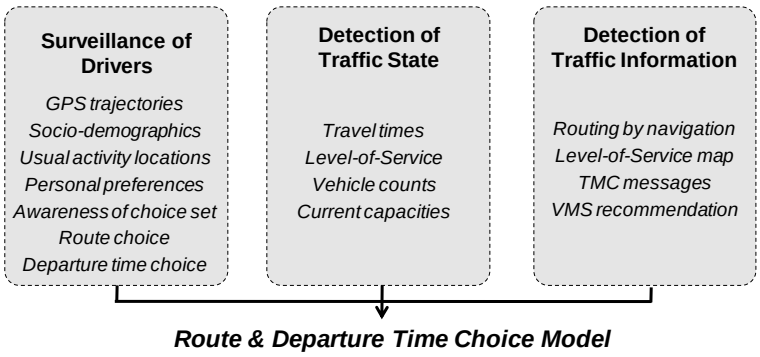

Figure 1: Overview collected data

The conducted survey provides a new data base in respect to data volume and quality. It brings together data on driver behaviour from observed trips as well as SP interviews, and data on traffic state, traffic information and socio-economic characteristics of drivers. Previous work on route choice behaviour concentrates mainly on the analyses of route-specific attributes, such as travel time, length of travel, speed etc., and person-specific attributes, such as age, local knowledge, and orientation etc. The *wiki* survey further allows detailed analyses of the impact of individual and collective traffic information on route choice. The respective data sources collected during the survey are dealt with in chapters 3.4 *Traffic State Data* to 3.7 *Departure Time Choice Data*. A detailed description of the SP experiments conducted in *wiki* and a comparison with other work dealing with the influence of traffic information on route and departure time choice will be given in chapter 3.6.2 *Stated Preference Data*.

3.2 Survey Area and Network Model

The project *wiki* focussed on the greater Munich metropolitan area for several reasons:

- The area includes a dense network of motorways, highways and arterial roads as well as inner-city roads with high transport volumes and frequent incidents.
- The network is equipped with approximately 100 road-side dynamic message signs for collective traffic information.
- The dense network of motorways and arterial roads leading into Munich city provides many alternative routes.
- There is a data archive with live as well as historical traffic data including all links of the major road network.
- Local authorities were willing to participate in the project and provided internal traffic management data for the entire survey period.

In total the survey area spans the southern half of Bavaria in south-east Germany in order to include all major traffic relations in the region.

To model the potential of traffic information to optimize route and departure time choice, this research requires a digital private transport network model of the survey area in order to address the three following tasks:

- Map-matching of GPS trajectories on a digital road network requires a high resolution *NAVTEQ* network of the Munich metropolitan area including all road levels, so that all recorded trips from origin to destination can be located on the map. This network is referred to as the localization network (LN) in the following.

- Analysing important attributes in route choice requires traffic state data on all existing alternative routes in the choice set. Matching traffic state data to the routes

of observed trips is done on a strategic network of the survey area, for which traffic state data is given as current travel time etc. on the major road network from detector data as well as from a real-time traffic forecast model on roads with no detection devices. This network contains 7,700 nodes and 22,600 links, covering 120,000 kilometres of road and is referred to as the project network (PN) in the following.

- Quantifying today's and forecasting possible future effects of traffic information on the reduction of transport time expenditure as well as fuel consumption, requires a well calibrated transport model of the survey area. Hourly demand data is given for five classes of day (Monday, Tuesday-Thursday, Friday, Saturday, and Sunday) for 844 zones in the PN.

Networks and demand data were provided and are the property of PTV AG, Karlsruhe. Figure 2 gives an overview of the whole survey area. The LN area is highlighted with the dashed line.

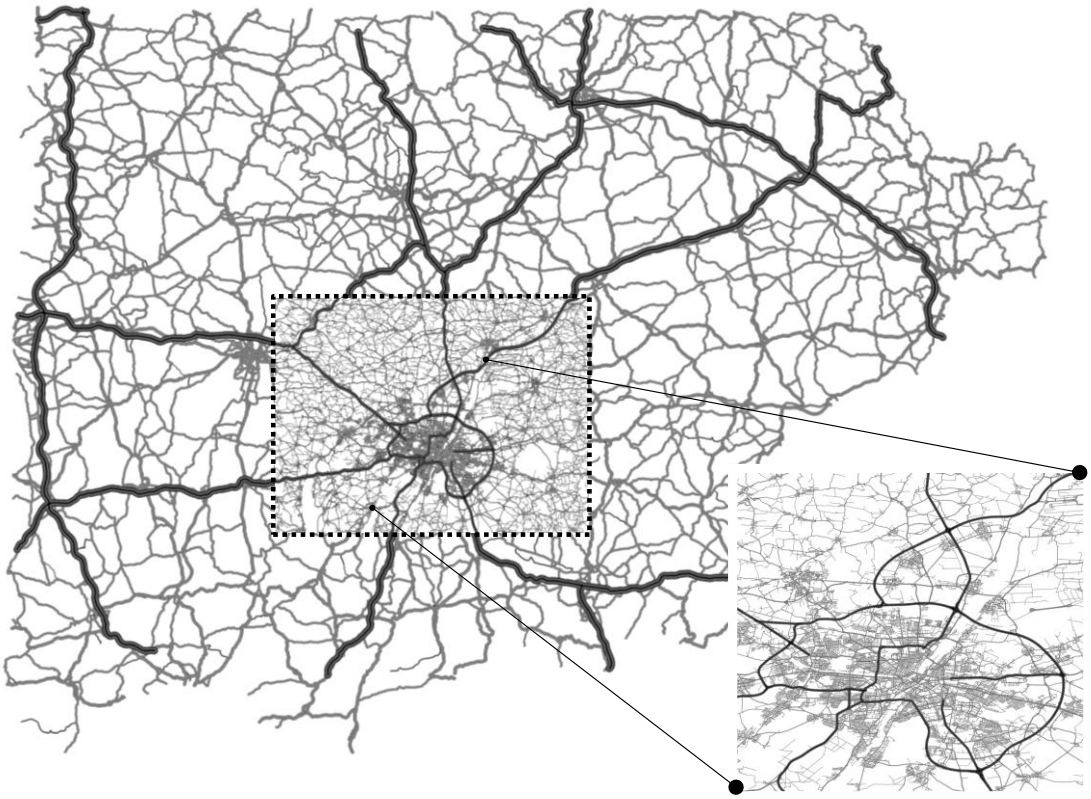

Figure 2: Overview of the survey area

3.3 Driver-Specific Data

Prior to the GPS survey all 278 participants (referred to as the sample in the following) completed an online questionnaire on their socio-demographic, socio-economic and transport relevant characteristics as well as information on their normative environment, regular activity locations and regular weekly non-work appointments.

The first part, on socio-demographic and socio-economic data, gives information on different person groups in the sample. Most of the sample (88%) was male. The small percentage of female participants can be explained by the employers, who participated in this survey and supported the recruitment of their employees via their internal information network. The largest part of the sample is employed by BMW, and the distribution between the genders reflects the structure of BMW staff.

A look at the age distribution shows an accumulation between 40 and 50 years of age. Consequently, for people of this age group and phase of life, the mean household size is 2.8 persons, see Figure 3. This is much higher than the typical values of 2.2 persons given by Mobility in Germany (*Mobilität in Deutschland* (MiD), (INFAS AND DLR (2008)) for average household size in rural areas with higher population density, the type of household typical of the sample.

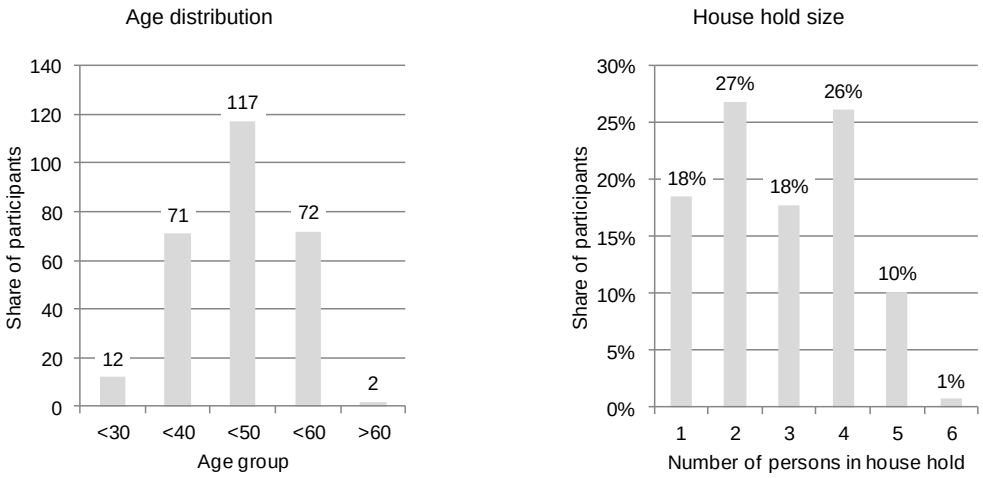

Figure 3: Age distribution and household size

People's occupation influences many decisions, like the frequency and location of activities as well as personal evaluation of time and cost, which directly or indirectly influence their route and departure time choice. In this sample nearly all the participants are full-time workers (99%) compared with 32.9% of the total population (MiD). Figure 4 shows the occupational status and working hours of the sample. The largest part consists of employees with flexible working hours. This also differs significantly from the total population (38.0% fixed working hours, 30.4% flexible working hours, 12.5% alternate shifts, 19.1% other: MiD data).

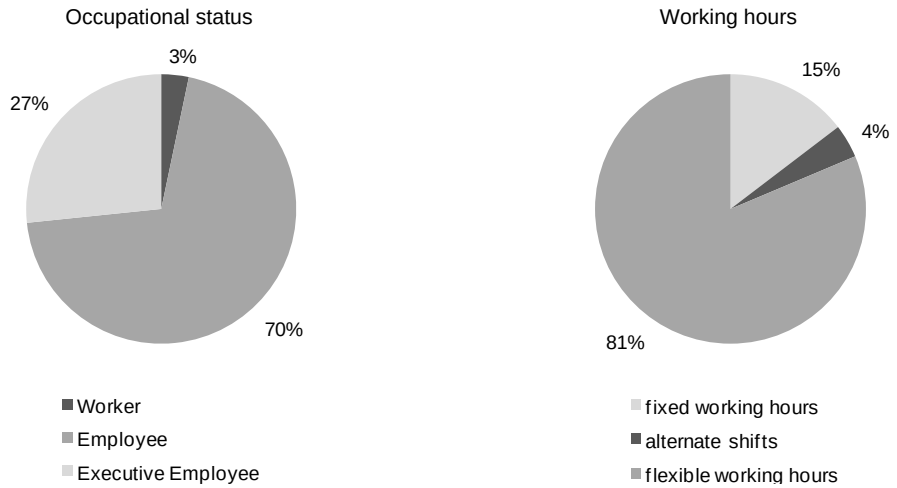

Figure 4: Occupational status and working hours

The second part of the questionnaire provides information relevant to transport and gives information on trip distances, mode of transport and average travel times.

The number of roadworthy cars per household at 2.1 is high compared with 1.8 cars per household for rural areas with higher population density (MiD 2008). Nearly every person in the sample (99%) has a car at their own disposal, compared with 71.8% of the total population (MiD 2008), and has a current drivers' licence, as these were criteria for participation in the survey. Not surprisingly for car-commuters, the percentage of people holding a public transport subscription is low at 8%.

Also mandatory for participating in the survey was a daily commute by car of more than 20 kilometres. This shows in 61% of the sample with a driving performance of above 20,000 kilometres per year using the car in more than 90% of their daily commuting trips, see Figure 5. This is well above the value of 18% of drivers with a driving performance above 20,000 kilometres per year for the total population of Germany (STATISTIKA GMBH (2010)).

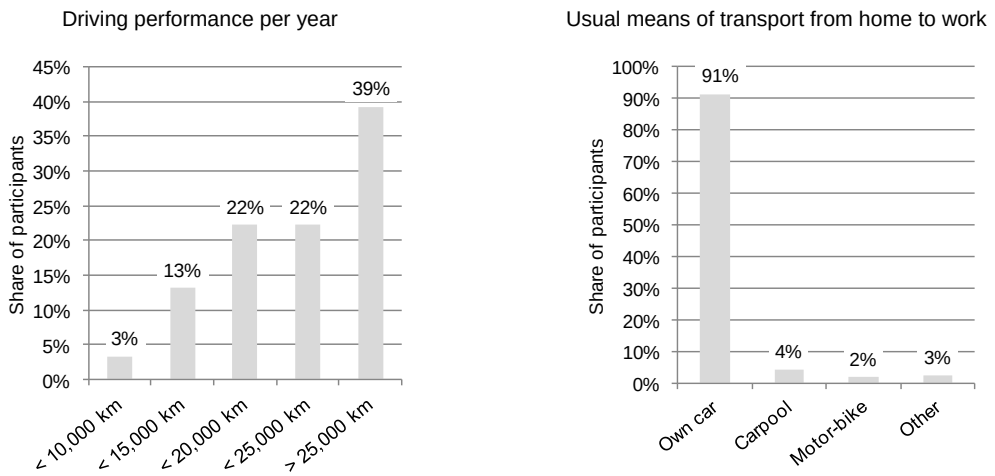

Figure 5: Driving performance and usual means of transport for commuting

The majority of observed trips are commuting either from home to work in the morning or from work to home in the evening. Thus, drivers' personal experience on their way to work is important as a reference for the observed travel times from GPS trajectories. Table 4 shows perceived travel times and delays on the daily commute stated by the participants. The mean travel time is approximately 40 minutes one way, compared with 26 minutes for employed persons in rural areas with higher density (MiD 2008). Experienced travel times fluctuate up to 62% for trips from home to work and up to 65% for trips from work back to home. Thereby, the participants experience a delay due to congestion every third day of 20 minutes on average.

	minimum	maximum	average
Daily travel time in the morning [min]	31	63	39
Daily travel time in the evening [min]	31	69	42
Delay due to congestion per day [min]			20
Number of days per week with delay time in the morning			1.4
Number of days per week with delay time in the evening			1.5

Table 4: Travel times and delays for daily commute

The third part of the questionnaire gives information on the normative environment and reveals personal preferences related to traffic information for a later estimation of a route choice model.

In this sample 75% state to have either a mobile (31%) or built-in (44%) navigation device in their car. This implies an interest in traffic information, in principle, as well as some experience in dealing with onboard route guidance.

In order to capture first indicators for important attributes in route choice, other than travel time, the participants were asked to name important sources of irritation when commuting as well as to prioritize improvement measures. Table 5 shows a ranking of the given answers. Congestion and information on the delay are the most important.

	Sources of irritation on daily commuting trips
1	Delay due to congestion
2	Stopping at red traffic lights
3	Behaviour of other road users
4	Not knowing the exact arrival time at departure
5	Not knowing what is the best route at departure
6	Searching for a parking place at the destination

	Prioritization of improvement measrues
1	It is important for me to know how long I will be delayed by the traffic jam
2	I would like to get information on alternative routes
3	Information on the cause of the congestion is important for me
4	I would approve of a measure to ensure that other road users can't cut in line, for example, by frequently changing lanes

Table 5: Sources of irritation and improvement measures on daily commute

Information on regular activity locations and trip purposes is later matched to recorded GPS trajectories. Table 6 shows activity locations ranked by trip purpose. The sample stated a total of 704 activity locations, which amounts to 2.5 activity locations other than home and work per participant during the observation period of eight weeks. Shopping for non-daily needs, for example hardware stores, is the most common trip purpose besides commuting. This is due to the fact that the majority of the sample consists of full-time employed men, who seldom do the grocery shopping for the family.

Trip purpose	Total number	Percentage
Shopping for non-daily needs	165	23%
Leisure	148	21%
Shopping for daily needs	98	14%
Visiting friends	95	13%
Other purpose	80	11%
Children pick-up or drop-off	71	10%
Other private duties	47	7%
Total	704	100%

Table 6: Regular activity locations

Regular weekly non-work appointments indicate the flexibility and time constraints of each participant and are valuable attributes for estimating a departure time model. Appointments were classified according to morning, afternoon and evening. These were further differentiated by appointments with a definite starting time (for example, evening classes) or a flexible starting time (for example, a work out at the gym). Figure 6 presents the percentage distribution of non-work appointments of the participants.

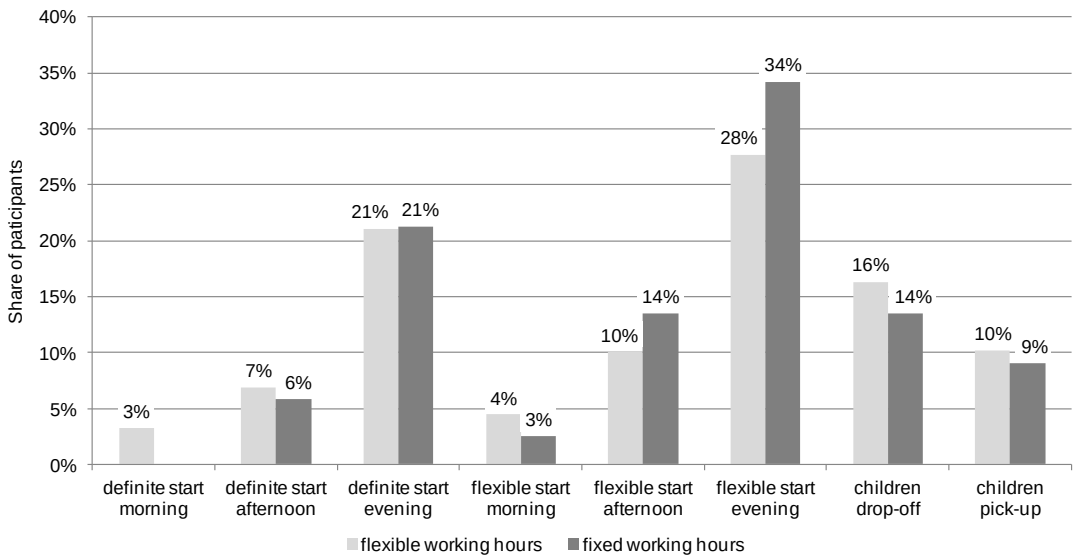

Figure 6: Percentage distribution of weekly non-work appointments

Participants with flexible working hours stated 943 appointments per week, an average of 3.4 per participant. Participants with fixed working hours stated 155 appointments per week, an average of 0.6 per participant. For all participants, evening activities play a major role. Appointments to drop-off and pick-up children are slightly more frequent among participants with flexible working hours.

Summarizing the driver-specific data collected in the online questionnaire, one can say that the sample of participants is not representative of the total German population or of the population in rural areas with higher density. Additionally, the sample is not representative in respect of travel behaviour. The average travel time to work and activity patterns are unusual for employees who own a car. This is due to the fact that the majority of the participants are fathers of families living in a rural environment, they have an above-average occupational status with presumably commensurately high incomes, and they are persons with an affinity for technical matters, among other unknown issues. Furthermore, as the sample size of 278 participants is comparatively small, it is difficult to subdivide the sample into even smaller person groups in choice model estimation (see chapter 5.1.3 *Route Choice Model* Estimation). All further analysis on quantifying the potential of traffic information in the survey area (see chapter 7 *Results for Munich Case Study*) are based on the assumption that the estimated route choice model accounts for the route choice behaviour of the total population. Whether the effects are considered to be underestimated or exaggerated is discussed in chapter 8 *Conclusion*.

3.4 Traffic State Data

Every decision on route or departure time can only be interpreted in the context of the current traffic situation. This implies that drivers not only consider the static characteristics of the given transport supply (such as the general condition of the road infrastructure, road type, number of lanes, scenery, trip length, number of traffic lights on route, free flow travel time or historical travel time, reliability of journey without delays etc.) but they also react to certain traffic state conditions (such as current travel time or velocities, LOS, traffic volume, and road works). Measuring the current traffic state data at the time of each trip on all considered alternative routes is necessary to evaluate the whole decision context and estimate a route choice model.

Traffic states are classified by a combination of travel time, mean speed along a section and other traffic variables such as flow [vehicles/hour] at the entry and exit points or density [vehicles/kilometre] along the section. The usual traffic state classes are; free, dense, bounded-flow and congested. Based on the fundamental diagram (LEUTZBACH (1972)), traffic states are derived from mean speed and density, see MARZ (BAST (1999)). Fuzzy-logic approaches allow the determination of a traffic state from a fuzzy rule set, for example (FOLKERTS ET AL. (2001)). The three-phase theory,

see (KERNER (2009)), provides a method for estimating the upstream and downstream propagation of wide moving jams and allocates current traffic states to the section. A comprehensive overview of this topic of traffic state estimation in transport networks is given in FGSV (2003). Today, traffic states are commonly translated to LOS, which is a qualitative interpretation of the performance of an element of infrastructure, see chapter 2.1 *Advanced Traffic Information Systems*.

Generally, the traffic states along network sections can be derived either by classifying measured traffic state variables or by using traffic forecast models to estimate traffic state variables between two stationary detectors.

Travel times along network sections can be measured directly by systems which identify a vehicle at an entry point and recognize the same vehicle at an exit point. The initial approaches for vehicle recognition were based on identifying vehicle signatures from their induced signal patterns when passing induction loop detectors. Today Automated Number Plate Recognition (ANPR) systems can be used to produce vehicle travel times by automatically recognizing number plates by video or infra-red cameras. A new approach uses Bluetooth signals to detect mobile devices in vehicles, for example, mobile phones which use Bluetooth to communicate with a speakerphone car kit. Other emerging technologies come from vehicle probes which provide more or less exact positions of vehicles while travelling in the actual traffic stream, such as Floating Car Data (FCD) or Floating Phone Data (FPD) from cellular phone networks.

If only stationary detectors measuring traffic flow and speed (at the entry and exit point of a section) are available, then traffic forecast models such as *ASDA/FOTO* (*Automatische Staudynamikanalyse/Forecasting of Traffic Objects*) can be used to estimate traffic states, mean velocity and travel time along the section. Other possibilities for forecasting travel times are discrete macroscopic traffic flow models such as the first-order model by LIGHTHILL AND WHITHAM (1955) or the cell-transmission model by DAGANZO (1994).

In the survey area the following data was used to generate a traffic state for every road section and every five-minute interval in the survey period:

- measured section travel times from ANPR cameras or GPS data
- forecasted link travel times from *ASDA/FOTO*
- LOS information from TMC messages as well as travel times and mean speed
- traffic flow from road side detectors

The traffic data was provided by PTV's online data archive, *Bayern Info*, authorized by the Board of Building and Public Works within the Bavarian Ministry of the Interior (see PTV AG (2011)). For better quality data, a data fusion of the single data sources was done by the Technical University of Munich (see BUSCH AND FIEDLER (2012)). The data fusion prioritized link travel times measured by either the participants' GPS trajectories or ANPR cameras over travel times modelled by *ASDA/FOTO*. If neither measured nor

modelled current travel times were available for a link, for example, if there are no detectors in parts of the minor road network or if consecutive detectors are more than three kilometres apart, travel times depending on day of the week and time of day from the PTV's transport model *VALIDATE* were used as historical travel times. Figure 7 shows an overview of the links with measured travel times and links with modelled travel times in the survey area. Although current travel times are only provided for the strategically relevant motorways and arterial roads, this covers the vast majority of relevant alternative routes for all trips observed during the survey (see also Figure 8).

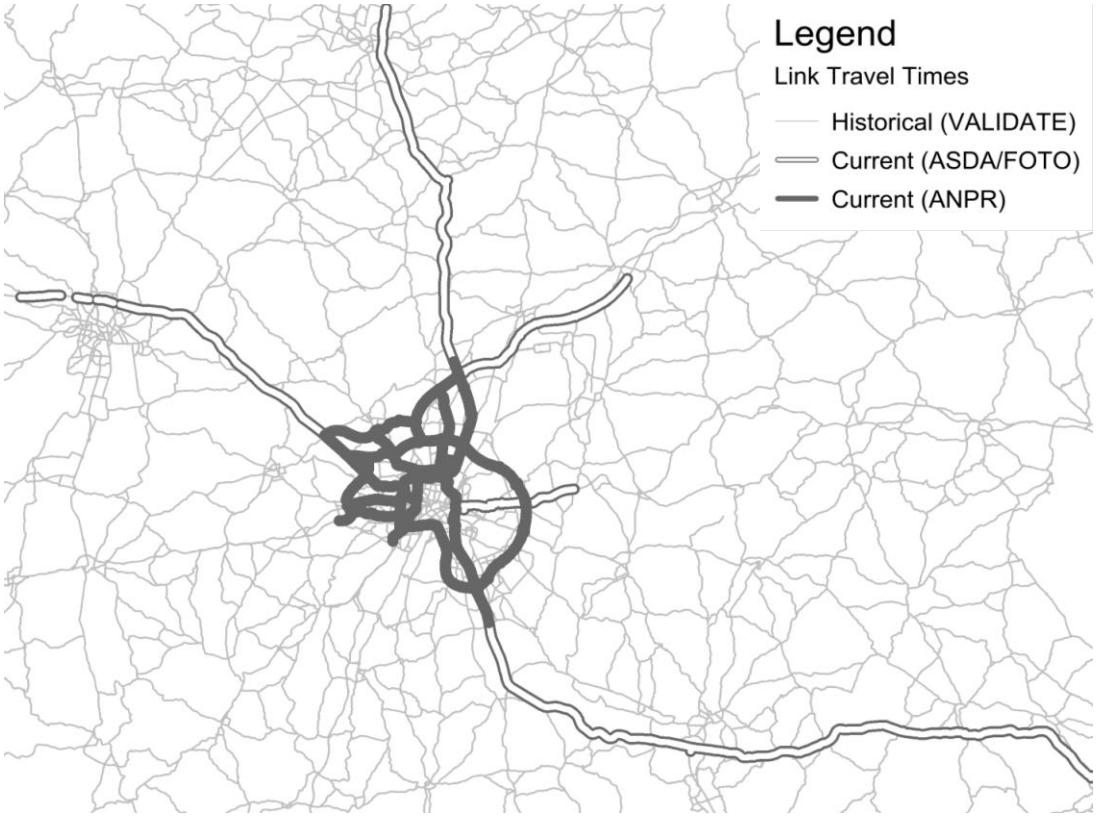

Figure 7: Measured and modelled current travel times in the survey area taken from *VALIDATE* (PTV AG), *ASDA/FOTO* (Bayern Info) and ANPR data (Autobahndirektion Südbayern)

3.5 Traffic Information Data

Although traffic state data is necessary to interpret the context of drivers' decisions on route or departure time, what is more important is the knowledge about the current traffic state on which drivers base their decisions. Today drivers do not have a complete overview of traffic conditions on all alternative routes for every possible departure time. Thus data on the traffic information provided at the time of travel as well as data about the usage of this information is essential to understand drivers' behaviour and preferences.

As discussed in chapter 2.1 *Advanced Traffic Information Systems*, ATIS can be classified into the influencing characteristics, the dependency on traffic conditions, the type of information, and the binding character. Of special interest for this research are ATIS that influence route and departure time choice by displaying non-binding information and recommendations based on current traffic conditions for individual drivers as well as the collective of all drivers.

During the survey the following traffic information data was collected:

- Time and content of routing information (navigation App on the user's smart phone)
- Time and content of LOS information (LOS map App on the user's smart phone)
- Time, location and content of radio traffic reports (TMC messages)
- Time and content of route recommendation (substitutive VMS)

To observe the effects of coordinated individual and collective information, the dynamic routing of the onboard navigation App was linked with strategic routing via VMS by the traffic control centre for southern Bavaria.

The collected data provides the opportunity to analyse decisions on route choice based on the knowledge of which traffic information data was available to the driver during his entire trip. Data on the usage of onboard traffic information is normally not available in other studies. The *wiki* data makes it possible to compare the impact of collective versus individual information devices on drivers' route choices in a large number of decision situations.

3.6 Route Choice Data

Chapter 3.3 *Driver-Specific Data* to 3.5 *Traffic Information Data* dealt with data describing the decision context the participant faced when choosing a route or departure time. The following two chapters – 3.6 *Route Choice Data* and 3.7 *Departure Time Choice Data* – now specify the data describing the actual decisions observed during the survey.

To analyse the effects of traffic information on route choice, two independent data sources for estimating a route choice model with focus on different utility attributes are available from the survey. GPS trajectories collected from all participants are used for estimating the effect of traffic information in general with respect to the current traffic state. As the effect and importance of single information devices cannot be determined from this data set, secondly data from SP interviews from all participants is analysed. This data contains choice situations in which traffic states are displayed by different information devices and is used to identify the importance of single devices in detail.

3.6.1 GPS Data

All participants were equipped with a smart phone and GPS sensor. The GPS sensor calculated a position every second whose latitudinal and longitudinal coordinates, date/time and speed were stored on the smart phone via Bluetooth connection. Every five minutes a GPS data package was transmitted to a server via the mobile phone network. The application started automatically when the smart phone was switched on. Because each smart phone's SIM card was registered on the server, GPS data can be analysed for each individual participant.

Figure 8 shows the network coverage of the observed data. The data illustrates that besides the freeways and major roads, the minor roads are frequented, especially in the north of Munich city. The motorway section on the A9 between junctions Neufahrn and München-Nord is the most frequented with up to 4,200 observed trips, see Figure 15 for a detailed map.

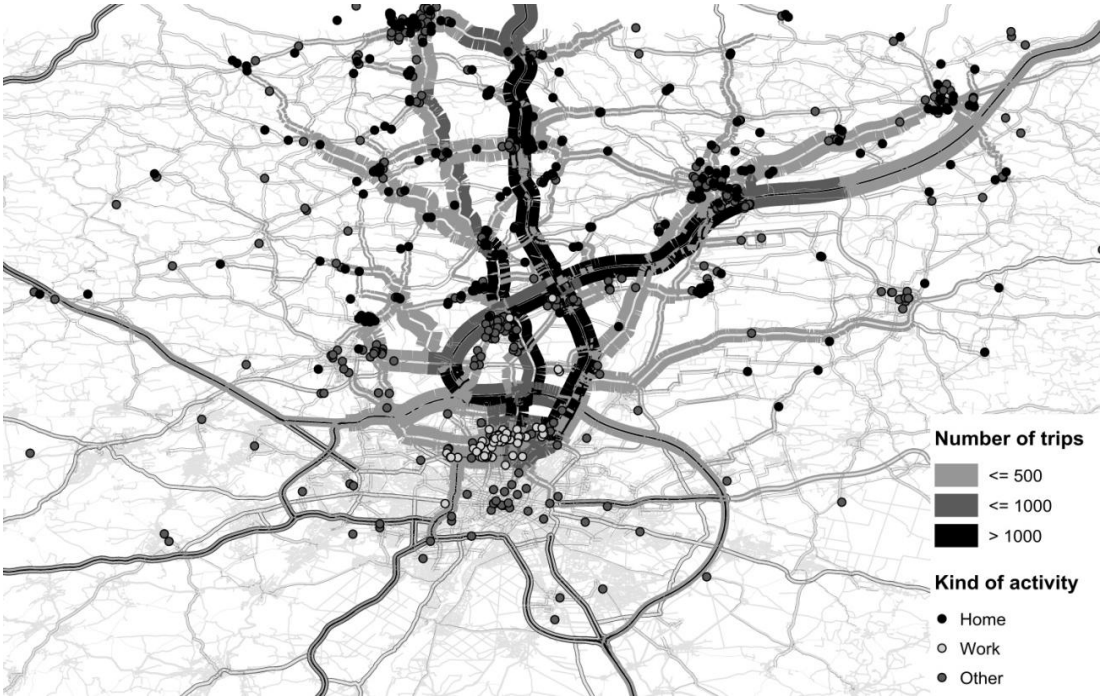

Figure 8: Overview of survey area with GPS trajectories and activity locations

The accuracy of the position logs was analysed by test trips and proved to be very high, with a maximum measured deviation of 13 metres in open space and up to 16 metres in built-up areas (see BUSCH AND FIEDLER (2012)). Although the time accuracy is very high, by recording a time stamp each second, sending data through the mobile phone network can result in data loss. This happens if the smart phone is switched off at the destination before the current data package is sent or if the global system for mobile communications (GSM) network connection fails during a trip. Moreover, the

recorded GPS tracks include data recorded between switching on and switching off the smart phone. This may include several trips.

The trips are map matched by assigning GPS logs to links and adding route elements to obtain complete trajectories without gaps. One problem in map matching GPS data on a digital map is that often towards the end of a trip the location cannot be found because minor roads are likely to be missing from the network model (SCHÜSSLER AND AXHAUSEN (2009)). To avoid these problems, the high-resolution *NAVTEQ* network (LN) was used.

Further processing is needed to advance from link trajectories to actual trips (partly published in PILLAT ET AL. (2011)). In this context, three criteria for trip identification are deduced:

1. Calculation of current speed and smoothed speed → current speed criterion
2. Calculation of current detour factor → detour criterion
3. Identification of space and time gaps → gap criterion

The first criterion deals with the varying accuracy with which the GPS data is recorded. This accuracy is related to the number of available satellites and generally ranges between five and ten metres (SCHÜSSLER AND AXHAUSEN (2009)). The current speed is based on the coordinate and can result in “jumping” speed values. Hence, a smoothed speed value is calculated using GPS coordinates and timestamps two seconds before and ahead of the current GPS log, see formula 16 below.

$$\mathrm{v}_{\mathrm{i,smoothed}} = \frac{x_{i-1\rightarrow i+1}}{t_{i+1} - t_{i-1}} \tag{16}$$

with:

	$v_{i,smoothed}$ [m/s]	Smoothed speed of ith GPS log of a trajectory
	t_i [s]	Time stamp (in unix time) of ith GPS log of a trajectory
	$x_{i-1\rightarrow i+1}$ [m]	Direct distance between the predecessor and the successor of the GPS log i, resulting from the coordinates

For each trajectory the time intervals are determined in which the smoothed speed is permanently lower than 0.7 metres/second. If this is the case for longer than 300 seconds, the trajectory is split and the GPS logs with low smoothed speeds are deleted. In doing so, intermediate activities within one trajectory can be identified, if they take longer than five minutes.

To identify intermediate activities of shorter than five minutes duration (e.g. drop-off or pick-up of passengers), secondly the detour factor is analysed. For every GPS log the detour factors $u_{1,500}$, $u_{5,000}$ and $u_{10,000}$ are calculated between the two GPS logs, which are 1,500 m, 5,000 m and 10,000 m respectively before or after the GPS log considered. The distances refer to the path length between the predecessor, the successor and the current GPS log respectively. If a detour factor of one of the three

categories exceeds a critical value for more than 90 seconds, the smoothed speed $v_{smoothed}$ is checked again.

If the value of $v_{smoothed}$ is less than four metres per second, the trajectory is split at the point with the lowest speed. Figure 9 shows this approach for an example trajectory. The left-hand diagram shows the graph of the detour factor u_{1500} and the graph of the speed. The diagram on the right shows the trajectory in the LN. Circled are the areas where the detour factor exceeds, and the speed drops below, the critical values.

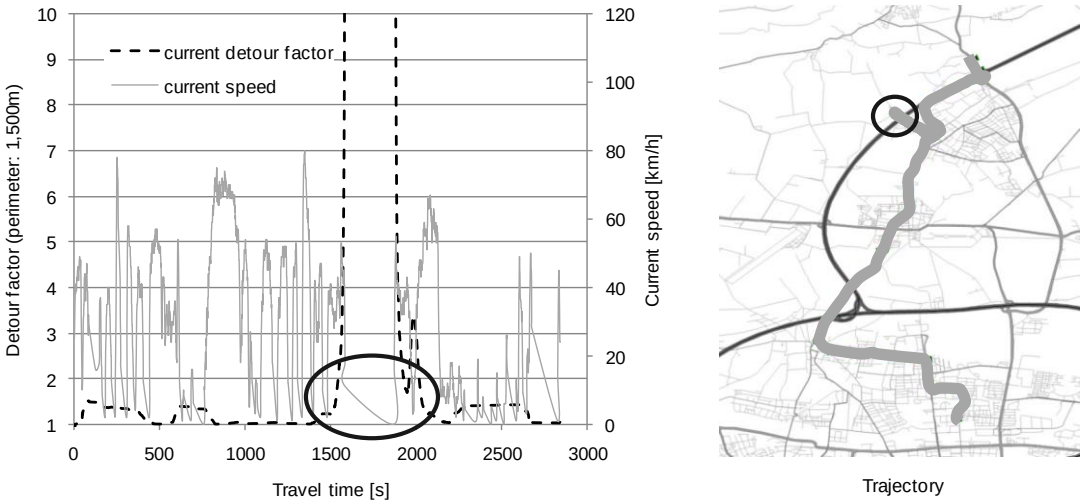

Figure 9: Detour factor and speed of trajectory

The third criterion deals with existing time and space gaps in recorded trajectories. For each GPS log, the distance to the subsequent GPS log x_{gap} and the difference of the respective time stamps t_{gap} are calculated. For time gaps of less than 300 seconds ($t_{critlow}$) the trajectory is always connected by a shortest path search. If the time gap is larger than 1200 seconds ($t_{crithigh}$) the trajectory is always split into two trips, because completing a trajectory with a gap larger than 20 minutes is not reasonable.

If however t_{gap} is between $t_{critlow}$ and $t_{crithigh}$, the gaps are analysed in more detail. In this case, the allowed time gap t_{acc} depends on the space gap x_{gap}. The larger the space gap the larger the t_{acc} becomes, see formula 17. The inverse value 0.625 of the parameter 1.6 in the formula can be interpreted as the threshold for a minimum accepted speed, in metres per second, to ensure there is no activity in between.

$$t_{acc} = \begin{cases} t_{crit.low}, & \text{if } t_{gap} \leq t_{crit.low} \\ x_{gap} \cdot 1.6, & \text{if } t_{gap} \leq t_{crit.high} \\ t_{crit.high}, & \text{if } t_{gap} > t_{crit.high} \end{cases} \tag{17}$$

with:	t_{acc} [s]	accepted time for activity detection
	x_{gap} [m]	space gap between two GPS logs
	$t_{crit,low}$ [s]	threshold for minimum activity duration
	$t_{crit,high}$ [s]	threshold for maximum accepted time gap

Knowing the purpose of the activity at the end and beginning of each trip is crucial for modelling route choice. Therefore, every activity location stated in the questionnaire within a perimeter of 2,500 metres is allocated to each trip end. The perimeter of 2,500 metres is chosen due to the average data loss at the beginning and end of a trip (cold start of GPS in smart phone at the beginning of trip, or loss of data package sent at the end of trip). If a trip end is related to more than one known activity location, a distinct activity match using arrival and departure time and duration between last and next trip is done. For example, if activities, “work” and “leisure”, are assigned to a trip ending at 7:05 a.m., with a duration of eight hours (the time until the next trip begins), the activity “work” is matched to the trip end. Each trip end, which is not related to any known activity, is clustered into groups with other unspecified trip ends within a perimeter of 2,500 metres. Thus, an additional 3,641 activity locations which are not stated can be derived. This amounts to 13 activity locations for each participant.

In the next step, the obtained trips need to be filtered to ensure that only plausible trips concerning the attributes to be analysed are taken as input data for estimating a route choice model.

Initially, trips are deleted which have been located in the PN or LN for a distance shorter than 5 kilometres. This is done because the allocation of destinations (trip ends) to activity locations is done with an accuracy of 2,500 metres. For trips shorter than 5 kilometres, the observed trip length compared with the direct distance of the origin-destination pair (OD pair) can be very small. The part of the trip for which the attributes of interest are unknown would be too high and very likely lead to a bias in the choice model estimation. As many of these short trips take place in the minor road network on rare occasions, they are not considered to be of high importance for understanding the main impacts of choice behaviour.

Two other filter criteria consider the allocation of activity locations to trip ends. On the one hand, all trips are deleted which start and end at the same activity location to avoid loops. On the other hand, only those activity locations were taken as origins or destinations which were either named in the questionnaire or at least assigned once to a trip not ending on a motorway. This ensures that trips beginning or ending on motorways, due to technical errors, are not included in the group of trips with unknown activity locations.

Furthermore, only trips with plausible map matching concerning the resulting speed values should be considered in later route choice analyses. All trips including speeds higher than 250 km/h at some point are deleted. Additionally, all trips are deleted for which the allocation to activity locations results in a detour factor exceeding 2.0 referring to the direct distance between the two activity locations. Finally, trips running entirely along minor streets only included in the LN are deleted because traffic state data is only given for links in the PN. For these trips only static data on important route attributes such as travel time is given.

Table 7 gives an overview of the total number of trips for applied filter criteria. The most important filter criterion is the trip length deleting almost 7,000 of the originally observed trips. This also shows in the resulting trip distance and travel time distributions, shown in Figure 10. Also, the percentage of deleted trips decreases with increasing trip distance and travel time.

Filter criteria	Deleted trips	Trips after applying filter
Total number of trips		27,500
Length < 5 km	6,915	20,585
Not part of PN	51	20,534
Loops	83	20,451
Trip end on motorway	3,606	16,845
Implausible map-matching	70	16,775
Other criteria	738	16,037

Table 7: Filter criteria for trips

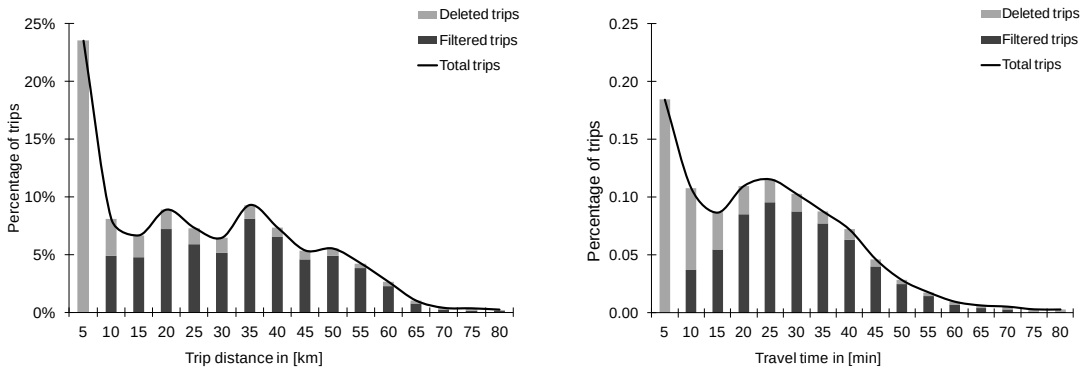

Figure 10: Trip distance and travel times distribution before and after filtering

After applying the trip filters, the route choice database includes 16,037 trips (60% of the original number) on 4,100 OD pairs (45% of the original number), see Table 8. Especially OD pairs on which few trips were observed are deleted. The number of trips per OD pair rises from 2.9 to 3.8 after filtering. As many trips are deleted because they are shorter than five kilometres, the mean trip distance and travel time rise after filtering.

Characteristics	Observed	After filtering
Number of trips	27,500	16,037
Number of activity locations	4,829	2,468
Number of OD pairs	9,420	4,100
Mean of trip distance [km]	24.8	31.3
Median of trip distance [km]	21.7	31.3
15th percentile of trip distance [km]	2.4	14.1
85th percentile of trip distance [km]	45.4	47.4
Mean of travel time [min]	21.7	27.5
Median of travel time [min]	20.4	26.2
15th percentile of travel time [min]	3.9	14.6
85th percentile of travel time [min]	37.7	39.6

Table 8: Characteristics of GPS trips before and after filtering

Table 9 gives an overview of the collected body of data and observed trips. The figure of 86 identified trips per person gives a low average of 1.5 detected trips per day (the average is 2.6 trips per day for a German commuter: MiD 2008), which can be ascribed to undetected trips and data filtering.

	Total 278 participants	Per participant
Total time of detection in hours	8,850	31.8
Number of detected GPS tracks	20,000	72
Number of identified trips	24,000	86
Number of trips between identified activity locations	16,037	58

Table 9: Total volume of route choice data

Figure 11 shows the daily traffic load curve as the share of total trips within an hour differentiated in different activity pairs. All activity pairs show the expected course over time of day. Trips starting at home mainly occur in the morning hours, whereas trips with starting point at work take place mainly in the evening hours. This results in characteristic morning and evening peak hours. The traffic volume between 9 a.m. and 3 p.m. is considerably lower.

A comparison of the observed GPS trips with trip data from MiD (2008) for the activity pairs home-to-work and work-to-home is given in Figure 12. Both data sources show a good match of departure time (see left-hand picture) as well as arrival time (see right-hand picture) for both activity pairs. For trips from work to home the GPS data shows a slightly later departure and arrival time when compared with the figures from MiD (2008).

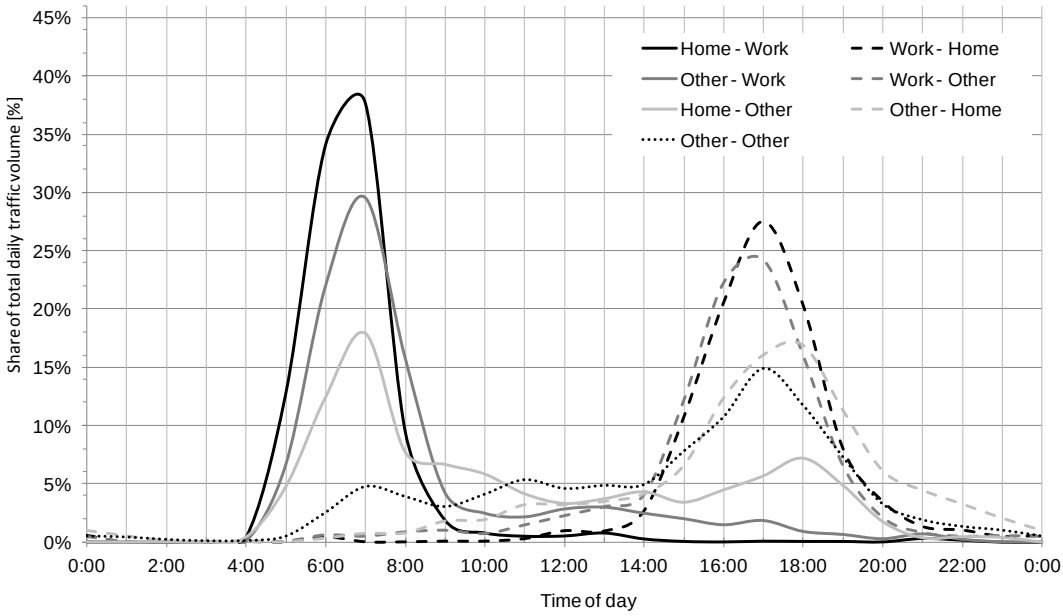

Figure 11: Daily traffic load curve differentiated in different activity pairs

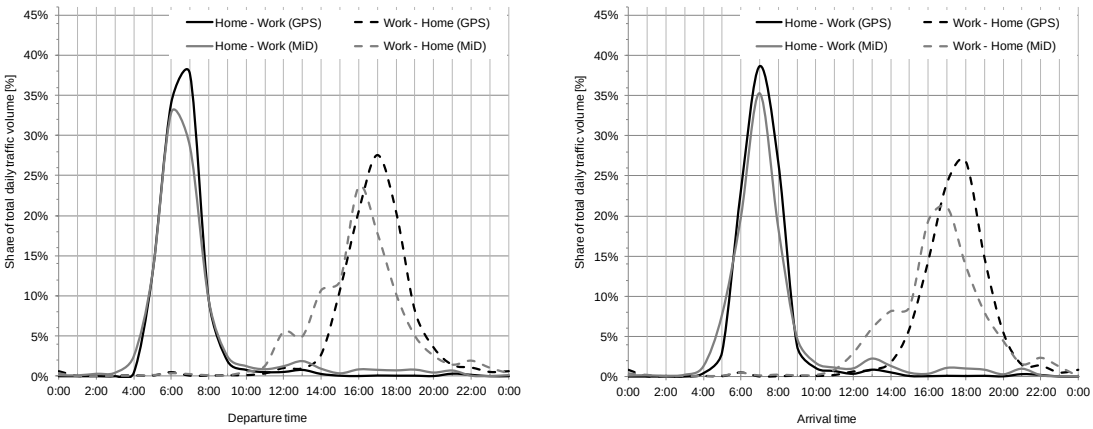

Figure 12: Comparison of daily traffic load curve for activity pairs home-work and work-home with MiD survey

Finally, the completeness as well as the correctness of trips with assigned activity locations is checked by analysing the number of observed trip types, see Table 10. In total, GPS data is available on 10,163 participant-days (meaning one or more trips of a participant on one day account for one participant-day). For roughly a quarter of all participant-days the recorded trips provide a complete trip chain, which starts and ends at home. A trip chain is thereby regarded as complete if all trips of the day end at the activity location at which the next trip starts.

	Number	Share
Participant-days in total	10,163	100 %
Participant-days with one detected trip	1,772	17 %
Participant-days with more than one detected trip	8,391	83 %
Participant-days with first origin and last destination at home	3,805	37 %
Participant-days with complete trip chain	5,565	55 %
Participant-days with complete trip chain starting and ending at home	2,611	26 %

Table 10: Completeness of trip chains from GPS data

The recorded trips provide an insight into route choice behaviour. Figure 13 shows an example of the observed routes from one participant. In a period of 61 days participant 185 recorded a total of 135 trips, of which 27 were from home to work. The participant clearly has a preference for his main route from home to work, yet still uses other routes occasionally.

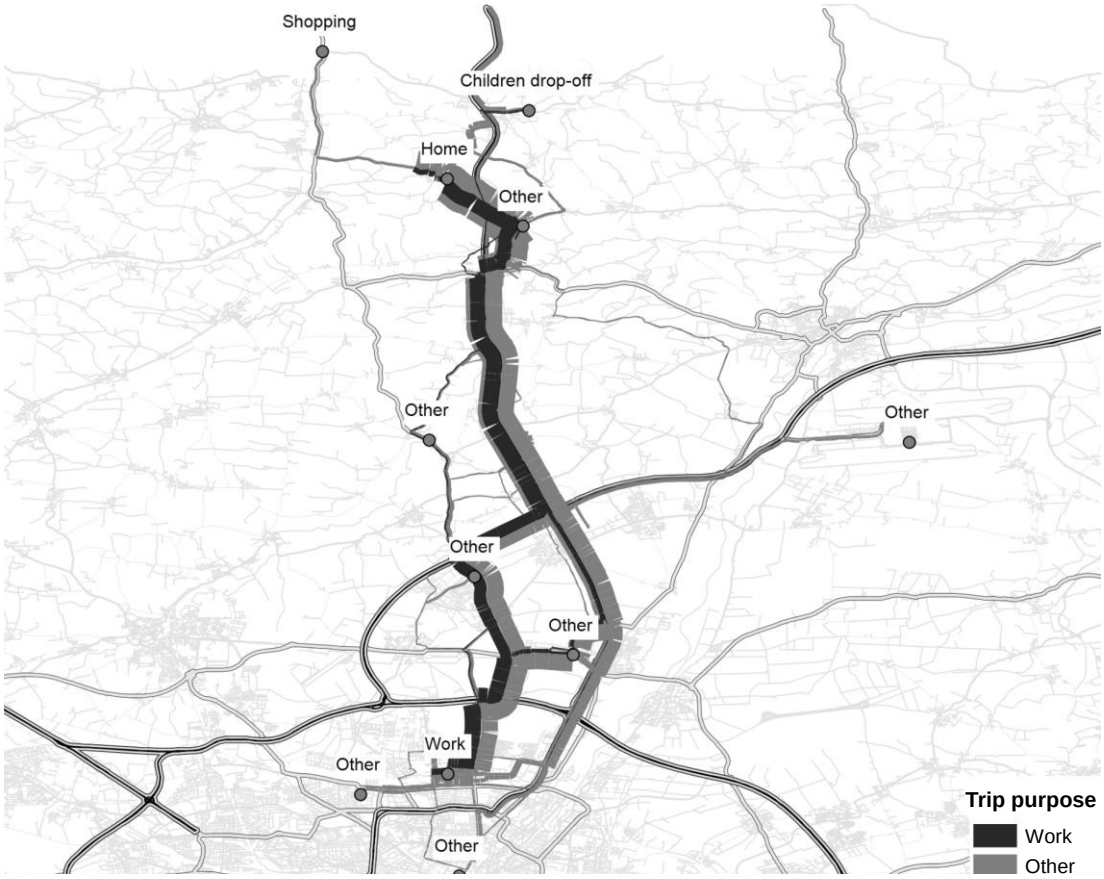

Figure 13: Observed GPS trajectories on the example of one participant

The collected data set is not only quantitatively a sound basis for route choice estimation, but includes recordings of trajectories for various traffic situations and travel times. Figure 14 shows the quality of chosen routes of participant 185 in comparison to all others.

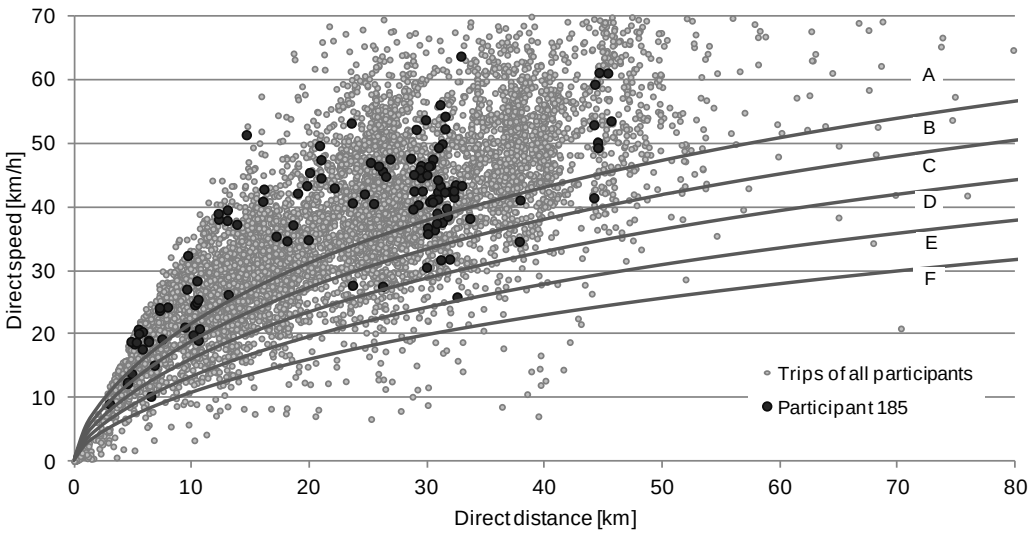

Figure 14: Quality of route travel times according to RIN (FGSV (2009)) with LOS A to F

The data clearly illustrates that this participant experienced different travel times on routes of a similar direct distance. The cluster of data points with a direct distance of approximately 32 kilometres indicates routes from home to work and return.

For all OD pairs the observed routes are later complemented with non-chosen alternatives from choice set generation (chapter 5.1.2 *Choice Set Generation*). All the routes in the choice set are then attributed with current traffic and information variables at the time of each trip.

3.6.2 Stated Preference Data

To complement the RP data, a SP interview was designed to retrieve information on the impact of different information devices and their relevance in route choice. The SP interview was complemented by an additional questionnaire on the participants' awareness of existing alternative routes on their daily trip to work in the morning. These known alternatives are important for choice set generation as they provide a reference for realistic choice set sizes and accepted detour factors. The known routes were drawn into a digital map by the participants.

The SP interview was designed to confront the participants with decision situations, in which he or she is informed about a given traffic situation through a certain information device and can choose between a given set of alternative routes. Similar work, for example by WARDMAN ET AL. (1997), confirms the hypothesis that the influence of traffic information largely depends on the way it is displayed. However, WARDMAN ET AL. (1997) only analyse VMS. BIERLAIRE ET AL. (2006) conduct a SP survey in Switzerland to analyze drivers' decisions on route choice when traffic information is provided during

their trip by the mean of radio reports (RDS) or VMS and determine a higher trust in traffic information via radio than via VMS. POLYDOROPOULOU ET AL. (1996) study commuters' decisions to divert to an alternative route when they become aware of congestion through different types of information sources in a SP experiment in the San Francisco Bay Area. Their results show that drivers are particularly likely to respond to quantitative information on delays and congestion. The impact of information on current travel times and cause of congestion on commuters' route choice is analysed in a SP questionnaire by ABDEL-ATY ET AL. (1997). It shows a strong potential to influence route choice in case of congestion. A study similar to the project *wiki* by TSAVACHIDIS (2002) deals with route choice behaviour of commuters on the same example of a motorway interchange to the north of Munich. As part of the BMBF project MOBINET, TSAVACHIDIS (2002) compares panel data on recorded trips with SP data and shows that the influence of VMS, radio with TMC, and section control (such as dynamic speed limits) on choosing either the A9 or the A92 to go into Munich depends on the current traffic state.

Based on these studies, the SP interview in *wiki* was carefully designed so that the given alternative routes and traffic states were realistic and mirrored daily experiences. The display of traffic information was chosen to include devices currently used by the participants as well as devices potentially used in the near future. The layout of the decision situations as well as the values of the characteristic variables is described in detail in the following.

The SP experiment on route choice includes twelve decision situations. Each decision situation is defined by a traffic state and an information device displaying the traffic state to the participant. Three different traffic states are each displayed by four information devices. The participant always has a choice between the same four alternative routes. Thereby, the order of the displayed decision situations is varied randomly.

The experiment was done as a computer-aided personal interview. Each participant was introduced to the general situation, in which he is driving on the motorway on his daily commute and approaches the Neufahrn motorway interchange, see Figure 15.

Without further assistance the participant was asked to choose one of the four alternative routes by clicking on the appropriate icon. Figure 16 shows one exemplary decision situation.

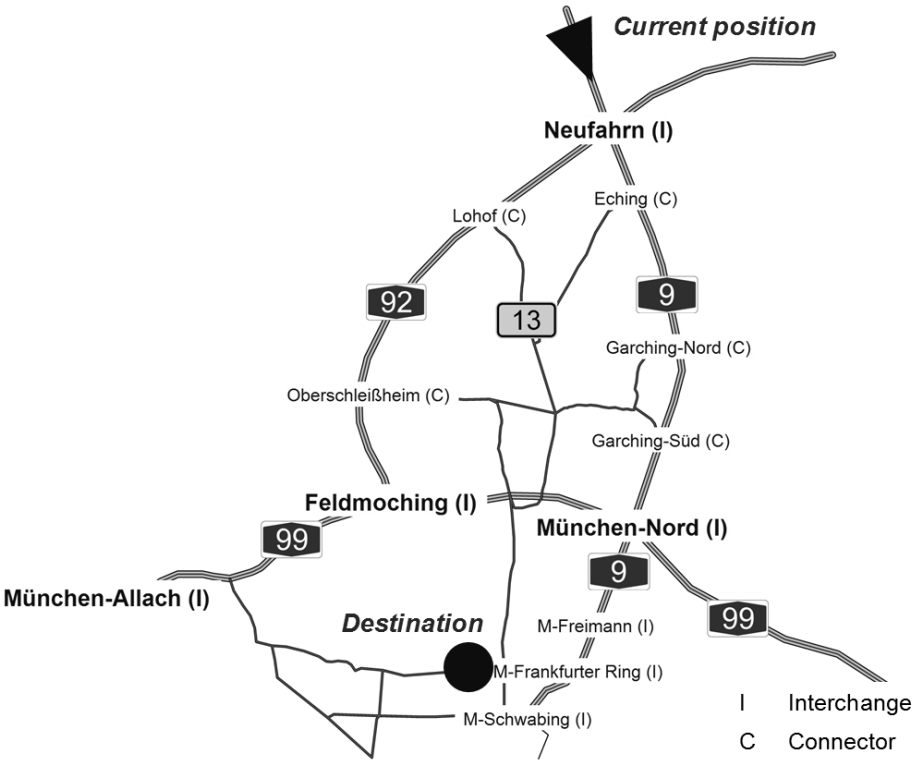

Figure 15: SP decision situation in Munich motorway network

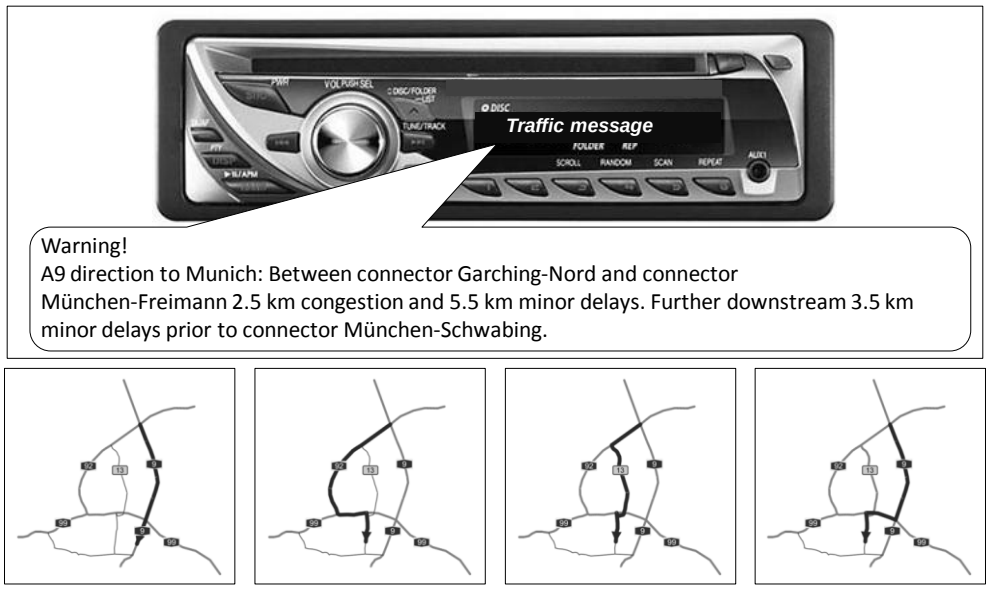

Figure 16: Exemplary SP decision situation for traffic state 1, information device 2

Selection of alternative routes

The selection of the four alternative routes was based on an analysis of the most frequently travelled routes in the GPS data during the pre-test of the survey. Other criteria for the selection of the choice set were

- manageable number of routes (so that the participant considers all alternatives)
- mostly independent route course (so that static route attributes as well as traffic states are not correlated and alternatives are easily distinguishable)
- preferable complete coverage of all important alternatives in the major road network (in order to avoid unrealistic choices due to a missing alternative)

Due to these criteria, the following routes were chosen (see Figure 16 from left to right):

- Route 1: A9
- Route 2: A92/A99/B13
- Route 3: A92/B13
- Route 4: A9/A99/B13

Route 4 follows the course of route 1 to a large extend, so that the travel times of both routes cannot be varied independently. However, route 4 was taken into the choice set to provide the participants with all necessary alternatives for entering Munich from the motorway. The communality of both routes is accounted later in choice model estimation.

Selection of information devices

The selection of the four information devices was based on the assumption, that the methods of presenting information as well as the contents displayed have an influence on the resulting route choice. Criteria for selecting information devices were:

- Level of familiarity (including devices currently used by the participant as well as possible future devices currently unknown)
- Content of displayed information in length of congestion, delay time and graphical level of service
- Kind of information (including pure information as well as information with route guidance)
- A possibly complete coverage of the information devices available in the field survey

Based on these criteria the following information devices were selected:

- Device 1: Cartographic LOS map (see Figure 17)
- Device 2: Traffic reports broadcasted over radio (see Figure 18)
- Device 3: Substitutive VMS (see Figure 19)
- Device 4: Travel time information signs (see Figure 20)

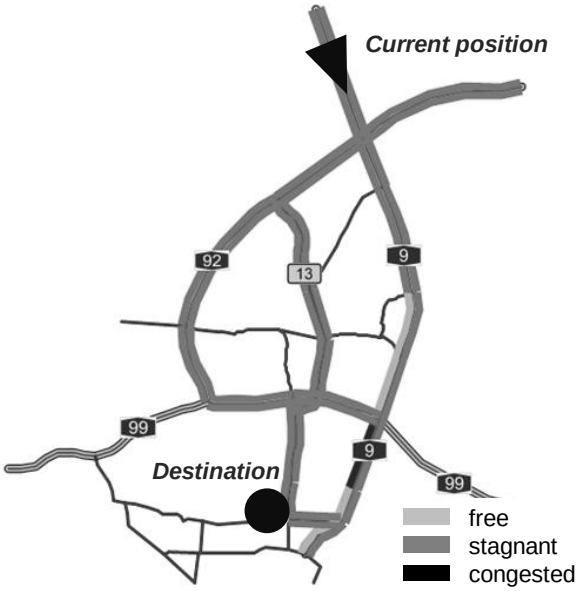

Figure 17: Cartographic LOS map with coloured congestion levels

Figure 18: Traffic reports via radio with information on length of congestion

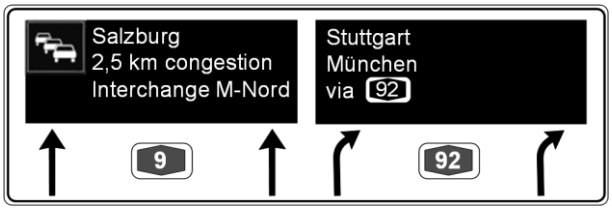

Figure 19: Substitutive VMS with information on kilometres of congestion and delays and route guidance

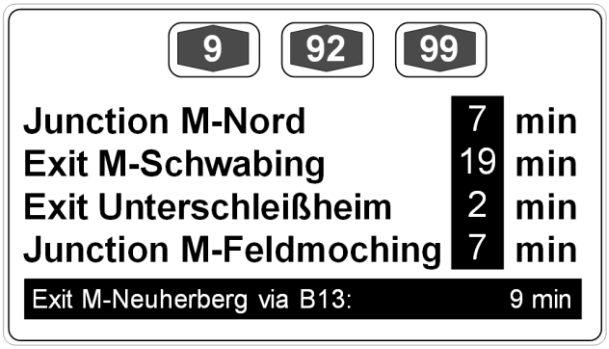

Figure 20: Travel time information sign with information on current travel times between exits and junctions

Selection of traffic states

The displayed traffic states along each alternative route were selected such that

- the usual main route of the respective participant is never the best alternative (because in this case a diversion from the usual route is unnecessary)
- none of the four routes is the best route in every decision situation (such that the participant should theoretically change his route choice in the course of the experiment)

Based on these criteria the following traffic states were defined:

- Traffic state 1: Minor delay on main route (MR) of respective participant
- Traffic state 2: Major delay on MR, minor delay on first alternative route (AR1)
- Traffic state 3: Major delay on MR, minor delay on second alternative route (AR2)

To generate traffic states as realistically as possible, a comparison of the matched GPS trajectories with the route courses of route1/route4, route 2 and route 3 shows the absolute travel frequency for each participant. According to their personal GPS data every participant can be assigned to a specific route group (RG). In total seven route groups are defined, which cover all possible combinations (MR, AR1 and AR2) for the four routes in the choice set, see Table 11. A participant is assigned to route groups 1, 2 or 3 if he has a distinct main route. Route groups 4, 5 and 6 are assigned to participants who have two equally frequented main routes. Route group 7 includes all participants without a distinct main route. All participants who cannot be assigned to one of the seven route groups are included in route group 1.

RG	MR1	MR1	MR3	AR1	AR 2
1	Route1/4			Route 2	Route 3
2	Route 2			Route1/4	Route 3
3	Route 3			Route1/4	Route 2
4	Route1/4	Route 2		Route 3	
5	Route1/4	Route 3		Route 2	
6	Route 2	Route 3		Route1/4	
7	Route1/4	Route 2	Route 3		

Table 11: Route groups for all combinations of main and alternative routes

For each route group three traffic states are defined by varying the delays on the main and alternative routes respectively. The free flow travel times in the uncongested network are taken from *Google Maps*™. A comparison with time-of-day-dependent travel times from *Bayern Info* provides realistic increases of travel time for the considered congestion incidents, see Table 12.

	Traffic State 1			Traffic State 2			Traffic State 3		
RG	Route1/4	Route 2	Route 3	Route1/4	Route 2	Route 3	Route1/4	Route 2	Route 3
1	+ 05 min	+ 00 min	+ 00 min	+ 10 min	+ 05 min	+ 00 min	+ 10 min	+ 00 min	+ 05 min
2	+ 00 min	+ 05 min	+ 00 min	+ 00 min	+ 10 min	+ 05 min	+ 05 min	+ 10 min	+ 00 min
3	+ 00 min	+ 00 min	+ 05 min	+ 00 min	+ 05 min	+ 10 min	+ 05 min	+ 00 min	+ 10 min
4	+ 10 min	+ 05 min	+ 00 min	+ 05 min	+ 10 min	+ 00 min	+ 05 min	+ 05 min	+ 10 min
5	+ 10 min	+ 00 min	+ 05 min	+ 05 min	+ 00 min	+ 10 min	+ 05 min	+ 10 min	+ 05 min
6	+ 00 min	+ 10 min	+ 05 min	+ 00 min	+ 05 min	+ 10 min	+ 10 min	+ 05 min	+ 05 min
7	+ 10 min	+ 05 min	+ 00 min	+ 00 min	+ 10 min	+ 05 min	+ 05 min	+ 00 min	+ 10 min

Table 12: Increase in travel time for considered congestion incidents

For displaying information on traffic states via radio, VMS or LOS map, delays in minutes are converted to kilometres or colour coded (green, yellow, red). The lengths of congestion in kilometres are calculated according to factors derived by SCHLAICH AND FRIEDRICH (2008). They derive standard values for average speed in congested (16.4 km/h) and stagnant (50 – 60 km/h) traffic flow conditions by analysing traffic messages on motorways.

For converting travel time to colour code (free flow → green, stagnant flow → yellow, congested flow → red) the values from the Bayern Info data archives are adopted. There the traffic states free, stagnant, or congested are based on a three-stage classification of the saturation (volume/capacity) on a link.

Table 13 shows the twelve decision situations based on the defined information devices and traffic states. The resulting characteristic values of the four route alternatives over all decision situations are given in Table 14 as minimum, maximum and average values.

Decision	Traffic State		Information Device	
Situation	No.	Description	No.	Description
1	1	Minor delays on main route	1	LOS map
2	1	Minor delays on main route	2	TMC via radio
3	1	Minor delays on main route	3	VMS
4	1	Minor delays on main route	4	TTIS
5	2	Delays on main route and first alternative route	1	LOS map
6	2	Delays on main route and first alternative route	2	TMC via radio
7	2	Delays on main route and first alternative route	3	VMS
8	2	Delays on main route and first alternative route	4	TTIS
9	3	Delays on main route and second alternative route	1	LOS map
10	3	Delays on main route and second alternative route	2	TMC via radio
11	3	Delays on main route and second alternative route	3	VMS
12	3	Delays on main route and second alternative route	4	TTIS

Table 13: Characteristics of SP decision situations

Variable	Characteristics		
	minimum	maximum	average
Length [km]	17.1	21.6	18.8
Detour factor [-]	1.1	1.4	1.2
Travel time index [-]	2.5	3.8	3.0
Historical travel time [min]	9.7	13.8	12.4
Current travel time [min]	13.6	23.8	18.1
Length of stagnant flow [km]˜	0.0	13.0	6.1
Length of congestion [km]˜	0.0	4.0	2.1
Length of free flow [km]*	4.5	21.6	12.5
Length of stagnant flow [km]**	2.2	13.3	6.8
Length of free [km]***	2.6	5.6	3.7
Recommended Route [-]	0	1	--

˜ reported via radio or VMS

* reported via green LOS ** reported via yellow LOS *** reported via red LOS

Table 14: Characteristics of route variables

3.7 Departure Time Choice Data

Departure time in contrast to route choice is not merely influenced by the traffic conditions occurring at the time of the journey, but mostly a result of other activities and commitments during the day. Furthermore, departure time is far more a habit than a conscious choice and therefore can only be observed and influenced over a long period of time.

GPS trajectories recorded during the eight-week survey period reveal departure time of trip chains over the day. Yet, trip chains vary significantly over days of the week as activities vary over days of the week. Therefore, many more weeks of observations are needed in order to identify the systematic behaviour on particular week days. Even more observations are needed to analyse the effect of traffic conditions and information on the departure time pattern for all trip purposes. The RP data collected in this survey is not suitable for analysing departure time behaviour and the causalities behind it.

The SP interview on departure time aims to identify the flexibility of the participants in order to quantify the potential of travel time information on the temporal distribution of the travel demand. Assuming drivers have a certain routine, a SP experiment is designed which confronts the participant with a decision situation in which he receives information on a possible travel time reduction corresponding to a change of his usual departure time on his daily commute. The combined analysis of the stated departure time (SP data), the revealed departure time (GPS data), and the regular outer office activities (questionnaire) allow considering person-specific flexibility in estimating a departure time model.

Other studies show that departure time flexibility is highly dependent on personal preferences (ROHR ET AL. (2005)). Based on these findings, this SP experiment is designed to reflect the usual daily departure time from home to work of each participant. The design and the variable characteristics of the decision situations are described in the following.

The SP experiment includes six decision situations, see Table 15. Each decision situation is defined by a suggested change of the usual departure time, a forecast travel time saving, and the reliability of the travel time forecast as well as the starting point of the trip. The characteristics of the variables are randomly varied within set boundaries. This is described in detail in the experimental design on page 51.

In the computer-aided interview the participant was asked to imagine that he is on his way to work (or on his way home, respectively) on a usual week day without any further appointments. Before departing he receives the following information on a forecast travel time saving subject to a given change of departure time. An exemplary decision situation is given in Figure 21.

Situation	Travel time savings [%]	Change of departure time [min]	Starting point [Home/Work]	Reliability of Information [%]
1	Savings s_1	Change c_1	Starting point sp_1	Reliability r_1
2	Savings s_2	Change c_2	Starting point sp_2	Reliability r_2
3	Savings s_3	Change c_3	Starting point sp_3	Reliability r_3
4	Savings s_4	Change c_4	Starting point sp_4	Reliability r_4
5	Savings s_5	Change c_5	Starting point sp_5	Reliability r_5
6	Savings s_6	Change c_6	Starting point sp_6	Reliability r_6

Table 15: SP decision situation for departure time choice

Figure 21: Exemplary SP decision situation for departure time choice

Selection of variables

The variables included in the SP experiment are chosen under the assumption that the expected travel time saving has a significant influence on departure time choice. This correlation can be observed for exceptional incidents, such as temporary road works or major sporting events, for example, in which case people change their departure time for better travel times at other times of day.

To confront the participant with significant, yet not unrealistic, travel time savings, relative travel time savings in percentage of the usual personal travel time rather than absolute savings in minutes are used as variable values. However, in the interview the relative savings were displayed in the corresponding minutes of saved travel time in order to keep the decision situation as simple as possible.

Besides the expected travel time savings, personal preferences, for example, related to morning habits, are a decisive factor for departure time choice. Therefore, the variable starting point is considered in the experiment. To keep the number of decision situations for each participant as small as possible, only commuting trips are analysed in the experiment. The starting point is either the participant's home or workplace.

In order to separate the effect of traffic information on departure time choice in estimation from the personal bias for or against the information quality itself, a variable for the reliability is included in the experiment. The reliability of the information on possible travel time savings is given as a probability of actually obtaining these forecast savings.

Characteristics of variables

The characteristics of variables are chosen such that at least the two extreme values provoke a difference in departure time choice behaviour. However, the bandwidth of extreme values needs to be set carefully to avoid one variable value dominating all other variables of the decision situation, for example, for travel time savings of 99%.

The necessary number of values for each variable depends on the intended choice model to be estimated. Usually linear models are used for which two values per variable are sufficient for estimating significant parameters. Further variable values are needed if there is uncertainty of a sensible bandwidth of extreme values. Table 16 shows the characteristics of the chosen variables in this SP experiment.

Variable	Characteristics					
Travel time savings [%]	10	30	50			
Change of departure time [min]	60	40	20	- 20	- 40	- 60
Starting point	Work	Home				
Reliability of Information [%]	50	70	90			

Table 16: Characteristics of departure time variables

Statistical experimental design

The quality of the estimated parameters depends on the statistical experimental design. A complete experimental design includes all possible variations of all variable values of the experiment. The four variables and their selected values result in $6 \times 2 \times 3 \times 3 = 108$ different value combinations. A statistical experimental design attempts to identify the interdependency of the influencing variables and the resulting choice with as few decision situations as possible. Using the statistics software SAS, the complete experimental design is reduced to 36 decision situations without losing accuracy in correlation and balance of parameters.

Each participant was confronted with six decision situations. The total 36 decision situations were randomly selected into groups of six and these were again randomly assigned to participants. Table 17 shows the experiment groups including six decision situations each.

Person-specific adjustments

The experiments were furthermore adjusted to match the personal trips of each participant. First, their usual travel time from home to work was taken from GPS trajectories. Second, the origin and destination displayed in the interview were matched to the actual home and work location of the participant.

Travel time savings [%]	Change of departure time [min]	Starting point [Home/Work]	Reliability [%]
Group 1			
10	- 20	Home	70
10	- 20	Home	70
50	+ 60	Home	90
30	+ 40	Home	70
50	+ 60	Home	70
30	- 40	Work	50
Group 2			
30	- 20	Home	70
30	- 40	Work	90
50	+ 60	Work	50
50	+ 40	Work	70
10	- 20	Work	90
50	+ 60	Work	90
Group 3			
10	+ 60	Home	50
30	- 20	Home	90
50	+ 40	Home	90
50	- 40	Home	50
30	+ 60	Work	70
30	- 20	Work	50
Group 4			
10	+ 60	Home	90
10	+ 60	Home	50
30	- 20	Home	90
30	+ 40	Home	50
50	- 40	Home	70
50	- 20	Work	50
Group 5			
50	- 20	Home	50
10	- 40	Home	90
10	+ 60	Work	70
10	+ 40	Work	50
30	+ 60	Work	70
50	- 20	Work	90
Group 6			
30	+ 60	Home	50
10	- 40	Work	70
10	+ 40	Work	90
10	- 20	Work	50
50	- 20	Work	70
30	+ 60	Work	90

Table 17: Experiment groups for departure time interviews

3.8 Summary of Data Sources

In combination, the data sources collected during this survey provide a detailed description of the context in which each of the 278 participants made decisions on route and departure time over a long period of time.

The total of 16,037 observed route choice situations makes it possible to estimate the influence of a large number of explanatory attributes for a predictive route choice model, see chapter 5.1.3 *Route Choice Model* Estimation.

For all choice situations the current traffic state is available on all alternative routes in the choice set for each OD pair.

Data of individual and collective traffic information devices used before or during a trip enhance the possibilities to single out the impact of traffic information on route choice in choice model estimation.

The total 3,324 route choice situations from the SP interview make a more detailed analysis of the impact of single traffic information devices possible.

Departure time choice is given for a total of 1,662 choice decisions for trips from home to work. With this data the willingness to change the usual departure time is interrelated to forecasted travel time savings.

Person specific attributes, given from the questionnaire, are used to single out effects of personal preferences in choice model estimation.

4 Driver Information

The following chapter focuses on driver information in the sense of provided traffic information as well as the state of knowledge of individual drivers. What is the role of traffic information in a larger traffic management picture? How good is the information provided today? How well are drivers informed about traffic conditions? And do drivers make use of the information provided?

4.1 Objectives, Conflicts and Potentials

Adaptive driver information is gaining importance in traffic management due to the growing availability of real-time traffic data and the increasing popularity of navigation devices. Government authorities seek to use traffic data to operate roadside traffic guidance systems in order to reduce congestion within the whole transportation network. Yet, public authorities do not merely focus on the reduction of travel time, but have a broader approach in defining their transport planning and management targets. The optimal utilization of existing network capacities stands in contrast to the general directive of retaining traffic flows on the major road network and reducing noise pollution and emission in urban areas.

At the same time, private sector companies compete in the growing market of in-vehicle information devices in order to provide travel time gains to their customers. Although there are considerations on the impact of navigation systems on network flows regarding the growing number of vehicles equipped with them, the main focus is to optimize the accuracy of real-time information for the individual driver.

Drivers seek flexibility of choice without regulations or restrictive guidance. They use traffic information to support their own network knowledge and experience and will reject information that is not to their personal benefit in the long term. However, drivers demand a reliable road network where travel times on particular days of the week and times of day are predictable, see research on robust route guidance by KAPARIAS (2007) and BELL (2009). This leaves room for them to accept traffic management routing strategies to some extent. Their objective of optimizing their individual journey can include additional criteria apart from travel time, such as distance travelled, scenery, safety issues, overall quality of traffic flow, number of traffic lights passed etc. Therefore, information needs to be adjustable to personal preferences as well as easy to understand rather than overly accurate.

To evaluate the potential of driver information, a closer look at the deficiencies in transport networks is needed. On the one hand, delays and congestion are caused by saturation of roads due to high transport demand. On the other hand, construction sites or accidents reduce existing capacity and cause delays.

Traffic information and guidance can only influence travel demand – in the sense of rerouting traffic or shifting demand to other times of day or other transport modes – and thus help to reduce delays caused by regular oversaturation.

Incident management by local authorities leads to a quicker clearance of accidents, helps to reduce the impact of road works as well as increasing the general reliability of the road network.

Better performance of the road network can be achieved by management of the transport supply through section control, hard shoulder running or selective improvement of infrastructure.

In the Munich motorway network delays occurred during 0.8% of all hours during the year 2009 based on an analysis of 160 motorway links done by the motorway authority of Southern Bavaria (*Autobahndirektion Südbayern*). This is within their performance goal of less than 1% of hours with oversaturation. At a closer look, 7% of these delays were caused by road works, 9% by accidents and 84% by saturation due to regular travel demand.

Data from the GPS survey shows that today the theoretical potential of rerouting traffic by information – meaning that every driver would use the fastest possible route instead of the route he actually used – amounts to three minutes or 9% travel time reduction on average for every driver. For 10% of all trips drivers could save up to 75% of the travel time. The theoretical potential of shifting demand to other times of day depend on the flexibility of the drivers. Assuming that every driver shifted his departure time by at most 10 minutes, to use a time slot with the fastest travel time to his destination instead of departing as he actually did, there would be a 6% travel time reduction on average for every driver.

A literature review on the potential of traffic management by ATIS shows substantial preliminary work in the field of compliance rates to single infrastructure facilities using VMS. BALZ (1995) studies on German motorways find a 5-20% compliance rate, similar to BECKMANN ET AL. (2001) and STEINAUER ET AL. (2001) with a range of 5-30%. On the basis of a large set of FPD SCHLAICH AND FRIEDRICH (2008B) determine the share of through traffic which can be rerouted by a VMS in the motorway loop Stuttgart-Heilbronn-Karlsruhe-Walldorf to be 10-12%. Research on the potential of these systems for spatial and temporal rerouting of traffic demand for a whole survey area is rare, however, and proves difficult due to the multiple influencing variables of each particular facility.

Earlier work by CONQUEST ET AL. (1993), HU AND MAHMASSANI (1997) and ABDEL-ATY ET AL. (1997) shows that individual information devices, such as in-vehicle navigation systems, have a larger effect on the route choice of individual drivers than roadside ATIS. However, the surveys conducted were mostly limited to certain corridors instead of observing long-term behaviour for a greater area. Network-wide effects of navigation

systems have been evaluated by ZACKOR ET AL. (1999) under the presumption of a fully equipped vehicle fleet. They conclude that rerouting vehicles away from congestion can reduce the transport time expenditure by a margin of 2-3%, if there is free capacity elsewhere in the network. MATSCHKE (2007) finds similar results of 5% reduction of transport time expenditure on the basis of microscopic simulation for a vehicle fleet equipped with dynamic navigation systems. The margin of travel time reduction is thereby dependent on the actualization rate of reported travel times in the navigation system.

The combined use of road-side ATIS and in-vehicle devices is analysed by BECKMANN ET AL. (2001) and shows verifiable interactions. Compliance rates are largely increased if routes are recommended by both systems. Additionally, the simulation performed on the motorway network of the region Rhein-Rhur in Germany determines major impacts of network geometry, demand situation, and cause of traffic delays on the transport time expenditure.

This leads to the conclusion that traffic information can be a major part of an overall traffic management scheme. However, the full potential of our road networks can only by achieved if traffic management is complemented with other measures to increase the performance and the reliability of the road network. Furthermore, the effect of traffic information is dependent on drivers' device acceptance and thus the potential of achieving system-optimal traffic flows by applying traffic information is *per se* limited. System-optimal behaviour can only be enforced by other additional measures such as mobility pricing.

To what extent traffic information can reduce the transport time expenditure on a network-wide scale, thereby considering drivers' evaluation of traffic information compared with other decision relevant variables, is analysed theoretically in chapter 6 *Optimisation of Traffic Flows* and quantified for the Munich metropolitan area in chapter 7 *Results for Munich Case Study*.

The following chapters analyse ATIS systems used in the *wiki* project for the quality of information and device acceptance as well as driver compliance.

4.2 Quality of Information

As route guidance by traffic information is not binding for the driver, high quality traffic information is necessary to increase device acceptance as well as driver compliance. This chapter analyses the quality of traffic information with respect to the accuracy and punctuality of contents, the comprehensibility of information devices and the reliability of forecasts.

The best possible state of information would be if all drivers received real-time traffic information for the road segments downstream of their current position along the route on which they are travelling. Yet even if traffic information is available in real-time there is room for error in forecasting future traffic conditions in order to give the driver the information on the travel time he will experience when he arrives at the relevant section, see BEN-AKIVA ET AL. (1997).

Today short-term forecasting of section travel times is usually based on data from stationary detectors. The data archive in the *wiki* project provides a travel time forecast which is updated every 15 minutes using data from stationary detectors as input for *ASDA/FOTO*. Based on Kerner's Three-Phase Theory (see KERNER (2009)), *ASDA/FOTO* detects and predicts the front and region of synchronized flow or a wide moving jam by analysing the traffic flow rate, vehicle speeds and the portion of trucks at a given time between two stationary detectors (see REHBORN AND PALMER (2008)). The prediction relies largely on matching current detector data to observed empirical traffic flow patterns on freeways measured by stationary loop detectors.

To evaluate the quality of the forecast travel times provided by the *wiki* archive, measured section travel times from ANPR cameras and forecast link travel times from *ASDA/FOTO* are compared in the following. Figure 22 shows the route section along the motorway A9 from Neufahrn junction towards München Nord junction highlighted with a black arrow in the direction for which the data is compared.

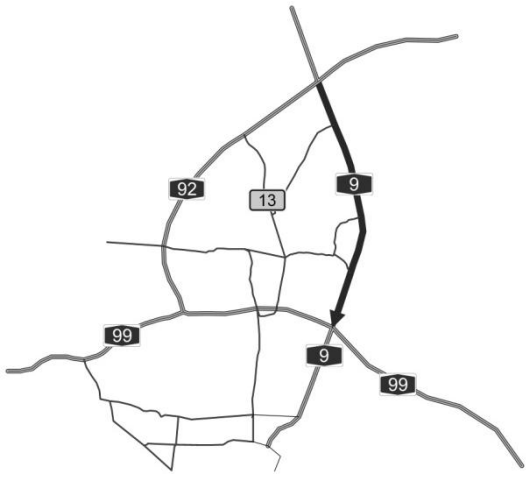

Figure 22: Route section for analysis of quality of travel time forecast

All measurements of the section travel time within a five-minute interval during the entire survey period are compared with the forecast travel time for the respective five-minute interval. Plotted in Figure 23 is the relative difference in forecast travel time to measured travel time, relative to the measured travel time in seconds. The distribution of travel time difference shows that there are some extreme errors in the travel time forecast. The forecast travel time can be much too low, for example, if stationary detectors did not provide data, or much too high, if congestion was wrongly detected.

Overall, the short-term forecast slightly overestimates current travel times. For 38% of all examined time intervals the forecast travel time is too low, which is why the distribution curve cuts the y-axis at 0.38. This is due to the fact that for most of the analysed five-minute intervals free flow conditions were observed. In free flow, vehicles were observed to travel at speeds higher than the official speed limit for these time periods. *ASDA/FOTO* forecasts a free flow travel time according to the given speed limits. The dashed lines show the 95th percentile or 90th percentile of five-minute intervals which are within a certain travel time difference. In total the predicted travel time differs less than $\pm$20% from the measured travel time in 95% of all examined five-minute intervals.

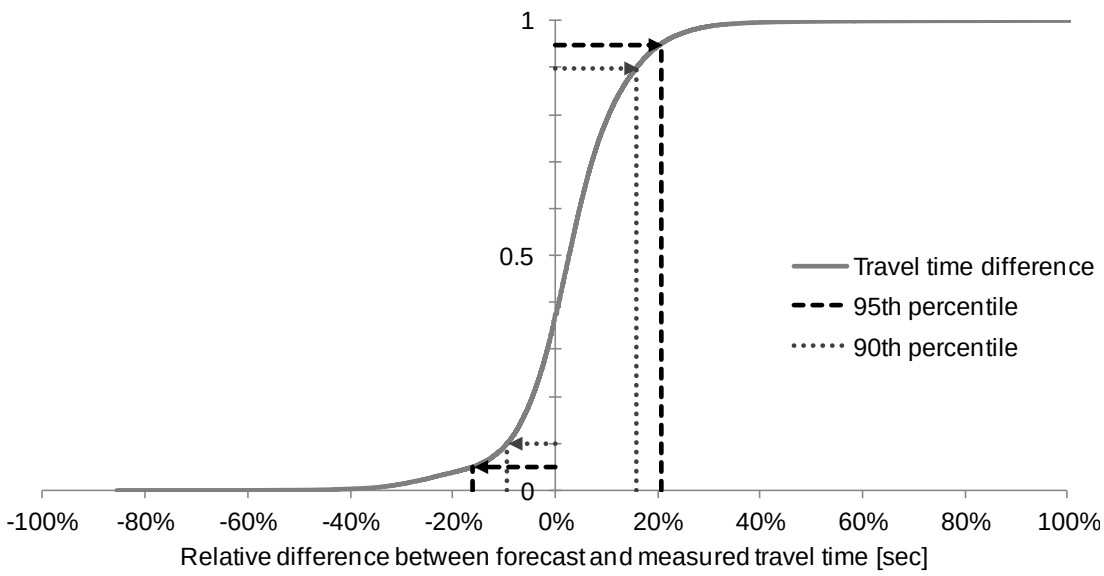

Figure 23: Distribution of difference in forecasted (*ASDA/FOTO*) and measured (ANPR) travel time

The analysed data includes travel time values for a period of 41 weeks from 16 February to 23 November 2009 along a route 9.1 kilometres in length. Thus, the data sample of 52,000 five-minute intervals is highly variable including 24-hour periods of all week days with very different peak and off-peak conditions as well as school holidays. A classic measure for evaluating the statistical dispersion of a quantitative data sample is the mean absolute deviation (MAD), see formula 18.

$$MAD = \sum \frac{|\text{actual} - \text{predicted}|}{N} \tag{18}$$

with:	MAD	Mean absolute deviation
	actual [s]	actual measured travel time from ANPR systems
	predicted [s]	predicted travel time from *ASDA/FOTO*
	N	number of observations (52,000 five-minute intervals)

The MAD for the off-peak hours 9 a.m. - 3 p.m. and 6 p.m. - 6 a.m. is 27.3 seconds and slightly lower than 28.4 seconds for the peak periods for which travel time predictions become more difficult in traffic break-down situations.

A robust statistical measure for quantifying the performance of short-term travel time forecasts is the mean absolute percentage error (MAPE) which provides a measure of accuracy for a fitted time series value in statistics, see formula 19.

$$MAPE = \frac{\sum \left| \frac{\text{actual} - \text{predicted}}{\text{actual}} \right|}{N} * 100 \tag{19}$$

with:	MAPE	Mean absolute percentage error
	actual [s]	actual measured travel time from ANPR systems
	predicted [s]	predicted travel time from *ASDA/FOTO*
	N	number of observations (52,000 five-minute intervals)

The MAPE comes to 8.7% for this sample. Considering the size and variability of the sample, the average distance of 0.5 kilometres between detectors as well as the prediction horizon of 15 minutes, this is a useful result. Other work mostly evaluates short-term travel time prediction on single links on freeways with a prediction horizon of one or two minutes (see VANAJAKSHI AND RILLETT (2007)). An overview on the field of travel time prediction methods is given by LIN ET AL. (2005). Herein, statistical techniques applied on different section sizes as well as prediction horizons showed a MAPE of 5-10%.

Taking a step further, the theoretical utility of traffic information can be interpreted as the total travel time saved if all drivers had fully complied with traffic information on all trips made during the survey period instead of driving along their chosen routes.

Examined in the following are route recommendations given by the onboard navigation device used in the survey. The travel time saved along the route recommended by the navigation system is calculated as the difference to

- the travel time along the currently fastest route (CFR),
- the current travel time along the historically fastest route (HFR),
- the travel time along the route chosen by the participant (CR).

Table 18 shows the travel time drivers would have saved if they had followed the route recommended by the navigation system compared to CFR (first row), HFR (second row), and CR (third row) for all trips on which the participants used the *wiki* navigation system (in total 745 in the observation period). For example, if the travel time along the recommended route was 20 minutes and the travel time along the chosen was 25 minutes, the drivers would have saved 5 minutes travel time by following the navigation system. A negative value in Table 18 indicates the navigation system recommended a

route which's travel time was higher than the compared alternative route, for example if the route recommended was not the currently fastest route.

The routing algorithm of the *wiki* navigation system is based on historical rather than actual network travel times. Consequently, the recommended routes are 2.2 minutes slower than the currently fastest route on average. Compared with the historical travel times the recommended routes are slower by a margin of 1.1 minutes on average. Compared with the driver's route choice based on his own knowledge of the network, the recommended route would have been the better choice and would have saved each participant 0.7 minutes on average. The maximum saved travel time and the maximum additionally spent travel time a driver would have experienced when always following the route recommended by the navigation system is as high as 60% of the total travel time for a single trip.

	Travel time saved by route recommendation					
compared to	**Average**		**Max. saved**		**Max. additional spent**	
	[min]	**[%]**	**[min]**	**[%]**	**[min]**	**[%]**
CFR	-2.2	-6.8	-	-	-26.1	-59.2
HFR	-1.1	-3.2	81.6	58.9	-26.1	-59.2
CR	0.7	2.1	40.9	46.5	-26.1	-59.2

Table 18: Travel time saved by compliance with navigation system in relation to the currently fastest, historically fastest and chosen route on each trip

The objective benefit drivers could gain from using traffic information is subject to the perceived reliability of the forecast as well as the comprehensibility of the device. Figure 24 shows how participants evaluate the reliability of different traffic information.

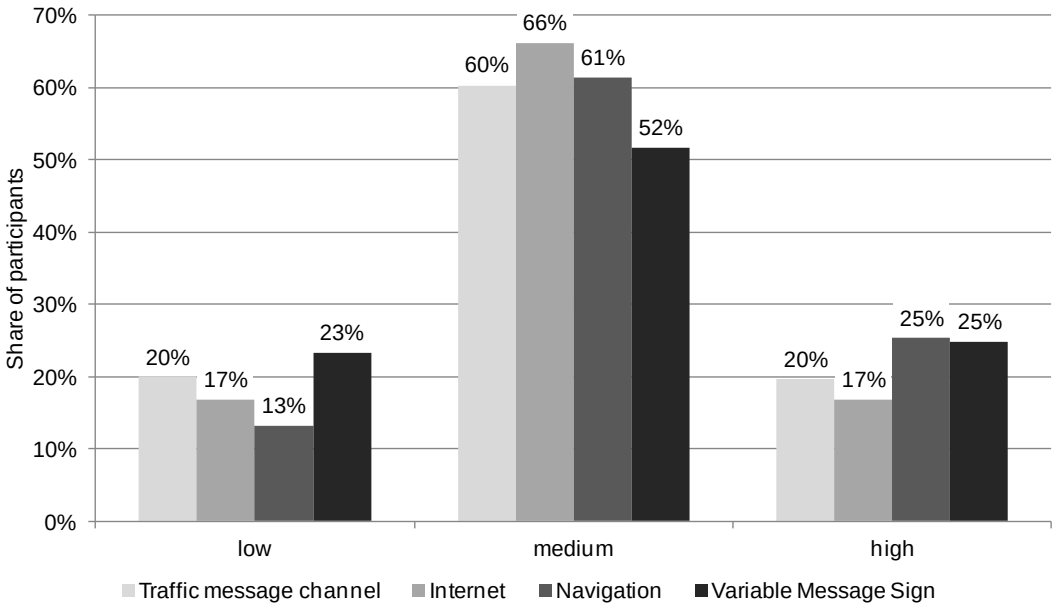

Figure 24: Perceived reliability of traffic information devices

In the online questionnaire the majority of people rated the reliability of traffic information as medium. They had a quite clear opinion that traffic information on internet portals, as well as that provided through navigation systems or TMC, are more trustworthy than information on route guidance etc. on VMS.

Information is useless if the contents are not easily comprehensible and therefore lead to biased decisions. The SP experiment provides decision situations in which the participants are informed about the current traffic state via four information devices, see chapter 3.6.2 *Stated Preference Data*. In this hypothetical choice experiment the traffic information is always accurate and other factors influencing route choice other than travel time, such as scenery or number of traffic lights, are limited to the preference of a main route by the set up of the interview. Thus, looking at the route choice the participants made when confronted with an information device, indicates the comprehensibility of different devices. Figure 25 displays for how many of their total 12 decisions the participants chose the fastest, the slowest or another of the four given routes. Clearly information on the current traffic state is most comprehensible when displayed on a LOS map. In this the participants chose the fastest route on 58% of trips. Although TMC only provides information on the length of sections with stagnant or congested traffic flow, the participants chose the fastest route in 48% of trips, an effect probably owed to their experience with this device. Information provided on road-side dynamic message signs, such as VMS or TTIS, is harder to understand.

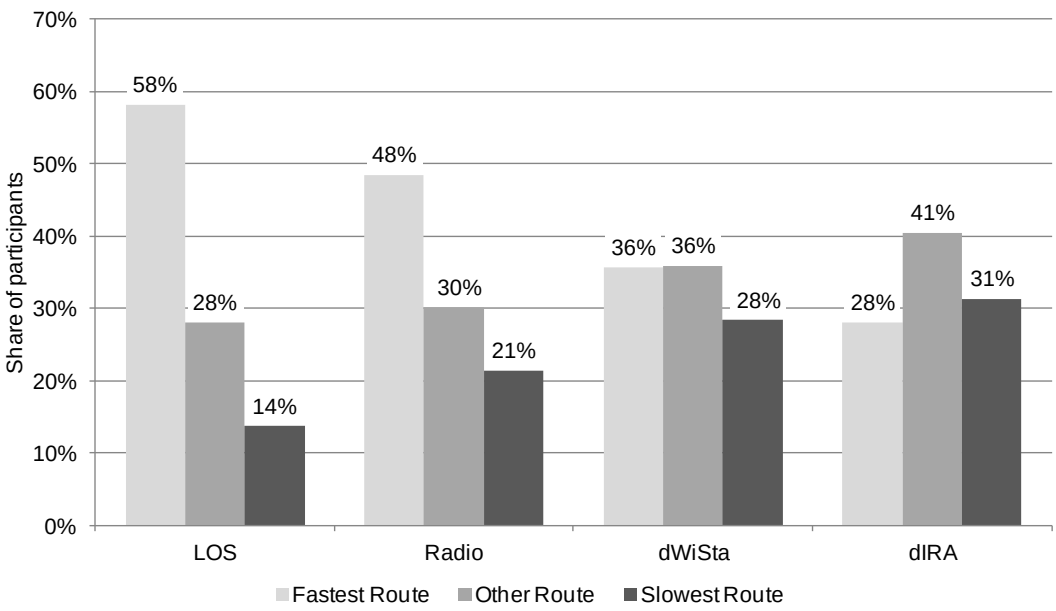

Figure 25: Route choice for different information devices taken from 3,228 choice decisions in the SP interview

The greater the drivers' experience of traffic conditions, the better the traffic information needs to be in order to provide a benefit to the users. An analysis of the observed trips during the survey shows that drivers are very well informed on everyday trips, such as

travelling from home to work under normal traffic conditions. In case of traffic incidents the probability of choosing non-optimal routes increases significantly, see Figure 26.

From home to work, drivers chose a sensible route on 97% of their trips. A sensible route is thereby a route with less than 5% travel time difference to the currently fastest route. Even in the case of incidents the level of experience is very high and results in a sensible route choice in 79% of trips.

For trips on rarely used OD pairs, drivers chose a sensible route in 55% of all trips. In case of incidents this fell to 43% of trips.

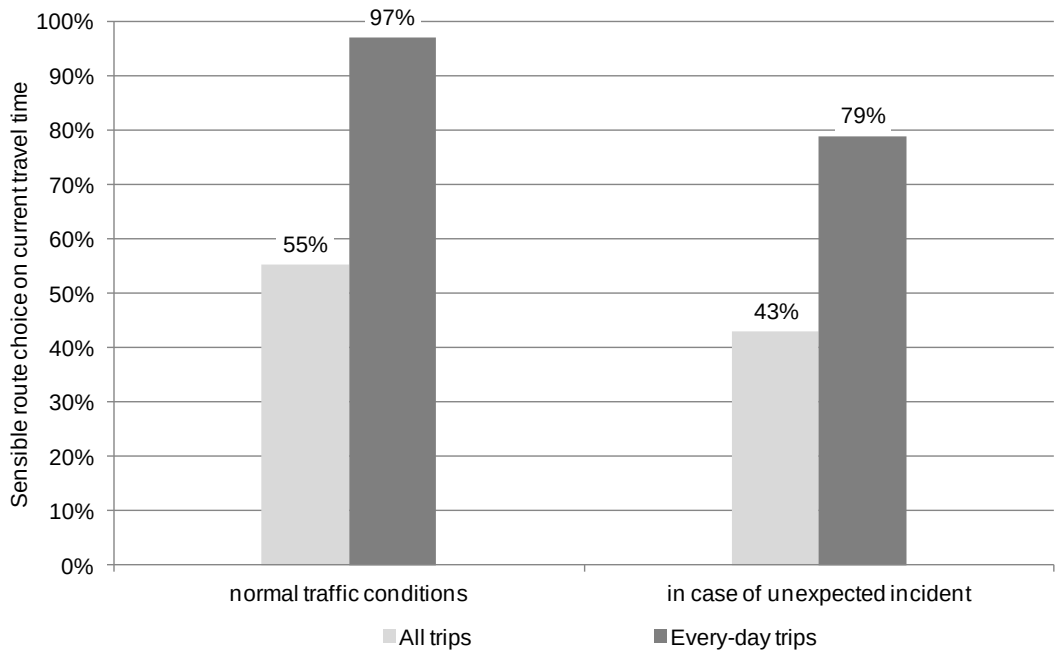

Figure 26: Probability of choosing optimal routes

The data shows that today drivers are fairly well informed about the usual traffic conditions on their frequently used routes. Traffic information has significant potential to reduce travel times on an everyday basis. These effects are even more noticeable in unexpected incidents.

4.3 Device Acceptance

It is clear that modern traffic information devices, especially onboard navigation systems, are becoming more and more popular. Furthermore, today drivers rely to some extent on modern traffic information for making route choice decisions. To analyse the route choice behaviour and to determine the influence of traffic information, it is necessary to understand how traffic information is used in daily life. The observed GPS data from the *wiki* survey gives some insight into the details of usage of traffic

information. Table 19 shows the number of trips observed during the GPS survey together with the trip purposes. The trip pattern is typical for commuters, with a high percentage of working trips, and leisure activities concentrated on weekends. Shopping hardly plays a role in the daily trip patterns of this sample.

Trips from GPS data	Total	Percentage
Number of OD pairs	4,100	100%
Number of trips	16,037	100%
Number of trips to work	7,418	46%
Number of trips to shopping	996	6%
Number of trips to daily leisure	471	3%
Number of trips to leisure/holiday	3,639	23%
Trips to other activities	3,513	22%

Table 19: Trips and activity purposes from GPS data

During the survey all interactions of the participants with the smart phone provided were logged. Thus, this data allows analysis of how often and for which trip purpose the participant used either the navigation or the LOS map service. In total the navigation service was used for 8% of all trips observed during the survey, see Table 20. It has to be noted that 44% of the participants had a built-in navigation system in their vehicle and 31% had a portable navigation system of their own. Therefore, it is likely they did not use the *wiki* navigation system additionally to their own navigation system on all trips. However, the RP data in Table 20 shows that participants did not merely use the navigation system for route guidance to unknown destinations, such as leisure/holiday, but primarily for traffic information to familiar destinations in congested traffic conditions, such as work.

Trips while using navigation service	Total	Percentage
Number of OD pairs	491	12%
Number of trips	1,303	8%
Number of trips to work	726	10%
Number of trips to shopping	63	6%
Number of trips to daily leisure	23	5%
Number of trips to leisure/holiday	300	8%
Trips to other activities	191	15%

Table 20: Usage of navigation service for observed GPS trips

This is also shown by looking at the answers to the online questionnaire where participants state the use of navigation systems for different trip purposes, see Figure 27. Route guidance is important for trips to unknown destinations. Whereas only 18% of the sample use a navigation service for route guidance to work, 57% use it to travel to holiday destinations. Using a navigation service for traffic information shows a

different pattern. Traffic information is especially important for commuting trips when traffic conditions in peak hours are hard to predict and is used on 52% of the trips from home to work or vice versa. For roughly one-third of all shopping and leisure/holiday trips, a navigation service is used for traffic information.

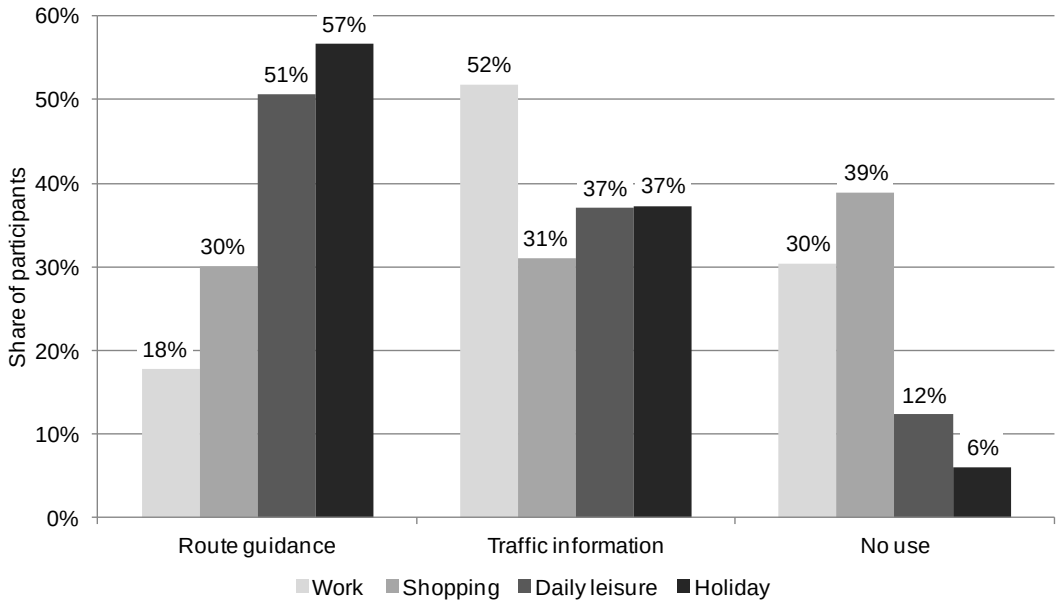

Figure 27: Usage of navigation device for trip purposes: from online questionnaire

In Table 21 the number of trips while using the LOS map service is given. In total the LOS map service was used for 20% of all observed trips during the survey. The service was used for traffic information to known and unknown destinations, again with usage primarily on trips to work or weekend leisure trips and holidays. This is presumably due to the general traffic conditions, which make traffic information more attractive in morning peak-hour conditions as well as in congested weekend hours.

Trips while using LOS map service	Total	Percentage
Number of OD pairs	892	22%
Number of trips	2,746	17%
Number of trips to work	1,500	20%
Number of trips to shopping	152	15%
Number of trips to daily leisure	57	12%
Number of trips to leisure/holiday	725	20%
Trips to other activities	312	11%

Table 21: Usage of LOS map service for observed GPS trips

The usage of other collective traffic information devices, such as TMC, is not logged for every single trip. Instead 241 of the total 278 participants stated in the questionnaire that they generally use radio as a source of traffic information on their daily trip to work. It can be assumed that if a car driver has his radio programmed to broadcast traffic

messages, then he is likely to receive those messages on all of his trips, rather than switching the service on and off each time. Under this assumption traffic information over TMC is used for 87% of all trips during the survey. This traditional information device still has a very high acceptance.

4.4 Driver Compliance

The potential of traffic information in the context of intelligent traffic management is always connected to the compliance of drivers with the given information or route recommendation. Compliance, on the other hand, is based on the quality of the given information, the comprehensibility of the information device, as well as its general acceptance and usage.

In contrast to the econometric choice model, estimated in chapter 5.1.3 *Route Choice Model* Estimation, this preliminary analysis is a mere examination of phenomena with statistical significance and serves as the basis for identification of a choice model. Choice models imply causal correlations between the given input variables and the drivers' decisions and have explanatory character, which is of importance for the prediction of future behaviour under changed conditions.

The term driver compliance is used in most literature as the ratio of the total traffic volume diverting to an alternative route as a reaction to route guidance (see formula 20 taken from WERMUTH AND WULFF (2008), page 15).

$$b = (p_1 - p_0) * 100\,\% \tag{20}$$

with:	b [%]	Driver compliance
	$p_1 = \frac{x_1}{n_1}$ [s]	Relative portion of vehicles on alternative route with route guidance
	$p_0 = \frac{x_0}{n_0}$ [s]	Relative portion of vehicles on alternative route without route guidance
	x_1	Number of vehicles on alternative route with route guidance
	x_0	Number of vehicles on alternative route without route guidance
	n_1	Total number of vehicles before diversion point in case with route guidance
	n_0	Total number of vehicles before diversion point in case without route guidance

This definition allows calculation of the compliance rate based on stationary traffic volume detectors without any further knowledge of the route choice of individual drivers, if the alternative routes meet again at some point downstream of the diversion

point examined. Traffic volumes need to be known for the section directly upstream of the diversion point at which route guidance is provided and downstream on the main and alternative route respectively. Usually, the traffic volume profile over a day without route guidance is compared with a day with route guidance.

Examined in the following is the compliance rate to the VMS at the Neufahrn motorway junction, see Figure 28. Although ANPR systems are available on the A9 directly upstream of the Neufahrn VMS as well as downstream on the A9, A92 and B13, it is not possible to use the vehicle counts from ANPR data for this analysis. As the alternative routes monitored by the ANPR systems do not join again downstream, it is necessary to know the destination of the vehicles passing the VMS in order to determine the compliance rate to route recommendation. A driver heading for Stuttgart is considering three alternative routes that join again at the junction of the A92/A99. A driver heading for Salzburg is choosing from three alternative routes joining again at the junction of the A9/A99. And the alternative routes for drivers to Munich city centre join again at the junction of the B13/A99 or A9/A99. It is unlikely that a driver travelling to Stuttgart will show any reaction to a routing strategy displayed by the VMS for travelling to Salzburg. In order to retrieve this information on the vehicles' destinations from ANPR data, one can look at vehicles recognized before the Neufahrn VMS and again at an exit point to Stuttgart, Salzburg or Munich city centre. However, the share of vehicles recognized is too small to make a projection on the destination of the traffic volume counts. The low recognition rate is due to the fact that there is no complete detection of all lanes at any of the ANPR sites.

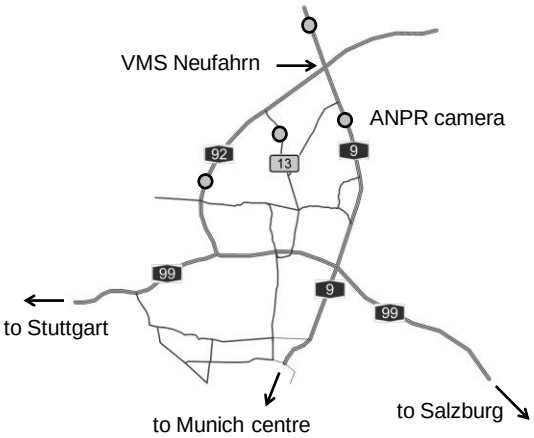

Figure 28: Road network downstream of VMS Neufahrn

GPS data includes the information on the destination of the vehicles. Therefore, it is possible to analyse whether a route recommendation was displayed at the time the driver passed the Neufahrn VMS and if the displayed information was of any relevance regarding the destination of the driver. Under these constraint 8,280 of the total 16,037 trips, that is 52%, were provided with relevant traffic information or route recommendation by a VMS. This high value is due to the fact that the majority of

observed trips are working trips which pass along the Neufahrn motorway junction (see Figure 28) to the north of Munich.

Each observed trip, on which a relevant route recommendation was available, is checked if the driven route course proceeds along the route section recommended by the VMS (via A9/A92 or B13). The same was done for all other VMS in the survey area.

The second information device which can be examined on GPS data for compliance is the *wiki* navigation system. Navigation systems provide routes from origin to destination. Yet, in many cases the driver does not type in his destination as a full address but will rather navigate to an area, for example, Munich Schwabing. The route recommended by the navigation system is identified among all existing alternative routes in the choice set (see chapter 2.2 *Discrete Choice Models*), as the route with maximum overlap with the route course displayed on the navigation device.

For many trips for which drivers used the *wiki* navigation systems they also passed a VMS. This can result in either conflicting or complementary route recommendations. Table 22 gives an overview of the number of trips for which route recommendations by navigation system or any of the VMS in the survey area were available. All trips are distinguished by three categories.

- Kind of information device which provided route recommendation (none, by navigation system only, by VMS only, or by both navigation system and VMS).
- Kind of recommendation (complementary recommendation by VMS and navigation system, conflicting recommendation between VMS and navigation system).
- Kind of route that was recommended (currently fastest, other than currently fastest).

For 7,498 observed trips there was no route recommendation, the navigation device was switched off and the driver did not pass a VMS. As many participants passed the Neufahrn VMS on their daily commute, the number of trips which passed a VMS (8,260 trips) is far higher than the number of trips on which drivers used the navigation device (745 trips). However, 4,876 trips passed by a VMS when a route other than the currently fastest was recommended. One has to mention here that the objective of route recommendation by VMS is not merely to optimize travel time along the alternative routes. For the operating authorities, more important objectives are keeping the traffic flowing on the motorway network without drivers taking excessively long detours or diverting to the subordinate road network. The VMS signs generally display route recommendations along the main routes. Route recommendations along the alternative routes were mainly given in case of special major events, such as major league soccer games. The Neufahrn VMS normally displays the A9 towards Munich city centre and was only activated to display routing along the alternative route A92 on 60 occasions during the survey period. In 41 cases the A92 actually was the currently fastest route, in 17 cases there were faster routes in the subordinate road network which are not part of the routing strategy, and in 2 cases the A9 was the currently

fastest route. Based on this input data, Figure 29 shows the compliance rate as classified in Table 22.

No.	Information device	Recommendation	Recommended route	Trips
0	none	none	none	7,498
1	navigation only	complementary	currently fastest	140
2	navigation only	complementary	other	139
3	VMS only	complementary	currently fastest	2,918
4	VMS only	complementary	other	4,876
5	both (VMS/navigation)	complementary	currently fastest	125
6	both (VMS/navigation)	complementary	other	95
7	both (VMS/navigation)	conflicting	currently fastest	141
8	both (VMS/navigation)	conflicting	other	105
Σ				**16,037**

Table 22: GPS trips with route recommendation from VMS and/or navigation system

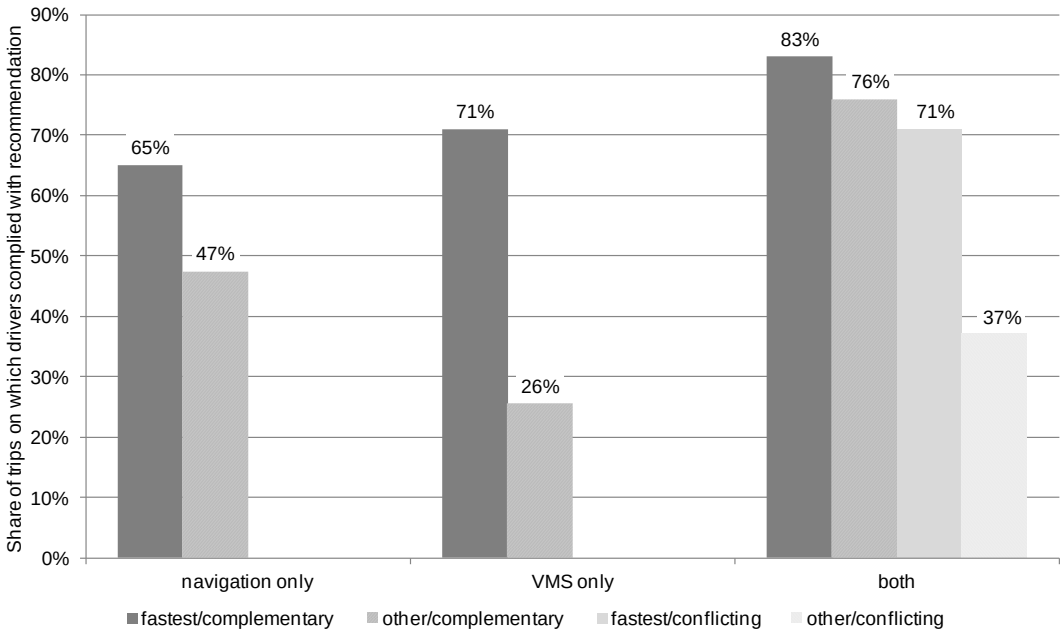

Figure 29: Compliance rate subject to kind of recommendation

The compliance rate of 65% to the navigation system when the recommended route was the currently fastest, displayed in the left-hand dark grey bar, is lower than expected. Participants proved to be reluctant to divert from their usual main route for insignificant travel time savings. The compliance rate to routes with less than 5% travel time difference to the currently fastest route recommended by navigation system is 75%. Driver compliance drops down to 47% when the navigation system recommends a route other than the currently fastest, displayed in the left-hand dashed dark grey bar.

The rate of compliance with VMS when it is recommending the currently fastest route is 71%. Higher compliance with VMS than with the navigation system is due to the fact that VMS generally do not recommend routes through the minor road network. However, the compliance rate falls down to 26% when VMS recommends a route other than the currently fastest. In these cases, drivers seem to have a profound knowledge of the historical travel times on all alternative routes provided by VMS and rely more on their own experience rather than on VMS routing. Furthermore, it has to be taken into account that the compliance rate is low in cases in which there exists a faster route in the minor road network when heavy congestion occurs on a motorway section. For the example of the Neufahrn VMS, a route recommendation along the alternative route A92 will provoke drivers to leave the A9. Yet, in many cases they divert to the B13, which is not part of the VMS routing strategy, rather than diverting to the A92.

If route recommendation is given by both a navigation system and VMS, there is a strong negative impact on compliance if the recommendations are conflicting. This impact proves to be more severe than travel time savings. If both devices recommend the currently fastest route, the compliance rate is 83% and thus far higher than for each device on its own. The compliance rate decreases to 76% if the recommendations are complementary yet recommend a route other than the currently fastest (the dashed dark grey bar). However, if the route recommendation of both devices is conflicting the compliance rate drops even further, to 71%, even if one of the devices displays the currently fastest route, as displayed in the light grey bar. In the case when both devices recommend a route other than the currently fastest and the recommendations are conflicting the compliance rate becomes as low as 37% (dashed light grey bar).

An analysis by Schiller, Winkler, and Zimmermann (2012) based on the route choice decisions observed in the *wiki* SP interview (see chapter 3.6.2 *Stated Preference Data*), allows to identify the compliance rate of the four information devices included. A reaction to the three different traffic states is observed in the interview when a participant diverts from his usual main route on to one of the three given alternatives. The compliance rates are determined as the number of times in which a participant reacts to a given delay depending on the information device which displayed the information. The data shows the following compliance rates: LOS 79%, TMC via radio 72%, VMS (dWiSta) 60%, TTIS (dIRA) 56%. Although the compliance rate differs slightly depending on the usual main route of the participants, the effect of the information devices is similar for all participants.

4.5 Primary Findings

The potential of traffic information lies in influencing travel demand, which accounts for 84% of delays that occurred in the survey area during 2009. To address additional delays, the reliability of network travel times and the performance of existing road capacities need to be improved by incident management or transport supply management respectively.

Rerouting traffic by information can theoretically reduce the average travel times of each driver by 10%. Shifting demand to other times of day, even by a minor margin of 10 minutes, holds the potential to reduce drivers' travel times as much as 6%.

Good traffic information includes real-time travel time data as well as forecasts for the next 5 to 15 minutes. Measured travel times as well as good short-term forecasts are given on the major road network in the survey area. Historical travel times are available in the rest of the network. A quality analysis shows that in total the predicted travel time differs less than $\pm 20\%$ from the measured travel time in 95% of all examined five-minute intervals. These travel times provide valuable data for attributing all alternative routes in a choice set for estimating a choice model.

Drivers today are well informed on their everyday trips, yet only chose sensible routes on 55% of all trips and only on 43% of trips in case of an unexpected incident. On average, traffic information today guides drivers on routes which are 2.1% faster than their normally chosen routes. However, route guidance is far from perfect and could be improved by 7% if the routing always indicated the actually fastest routes.

The comprehensibility of traffic information devices is an important factor for drivers' route choice. If information is hard to interpret, drivers tend to ignore information and recommendations. Traffic information via LOS map or radio is the most comprehensible. Roadside dynamic message signs (VMS, TTIS) required network experience and are shown to be harder to understand.

Even though the *wiki* smart phone was not high-end equipment, drivers used the navigation service for 8% and the LOS map service for 20% of all trips during the survey period. The navigation system as a traffic information tool was stated to be used by 52% of drivers for their daily commute.

Compliance with route recommendation given by navigation systems or roadside VMS differs significantly if the currently fastest or another route is recommended. The compliance rates rank between 47% and 65% for navigation systems and between 26% and 71% for VMS. Complementary routing, in the sense that the same route recommendation is given by navigation systems as well as VMS, is even more important than the actual route recommended. Compliance rates for complementary recommendations by navigation systems and VMS rank between 76 and 83%, and drop to 37-71% in the case of conflicting recommendations.

5 Choice Models

In order to forecast traffic distribution for a whole survey area and determine the potential of traffic information to reduce the transport time expenditure as well as fuel consumption, the effects of traffic information on route and departure time choice need to be known. Therefore, choice models are necessary that capture the influence of certain variables and the resulting route and departure time choice behaviour.

This chapter describes how route and departure time choice models are derived from survey data and how they are represented in macroscopic traffic assignment procedures.

The focus of this research is on the choice set generation for the route choice model as well as the incorporation of the estimated choice models in macroscopic traffic assignment. The actual estimation of the route and departure time choice models was done by SCHILLER ET AL. (2012).

As a result a validated macroscopic transport model of the Munich survey area is presented, capturing route and departure time choice behaviour. On the basis of this model, advanced concepts for modelling the effects of traffic information devices in macroscopic assignment are introduced in chapter 6 *Optimisation of Traffic Flows*.

5.1 Route Choice Model

The primary goal of this research, in analysing route choice with discrete choice models, is to determine the effect of traffic information. Data from SP interviews include route choice decisions based on information of single traffic information devices (LOS map, TMC via radio, VMS, TTIS). Data from the RP survey using GPS tracking enable the analysis of the combined effect of traffic information by several devices (navigation system/LOS map, VMS, TMC via radio). The comparison of the estimated parameters provides insight into the question of how drivers evaluate different traffic information devices and their combination.

5.1.1 Primary Statistical Analysis

Prior to the estimation of the parameters of the route choice model, some statistical analyses were made on the SP and RP data. An analysis for the trips from home to work shows that the average *wiki* participant uses 2.3 different routes in the course of the eight-week survey. In total they claim to know 3.7 different routes to their work destination. Within the road network of the study area there are 22 sensible alternative routes on average for the home-work OD pair (this is the result of the choice set

generation described below in chapter 5.1.2). Yet these routes partly overlap, so that only four independent routes are available under the constraint that more than 80% of the route must use motorway links. Thus, a redistribution of travel demand on alternative routes is per se limited. For choice model estimation in chapter 5 *Choice Models* this problem is dealt with by using a commonality factor, see chapter 2.2 *Discrete Choice Models*.

On their way from home to work, the *wiki* participants show different flexibility in route choice (see Figure 30). Almost 65% of all participants use only one or two routes from home to work during the entire survey. Only 17% use more than three routes.

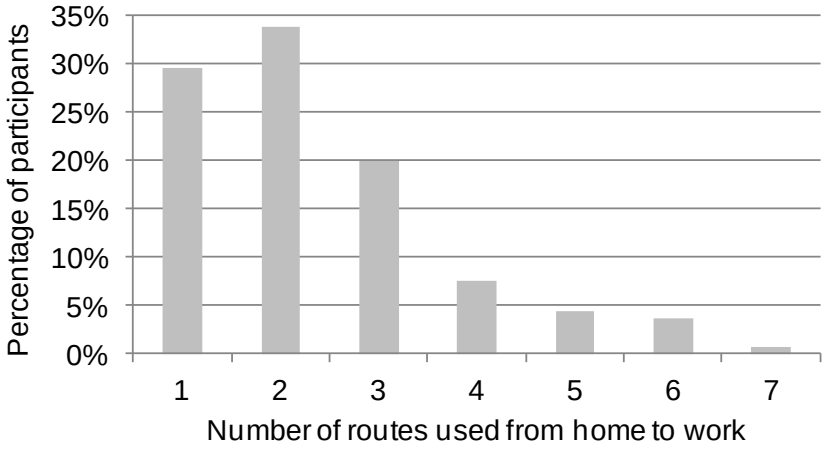

Figure 30: Drivers flexibility in route choice from home to work

The GPS data show strong a preference of the participants for using their main route from home to work. In total 4,291 trips from home to work were recorded by GPS. Of these, 3,605 (84%) travelled along the main route. Figure 31 shows the percentage of participants using their main route for a certain proportion of their total trips from home to work.

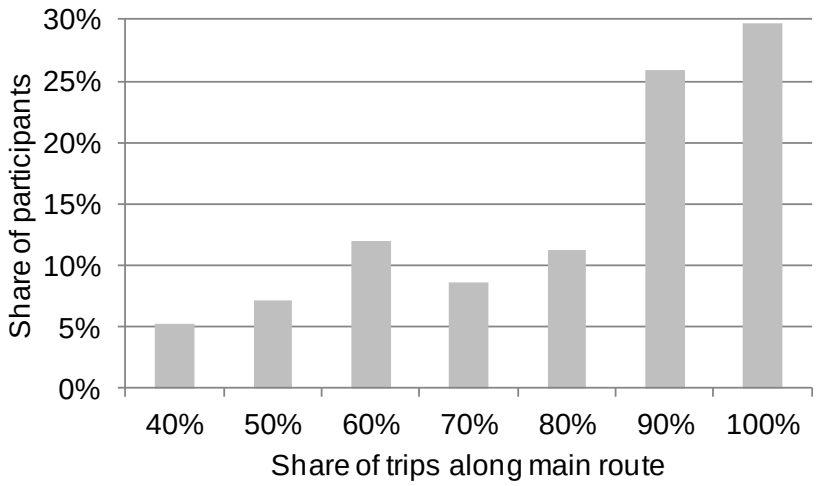

Figure 31: Drivers preference to main route on trips from home to work

Strikingly, a large group of almost 30% of participants uses their main route completely for every single trip from home to work. Only 15% of participants divert from their main route at least every second trip.

How participants choose their main route is determined by various factors. The participants' free text answers from the questionnaire suggest eight major reasons why they choose their main route over other alternative routes. Table 23 gives the ranking of reasons for choosing their main route from home to work.

Ranking of reasons for main route		Number of entries
1	Fastest route	208
2	Comfortable, relaxed, low traffic	129
3	Shortest route	112
4	Low risks of congestion, reliable	94
5	Economic	71
6	Habit	58
7	Low risk of accidents, save	42
8	Convenient for intermediate activity	43
Answers given in free text by 278 participants		

Table 23: Reasons for choice of main route from home to work

A comparison of the main route with all other alternative routes from home to work (as a result of choice set generation) for all 278 participants gives the average values shown in Table 24. Main routes are not surprisingly the fastest and shortest routes on average. It is interesting that the reliability of the main routes is not as good as that of the average alternative routes.

Average characteristics	Main route	Alternative routes
Travel time [min]	37	41
Length [km]	37	42
Share of total length on motorway [%]	53	45
Reliability [-]	1.38	1.33

Table 24: Comparison of main route and alternative routes from home to work

The reliability is given in terms of a travel time index (TTI). The TTI is the quotient of average travel time in case of congestion and reference travel time in free flow conditions, as shown in formula 21. Here the TTI is calculated as the quotient of the 95th percentile and the 15th percentile.

$$TTI_{95} = \frac{\mathrm{t95\%}}{\mathrm{t15\%}} \tag{21}$$

with: TTI Travel time index

$\mathrm{t95\%}$ [s] 95th percentile of all measured travel times

$\mathrm{t15\%}$ [s] 15th percentile of all measured travel times

Reasons for diverting to an alternative route were also given by the participants in the questionnaire. This time, however, the participants were asked to tick the reasons on a given list as relevant or irrelevant. Figure 32 shows the reasons for diverting to an alternative route and the number of participants for whom these are relevant. Travel time reduction or the avoidance of congestion are the predominant reasons for leaving the main route. Traffic reports over the radio and onboard devices, such as navigation systems, are obviously seen as reliable traffic information sources and can persuade drivers to change routes.

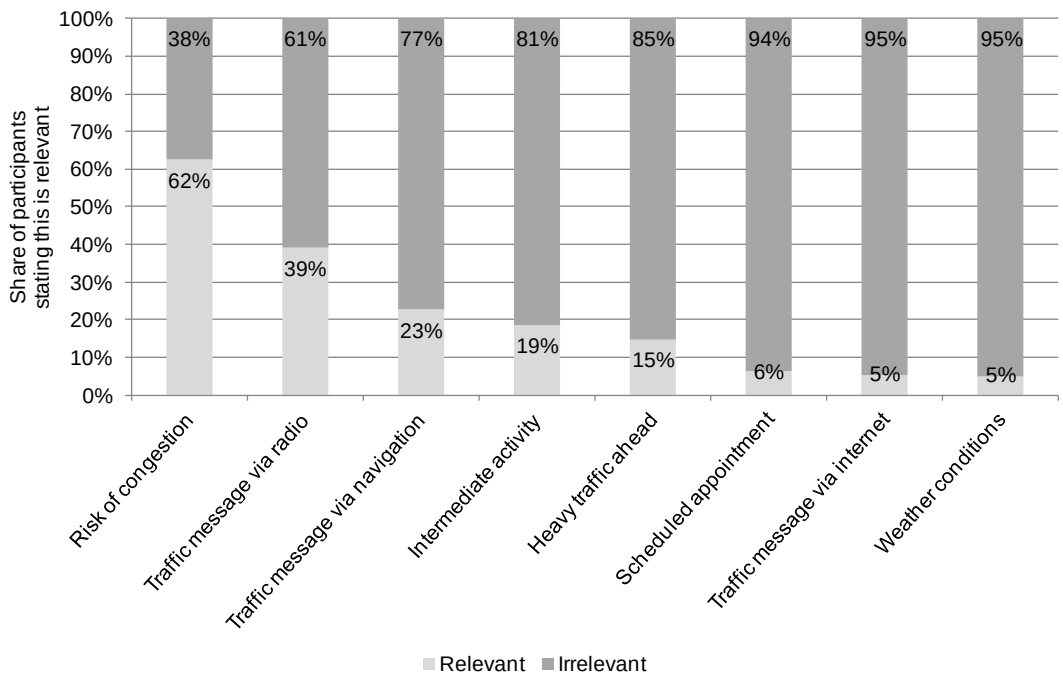

Figure 32: Possible reasons for diverting to alternative route

On the other hand, the GPS data allow looking at how effective the participants were in practice in diverting to alternative routes in terms of travel time reduction:

- Diverting to an alternative route paid off in 50% of the trips for which the main route was not the fastest route at the time.
- On the whole, when diverting to an alternative route, the participants experienced a travel time reduction of four minutes (or rather 10%) compared with travel times on

the main route for 34% of all trips. For 66% of all trips the participants experienced a travel time increase of 14% compared with the main route.

- The selection of an alternative route, when participants diverted from the main route, was therefore far from optimal and resulted in a 5% travel time increase on average.
- In the case when participants made a wrong decision in terms of the travel time experienced, 63% of all cases should have stayed on the motorway network and 37% of all cases should have diverted to the subordinate road network.

5.1.2 Choice Set Generation

All discrete choice models calculate the probability of choosing an alternative out of a given choice set. A choice set includes all considered alternatives on which a decision is based. For some decisions, such as mode choice, the existing alternatives are known a priori (car, public transport, bike, walking). For other decisions, such as route choice, the existing alternatives become uncountable in real-size transport networks and therefore the alternatives actually considered need to be determined.

In the case of the SP experiment the choice set consists of four given alternative routes from which the participants could choose. The RP data from the GPS survey include all chosen routes throughout the eight weeks of observation. However, the non-chosen alternative routes remain unknown. Information on known routes is given by the data from the personal interview in which every participant was requested to state his or her known routes from home to work.

A combination of the revealed routes (GPS) and known routes (interview) does not result in a compete choice set, however. The number of revealed routes from an origin to a destination is highly dependent on the number of trips made on the particular OD pair during the survey period. For example, for nearly 2,000 of the total 4,100 OD pairs there was only one single trip during the entire survey and therefore only one revealed route exists for these OD pairs. On the other hand, known routes are only provided from personal interviews for the OD pair from home to work. For all other OD pairs no information on known routes is available. Even for the OD pairs from home to work, the revealed and known routes do not provide a complete choice set of all sensible routes, as only 27% of all routes were actually stated in the interview as well as observed in the GPS survey. A computational generation of the missing alternative routes for all 4,100 OD pairs is therefore necessary to complete the choice set. The general methodology as well as the single computation steps is explained in the following chapters.

5.1.2.1 Methodology

Generally, choice set generation is based on identifying existing routes from origin to destination and determining those among them which are sensible to consider (based on some sort of detour criteria compared with the best route on the OD pair), see chapter 2.3 *Route Search Algorithms*. An overview of the applied method is given in Figure 33.

First, a route set is generated for each OD pair for which a trip was observed via GPS. This consists of three different kinds of routes. On the one hand, routes from survey data (revealed as well as known routes) are included. On the other hand, computationally generated routes are added. The computed routes consider accepted detour factors derived from routes stated in the personal interview. Second, a spatial choice set is composed taking into account communality factors among all routes (revealed, known and generated). Third, for each trip during the survey the spatial choice set for the respective OD pair is attributed with time-dependent traffic variables from the data archive (see chapters 3.4 *Traffic State Data* and 3.5 *Traffic Information Data*).

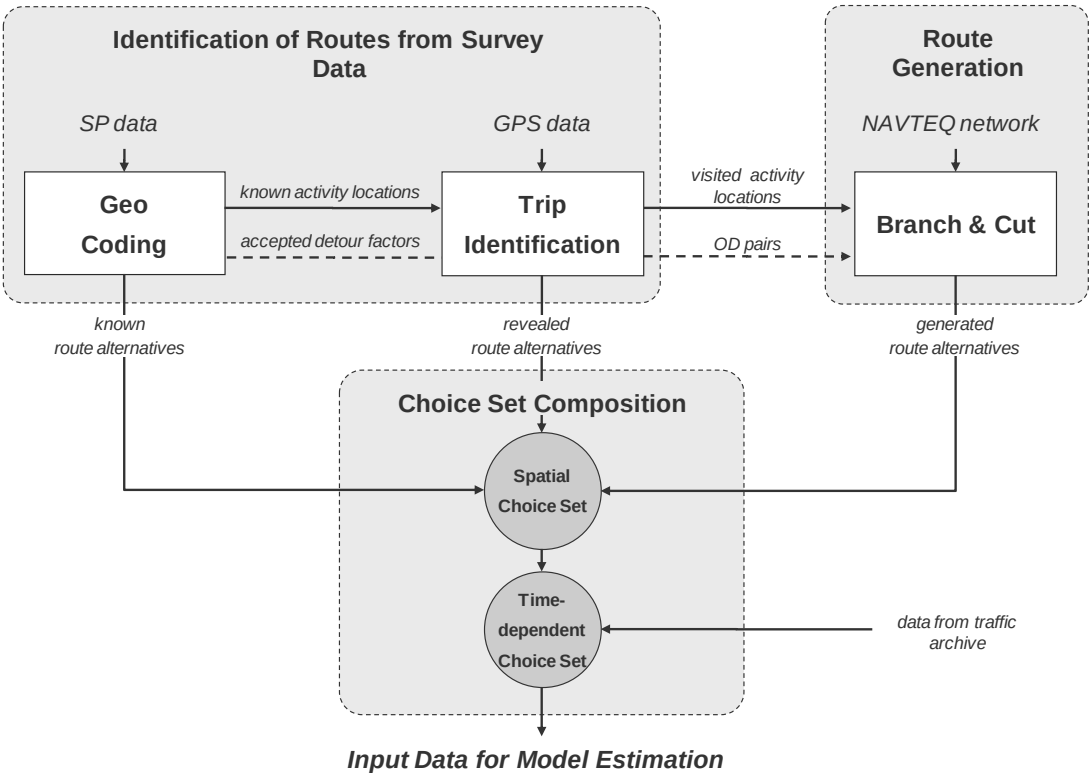

Figure 33: Methodical overview for choice set generation

For the computation of alternative routes the size of the transport network is crucial. Network resolution (in the sense of included road levels) has a major effect on the number of generated routes and therefore the size of the resulting choice set. The

more roads there are included in the network model, the more alternative routes are available. Furthermore, the number of nodes and links in the network model is critical for computational feasibility of the applied Branch and Cut algorithm of route generation.

The original *NAVTEQ* network (LN) of the survey area, in which the GPS trajectories have been localized, is therefore reduced to a strategic road network (including only higher road class levels). This project network (PN), introduced in chapter 3.2 *Survey Area and Network Model*, contains all time-dependent traffic data and is therefore the base network for choice set generation. For modelling strategic route choice this is a legitimate representation of network detail. In contrast to a spontaneous route choice in an unexpected incident condition, for everyday route choice it is sensible to consider routes along the higher level road network. The access from the origin (and egress to the destination) to the higher level road network is represented by connectors, covering travel times in the minor road network. To achieve computational feasibility the PN is further simplified in terms of modelling detail (to reduce the number of existing nodes and links). This preliminary step of network simplification is described in chapter 5.1.2.2 *Network Simplification*.

Chapter 5.1.2.3 *Route Generation* describes the applied Branch and Cut algorithm of route generation in the simplified project network (SPN). In a last step, the generated routes need to be transformed back onto the PN. This is explained in chapter 5.1.2.4 *Route Transformation*.

In chapter 5.1.2.5 *Composition of Choice Set* all three kinds of routes (revealed, known and generated) are then composed to spatial choice sets for each OD pair, which are then attributed with time-dependent traffic data in chapter 5.1.2.6 *Time-dependent Attribution of Choice Sets*.

5.1.2.2 Network Simplification

For computational feasibility the PN is simplified as far as possible without reduction of the number of roads and therefore routes. This is done by replacing parallel links, which represent twin-track major roads in the network model, with single links. Furthermore, detailed modelled intersections with multiple nodes and ramps, such as motorway junctions, are aggregated in single nodes. Figure 34 shows the simplification of a complex node with ramps and parallel links.

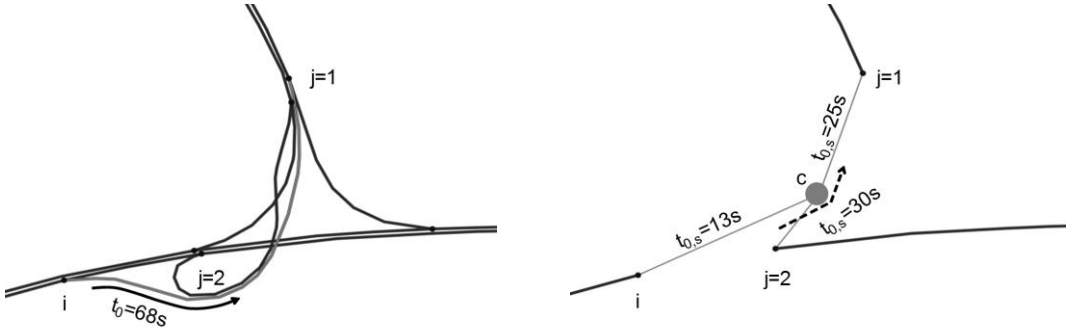

Figure 34: Simplification of complex node

The left-hand picture shows a complex node in the original PN, which includes parallel links as well as ramps for the real turning movements. NAVTEQ data model allow identification of all network nodes which belong to the same intersection by reference to a ComplexNode-ID (or Intersection-ID for t-junctions of minor roads). The simplification algorithm performs the following steps for every complex node in the network:

1. Setting of new centroid nodes:
   All original nodes with the same ComplexNode-ID are grouped (displayed in dark grey dots in the left-hand picture). Form the coordinates of the grouped original nodes a centroid node is calculated which represents the original complex node (displayed in a light grey circle in the right-hand picture).

2. Identification of border nodes:
   Border nodes are identified through links which connect the original complex node to other nodes in the network. The identified border nodes are marked with the letters *i* and *j* in the left-hand and right-hand pictures.

3. Identification of parallel links:
   Parallel links are identified as two or more links between identical complex nodes. The shortest one is selected to represent all others in the SPN. All others are deleted. All attributes of the deleted links for travelling in the opposite direction are adopted in the remaining link.

4. Deletion of original nodes and addition of new links:
   In this step, all original nodes belonging to a complex node which are not border nodes are deleted. Thus, all links between original nodes belonging to a complex are also deleted. The border nodes are now connected to the centroid node by the addition of new links (displayed in the light grey lines in the right-hand picture).

5. Recalculation of travel times:
   The travel times t^S of the new links and the turns in the simplified network are based on the shortest path travel time t^O through the complex node in the original network (highlighted in the light grey path in the left-hand picture). The shortest path travel time t^O in the original network needs to be segmented into links and turns in the simplified network. Therefore, the travel time for a new $link_{i\to C}$ (from a border node i to the centroid node C) in the simplified network is calculated as the proportion of shortest path travel time $t^O_{i\to j}$ in the original network which corresponds to a proportion of the length of $link_{i\to C}$ in relation to the total length of the shortest path through the complex node in the simplified network ($link_{i\to C}$ + $link_{C\to j}$). A link in the simplified network is part of several shortest paths in the original network starting at node *i* and traversing the complex node to all other nodes *j*. In the displayed example the $link_{i\to C}$ belongs to the shortest path from *i* to *j=1* and from *i* to *j=2*. The link and turn travel times in the simplified network need to be determined in such a way that they add up to the shortest path travel time of the original network for all shortest paths. Therefore, the travel time $t^S_{i\to C}$ assigned to $link_{i\to C}$ is determined as the minimal proportion of travel time out of all shortest paths connecting node *i* to all other nodes *j* in the complex node (see formula 22). The travel time which is missing in order to match the shortest path travel time of the original network is then added to the appropriate turn from border node *i* over centroid node *C* to border node *j* (see formula 23). Travel times for $link_{C\to j}$ are set to zero.

$$t^S_{i\to C} = \min\left\{ t^O_{i\to j} \cdot \frac{l^S_{i\to C}}{l^S_{i\to C} + l^S_{C\to j}} \forall i \neq j \in [1,n] \right\} \tag{22}$$

$$t^S_{i\to C\to j} = \min\left\{ t^O_{i\to j} - t^S_{i\to C} \forall i \neq j \in [1,n] \right\} \tag{23}$$

with:

$t^S_{i\to C}$	Link travel time in simplified network from node *j* to node *C*
$t^S_{i\to C\to j}$	Turn travel time in simplified network from node *i* to node *j*
$t^O_{i\to j}$	Travel time in original network from node *i* to node *j*
$l^S_{i\to j}$	Length in simplified network from node *i* to node *j*
N	Number of border nodes within complex node

6. Deletion of two-arm nodes:
   Finally, two-arm nodes are deleted from the network, thereby merging the related links. Only nodes whose related links have identical permitted transport systems are deleted.

With this simplification, the number of network elements is reduced from the original 17,004 nodes and 48,354 links to 7,703 nodes and 22,620 links without any reduction in the number of existing alternative routes. A comparison of shortest path travel times from origin to destination for all OD pairs in the original and the simplified network

shows a high conformity of transport supply (see Table 25). As the SPN is only used for route search, the deviations can be seen as marginal. The described algorithm is generally applicable in all transport network models which include ComplexNode-ID and Intersection-ID references in their data structure.

Difference of shortest path travel time on OD pair in original and simplified network [%]	Share of OD pairs [%]
< 5	74
< 10	97
< 15	100

Table 25: Comparison of shortest path travel times for all OD pairs between original and simplified network

5.1.2.3 Route Generation

Common choice set generators calculate *k* shortest paths as an iterative shortest path search, either heuristically or stochastically, by varying network impedances. The number of routes and resulting detour factors (according to general route impedance) depend on the number of different impedance criteria as well as the number of search iterations. Although routes exceeding a maximum allowed detour factor can be subsequently excluded from the choice set, it is not possible to consider detour factors on parts of the route (as opposed to the entire route). Choice set generators, which consider detour factors only after the actual generation process is completed, have a major disadvantage. Maximum allowed detour factors on route level are often chosen to be constant or decreasing with increasing route length. The shortcomings of these approaches are that a constant detour factor will result in biased choice sets, with more routes for longer distance OD pairs. A decreasing detour factor solves this problem partially, yet is unable to exclude long routes with minor and implausible detours along the way from the choice set. Therefore, it is desirable to include criteria for maximum detour factors on route parts within the generation process.

To include detour factors within the choice set generation process a path enumeration based on a Branch and Cut algorithm is needed where certain branches of the route tree are deleted owing to an excessively high detour factor. Complete enumeration (in its classical meaning) aims to identify every possible route from origin to destination using a directed graph of the road network to build a route tree, where the origin is the tree source and the tree branches are the routes in the network. By including branch cutting criteria as the allowed detour factors, this method of choice set generation allows control of the generated routes (Branch and Cut). The resulting routes are highly dependent on the allowed detour factors of the tree branches compared with the corresponding shortest path from the origin to the final destination. With every new node that is added as a branch element to the route tree the branch cutting criteria are

checked. SCHLAICH (2009) developed a method in which three branch-cutting criteria are checked for each current node added to a branch end:

1. No cycles in route (branch is cut if current node is already an element of this branch)
2. Maximum detour factor for entire branch (branch is cut if detour factor from origin to current node is larger than a defined maximum difference to shortest path)
3. Maximum detour factor for rear part of branch (branch is cut if detour factor from the current node to a node 15 minutes upstream is larger than a defined maximum difference to shortest path)

The more complex the network structure and the more diverse the trips for which choice sets need to be generated (short distance trips, long distance trips, inner city trips, motorway commute), the more branch cutting criteria for various lengths of rear route sections are recommended to include. Figure 35 shows a generated route for an OD pair in the north of Munich (highlighted with a black line). The black circle indicates the current node and the dashed black line denotes the shortest path within a traversed pair of alternative route segments (called loop in the following). The left-hand picture illustrates the checking of the detour factor for the entire branch from the origin to the current node (indicated by the light grey arrow). The right-hand picture shows loops of different sizes for which the defined detour factors are checked.

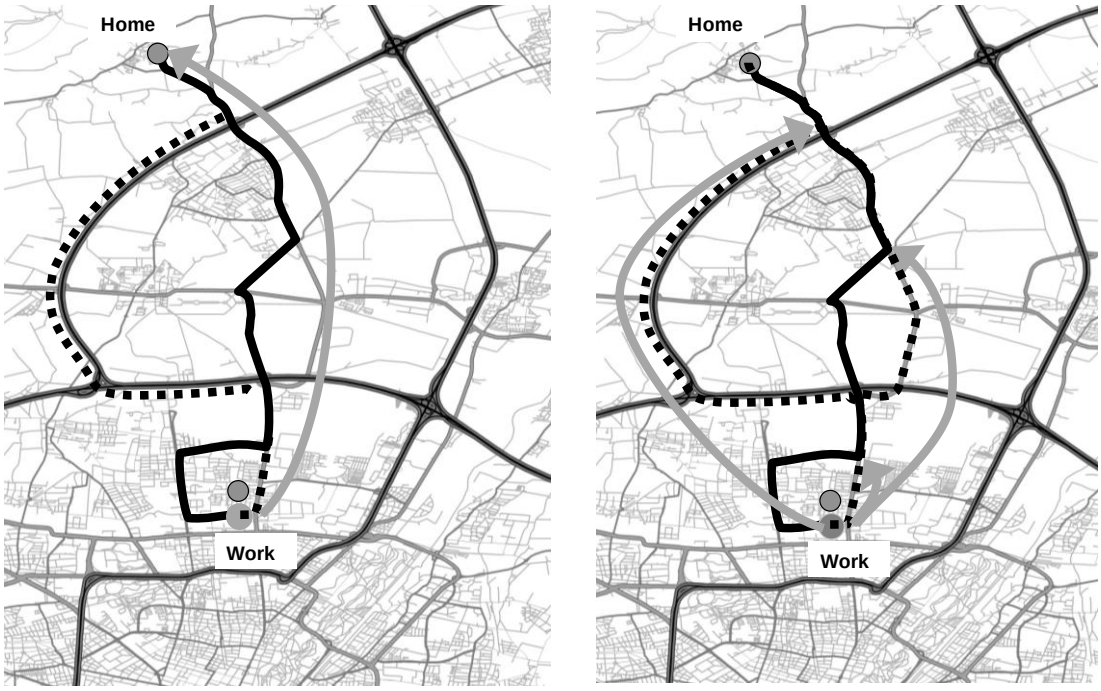

Figure 35: Checking entire and rear parts of branch for allowed detour factors

The case study area of Munich spans the southern half of Bavaria and includes network parts with less density in rural areas as well as high density in the city centre of

Munich. Four maximum detour factors are defined and lead to the following function for the maximum travel time t_{max} from the origin (respectively an upstream node in the branch) to the current node at the end of the branch:

$$t_{max} = \min\left[\left\{\begin{array}{l} 1.0 \cdot t_{min}, \text{if } t_{min} < 250 \\ 2.0 \cdot t_{min}, \text{if } t_{min} < 450 \\ 1.6 \cdot t_{min}, \text{if } t_{min} < 1000 \\ 1.4 \cdot t_{min}, \text{if } t_{min} \geq 1000 \end{array}\right\}, t_{min} + 1800\right] \tag{24}$$

with: t_{max} [sec] Maximum allowed travel time of examined path between loop entry point and current node

t_{min} [sec] Travel time of shortest path between loop entry point and current node

As the generated routes depend strongly on the defined maximum detour factors, these parameters need to be chosen carefully, matching the network topology of the survey area. In this case study, the choice set generator is fitted to produce choice sets so that the routes capture the main network loops in the motorway network north of Munich.

Through comparison of known routes from personal interviews, which traverse the same network loops, minimum and maximum travel times within a loop, and thus accepted detour factors for each participant of the survey, can be determined. Figure 36 illustrates this concept with the example of a participant who stated five different alternative routes from home to work. Highlighted are two loops for which accepted detour factors are given (loop 1 in dark grey, loop 2 in light grey).

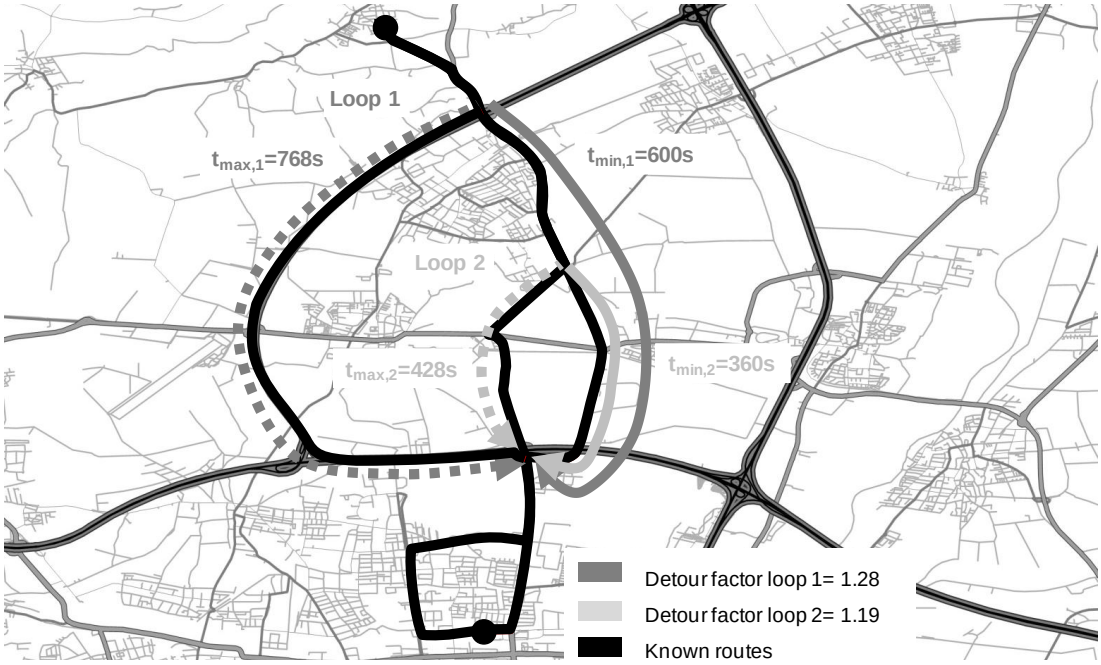

Figure 36: Known route alternatives from home to work

Comparison of the minimum and maximum travel times along alternative loop segments for merged data from all 278 participants leads to a sound basis of empirically derived accepted detour factors. Figure 37 shows the detour factors for the analysed network loops as data points plotted over the minimum travel time in the loop t_{min} against the detour factor within that loop t_{max}/t_{min}. From these data points, the function for the maximum loop travel time t_{max} for route generation is derived. The grey line in Figure 37 shows the t_{min}-sections from which the corresponding maximum travel times are chosen to cover most of the survey detour factors except for single extreme values. All survey detour factors below $t_{min}=250$ seconds are ignored because route choice for very short distance trips is not the primary focus of this analysis. In addition, allowing detour factors as large as 2.1 for $t_{min}<250$ seconds, as indicated by the survey data points, would result in unreasonably large choice set sizes. The threshold line shown is the result of iterative optimization to find the best match-to-survey detour factors and, at the same time, to keep the number of generated routes to a computable size.

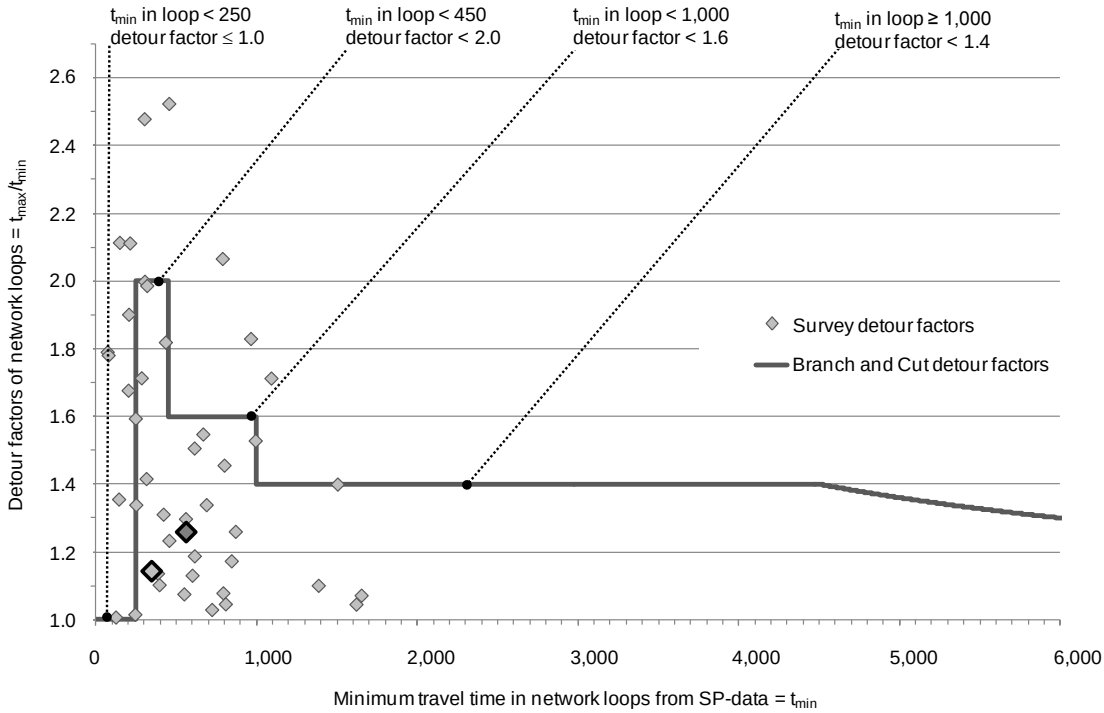

Figure 37: Observed detour factors in network loops and function of maximum allowed detour factors for route generation

As an example, Figure 38 illustrates a generated route tree using this method for a seven-node network. For each possible route in the network from origin to destination, there is a branch. With complete enumeration, there would be eight possible routes (branches), excluding routes with cycles. Every branch with node elements highlighted with a dashed frame is not part of the generated route tree, because it is subject to one of the branch-cutting criteria (detour factor exceeded). For each current node (the branch end at the current route tree generation step), the impedance of the rear part of

the branch is compared with t_{min} of the shortest path from the respective loop entry point. In Figure 38, this comparison is highlighted, for example, in dark grey for the route section from node 1 to node 2. The shortest path between the two nodes is the direct connection from 1→2 and has a travel time of 10 minutes. The middle branch of the route tree includes the path from 1→3→2, which has a travel time of 12 minutes. Thus, the impedance is lower than the maximum allowed impedance for this t_{min}-section, and the branch remains in the route tree. Two examples of branches which are excluded from the route tree because their impedance exceeds the allowed impedance are displayed in dashed nodes.

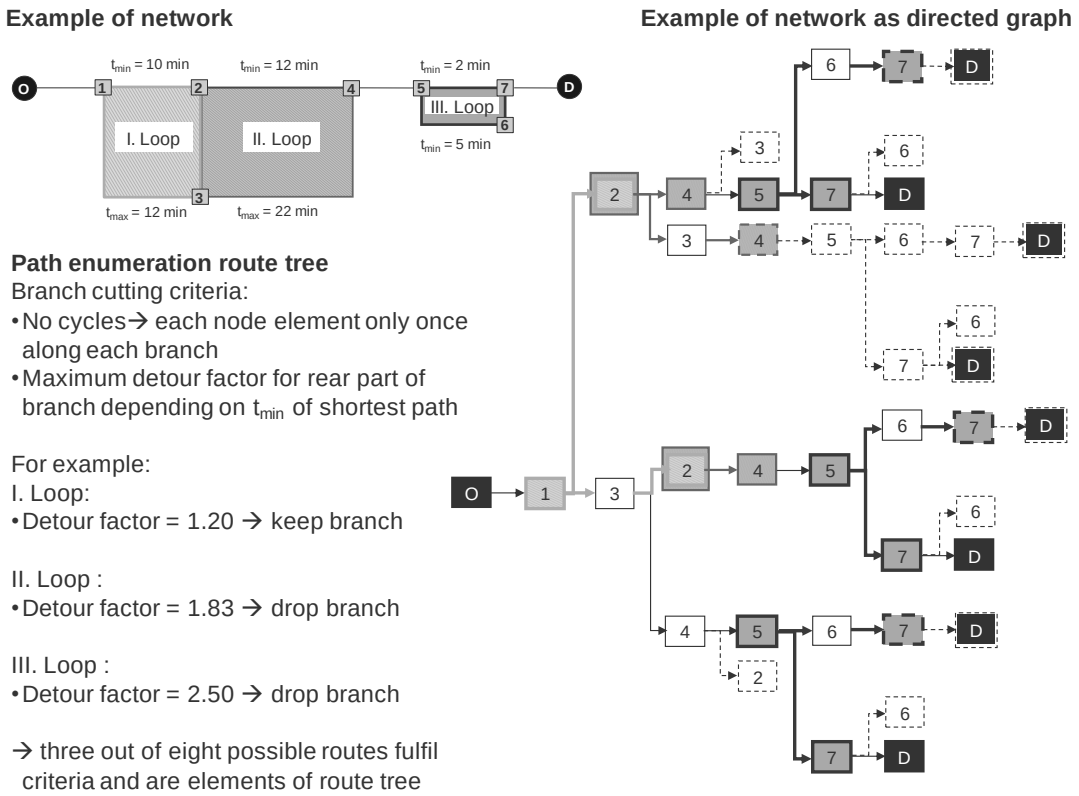

Figure 38: Route tree for seven-node example network

5.1.2.4 Route Transformation

In order to merge the generated routes with the known and revealed routes from survey data as well as attribute the final choice sets with time-dependent traffic data, the generated routes need to be transformed back to the original network PN. As all nodes within a complex node of the original network are assigned to a centroid node in the simplified network, the reverse transformation cannot be done by an explicit reference list. If a route in the simplified network contains a centroid node it is not clear which nodes of the original complex node are traversed. The same problem occurs in the case of parallel links. All network elements of the original network which are not part of the simplified network have an explicit reference to a network element in the

simplified network. Based on this reference, a set of all network elements in the original network can be flagged for every element within a route generated on the simplified network. Figure 39 shows a generated route course in the simplified network (black line in left-hand picture) and the flagged network elements in the original network (right-hand picture, marked in bold grey). For motorway segments links in both directions are flagged. Within the complex nodes all network elements, such as ramps and merging lanes, are also flagged. To obtain a route course in the original network, that matches the route course in the simplified network, a shortest path search with an adjusted impedance function is performed (see formula 25). This impedance function ensures that routes along non-flagged network elements are highly unattractive.

$$\mathrm{w}_{route} = \sum_{l=1}^{L} t_l \cdot \left(a \cdot flag_l + 1\right) \tag{25}$$

with:	w_{route}	Impedance of route in original network
	t_l	Travel time of network element *l*, Set of 1 to *L* includes all elements of route in original network
	a	Parameter, *a=1,000* in this application
	$flag_l$	0, if network element *l* is flagged, 1 if network element is not flagged

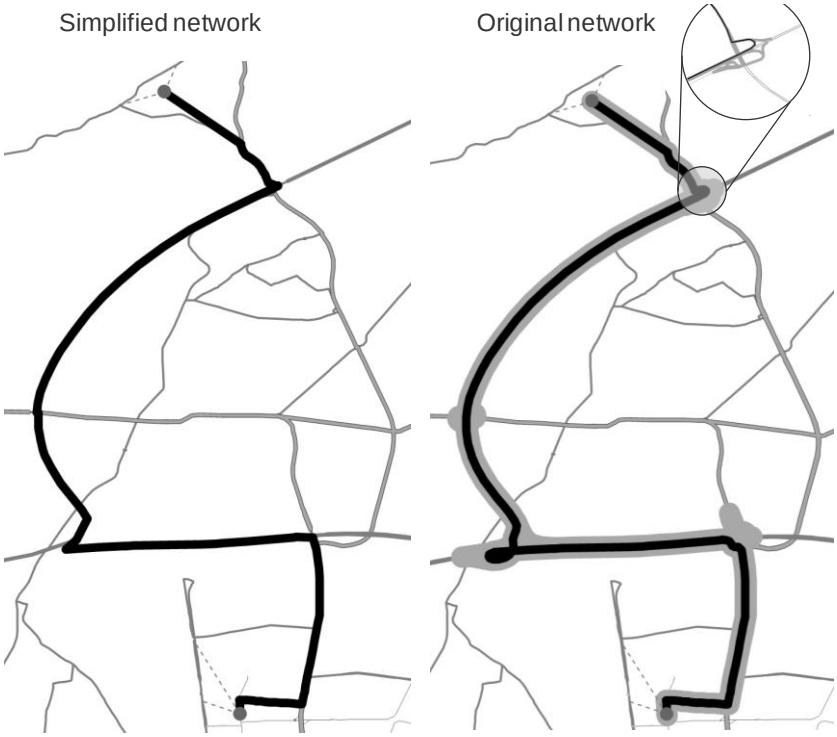

Figure 39: Transformation of route from simplified to original network

5.1.2.5 Composition of Choice Set

For each surveyed OD pair revealed, known and generated routes are fused to a spatial choice set. To ensure each included route is unique one route is added to the choice set after another, applying a commonality factor C (CASCETTA (2001)) introduced in chapter *2.2 Discrete Choice Models*.

Before a route is added to the choice set, the commonality factor to all routes already included in the choice set is checked pair-wise. Only routes with a maximum commonality factor of 0.9 (see SCHÜSSLER ET AL. (2010)) are added to the choice set. First, all revealed routes resulting from observed GPS trips are added. Second, stated routes and, third, generated routes are added. This means, for example, that a generated route, which is similar to a revealed route, is not included. Figure 40 illustrates the spatial choice set for one participant from home to work.

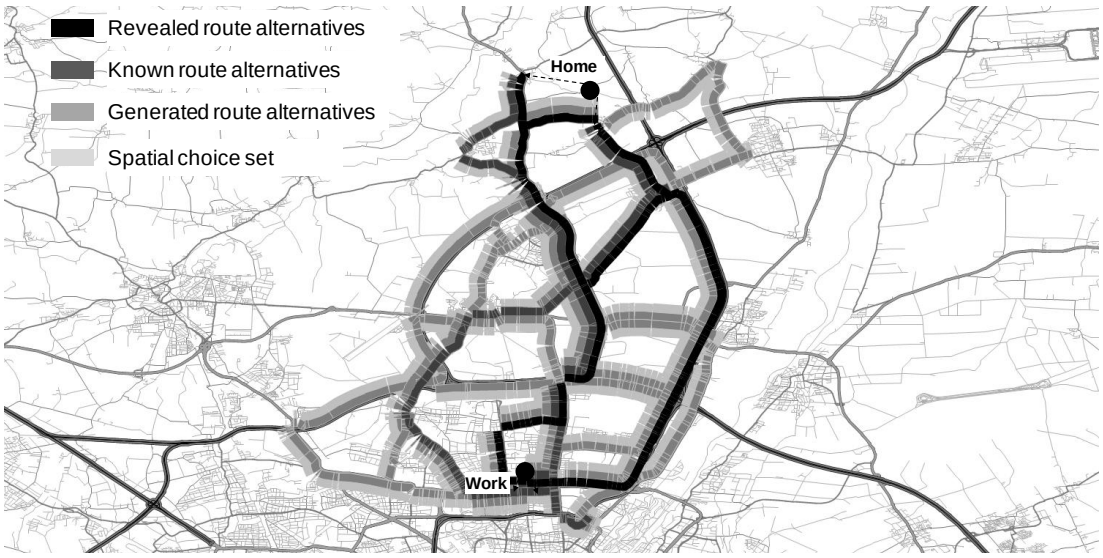

Figure 40: Spatial choice set for one participant from home to work

For this participant 16 trips were observed in total during the GPS survey. The communality check of the revealed routes shows that three unique routes were used on this OD pair. In the personal interview the participant stated four different routes which he knows. Of these four the participant actually used two routes according to the GPS data. Thus, two of the original stated routes are added to the choice set. Of the total 35 generated routes two routes were used during the GPS survey and one was stated in the interview. Accordingly, the choice set is supplemented by 32 generated routes and includes 37 unique routes in total.

Table 26 shows the choice set numbers and composition of the three route types. In relation to the total of all 4,100 OD pairs 1.5 routes are used and 20.5 are generated on average. The average choice set size amounts to 22.2 routes per OD pair. These numbers are based on routes generated on free flow travel times. According to DUGGE

(2006), who analysed the number of routes in choice sets for classical traffic assignment procedures in metropolitan networks and found approximately 30 to 35 routes per OD pair, this is a reasonable value.

Kind of route	All OD pairs (Quantity 4,100)	Home - Work (Quantity 266)	Average for all OD pairs	Average for Home - Work
Revealed	6,208	632	1.5	2.4
Known	384	384	-	1.4
Generated	84,270	8,364	20.5	31.4
Total	90,862	9,380	22.2	35.3

Table 26: Numbers and composition of choice sets

5.1.2.6 Time-dependent Attribution of Choice Sets

For every participant a certain number of OD pairs exists for which a spatial choice set is provided. For every observed trip of a participant the spatial choice set of the according OD pair is now attributed with dynamic, meaning time-dependent, traffic data (see Figure 41).

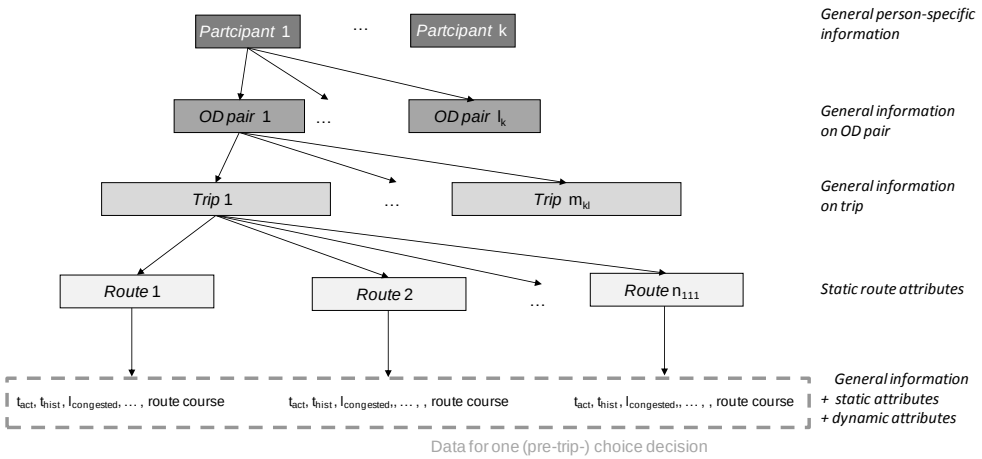

Figure 41: Structure of a choice situation (see PILLAT ET AL. (2011)

The assignment of the time-dependent attributes is carried out on the basis of the actual travel time from the traffic archive in accordance with the method by FRIEDRICH AND LOHMILLER (2011). On the basis of the departure time the entry time and exit time of each link along the route course is determined. In addition, the time-dependent attribute (such as reported length of congestion, displayed LOS, etc.) at the time a link is traversed can be determined for each link as well as the entire route course. After the attribution process a choice set is given for each trip including alternative routes with the following attributes (see Table 27). In total this includes 418,666 routes for 16,037 trips.

General attributes	Static attributes	Time-dependent attributes
• Person specific attributes • Information on OD pair (origin, destination, trip purpose, travel frequency) • Information on trip (departure time, duration, usage of navigation system, usage of LOS map)	• Total length • Length on motorway or interurban roads • Free flow travel time • Detour factor • Independence factor • Commonality to main route • Level of familiarity	• Reported length of congestion or delays • Displayed LOS (free, stagnant, congested) • Length recommended by VMS • Length recommended by navigation system • Actual and historical travel time • Travel time index

Table 27: Overview of static and time-dependent route attributes

5.1.3 Route Choice Model Estimation

The analysis of route choice behaviour is done by using econometric choice models and includes driver-specific, traffic-related and information-related variables. The focus of this research is therefore on identifying the influence of pre-trip and on-trip traffic information on route choice behaviour.

How traffic information in general, and also single information devices in particular, affects drivers' route choice can be derived from the large sample of choice situations from survey data. The influence of single information devices (LOS, TMC via radio, VMS and TTIS) can be estimated from the SP data, where route choice decisions are based on information given via one information device at a time (see chapter 3.6.2 *Stated Preference Data*). Combined effects of information via multiple devices (navigation system, LOS, TMC via radio, and VMS) are estimated on revealed choice situations observed during the GPS survey.

The actual choice model estimation was carried out by the Technische Universität Dresden (see SCHILLER ET AL. (2012)) as part of the *wiki* project. In the following, this chapter summarizes the work of Schiller et al. by describing the general approach and stating selected results and general findings which are of relevance to this research. At the end of the chapter, a comparison between former studies and Schiller et al. is given.

The particular choice model introduced below is the basis for the following chapters of this research and is incorporated in a macroscopic transport model of the survey area, (see chapter 5.3.2 *Choice Set Generation in Assignment*).

General Approach

The relevance of the variables to route choice is quantified with a Maximum-Likelihood estimation (see chapter 2.2 *Discrete Choice Models*). Parameter estimation is done on both data sets (SP and RP data) separately as well as on a combined SP/RP model,

thereby testing various models which differ in the design of the utility function and model structure (see chapter 2.2 *Discrete Choice Models* for elasticity).

All estimations discussed in this research are done with a multinomial Logit model with linear utility functions. Non-linear utility functions are also tested by SCHILLER ET AL. (2012). In some cases this increases the significance of single parameters but does not achieve a significant improvement of the overall model fit.

Models with person-specific attributes (such as age, gender, working hours, number of weekly non-work appointments etc.) are estimated additionally to the full model which includes the total participant sample without specific person groups. The result shows that the analysed person groups all have similar preferences concerning the traffic information devices (same sign as well as magnitude of parameters). Furthermore, no significant improvement of model fit is achieved by introducing person groups. The full model of the total participant sample provides the most realistic fit to the survey data.

Apart from the direct goal of explaining route choice behaviour with all possible variables, a route choice model is needed which can be incorporated in a macroscopic transport model. For this specific application, a model is estimated that meets the following requirements:

- Design of utility function:
  In common transport models the utility of a route is calculated as the sum of utilities of all network elements (connectors, links, and turns) along the route. Therefore, the utility functions cannot include variables which are only given on route level (such as the commonality factor to the main route, the travel time index and the detour factor).

- Sample of choice situations:
  Macroscopic transport models use equilibrium assignment (see chapter 2.4 *Traffic Assignment Methods*) in order to forecast everyday behaviour without unexpected incidents. The route choice model needs to represent behaviour in normal traffic conditions without non-recurrent additional delays based on personal experience and network knowledge. Therefore, a model is estimated on observed choice situations which took place on frequently travelled OD pairs including only those trips for which no extraordinary delays occurred. Observations are taken from RP data from the GPS survey for the home-work OD pair where a long personal experience and network knowledge can be assumed for all participants. For each participant all home-work GPS trips, for which no unexpected delays occurred (in total 2,760 observations over all participants), are analysed and aggregated to one choice situation in which the participant chooses his or her observed main route on the basis of the historical travel times. On this data a so-called base model is estimated which includes only the historical travel time together with static route attributes such as length, length traversing motorway, etc. in the utility function. The choice set is thereby limited to the four routes used in the SP interview in order to

provide comparable results and enable this condensed RP model to be used as a basis for additional models estimated on SP data. After the SP/RP base model (RP data on SP choice set) is estimated, the respective parameters are fixed and remain constant for all following model estimations.

To identify the effect of traffic information devices on route choice behaviour, the reactions of drivers to unexpected delays are analysed. The reactions are based on the drivers' experience and network knowledge as well as the information on the current traffic state provided by different information devices. Parameters for traffic information devices are added to the base model and estimated together with the fixed base model parameters. Traffic information is thus modelled as a surplus utility, with a specific value for each device.

The observations of the SP interview provide choice situations with additional information on the current traffic state from one device at a time. By fixing the base model parameters and estimating parameters for each information device separately, the estimated models on SP data allow the information devices to be ranked. These models cannot, however, be used to predict effects of combined information given by several devices as the SP interview only provided information via one device at a time.

RP data allows analysis of the combined effect of information provided by several information devices for the following combinations of traffic information devices.

- LOS and TMC via radio
- TMC via radio and VMS
- LOS, TMC via radio and VMS
- Radio, VMS and navigation system

For all other combinations of information devices the number of observations is too small to provide robust model estimation. The additionally estimated RP models are not discussed explicitly in this research but rather summarized to general findings as the models are not used for further analysis of traffic information potential in the macroscopic transport model.

Table 28 gives an overview of the number of observations and the kind of traffic information provided by SP and RP data.

	Provided traffic information					No. of observations	
ID	**Navigation system**	**LOS**	**TMC (via radio)**	**VMS**	**TTIS**	**SP**	**RP**
0	--	--	--	--	--	269	992
1	x	--	--	--	--	-	22
2	--	x	--	--	--	807	186
3	--	--	x	--	--	807	5,385
4	--	--	--	x	--	807	702
5	--	--	--	--	x	807	-
6	--	--	x	x	--	-	5,751
7	--	x	--	x	--	-	174
8	--	x	x	--	--	-	935
9	x	--	--	x	--	-	44
10	x	--	x	--	--	-	257
11	--	x	x	x	--	-	1,167
12	x	--	x	x	--	-	422
RP	**745**	**2,462**	**13,917**	**8,260**	**-**	**-**	**16,037**
SP	**-**	**807**	**807**	**807**	**807**	**3,497**	**-**

-- information not provided by this device

x information provided by this device

Table 28: Number of observations with traffic information provided

Results and Model Interpretation

To test the overall data structure a model with constant parameters is estimated (see Table 29). All constants are highly significant according to the t-test values (see chapter 2.2 *Discrete Choice Models*). The data show a well balanced choice split over the given route alternatives. As expected, route 4 (along A9/A92/A99; see chapter 3.6.2 *Stated Preference Data*) is dominated by the other three alternatives since it has a very high commonality to route 1 (along A9) and was only included in the choice set to provide all possible options.

The overall model quality, given by $\rho^2=0.040$ (see chapter 2.2 *Discrete Choice Models*) is poor, and thus the model does not have a good explanatory character. Yet the constants provide a highly significant improvement of model fit compared with the zero-model, where all parameters are set to zero and thus all alternatives have the same probability, given by the Log-likelihood ratio (see chapter 2.2 *Discrete Choice Models*).

$V_j = \alpha_j$			Number of observations: 3,497
Parameter	**Value**	**Standard Error**	**t-test**
α_1	0.611	0.0604	10.11
α_2	0.734	0.0592	12.40
α_3	0.996	0.0569	17.50
α_4	0.000		
Zero-Log-likelihood (L_0)	-4,474.985		
Log-likelihood (L)	-4,297.848		
Log-likelihood ratio (LR_0)	354.220		
ρ^2	0.040		

Table 29: Parameter results and statistics for model with constant parameters

Second, the base model is estimated as everyday behaviour of the participants including 269 observations (one for each participant) in which the observed main route (determined from 2,760 GPS observations) is chosen on the basis of long-term historical travel times (see Table 30). A panel effect can be neglected as the drivers are in a steady state of long-term experience. The model includes historical travel time and length as variables in the utility function. All other static route attributes, which are representable on link level, are not significant. Both parameters have the expected sign and reduce the utility of an alternative. The historical travel time is therefore highly significant, whereas the length is not significant. This is because the length does not differ largely over the four routes in the choice set (see Table 14 in chapter 3.6.2 *Stated Preference Data*) and the two variables also show some correlation. Including the length, however, improves the overall model quality and the two parameters provide a highly significant improvement of model fit. Parameter values allow analysis of the change in utility related to changes in the variable values. Elasticities capture the change of choice related to changes in a variable value. The elasticity of t_{hist} ranges between -1.46 to -7.98. This means an increase of 1% of historical travel time on a route can result in a change of choice probability of this route of up to 7.98% depending on the characteristics of all alternatives in the choice set.

$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j$					Number of observations: 269
Parameter	**Value**	**StdErr**	**t-test**	**Elasticity**	
				from	**to**
β_{t_hist}	-0.616	0.0564	-10.93	-1.4648	-7.9758
β_l	-0.016	0.0494	-0.32	-0.0698	-0.3247
L_0	-295.527				
L	-216.010				
LR_0	159.034				
ρ^2	0.269				
Adjusted ρ^2	0.262				

Table 30: Parameter results and statistics for model no. 1 (base model)

In the following, four models are estimated including variables for traffic information devices, supplementing the base model variables with fixed parameters (see Table 31). An explanation of the terms in the utility functions is given in Table 32.

Model No.	β_{t_hist} [min]	β_l [km]	β_{l_LOS2} [km]	β_{l_LOS3} [km]	β_{l_VMScon} [km]	β_{VMS} [-]	$\beta_{l\_TMCstag}$ [km]	β_{l_TMCcon} [km]	β_{DT} [min]
0	$V_j = 0$; Null - Log - Likelihood								
	---	---	---	---	---	---	---	---	---
1	$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j$								
	-0.616	-0.016	---	---	---	---	---	---	---
2	$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j + \beta_{l\_LOS2} \cdot l_{LOS2,j} + \beta_{l\_LOS3} \cdot l_{LOS3,j}$								
	-0.616	-0.016	-0.281	-0.483	---	---	---	---	---
3	$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j + \beta_{l\_VMScon} \cdot l_{VMScon,j} + \beta_{VMS} \cdot VMS_j$								
	-0.616	-0.016	---	---	-0.702	-0.217	---	---	---
4	$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j + \beta_{l\_TMCstag} \cdot l_{TMCstag,j} + \beta_{l\_TMCcon} \cdot l_{TMCcon,j}$								
	-0.616	-0.016	---	---	---	---	-0.312	-0.148	---
5	$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j + \beta_{DT} \cdot DT_j$								
	-0.616	-0.016	---	---	---	---	---	---	-0.192

Table 31: Overview of estimated models

Abbreviations	Description
β_{t_hist} *t_{hist} [min]	Term for historical travel time of route
β_l *length [km]	Term for length of route
β_{l_LOS2}*l_{LOS2} [km]	Term for length of stagnant flow reported by yellow LOS
β_{l_LOS3}*l_{LOS3} [km]	Term for length of congested flow reported by red LOS
β_{l_VMScon}*l_{VMScon} [km]	Term for length of congested flow reported by VMS
β_{VMS}*VMS [-]	Term for route recommendation
$\beta_{l\_TMCstag}$*$l_{TMCstag}$ [km]	Term for length of stagnant flow reported by TMC via radio
β_{l_TMCcon}*l_{TMCcon} [km]	Term for length of congested flow reported by TMC via radio
β_{DT} *DT [min]	Term for travel time difference of route compared with free flow travel time

Table 32: Description of utility function terms in route choice models

Model no. 2 includes variables for the length of stagnant and congested flow reported to the participants via a LOS map (see Table 33). Both parameters β_{l_LOS2} and β_{l_LOS3} are highly significant and have the expected negative sign. Drivers evaluate one kilometre of reported congestion 1.7 times more negatively than one kilometre of stagnant flow. The overall model quality is good and the two LOS parameters provide a highly significant LR_0.

Compared with the base model, the LOS parameters improve the model fit to a highly significant level, given by the LR_1. The LR_1 is calculated as the ratio of the Log-likelihood of model no. 2 (fixed base model parameters + LOS parameters) and the

Log-likelihood of the base model on the total LOS data sample of 807 observations (see formula 26).

$$LR_1 = 2 \cdot (L_i - L_1) \tag{26}$$

with: LR_1 Log-likelihood ratio between model *i* and base model (model no. 1)

L_i Log-likelihood of model *i*

L_1 Log-likelihood of model 1

L_1 is thereby computed on the base model utility function with fixed parameters $\beta_{t\_his}t = -0.616$ and $\beta_l = -0.016$. The base model has a smaller Log-likelihood than the zero-model and therefore has a worse model fit than assuming random choice of alternatives. This is because the base model is estimated on choice decisions without unexpected delays on the alternatives. In case of additional delays, the historical travel time differs considerably from the current route travel times.

$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j + \beta_{l\_LOS2} \cdot l_{LOS2,j} + \beta_{l\_LOS3} \cdot l_{LOS3,j}$				**Number of observations: 807**	
Parameter	**Value**	**StdErr**	**t-test**	**Elasticity**	
				from	**to**
β_{t_hist}	*-0.616*	*fixed*		-3.4926	-7.4842
β_l	*-0.016*	*fixed*		-0.1124	-0.3087
β_{l_LOS2}	-0.281	0.0111	-25.33	-0.2069	-2.0352
β_{l_LOS3}	-0.483	0.0237	-20.35	-0.0043	-2.0721
L_0	-1118.740				
L_1	-1841.602				
L	-829.172				
LR_0	579.135				
LR_1	2024.860				
ρ^2	0.259				
Adjusted ρ^2	0.257				

Table 33: Parameter results and statistics for model no. 2 (base model + LOS)

Model no. 3 includes variables for the length of congested flow reported to the participants via a VMS as well as a dummy variable for routes which are recommended by VMS, see Table 34. Both parameters β_{l_VMScon} and β_{VMS} are highly significant. The length of reported congested flow on a route has the expected negative effect. Surprisingly, the recommendation of a route by VMS also has a negative sign. Data analysis shows that drivers react to a route recommendation given by VMS in the sense of diverting from their usual main route if another alternative is recommended. VMS never recommended routing along route 3 (B13), however, because a routing recommendation through the subordinate road network is never given in practice. In the SP experiment a routing recommendation along route 2 (A92) often caused

participants to leave route 1 (A9) and divert onto route 3 (B13). The variable VMS is therefore not suitable to express the effect of VMS.

The overall model quality is very poor and the two VMS parameters reduce the model fit in comparison with the zero model as LR_0 is negative. The LR_1 is highly significant, however. VMS as a traffic information device does therefore influence the decisions of the participants. Yet the resulting behaviour is to some extent random, which leads to the conclusion that the participants did not clearly understand the information displayed by the VMS. As the participants are not familiar with a substitutive VMS (dWiSta) with integrated information text on congestion and delays, which is not installed in the Munich network, this is not implausible.

$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j + \beta_{l\_VMScon} \cdot l_{VMScon,j} + \beta_{VMS} \cdot VMS_j$				**Number of observations: 807**	
Parameter	**Value**	**StdErr**	**t-test**	**Elasticity**	
				from	**to**
β_{t_hist}	*-0.616*	*fixed*		-3.1522	-7.6353
β_l	*-0.016*	*fixed*		-0.1502	-0.3150
β_{l_VMScon}	-0.702	0.0256	-27.46	-0.0017	-1.7919
β_{VMS}	-0.217	0.0928	-2.34	-0.0144	-0.1353
L_0	-1118.740				
L_1	-1538.144				
L	-1127.113				
LR_0	-16.748				
LR_1	748.638				
ρ^2	-0.007				
Adjusted ρ^2	-0.009				

Table 34: Parameter results and statistics for model no. 3 (base model + VMS)

Model no. 4 includes variables for the length of stagnant and congested flow reported to the participants via TMC over the radio (see Table 35). Both parameters $\beta_{l\_TMCstag}$ and β_{l_TMCcon} are highly significant and have the expected negative effect. Drivers, however, evaluate the reported length of stagnant flow 2.1 times as negatively as the reported length of congestion. This is unexpected and contrary to other studies, for example SCHLAICH AND FRIEDRICH (2008B) where the effect of β_{l_TMCcon} is greater than that of $\beta_{l\_TMCstag}$. Data analysis suggests that the characteristic values of the variable l_{TMCcon} are too small in all choice situations compared with the values of $l_{TMCstag}$ and thus participants reduced the given information about the current traffic state to the reported length of stagnant flow. The overall model quality is poor, but the two TMC parameters provide highly significant LR_0 and LR_1.

$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j + \beta_{l\_TMCstag} \cdot l_{TMCstag,j} + \beta_{l\_TMCcon} \cdot l_{TMCcon,j}$				Number of observations: 807	
Parameter	**Value**	**StdErr**	**t-test**	**Elasticity**	
				from	**to**
β_{t_hist}	*-0.616*	*fixed*		-4.3833	-7.0594
β_l	*-0.016*	*fixed*		-0.1411	-0.2721
$\beta_{l\_TMCstag}$	-0.312	0.0134	-23.37	-0.0023	-2.6736
β_{l_TMCcon}	-0.148	0.0410	-3.60	-0.0005	-0.4112
L_0	-1118.740				
L_1	-1853.194				
L	-1028.454				
LR_0	180.572				
LR_1	1649.480				
ρ^2	0.081				
Adjusted ρ^2	0.079				

Table 35: Parameter results and statistics for model no. 4 (base model + TMC)

Model no. 5 includes a variable for the travel time difference on routes compared with free flow travel time (see Table 36). Travel times are reported to the participants via a TTIS. The parameter β_{DT} is highly significant and has the expected negative effect.

The overall model quality is low and the TTIS parameter reduces the model fit in comparison with the zero model. As in model no. 3 (base model + VMS) the LR_1 is highly significant. Looking at the Log-likelihood ratios, the resulting behaviour is even more random as in the VMS case. Considering that TTIS are not widely spread in Germany, it is likely that the participants were totally unfamiliar with this information device and found it hard to interpret the travel time differences given.

$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j + \beta_{DT} \cdot DT_j$				Number of observations: 807	
Parameter	**Value**	**StdErr**	**t-test**	**Elasticity**	
				from	**to**
β_{t_hist}	*-0.616*	*fixed*		-3.4738	-7.2557
β_l	*-0.016*	*fixed*		-0.1656	-0.2960
β_{DT}	-0.192	0.00769	-24.92	-0.1219	-1.9236
L_0	-1118.740				
L_1	-1538.144				
L	-1239.124				
LR_0	-240.768				
LR_1	598.040				
ρ^2	-0.108				
Adjusted ρ^2	-0.109				

Table 36: Parameter results and statistics for model no. 5 (base model + TTIS)

The build-up of the discussed models allows ranking of information devices by their effect on changing the usual route choice behaviour by comparing the L_1 and the LR_1 of the different models. If participants behave as usual (relying on their experience of historical travel times), and therefore not considering the non-recurrent congestion given in all choice situations, the L_1 should be a small negative number. If the L_1 is a high negative number the participants obviously based their decisions on other criteria than the historical travel time or length of the given route alternatives. Consequently, LOS and TMC via radio have the strongest effect on route choice, since the participants show very different behaviour compared with their usual route choice, shown by a poor model fit (L_1). Beyond that the LR_1 determines how much the explanatory character of the estimated model increases compared with the base model if additional variables for a traffic information device are introduced. Thus, the LOS model has the largest descriptive quality of all four models (based on LR_1), which leads to the conclusion that drivers understand the information displayed by LOS particularly well. The overall effect of different information devices is ranked as follows (in descending order):

LOS → TMC via radio → VMS → TTIS

Further insight into the interrelation between traffic information and route choice is given by comparing the magnitude of parameters. Table 37 shows the trade-offs between historical travel time and lengths of stagnant or congested flow reported via traffic information devices by calculating the ratio of the β-parameters. For example, a reported length of one kilometre of LOS2 (stagnant flow) is evaluated as equivalent to an increase of travel time of 0.46 minutes by the participants. One kilometre of congestion (LOS3) is further weighted 1.7 times higher than one kilometre of stagnant flow (LOS2).

β_i / β_j		LOS		TMC via radio		VMS	TTIS
		l_{LOS2} [km]	l_{LOS3} [km]	$l_{TMCstag}$ [km]	l_{TMCcon} [km]	l_{VMScon} [km]	DT [min]
t_{hist}	[min]	0.46	0.78	0.51	0.24	1.14	0.18
l_{LOS2}	[km]	--	1.72	1.11	0.53	2.50	0.39
l_{LOS3}	[km]	0.58	--	0.65	0.31	1.45	0.23
$l_{TMCstag}$	[km]	0.90	1.55	--	0.47	2.25	0.35
l_{TMCcon}	[km]	1.90	3.26	2.11	--	4.74	0.74
l_{VMScon}	[km]	0.40	0.69	0.44	0.21	--	0.16
DT	[min]	2.58	4.43	2.86	1.36	6.44	--

Table 37: Trade-offs between historical travel time and traffic information parameters

Conclusions and major findings

The design of the SP interview as a familiar decision situation in the Munich motorway network with realistic travel times allows SP and RP data to be combined but limits the characteristic values of the variables such as route length and the possible total length of congestion. Further restrictions needed for integrating the route choice model in a macroscopic transport model exclude important variables from the utility function and weaken the explanatory character of the estimated models. Full models, estimating all parameters instead of fixing the base model parameters, show a higher model quality and reveal that a constant indicating the main route as well as the travel time index is highly significant.

The general approach of estimating a base model and subsequently adding information variables proved valuable, however, for comparing the effect of single information devices. Model no. 1 (base model) and model no. 2 (base model + LOS) show particularly valuable results. Models no. 3 (base model + VMS) and 4 (base model + TMC) need to be taken with a pinch of salt owing to poor model quality or irritating magnitude of parameters.

Summing up all estimated models, it can be concluded that if

- traffic information is easily comprehensible (especially LOS and TMC via radio), the displayed information is highly relevant to route choice decisions.
- traffic information devices such as TTIS (dIRA) are unknown to drivers, they do not immediately have a positive effect on route choice and drivers require some practice in comprehending the information.
- VMS give route recommendations along an alternative route, this can lead to drivers reacting by diverting from the main route onto a route in the subordinate road network instead of the recommended alternative (for example B13 instead of A92).
- route recommendations are given by VMS, they affect drivers route choice in a positive way (proved in models estimated on full models for both SP and RP data).
- traffic information of several devices is combined (analysis of full models on RP data) and the available information is logical and consistent across several devices, the impact on route choice is significantly increased. In particular, LOS and TMC via radio prove to complement one another.

Comparison to other studies

It must be noted that this analysis of route choice behaviour is based on frequent commuters whose network knowledge and choice set awareness are far above average. Therefore, the effect of traffic information is probably underestimated compared with uninformed drivers. Among others, EMMERINK ET AL. (1996) point out

that men are more likely to be influenced by information than women, but commuters in general tend to be influenced less than drivers with other trip purposes.

The impact of ATIS has been widely studied. Most studies focus on the effects of information on travel time and delays given by either VMS or radio reports (TMC). ABDEL-ATY ET AL. (1997) prove that a roadside VMS which estimates travel time on one of two alternative routes and provides the cause of delays significantly affects the frequency of diversion to the alternative route, a result also confirmed in the model at hand estimated by SCHILLER ET AL. (2012). WARDMAN ET AL. (1997) present a study on the effect of VMS on route choice and conclude that the delay time constitutes more important information to drivers than the actual travel time. This effect is also found in Schiller's work, as introducing a variable for the travel time difference compared with free flow conditions significantly improved the model fit compared with using a variable for the travel time actually displayed to the participants. Research by PEETA AND RAMOS (2006) identifies a sizeable effect of VMS on route choice and points out that drivers' reaction is very much dependent on the type of message displayed. SCHILLER ET AL. (2012) do not analyse the effect of different contexts of information explicitly, but the models show that different information devices have strongly different effects. Traffic reports via radio are analysed by KHATTAK ET AL. (1993). Provision of travel times is determined as important and length and location of delay show significant influence on route choice. Therein, traffic information is more effective if tailored to drivers' routing criteria and if selected information is provided on alternative routes. The study at hand adds to this finding in that it proves that information needs to be easily comprehensible.

A comparison between the effect of VMS and traffic reports via radio is given by EMMERINK ET AL. (1996). Here traffic reports on congestion and delays via radio or via dynamic roadside message signs have a similar effect. In compliance with SCHILLER ET AL. (2012), a higher acceptance of traffic reports by radio than by VMS is observed by SPYRIDAKIS ET AL. (1991). In KIM AND CHON (2005) this preference is confirmed and the effect of traffic reports via radio is ranked slightly higher than that of VMS. TSAVACHIDIS (2002) also concludes that radio reports are far more effective in causing route diversion. The effects are highly dependent, however, on the current traffic state.

Studies estimating the effect of traffic information given in detail as reported length of stagnant flow or congestion (provided by TMC or LOS maps) are rare. MAHMASSANI (1999) studies the repeated reaction of drivers to traffic information in an SP experiment displaying colour-coded traffic states on links as uncongested, mild congestion, moderate congestion and severe congestion. It proves that the reliability of travel time information is crucial and drivers become more reluctant to switch routes if they experience travel times as overestimated than underestimated. A study comparable to SCHILLER ET AL. (2012) including a more quantitative analysis of the reported length of stagnant flow and congestion is provided by SCHLAICH (2009). One kilometre of congestion (LOS3) is thereby weighted 1.2 times higher than one kilometre of stagnant flow (LOS2) based on observations of FCD. TSAVACHIDIS (2002)

determines a weight of 1.7 between LOS and LOS3, equal to the results in the research at hand. KOLLER-MATSCHKE AND BELZNER (2012) carry out a driving simulator experiment in which participants experience different travel times and traffic states along a route. Before the experiment the drivers weighted LOS3 1.6 times higher than LOS2, and LOS2 2.27 times higher than LOS1 (free flow conditions). After the drive in the simulator they stated a weight of 1.7 between LOS2 and LOS3 as well as between LOS1 and LOS2.

All studies show that drivers are more sensitive to delays reported as length of stagnant flow and congestion than the usual colour-coding in today's LOS maps assumes. Usually, LOS maps display stagnant flow as yellow if the travel time is twice as high as in free flow conditions, and congestion as red if travel time is four times as high as in free flow conditions; for example, PTV's online traffic information portal *Bayern Info* uses these factors.

5.2 Departure Time Choice Model

To analyse the effect of pre-trip information on departure time choice an SP interview is conducted (see chapter 3.7 *Departure Time Choice Data*). The experiment determines long-term departure time flexibility under certain travel time assumptions.

5.2.1 Primary Statistical Analysis

Before choice model estimation, a primary statistical analysis gives insight into how the influencing variables provoke a change of departure time. In each decision situation a participant can decide between keeping his usual departure time or changing his departure time to the suggested time of day. Thereby, only trips from home to work or vice versa are considered in this experiment.

A decision situation is defined by

- a suggested change of departure time,
- a forecast travel time saving,
- the reliability of the forecast,
- the origin and destination of the respective trip

As the departure time and temporal flexibility are very much dependent on individual trip chains and personal engagements, Figure 42 shows the departure time behaviour grouped by the participants' working hours. The data show that participants with flexible working hours change their usual departure time far more often than participants with fixed working hours or participants with alternate shifts. Therefore, a person-specific attribute defining the participants' working hours (fixed working hours,

flexible working hours, alternate shifts) is included in the utility function in choice model estimation (see chapter 5.2.2 *Departure Time Choice* Model Estimation).

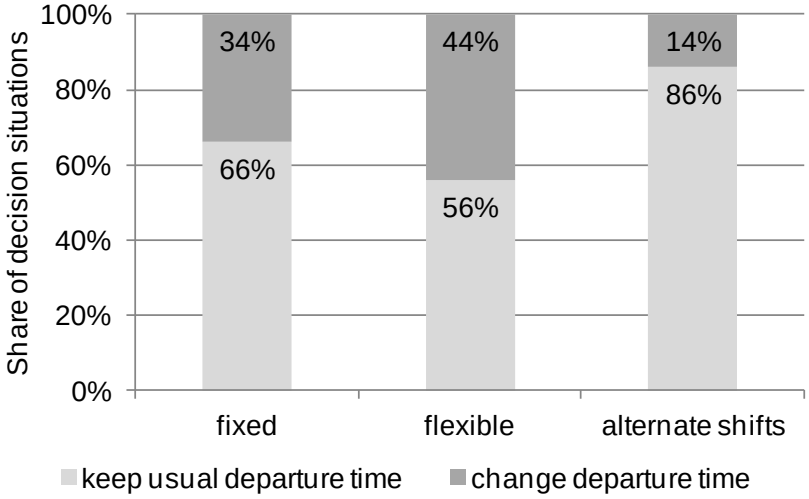

Figure 42: Departure time depending on working hours of participants

Figure 43 displays the departure time behaviour depending on the time difference between the suggested departure time and the usual departure time. The higher the total time difference, the less the willingness to change departure time. Interestingly, a suggested departure time 40 minutes earlier than the usual departure time is evaluated as considerably more unattractive than a departure time 40 minutes later than usual.

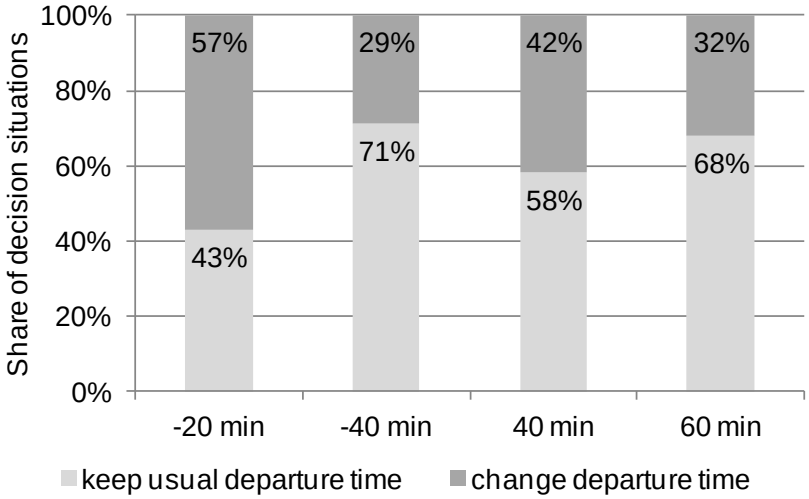

Figure 43: Departure time depending on time difference between the suggested departure time and the usual departure time

Departure time behaviour depending on the forecast travel time saving is shown in Figure 44. As expected, the higher the forecast travel time saving at the suggested departure time, the greater the willingness to change departure time. The travel time

saving in minutes is thereby calculated as a percentage of the usual travel time (see Table 16 and chapter 3.7 *Departure Time Choice Data*).

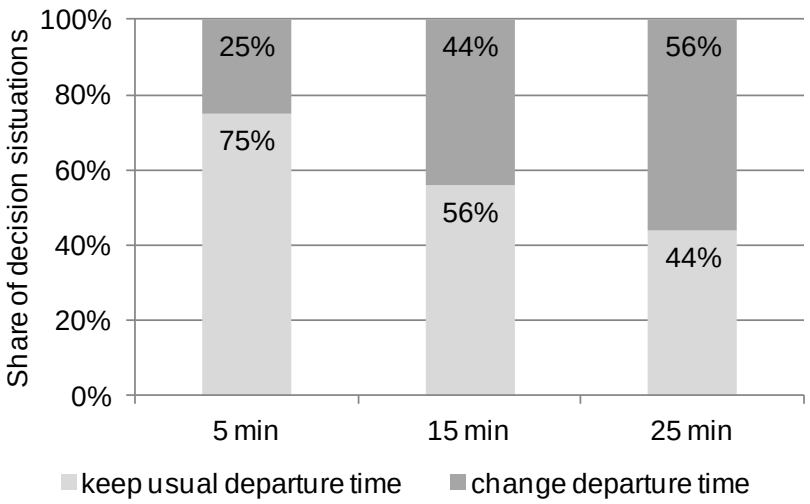

Figure 44: Departure time depending on the forecasted travel time saving

Figure 45 shows the departure time behaviour depending on the reliability of the forecast about which the participants were also informed before each decision (see Figure 21 and chapter 3.7 *Departure Time Choice Data*). A forecast of 90% reliability means that the forecasted travel time saving will occur with a probability of 90% when changing departure time as suggested by the traffic information. The magnitude of the reliability has only marginal effect on departure time behaviour. Although higher reliability slightly increases the willingness to change departure time, it has to be assumed that the participants did not fully comprehend the reliability of the information displayed to them. Participants with fixed working hours show more sensitivity towards reliability of information, however, than participants with flexible working hours.

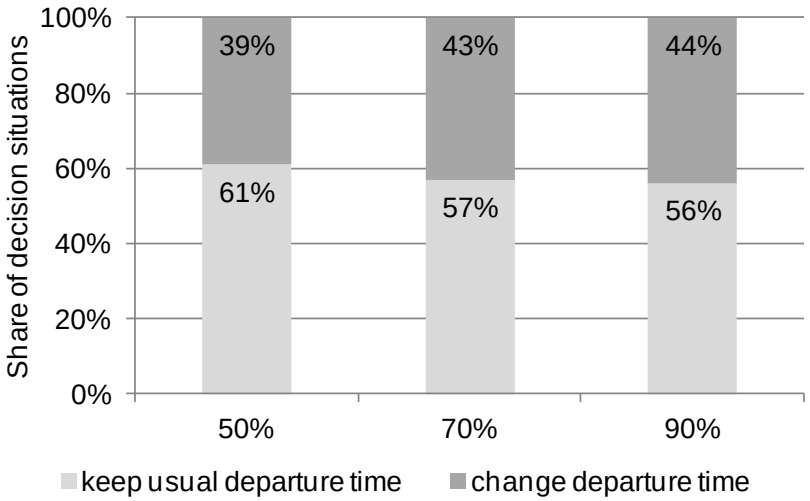

Figure 45: Departure time depending on reliability of forecast

Assuming that departure time preferences are not symmetrical for trips from home to work and trips from work to home, each decision situation included the starting-point of a trip. Although individual trip chains are not equally distributed over a day, the flexibility of participants does not vary very much, depending on the starting-point of the trip (see Figure 46). Participants show a slightly greater willingness to change departure time on trips starting at work and heading home in the evening. Thereby participants with fixed and flexible working hours show very similar behaviour.

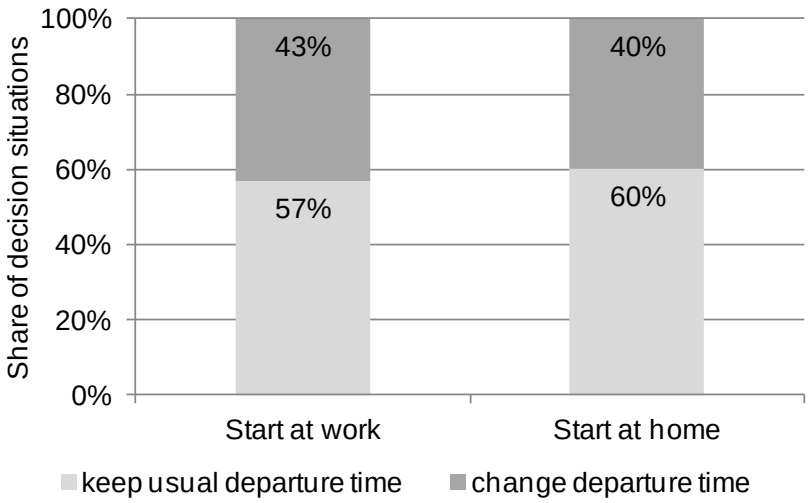

Figure 46: Departure time depending on starting-point of trip

5.2.2 Departure Time Choice Model Estimation

The departure time choice behaviour is analyzed by estimating econometric choice models which include driver-specific variables (working hours), traffic-related variables (forecasted travel time saving) and information-related variables (reliability of forecast). This research thereby focuses on identifying the influence of pre-trip traffic information on departure choice behaviour.

The actual choice model estimation was carried out by the Technische Universität Dresden (see SCHILLER ET AL. (2012)) as part of the *wiki* project. In the following, this chapter summarizes the work of SCHILLER ET AL. (2012) by describing the general approach and stating selected results and general findings. At the end of the chapter, a comparison between former studies and Schiller et al. is given.

General approach

The relevance of the influencing variables on departure choice is quantified by Maximum-Likelihood estimation. Parameter estimation is done by testing various models which differ in the design of the utility function and model structure.

The given parameters of the utility function are estimated for the following model types:

- constant models
- linear models
- linear models with relative variables
- linear models with socio-demographic variables
- non-linear models

Linear models and linear models including socio-demographic values provided the best results. Linear models with relative variables included the ratio of certain variables in the utility function but could not improve model fit. All linear estimations are estimated with a multinomial Logit model. Non-linear utility functions are also tested, but they do not achieve a significant improvement of model fit.

Models with person-specific attributes (fixed or flexible working hours) are estimated additionally to the full model including the total participant sample without specific person groups.

Results and model interpretation

A decision situation asks the participant to choose between the two alternatives:

- Alternative 0: keep usual departure time
- Alternative 1: change departure time

The assumption is that a driver is generally reluctant to change his or her usual departure time, because this departure time is considered the best alternative by the participant under partly unknown constraints (such as working hours, daily engagements, personal preference for starting work at a certain time of day, etc.). Thus, keeping the usual departure time has a positive utility. This is proved by a positive constant for alternative 0 (see Table 38). As the constants are not significant and the overall model quality is poor, the model does not have a good explanatory character. Yet the constants provide a highly significant improvement of model fit compared with the zero-model.

$V_j = \alpha_j$			**Number of observations: 1,614**
Parameter	**Value**	**Standard Error**	**t-test**
α_0	0.338	0.000000121	0.00
α_1	0.000		
Zero-Log-likelihood (L_0)	-1118.740		
Log-likelihood (L)	-1096.049		
Log-likelihood ratio (LR_0)	45.380		
ρ^2	0.020		

Table 38: Parameter results and statistics for model with constant parameters

A change of departure time will therefore result in reduction of utility. A measurement for the utility reduction is the time difference between the chosen departure time and the usual departure time. The larger the time difference, the smaller the utility of changing departure time becomes. On the other hand, changing departure time can result in a positive utility, if travel time savings can be achieved compared with the travel time at the usual departure time. Additionally, it is examined whether participants have a greater willingness to change the departure time to an earlier time of day as compared to a later time of day.

The estimated utility function therefore includes three influencing variables (Table 39).

- Time difference between chosen and usual travel time (not only in terms of magnitude but also in terms of direction in the sense of earlier or later)
- Travel time savings between chosen and usual travel time
- Reliability with which the forecast travel time savings will be achieved

Abbreviations	Description
β_{TD_later} *TD_{later} [min]	Term for time difference (later) between chosen and usual departure time
$\beta_{TD\_earlier}$ * $TD_{earlier}$ [min]	Term for time difference (earlier) between chosen and usual departure time
β_{TS} *TS [min]	Term for travel time saving between chosen and usual travel time
β_{R} *R [%]	Term for reliability of forecasted travel time saving

Table 39: Description of utility function terms in departure time choice models

The estimation shows that not only the magnitude but also the direction (earlier or later) of the time difference between chosen and usual departure time is relevant (Table 40). Participants are more willing to leave later than earlier compared with their usual travel time. If this preference comes from personal experience of congestion levels for certain times of day or is owed to other reasons cannot be verified in this experiment. The forecast travel time saving has a positive sign, as expected, and has the strongest influence on departure time choice. All parameters, except reliability, are highly significant. The reliability has only a marginal positive value, although it is significant, which increases willingness to change departure time with rising reliability of the travel time saving forecast.

$V_j = \beta_{TD\_later} \cdot TD_{later,j} + \beta_{TD\_earlier} \cdot TD_{earlier,j} + \beta_{TS} \cdot TS_j + \beta_R \cdot R_j$				Number of observations: 1,614	
Parameter	**Value**	**StdErr**	**t-test**	**Elasticity**	
				from	**to**
β_{TD_later}	-0.0379	0.00399	-9.49	-1.620	-0.449
$\beta_{TD\_earlier}$	-0.0563	0.00740	-7.61	-1.517	-0.252
β_{TS}	0.0718	0.00679	10.56	0.245	1.032
β_R	0.0056	0.00333	1.68	0.045	0.223
L_0	-1118.740				
L	-990.352				
LR	256.776				
ρ^2	0.115				
Adjusted ρ^2	0.109				

Table 40: Parameter results and statistics for model no. 6 (full sample)

To include ordinal variables, such as working hours or starting-point of the trip, within the model, the total data sample is divided into the following subsets:

- participants with fixed working hours (sample no. 1)
- participants with flexible working hours (sample no. 2)
- decision situations with starting-point of trip at home (sample no. 3)
- decision situations with starting-point of trip at work (sample no. 4)

Tables 41 to 44 show the parameter results and statistics for the models of the four data subsets. The parameter values indicate that participants with fixed working hours (see Table 41) are more reluctant to leave later than their usual departure time than they are to leave earlier. Whereas the forecast travel time saving is not as important as in model no. 6, the reliability plays a bigger role in decision-making although the parameter is still not significant.

$V_j = \beta_{TD\_later} \cdot TD_{later,j} + \beta_{TD\_earlier} \cdot TD_{earlier,j} + \beta_{TS} \cdot TS_j + \beta_R \cdot R_j$					
Sample no. 1				**Number of observations: 300**	
Parameter	**Value**	**StdErr**	**t-test**	**Elasticity**	
				from	**to**
β_{TD_later}	-0.0410	0.00680	-6.03	-2.278	-0.838
$\beta_{TD\_earlier}$	-0.0511	0.01240	-4.13	-1.785	-0.367
β_{TS}	+0.0666	0.01560	4.26	0.229	1.283
β_R	+0.0084	0.00767	1.09	0.059	0.649
L_0	-207.944				
L	-161.587				
LR	92.715				
ρ^2	0.223				
Adjusted ρ^2	0.204				

Table 41: Parameter results and statistics for model no. 7 (sample no. 1)

Accordingly, participants with flexible working hours (see Table 42) are more willing to shift their departure time, as the *β*-parameters for the time difference between the chosen departure time and the usual departure time are smaller than in model no. 7 (both for departing earlier and for departing later). The reliability plays a minor role in this person group, as neither the parameter is significant nor is the magnitude as large as in the prior models.

$V_j = \beta_{\text{TD\_later}} \cdot TD_{\text{later, j}} + \beta_{\text{TD\_earlier}} \cdot TD_{\text{earlier, j}} + \beta_{\text{TS}} \cdot TS_j + \beta_R \cdot R_j$					
Sample no. 2				**Number of observations: 1,314**	
Parameter	**Value**	**StdErr**	**t-test**	**Elasticity**	
				from	**to**
$\beta_{\text{TD\_later}}$	-0.0311	0.00301	-10.33	-1.526	-0.411
$\beta_{\text{TD\_earlier}}$	-0.0444	0.00556	-7.99	-1.412	-0.226
β_{TS}	+0.0777	0.00708	10.97	0.243	0.956
β_R	+0.0010	0.00339	0.31	0.013	0.074
L_0	-890.001				
L	-798.527				
LR	182.949				
ρ^2	0.103				
Adjusted ρ^2	0.098				

Table 42: Parameter results and statistics for model no. 8 (sample no. 2)

The model estimated on morning commuting trips starting at home (see Table 43) show the same preference for leaving later than usual than for leaving earlier. Reliability of forecast travel time savings proved to be more important in the morning as the *β*-parameter is larger than in previous models as well as statistically significant.

$V_j = \beta_{\text{TD\_later}} \cdot TD_{\text{later, j}} + \beta_{\text{TD\_earlier}} \cdot TD_{\text{earlier, j}} + \beta_{\text{TS}} \cdot TS_j + \beta_R \cdot R_j$					
Sample no. 3				**Number of observations: 851**	
Parameter	**Value**	**StdErr**	**t-test**	**Elasticity**	
				from	**to**
$\beta_{\text{TD\_later}}$	-0.0311	0.00409	-7.61	-1.622	-0.434
$\beta_{\text{TD\_earlier}}$	-0.0407	0.00742	-5.48	-1.346	-0.214
β_{TS}	+0.0776	0.00940	8.26	0.245	1.149
β_R	+0.0089	0.00459	1.94	0.115	0.669
L_0	-589.868				
L	-519.795				
LR	140.147				
ρ^2	0.119				
Adjusted ρ^2	0.112				

Table 43: Parameter results and statistics for model no. 9 (sample no. 3)

Evening commuting trips starting at work (see Table 44) differ from the morning commuting in the willingness to leave earlier as the departure time has harsher constraints owing to the end of the working shift, etc. Also, it is plausible that reliability is less important in the evening as it is not so important to arrive at a certain time as it is when coming to work in the morning.

$V_j = \beta_{\text{TD\_later}} \cdot TD_{\text{later, j}} + \beta_{\text{TD\_earlier}} \cdot TD_{\text{earlier, j}} + \beta_{\text{TS}} \cdot TS_j + \beta_R \cdot R_j$					
Sample no. 3					**Number of observations: 763**
Parameter	**Value**	**StdErr**	**t-test**	**Elasticity**	
				from	**to**
$\beta_{\text{TD\_later}}$	-0.0316	0.00360	-8.78	-1.609	-0.461
$\beta_{\text{TD\_earlier}}$	-0.0500	0.00677	-7.38	-1.687	-0.298
β_{TS}	+0.0746	0.00869	8.57	0.246	1.043
β_{R}	-0.0024	0.00410	-0.58	0.031	0.151
L_0	-528.871				
L	-469.580				
LR	118.583				
ρ^2	0.112				
Adjusted ρ^2	0.105				

Table 44: Parameter results and statistics for model no. 10 (sample no. 4)

Further insight into the weight of the estimated *β*-parameters is given by the trade-offs in Table 45. For example, for 10 minutes of saved travel time drivers are willing to depart 19 minutes later than usual. Furthermore, assuming again a forecasted travel time saving of 10 minutes, an increase of the reliability of the forecast by 10% can provoke drivers to change their departure time by additional 15 minutes later or 10 minutes earlier.

β_i / β_j		**TD_{later}**	**$TD_{earlier}$**	**TS**	**R**
		[min]	**[min]**	**[min]**	**[-]**
TD_{later}	**[min]**	--	1.49	-1.89	-0.15
$TD_{earlier}$	**[min]**	0.67	--	-1.28	-0.10
TS	**[min]**	-0.53	-0.78	--	0.08
R	**[-]**	-6.77	-10.05	12.82	--

Table 45: Trade-offs between departure time parameters for full data sample (model no. 6)

Conclusions and major findings

The design of the SP interview as pre-trip information on commuting trips proved valuable. The interview analyses the flexibility of drivers to adjust their usual day-to-day

travel time as a reaction to information. All estimated models show plausible parameter results as well as passable statistical robustness. In particular, model no. 7 (data subset of participants with flexible working hours) has high overall quality.

Summing up all estimated models, it can be concluded that

- the participants' willingness to change the usual departure time on their daily commuting trips depends on the potential travel time saving, the time difference between the usual and considered departure time, and the reliability of the forecast.
- participants are more sensitive to shifting their departure time to an earlier time of day than to a later time of day.
- people with fixed and flexible working hours have different preferences and flexibilities with regard to changing their usual departure time.
- departure time behaviour is different for morning and evening commuting when other personal circumstances come into play.
- generally, the participants in this survey are not very flexible about changing their departure time and expect high travel time savings in return.

Comparison to other Studies

Many studies have been conducted over the past two decades focusing on departure time behaviour of commuters. Pre-trip information has been proved to have a significant effect on how often commuters change their departure time per month. KHATTAK ET AL. (1995) show that the more accurate and reliable information is, the more likely commuters are to change their usual departure time. JOU (2001) concludes that commuters with pre-trip information are generally more likely to change their departure time than commuters relying only on their personal experience. Furthermore, departure time of commuters is not as sensitive to current congestion and travel times as route choice according to MANNERING (1989). Therefore, pre-trip information should be part of a long-term campaign to change departure time preferences, instead of constituting mere travel time information. In an additional study MANNERING ET AL. (1994) show that frequent commuters are generally less likely to use pre-trip information than drivers with other trip purposes, owing to their extensive personal experience, a finding also confirmed by DE PALMA ET AL. (2003). This leads to the conclusion that the general willingness to change departure time is probably underestimated in this research as the participants are all frequent commuters. This needs to be remembered when quantifying the potential of pre-trip information to reduce the transport time expenditure and the fuel consumption for the survey area with a macroscopic transport model for all trips made in a day (see chapter 7.3 *Optimization of Departure Time*).

The impact of person-specific attributes has been shown by SMALL (1982) who determines a considerable variation in departure time behaviour for working hour

flexibility, family status and occupation. MANNERING (1989) and MANNERING ET AL. (1994) confirm that commuters with flexible working hours make considerably more departure time shifts. However, KHATTAK ET AL. (1995) cannot confirm this correlation as working hours are not significant in their survey on drivers commuting to downtown Chicago.

Most of the past studies focus on the morning commute with trips made from home to work, see SMALL (1982), CHANG AND MAHMASSANI (1988), MANNERING (1989). Only MANNERING ET AL. (1994) and JOU (2001) consider trips from home to work and vice versa. Their work does however not cite the implications of asymmetric behaviour for the inbound or outbound commute, unlike the work by SCHILLER ET AL. (2012) discussed in this research.

The finding of this research that commuters evaluate departing early or late in respect to their usual departure time is confirmed in many other studies. Yet it has to be mentioned that most of them examine drivers' evaluation of arriving early or late in respect of their preferred arrival time at work (see SMALL (1982), CHANG AND MAHMASSANI (1988), DE PALMA ET AL. (2003)).

The major goal in analysing departure time behaviour is to answer the question of how many minutes drivers are willing to shift their departure time by in order to save one minute of travel time. This trade-off is given in other studies as the ratio of travel time and schedule delay (i.e. the difference between the actual and the preferred arrival times). Table 46 shows a comparison of other studies with the work by SCHILLER ET AL. (2012). It lists trade-offs between a ten-minute travel time saving and the corresponding accepted departure time shift classified as early and late departures.

Study	Travel time saving	Departure time shift		Trade-off	
	[min]	[min]	[min]	[-]	[-]
		early	late	early	late
SCHILLER ET AL. (2012)	10	12.8	18.9	0.78	0.53
SMALL (1982)	10	19.2	9.1	0.52	1.10
CHANG AND MAHMASSANI (1988)	10	22.8	14.6	0.44	0.68
DE PALMA ET AL. (2003)	10	18.2	5.8	0.55	1.71

Table 46: Comparison of studies on the trade-off between travel time saving and departure time shift

Remarkable is that SMALL (1982), CHANG AND MAHMASSANI (1988) and DE PALMA ET AL. (2003) all determine commuters' preference for departing earlier instead of later than their usual departure time. SCHILLER ET AL. (2012) find the opposite preference. It can only be assumed that this is owed to the design of the interviews. SMALL (1982), CHANG AND MAHMASSANI (1988) and DE PALMA ET AL. (2003) all include the arrival time at the destination in the decision situation, making the participant consider strongly whether

he or she will be late for work. In CHANG AND MAHMASSANI (1988) participants are further instructed that absolutely no lateness is permitted at the workplace. SCHILLER ET AL. (2012) do not introduce this as a relevant boundary condition in their interview, so it can be assumed that the participants consider other constraints such as child pick-up and drop-off or family car-pooling more seriously than arrival time at work. Furthermore, the compared studies focus on the morning commute to work, whereas SCHILLER ET AL. (2012) include evening commute trips in which arrival at the destination plays a minor role.

5.3 Transport Model

The route and departure time choice models introduced above are now integrated in a transport model in order to determine the effects of travel behaviour with and without information for the survey area. In the following chapters an appropriate modelling approach and assignment method is first discussed, then the presumption of user equilibrium driver behaviour is validated, and a joint route and departure time model is presented.

5.3.1 Assignment Classes

The purpose of a model is to give the best possible representation of reality, keeping it as simple as possible. Transport-related questions range from forecasting future travel demand, over forecasting future network performance under changed travel demand conditions, to simulating the performance of planned transport infrastructure. This has resulted in an extensive landscape of different model classes (see chapter 2.4 *Traffic Assignment Methods*). In the following, the model used in the remaining chapters of this research is introduced and the reasons for the selected model class are discussed.

Macroscopic vs. microscopic:

Simulation or microscopic assignment (see chapter 2.4 *Traffic Assignment Methods*) is computationally expensive. Whether a time-consuming computation of a large number of simulation runs, which is needed in order to obtain robust results, is necessary should be carefully considered. Furthermore, the level of detail required for a microscopic model of the transport supply makes this an unrealistic option for the size of the survey area analysed in this research.

Microscopic assignments include traffic flow models on a vehicle-to-vehicle interaction level. The level of detail of traffic movement of these models is generally capitalized for tasks such as dimensioning road infrastructure elements (for example to determine the number of lanes in front of a signalised intersection). This research aims at analysing

potential information to optimise spatial and temporal traffic volume distribution by looking at the reduction of transport time expenditure as well as fuel consumption for the whole survey area. To model overall congestion levels a macroscopic interrelation between travel demand and transport supply represented by saturation degrees on a link level is appropriate.

Travel demand can be represented at single person level in microscopic models, thereby focusing on trip chains taken by each traveller in one day. This research focuses on overall traffic volumes produced by a given travel demand rather than modelling different behaviour for single drivers. Therefore, a macroscopic approach that uses travel demand matrices for certain times of day is appropriate.

Static vs. dynamic:

Dynamic assignments consider time-varying congestion in a transport network, thereby only affecting the route choice of drivers who pass congested network segments at the time when the congestion occurs. If the congestion dissolves before a driver reaches the road or intersection he or she will not experience delays and route choice is unaffected. The effect of time-varying congestion on assignment results becomes even larger if the assignment includes the phenomena of blocking-back resulting from vehicles queuing behind an intersection. In this concept traffic congestion is modelled as a spatial and time-varying object in the network, which makes it more important to know when drivers arrive at congested segments because more drivers on cross-directional routes may be affected by the congestion. Modelling these effects is especially important in inner urban networks where a major part of congestion occurs at intersections and short housing blocks increase the problem of queues spilling back on upstream links. In this research the major focus lies on route choice behaviour in motorway networks which mainly includes grade-separated intersections so that blocking back is assumed to be negligible.

Another important entitlement of dynamic assignment methods is to consider on-trip decisions in route choice behaviour as a reaction to sudden non-recurrent congestion. By contrast, static assignment methods model route choice behaviour in the sense of computing the main routes normally chosen by all drivers in the network under normal everyday conditions. This research quantifies how traffic information can change everyday behaviour in order to determine benchmarks for the potential of traffic information. Clearly the effect of traffic information in non-recurrent congestion situations is largely higher (see chapter 4.2 *Quality of Information*, page 63) but traffic incidents are hardly comparable scenarios, which makes it difficult to use computed potentials as benchmark values. Therefore, non-recurrent congestion is not considered here and a static traffic assignment is appropriate.

Although route choice itself is modelled using static assignment, time-varying congestion levels are considered in the following, at the level of departure times. A jointed route and departure time model is introduced in chapter 5.3.3.

Optimization vs. approximation:

A very common approach in traffic assignment is to optimise the distribution of traffic flows under the assumption that all drivers wish to travel on the route with the lowest travel time (or highest utility) from their origin to their destination (see Wardrop's first principle, chapter 2.4 *Traffic Assignment Methods*). This condition, the so-called user equilibrium, is reached when every driver succeeds in finding such a route, and therefore every used route in the network has the minimum and also equal travel time for each OD pair. Such a distribution of traffic flows is assumed to be an appropriate model for everyday behaviour when drivers have time to learn about the network conditions and occurring delays. To model the reaction of drivers and resulting traffic distributions in non-recurrent congestion, approximation models such as incremental assignment (see chapter 2.4 *Traffic Assignment Methods*) are more suitable.

The question at hand is: Do drivers today really follow the user equilibrium principle, thereby trying to maximise their personal utility? To obtain answers, travel time data along alternative routes on the Munich motorway network is analysed from data collected by ANPR cameras for the whole survey period. Figure 47 shows the alternative routes analysed. There are two loops, with alternative routes to Munich city centre via the München-Neuherberg exit junction. Loop 1 contains the routes along the A9, A92 and B13 starting at Neufahrn junction. Loop 2 contains the routes along the A92 and B13 starting at Unterschleißheim junction.

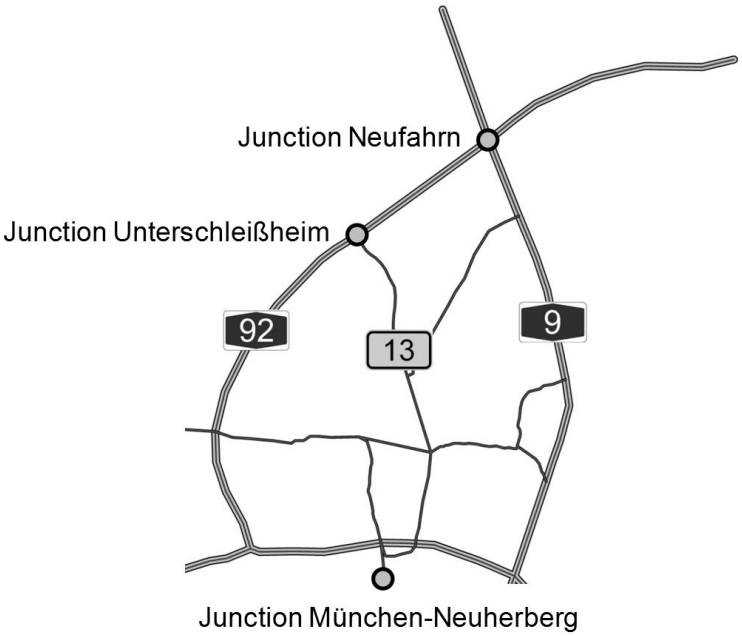

Figure 47: Travel times on alternative routes in the Munich motorway network

Figure 48 shows the route travel times in normal traffic conditions over the course of a weekday. In the morning hours before rush hour begins, the A9 is clearly the most attractive route for drivers coming from the Neufahrn junction as the route travel times in Loop 1 differ greatly (13 minutes along A9, 15 minutes along A92, and 17 minutes along B13). For drivers coming from the Unterschleißheim junction the A92 is the most attractive route. As travel demand increases around 6:00 a.m. saturation increases the travel times and the B13 becomes an attractive alternative in Loop 2. Drivers distribute among the two alternative routes such that travel times are approximately equal until the demand drops again at 7:00 p.m.

This user optimal behaviour is also observed in Loop 1 for a weekday with an unexpected incident (see Figure 49). At 7:30 a.m. an accident on the B13 causes high delays on both alternative routes in Loop 2. After a time-delay of 30 minutes the congestion leads to additional demand on the A9 and causes travel times to increase. The alternative routes in Loop 1 are in a user optimal state with equal travel times until the congestion dissolves at around 9:00 a.m.

The travel time data on this particular part of the Munich motorway network indicates that drivers try to distribute between alternative routes in user optimal way and come close to a user optimal state if they are well aware of traffic conditions. Therefore, the use of equilibrium assignment seems an appropriate approach.

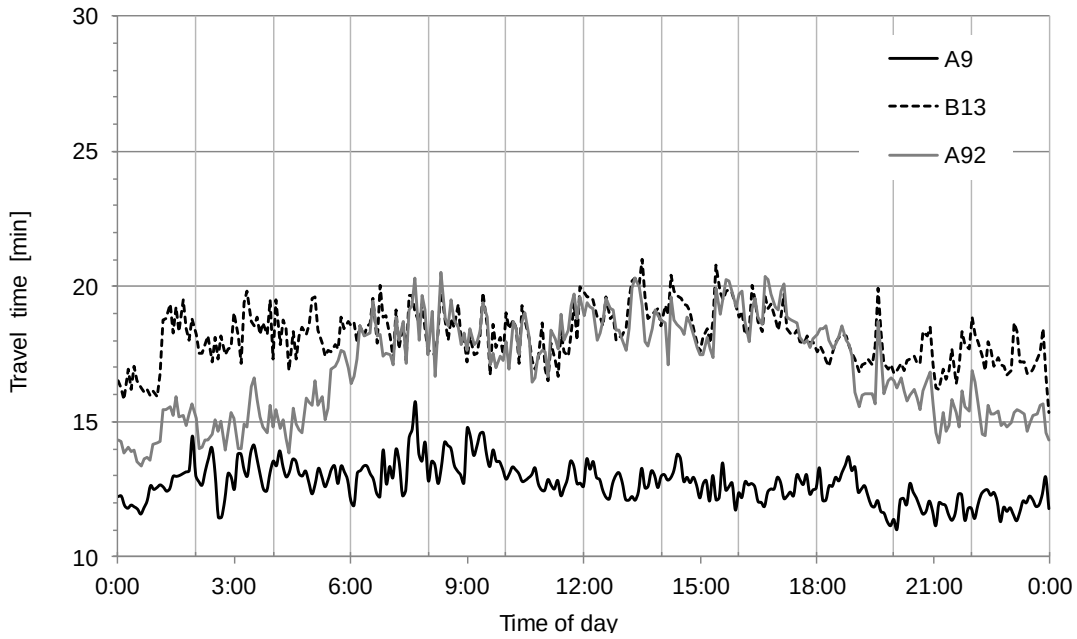

Figure 48: Route travel times between junctions Neufahrn and München-Neuherberg in normal traffic conditions on alternative routes in the Munich motorway network on weekdays

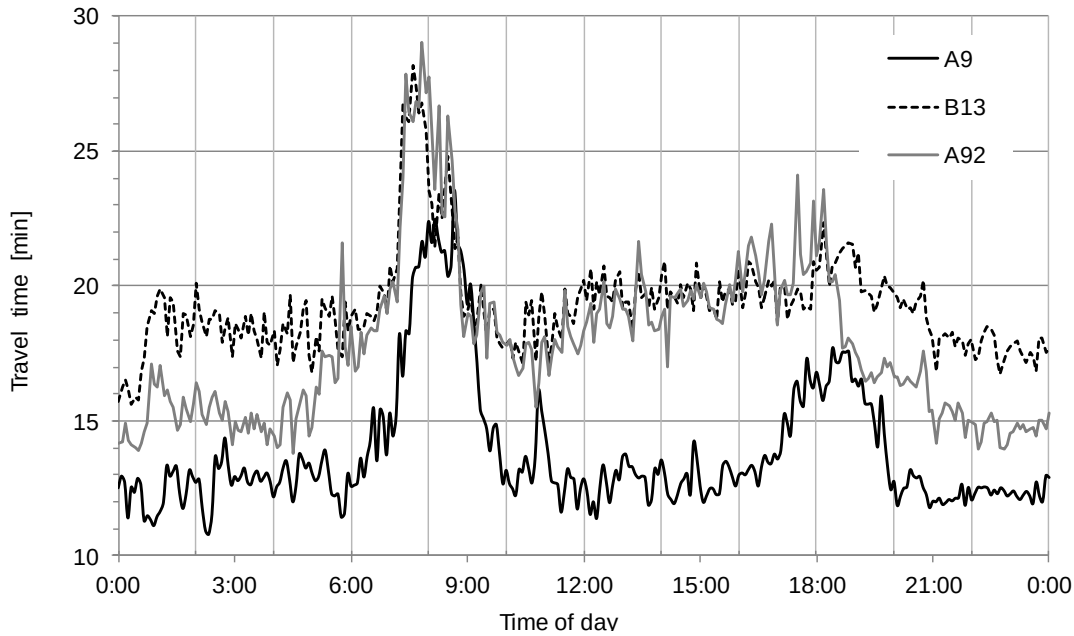

Figure 49: Route travel times between junctions Neufahrn and München-Neuherberg in incident traffic conditions on alternative routes in the Munich motorway network on weekdays

Stochastic vs. deterministic:

The analysis of today's route choice behaviour in chapter 4.2 *Quality of Information* proves that drivers are normally not fully aware about traffic conditions in the whole network at all times of the day. Furthermore, drivers choose routes relying on a biased perception of the given transport supply based on partly perfect information as well as personal experience. To model realistic route choice behaviour in traffic assignment, the estimated route choice model (see chapter 5.1.3 *Route Choice Model* Estimation) needs to be applied to a choice set that includes non-optimal routes. An equilibrium assignment based on a deterministic route search results in user optimal traffic flows. However, observed traffic flows are far from optimal today. Stochastic user equilibrium, based on a stochastic route search (see chapter 2.3 *Route Search Algorithms*), results in realistic traffic flows where each driver aims to travel on the best route, but not all drivers achieve this goal. The assignment results in travel times which vary on different routes for one OD pair. Chapter 5.3.2 *Choice Set Generation in Assignment*, describes how sensible choice sets, similar to the choice set derived in chapter 5.1.2 *Choice Set Generation* can be computed using stochastic route search.

The following modelling work in this research is done using the software package *VISUM*, a PTV Vision product developed and distributed by PTV AG. Wherever possible, the underlying modelling concepts are discussed in a general manner, so that they are adaptable to other modelling environments.

5.3.2 Choice Set Generation in Assignment

Standard traffic assignment procedures do not allow to pre-define externally calculated choice sets on which the demand is distributed. Rather, an assignment step includes firstly a route search and secondly the demand distribution. As assignment results depend heavily on the choice set structure, it is necessary to ensure that the choice set generated in chapter 5.1.2 *Choice Set Generation* is matched as closely as possible in the assignment route search.

In the following the process of adapting the parameters of the route search in a stochastic equilibrium assignment are presented. Stochastic route search is based on an iterative shortest path search on stochastically modified network impedances. For every new shortest path the global detour factor and commonality are analysed before the route is added to the choice set. Demand is then distributed on this choice set using discrete choice models.

The nomenclature is taken from stochastic assignment as it is represented in *VISUM*. However, the general characteristics are similar in other stochastic assignment procedures.

VISUM provides a so-called randomised route search, which allows the number of search iterations to be specified as well as the parameters of the normally distributed impedance I_i with the mean value I'_i and the variance σ see formulas below.

$$I_i = I'_{i_{ex}} + \sigma \cdot N_i \tag{27}$$

$$\sigma = a \cdot \left(\frac{1}{(i_{ex})^b} \right) \cdot \left(I'_{i_{ex}} \right)^c \tag{28}$$

with:

I_i	Random impedance in search iteration *i*
$I'_{i_{ex}}$	Estimated impedance based on traffic flows in assignment step i_{ex}
σ	Variance of impedance for all route search iterations in current assignment step $i_{ex}+1$
N_i	Normally distributed random number in search iteration *i*
i_{ex}	Number of external assignment steps (route search + demand distribution)
a, b, c	Parameters

It is clear that the number of generated routes depends heavily on the number of search iterations as well as the allowed variance of impedance. Therefore, it is important to set the number of iterations and variance so that no potentially plausible routes are excluded in the route search step. The following results are computed with 25 search iterations per assignment step, $i_{ex}=10$ and the variance parameters $a=30$, $b=1$, $c=0.5$.

After every route search iteration, a pre-selection is performed, in which the newly found route is deleted if its total impedance exceeds a global detour factor (see formula 29.

$$I'_i > d \cdot I'^{SP}_{i_{ex}} + e \tag{29}$$

with:

I'_i	Estimated impedance of route found in search iteration *i*
$I'^{SP}_{i_{ex}}$	Estimated impedance of shortest path in assignment step i_{ex}
d, e	Parameters

To make the results of the *VISUM* route search comparable to Branch and Cut choice set generation, the parameters *d* and *e* are chosen to reach the best possible match to the survey detour factors (Figure 50). Including all relevant data points of loop detour factors, as for the Branch and Cut algorithm, results in parameter values of *d=1.23* and *e=300*.

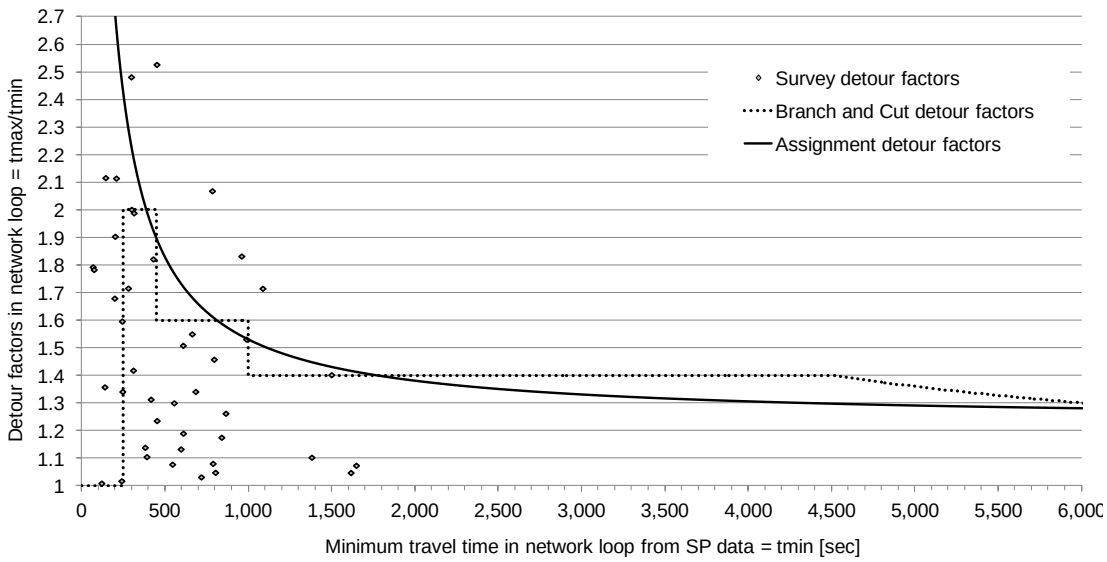

Figure 50: Fitting assignment detour factors to survey data

As well as detour factors for an entire route, *VISUM* allows to specify a global detour factor for all traversed loops (formula 30). From survey data, (Figure 50), the parameters for the detour test are taken as *f=2*, *g=0*.

$$t_0 > f \cdot t_{0\,i_{ex}}^{SP} + g \tag{30}$$

with:

t_0	Free flow travel time of of route found in search iteration *i*
$t_{0\,i_{ex}}^{SP}$	Free flow travel time on the shortest path in the loop in assignment step i_{ex}
f, g	Parameters

Table 47 shows statistical results of the observed choice set (GPS), the Branch and Cut choice set, and a choice set generated using stochastic route search in *VISUM*.

Study	Observed Routes	Branch and Cut	Stochastic route search*
Number of OD pairs	4,100	4,100	4,100
Number of routes	6,592	90,862	97,438
Mean number of routes per OD pair	1.60	23.60	23.70
Max. number of routes per OD pair	12.00	382.00	143.00
Mean route length [km]	33.60	41.00	42.50
Mean detour factor (direct distance)	1.45	1.67	1.52
Mean travel time in free flow [min]	30.30	37.10	33.50
Mean detour factor (travel time)	1.20	1.25	1.13

* including route search with pre-selection, detour test on entire routes and loops, commonality criteria

Table 47: Comparison of choice set characteristics (GPS observations, Branch and Cut, stochastic route search)

The Branch Cut algorithm results in a mean detour factor (ratio of route travel time to shortest path on OD pair) for the total choice set of 1.25, which is slightly higher than the value 1.20 for the observed routes. The mean number of routes generated by this approach is 23.6 routes. Stochastic route search in *VISUM* produces good results in respect to the average number of routes per OD pair and the main route length. However, the stochastic route search has a lower detour factor (based on travel time) than both the observed as well as the Branch and Cut choice sets. Computing a choice set in *VISUM* that has an average detour factor as high as 1.20 for this particular network resulted in an unmanageable number of routes. The number of computed routes can be significantly decreased by introducing a loop detour factor (from 181,171 without loop detour factor to 97,438 with loop detour factor). However, detour factors defined for an entire route or as a global value for all traversed loops without considering the size of the loop (in travel time) cannot compete with the flexibility of a Branch and Cut search.

The following example of one of the 4,100 OD pairs in the network displays the effect of a loop detour factor by a graphical comparison of the choice sets (Figure 51). The Branch and Cut choice set contains 13 different routes covering all relevant loops. The *VISUM* choice set without detour factor for loops contains 22 different routes with only minor differences. Running the same route search with a loop detour factor reduces the number of routes to 14 and comes close to the Branch and Cut solution. However, this example shows that a detour criterion for one particular loop size cannot erase all unreasonable loops. One of those unreasonable loops is marked with a black dashed circle in Figure 51. For large networks with diverse network topologies, it is important to include detour criteria for various loop lengths in the detour test, as is done in the Branch and Cut approach.

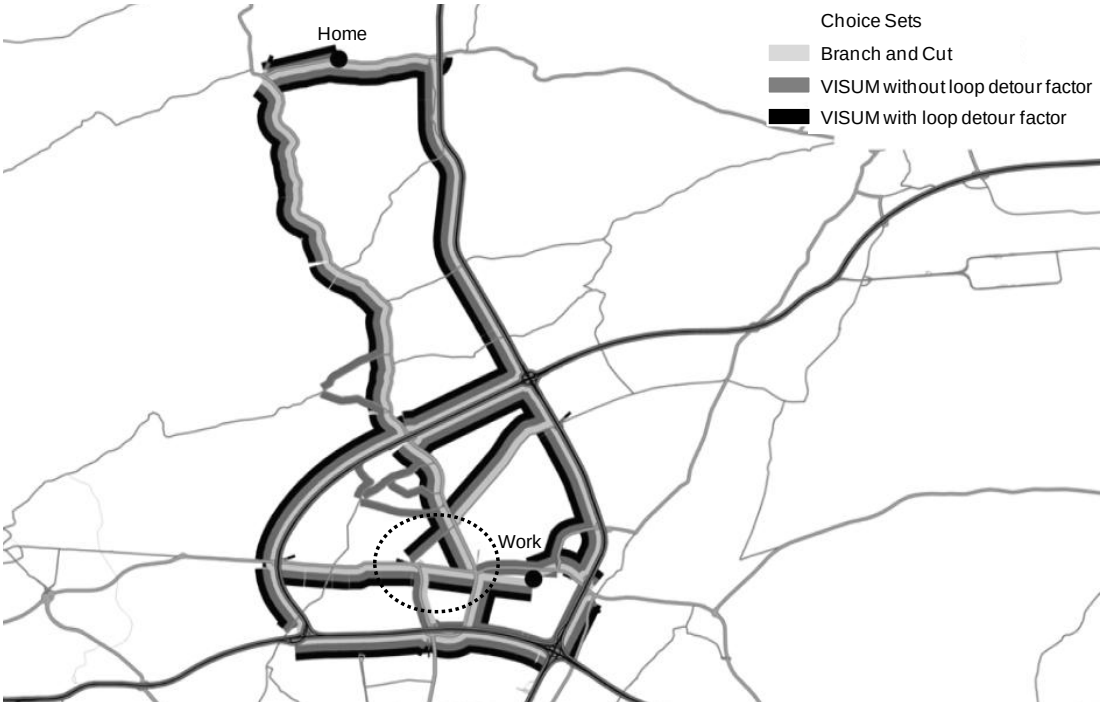

Figure 51: Graphical Comparison of Choice Sets

Moving from a comparison of mere numbers to an analysis of choice set quality, two indicators are of interest. The effectiveness of a choice set generator describes how many links the choice set shares with the observed routes in relation to the total number of links covered by the observed routes. Both choice sets have a very high coverage of the observed links. So as to take into account the fact that a large number of routes or links are more likely to result in a high coverage of observed links, the indicator efficiency is of interest. The efficiency describes how many links the choice set shares with the observed routes in relation to the total number of links in the choice set. Branch and Cut has advantages in both efficiency and effectiveness.

Quality measure	Branch and Cut	Stochastic route search
Effectiveness [%]	98	90
Efficiency [%]	45	39

Table 48: Quality measures of choice sets

Although, performing choice set generation in stochastic assignment has its difficulties, the parameter setting provides a good match to choice sets used for choice model estimation and enables the assignment to represent realistic route choice behaviour and resulting traffic flows.

5.3.3 Joint Route and Departure Time Model

In this research, departure time choice is considered to be a drivers' long-term decision to change their usual travel behaviour which will change the reached network equilibrium. As discussed in chapter 5.2.2 *Departure Time Choice* Model Estimation, departure time choice depends on the trade-off between minutes of departure time shift and minutes of travel time saving in reference to the drivers' usual departure time. The route travel times and thus possible travel time savings depend on the overall demand at certain times of day. Therefore, the choice set for a joint route and departure time model consists of a set of journeys *J* specified as follows:

$$J_{i,j} \in \{D_i, R_j\} \tag{31}$$

$$D_i \in \{D_1 \ldots D_I\} \tag{32}$$

$$R_j \in \{R_1 \ldots R_J\} \tag{33}$$

with:

$J_{i,j}$	Journey
D_i	Departure time
R_j	Route
I	Number of different departure times in choice set
J	Number of different routes in choice set

Similar formulations to model the choice of journeys in traffic assignment are given amongst others by NOLAND AND SMALL (1995) or FRIEDRICH ET AL. (2001) who apply this concept to transit assignment.

Hierarchical decisions are often represented by using Nested Logit models in which the decision maker considers some of the alternatives similar to each other due to some unobserved factors, see TRAIN, K. E. (2006). In this case the set of alternatives can be partitioned into subsets, the so-called nests. For example, commuters using the train every morning to travel to work are more likely to change from train to bus in case the train is cancelled than to change from train to car. The alternatives bus and train can be grouped into one nest whereas car is grouped in a second nest. Formulas 34 and 35 show the general structure of a Nested Logit model.

$$P_{i,n} = P_n \cdot P_{i|n} = \frac{e^{Z_n + \lambda \cdot IV_n}}{\sum_m e^{Z_m + \lambda \cdot IV_m}} \cdot \frac{e^{Y_i}}{\sum_{j \in n} e^{Y_i}} \tag{34}$$

$$IV_n = \ln \sum_{j \in n} e^{Y_j} \tag{35}$$

with:

$P_{i,n}$	Probability of choosing alternative *i* in nest *n*
P_n	Probability of choosing nest *n*
$P_{i\|n}$	Conditional probability of choosing alternative *i* in case of having chosen nest *n*
Z_n	Utility containing variables varying across nests
Y_i	Utility containing variables varying within nests
IV_n	Log-sum or inclusive value of nest *n*

The probability of choosing alternative *i* in nest *n* is a product of the probability of choosing nest *n* and the conditional probability of choosing alternative *i* in case of having chosen nest *n*. The parameter λ is a coefficient of correlation in the unobserved factors within each of the nests. Whether such a model is appropriate needs to be determined through estimation. However, the data at hand consists of highly different decision situations. Route choice data comes from GPS surveys as well as a SP-experiment which excludes departure time choice. Departure time choice data, on the other hand, comes from a SP-experiment that excludes route choice. Therefore, an approach of a combined utility function of route and departure time choice through substitution is presented in this research. In the following, the variables of departure time choice are first included in the utility function. Then the alternative journeys are represented in the network structure.

Joint route and departure time utility function

Route choice depends on the route's travel time *t* and length *l*. The utility of a route *j* is given by formula 36. As equilibrium assignment converges in usual everyday travel times, the variable historical travel time (t_{hist}) estimated in chapter 5.1.3 *Route Choice Model* Estimation is replaced by the current travel time (t_{cur}).

$$V_j = -\beta_{t\_cur} \cdot t_{cur,j} - \beta_l \cdot l_j \tag{36}$$

Departure time depends on the possible travel time saving *TS* between the travel time at departure time *i* and the travel time at the usual departure time, the time difference $\Delta T_{earlier}$ or ΔT_{later} between the departure time *i* and the usual departure time, and the reliability *R* of the forecasted travel time saving see chapter 5.2.2 *Departure Time Choice* Model Estimation. The utility of departure time *i* is given by formula 37. The reliability of pre-trip information is not represented in the transport model as it only

marginally influences driver behaviour and is difficult to calculate based on current traffic conditions.

$$V_i = -\beta_{TD\_later} \cdot TD_{later,i} - \beta_{TD\_earlier} \cdot TD_{earlier,i} + \beta_{TS} \cdot TS_i \tag{37}$$

A journey at departure time D_i along route R_j has the joint utility given in formula 38. Under the assumption that drivers evaluate a travel time saving gained through changing departure time equivalent to a travel time saving gained through changing routes, the travel time saving in formula 37 can be substituted with the route utility from formula 36. Thereby the travel time saving TS_i at departure time D_i is determined by the difference of the travel time between the usual route R_0 chosen at the usual departure time D_0 compared to a route R_j chosen at the departure time D_i. If the travel time along the route R_j at departure time D_i is less than the travel time between the usual route R_0 chosen at usual departure time D_0, this term of the utility function is positive and thus gives a positive travel time saving.

$$V_{i,j} = \beta_{TS} \cdot \left[\frac{1}{\beta_{t\_cur}} \cdot V_{R_0}^{DT_0} - \frac{1}{\beta_{t\_cur}} \cdot V_{R_j}^{DT_i} \right] - \beta_{TD\_later} \cdot TD_{later,i} - \beta_{TD\_earlier} \cdot TD_{earlier,i} \tag{38}$$

The parameter β_{TS} converts the travel time saving (in minutes) to utility units. The utility V_j of a route therefore needs to be converted in minutes in order to be weighted with β_{TS} in the joint utility function. This is done by dividing V_j by β_{t_cur}.

The Logit model, which is used for choice model estimation in the previous chapters, calculates the probability of choosing an alternative depending on its utility as well as the utilities of all other alternatives in the choice set, see chapter 2.2 *Discrete Choice Models*. A property of Logit models is that the choice probability of an alternative *a* depends only on the difference of utilities between alternative *a* and every other alternative $n \in N$. Therefore, a constant added to the utility of all alternatives in the choice set does not change the probability of choosing alternative *a*. As the usual travel time along route R_0 chosen at the usual departure time D_0 is the same for all alternative journeys $J_{i,j}$, the joint utility function can be reduced to:

$$V_{i,j} = \beta_{TS} \cdot \left[-\frac{1}{\beta_{t\_cur}} \cdot V_{R_j}^{DT_i} \right] - \beta_{TD\_later} \cdot TD_{later,i} - \beta_{TD\_earlier} \cdot TD_{earlier,i} \tag{39}$$

This formulation of the utility function can be interpreted as a Nested Logit model with λ=1. For λ=1 the utility containing variables varying across nests (β_{TD_later} and $\beta_{TD\_earlier}$) is weighted equally important to the utility containing variables varying within nests (β_{t_cur} and β_l). This is equivalent to assuming travel time saving through departure time

shift is substitutable with travel time saving through changing routes. In this case the Nested Logit model (see formula 34) collapses in a multinomial Logit model (see formula 4).

Network structure to model alternative journeys

In a second step, the alternative journeys need to be represented in the model structure. Thereby the model needs to consider the fact that a driver is competing for existing network capacities (given in vehicles per hour) with a certain number of other drivers at different times of day. Daily travel demand curves show that more drivers compete for existing capacities during peak hour (higher total travel demand) than during off-peak hours (lower total travel demand). Every driver can therefore decide between different departure times at which they will experience different travel times due to network congestion. By modelling network capacities for pre-defined time intervals, alternative journeys can be represented in a standard assignment. For journeys within the time interval of the preferred departure time, no additional negative utility occurs. For journeys entering a time interval related to a departure time other than the preferred departure time, an additional negative impedance occurs. The magnitude of the additional impedance depends on the time difference of the chosen departure time to the preferred (usual departure time). Figure 52 gives a schematic overview of the proposed approach. The sample network includes three traffic zones. Travel demand between these three zones is given for two demand segments. Demand segment *A* includes all drivers with a preferred departure time between 7:00a.m.- 7:30a.m. Demand segment *B* includes all drivers with a preferred departure time between 7:30a.m.- 8:00am. The road network includes three links, resulting in two different routes for each OD pair, and has the same network capacities for both time intervals (7:00a.m.- 7:30a.m. and 7:30a.m.- 8:00am) given in vehicles per 30 minutes. However, the total travel demand is 20% higher in time interval 7:00a.m.- 7:30a.m. A delay of departure time, in this example be pre-defined 30 minutes, offers travel time savings due to a reduced total demand between 7:30a.m. - 8:00a.m. The assignment results in a departure time shift for trips of demand segment A if there is a route R_j in time interval 2 that has a travel time which is small enough to compensate the additional negative utility of entering time interval 2. The additional negative utility is included as attributes on the connectors in the transport model (displayed in black dashed arrows). Usually a connector represents the access or egress time from the zone centroid to a node in the network. This is interpreted here as a spatial as well as temporal connection.

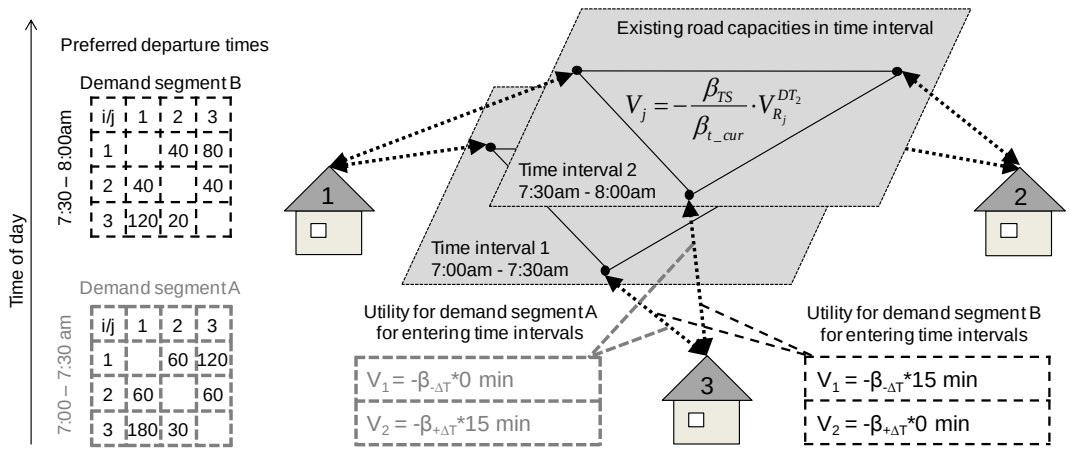

Figure 52: Network structure for alternative journeys (departure time + route)

If the pre-defined time interval was one hour, the travel time difference in this sample network would be too small to provoke a departure time shift and the assignment would deliver the same results as for a mere route choice model. Therefore, the pre-defined time intervals have a large effect on the assignment results and need to be chosen carefully. According to the characteristic values of the SP interview, see Table 16 on page 51 in chapter 3.7 *Departure Time Choice Data*, the values for the time intervals are chosen as shown in Table 49.

Pre-defined minutes of departure time shift							
Time interval no.	1	2	3	4	5	6	7
Time shift [min]	-35	-25	-15	0	15	25	35

Table 49: Values of pre-defined time interval for departure time model

The joint route and departure time model for the survey area is designed to analyse the traffic flows of a given hourly travel demand of time interval no. 0. Journeys can be made in seven pre-defined seven time intervals. To account for travel demand in the network during different times of day, the time intervals no. 1, 2, 3, 5, 6, and 7 are pre-loaded with the corresponding demand. Pre-loading is based on route choice assignment of hourly demand matrices with no departure time shift.

In contrast to standard dynamic traffic assignment procedures which include trip starting times and journey utilities in their internal processing, this method allows pre-defining trade-offs between travel time savings and departure time shifts. Due to the model structure of time intervals, temporal shifts in travel demand can be easily identified in the assignment results.

5.4 Primary Findings

The observed GPS trips as well as the results of the SP interviews allow determining the relevant influencing parameters on route and departure time choice. First and foremost, the travel time strongly influences route choice as the estimated β-parameters show. Additionally, drivers show a strong preference for their usual main route so that alternative routes are only considered if travel time on the main route increases beyond a certain threshold. The analysis focuses on the influence of information devices such as TMC via radio, VMS and navigation systems. Strong effects on route choice behaviour are discovered, especially when driver use a LOS map service on navigation devices as well as standard traffic reports via radio.

Possible travel time savings prove to be decisive for driver willingness to shift their usual departure time. A change of departure time (earlier or later than usual) is generally seen as unappealing, however later departure is more acceptable than departing earlier than usual. For a typical commuting distance, a departure time 10 minutes earlier than usual is acceptable for a travel time saving of between 6 and 7 minutes. Drivers have high expectations of travel time saving if this means they need to consider changing their daily routine.

For estimating a route choice model on the RP data from the GPS survey, choice sets on a network spanning the southern half of Bavaria need to be generated. This task is especially challenging due to the network detail and diverse density structure, as is mastered using a Branch and Cut choice set generation fitted to empirical detour factors.

To apply the estimated route choice model to a transport model of the survey area, choice set generation in stochastic assignment is adapted to give similar results to the Branch and Cut choice set generation.

The departure time model is integrated in the transport model by introducing a joint route and departure time utility function as well as adapting the network structure to model alternative journeys.

6 Optimisation of Traffic Flows

In chapter 5 *Choice Models*, route and departure time models are derived and integrated in a transport model for the survey area. This allows determining the interactions between the total travel demand and the given transport supply. In this chapter, these models are developed further to incorporate the effects of traffic information on traffic flows in the network. Firstly, typical demand situations are derived for the survey area for which the effects are quantified in chapter 7 *Results for Munich Case Study*. Second, states of traffic information are introduced which define benchmarks of performance in optimization of traffic flows with information. Lastly, approaches to modelling states of traffic information in general, as well as single information devices in particular, are introduced.

6.1 Typical Demand Situations

A typical demand situation is characterised by a regular recurrent demand situation of everyday traffic flows. Demand situations caused by non-recurrent congestion during incidents such as construction sites, accidents, or major events do not count as typical demand situations and are not examined in this research.

An analysis of strategically important cross-sections in the survey area reveals that the daily traffic load curves distinctly depend on the day of the week. For the survey area, travel demand is given in hourly matrices for every hour of a day. Thereby five different types of day are distinguished (Monday, Tuesday-Thursday, Friday, Saturday, Sunday) so that in total there are 120 matrices (5 types of day * 24 hours). The traffic load curves for the whole survey area are displayed by type of day in Figure 53.

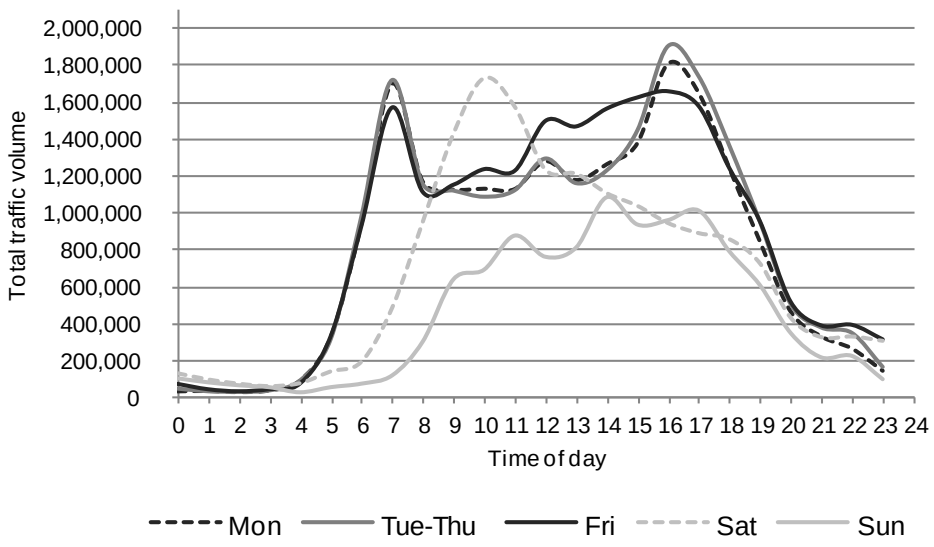

Figure 53: Total traffic volume in survey area for different week days (provided by the transport model *VALIDATE*, PTV AG)

With Munich being a mono-centric agglomeration area, it appears that there is a change of direction of the main traffic stream in the mornings (inbound direction) and the afternoons (outbound direction). For example, the total traffic volume in the survey area for the morning peak hour Tue-Thu 7 a.m. - 8 a.m. amounts to 960,000 vehicles and shows direction-oriented traffic volumes in the major road network. Especially, traffic volumes on the motorway A9 are higher inbound than outbound. For this reason, it is sensible to analyse the morning and evening peak hours.

From the hourly demand matrices those are selected which represent typical demand situations on the basis of the following criteria:

- Spatial distribution of major origins and destination according to travel demand
- Total traffic volume of respective hourly demand matrix
- Traffic volume of strategic cross-sections

The 120 hourly matrices can be reduced to eight typical demand situations, which represent regular everyday traffic flows in peak and off-peak hours, see Table 50. Other week days do not show differences which are noteworthy enough to be included in an analysis of typical demand situations.

Selected matrices		**Traffic volumes (both directions)**			
Week day	**Time of day**	**Survey area**	**A9**	**A92**	**B13**
Tue-Thu	7 - 8 a.m.	968,200	5,550	2,950	1,200
Tue-Thu	12 noon - 1 p.m.	730,400	3,500	1,700	450
Tue-Thu	2 - 3 p.m.	697,500	3,800	1,800	500
Tue-Thu	5 - 6 p.m.	987,600	4,050	2,350	700
Fri	7 - 8 a.m.	879,700	5,150	2,150	900
Fri	2 - 3 p.m.	888,400	4,250	2,050	600
Fri	5 - 6 p.m.	897,400	4,250	2,100	600
Fri	9 - 10 p.m.	226,300	2,150	1,000	200

Table 50: Typical demand situations in survey area

6.2 Benchmark States of Traffic Information

A state of traffic information describes the level of information that some or all drivers are provided with. The spatial and temporal distribution of traffic flows in the road network result from the drivers' perceptions of a demand situation and the delays which arises as a result of the available information. In order to quantify the potential of traffic information for optimizing route and departure time choice, the reduction of the transport time expenditure as well as fuel consumption are analyzed for different states of information (see chapter 7 *Results for Munich Case Study*). For this purpose, five benchmarks states of traffic information are defined.

State of uninformed drivers (UD):

In order to evaluate the benefits that the traffic information available today provides for drivers, a reference state without traffic information is defined. In this state all drivers are uninformed about current traffic conditions in the road network and make route and departure time decisions based on their personal experience and network knowledge only.

State of information available today (IAT):

The traffic flows observed today are a product of a biased perception of the given traffic conditions based on presently available information as well as personal experience and network knowledge. Although the information provided to drivers is not yet perfect, it affects route and departure time choice by giving more or less accurate information on occurring delays in the network. This state defines the benchmark for what traffic information today has achieved in terms of optimizing route traffic flows.

State of perfect information (PI):

This state of information assumes that all drivers have perfect information about the current traffic conditions in the whole network for all times of day. Route and departure time decisions are based on accurate and real-time information. Personal perceptions and evaluation of traffic conditions are not considered. This state defines the benchmark for what traffic information could achieve in the optimal case in terms of optimizing route traffic flows.

State of partly perfect information through single devices (PPI):

Traffic information delivered by various information devices affects drivers' route and departure time decisions in different ways. This state of partly perfect information assumes that all drivers get perfect information displayed by a LOS map. Here accurate travel times are available for the whole network for all times of the day, yet the information is condensed to three levels of traffic flow (free, stagnant, and congested). As a comparison, partly perfect information is provided to some but not all drivers through a navigation system. This state defines the benchmark of what single traffic information devices could achieve in the optimal case in terms of optimizing route traffic flows.

State of perfect information on marginal costs (PIC):

Although traffic information is often seen as a traffic control measure to optimize traffic flows in a system optimal way, drivers generally do not comply with information or route guidance which is not to their personal benefit. To achieve a system optimal state, other mandatory traffic control measures, such as mobility prizing, are needed. In this

state it is assumed that all drivers have perfect knowledge about the travel costs in the whole network at all times of the day. The additional costs imposed on top of the actual journey costs are designed in such a way that user optimal behaviour results in system optimal traffic flows. This state defines the benchmark of a theoretical optimum in terms of optimizing traffic flows under the objective of minimizing transport time expenditure as well as fuel consumption in the whole transport network.

6.3 Traffic Information Models

In the following, approaches for modelling states of traffic information are introduced. This includes interpretations of existing modelling techniques as well as developing new modelling concepts. Whereas quantitative results are given in chapter 7 *Results for Munich Case Study*, the following chapters focus on description, interpretation and evaluation of convergence of the introduced models.

6.3.1 Modelling Level of Information

In order to model different levels of information (uninformed drivers, information available today, and perfect information) as defined in chapter 6.2 *Benchmark States of Traffic Information*, route and departure time choice behaviour needs to be adjusted to account for drivers' knowledge of current traffic conditions.

Without information about current traffic conditions, drivers make decisions under wrong assumptions about each alternative in the choice set. As their perception of traffic conditions is based solely on their personal experience and network knowledge, drivers are less sensitive to current travel times (or utilities in general) between alternatives. This effect can be modelled by introducing a sensitivity parameter α in the choice model. How α affects the choice probability of a Logit model is illustrated by the example of a decision situation in a network with two alternative routes for one OD pair. The probability P_1 of choosing alternative 1 is formulated as follows for the binary example:

$$P_1 = \frac{e^{\alpha \cdot V_1}}{e^{\alpha \cdot V_1} + e^{\alpha \cdot V_2}} = \frac{1}{1 + e^{\alpha \cdot (V_2 - V_1)}} \tag{40}$$

with:

P_1	Probability of choosing alternative 1
V_1, V_2	Utility of alternative 1 respectively alternative 2
α	Sensitivity parameter

Figure 54 shows P_1 as being dependant on the difference in utilities V_2-V_1 between both alternatives. If both alternatives have equal utilities (V_2-V_1=0), P_1 is 0.5, showing

that both alternatives have the same probability. If $V_1>V_2$ (alternative 1 being more attractive than alternative 2), P_1 is higher than 0.5 meaning the choice of alternative 1 is more likely. In the other case ($V_1<V_2$), P_1 is smaller than 0.5, showing that the choice of alternative 2 is more likely.

Furthermore, P_1 is displayed for different values of parameter α. A perfectly informed driver who is precisely aware of current traffic conditions would show deterministic behaviour (α=*infinite*). By decreasing α and keeping V_2-V_1 constant, drivers grow more and more indifferent to current traffic conditions on each alternative in the choice set (highlighted with arrow indicating decreasing α). If α is zero, P_1 is constantly 0.5 regardless of the difference in utilities V_2-V_1.

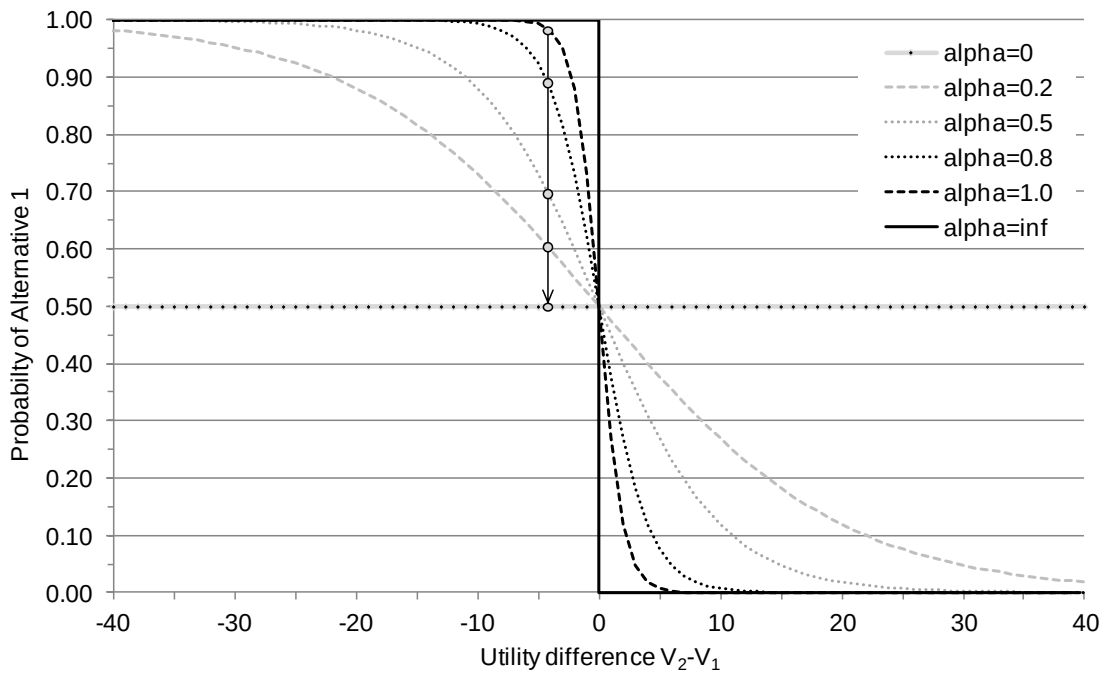

Figure 54: Choice probability in binary Logit model with sensitivity parameter α

The information available today (IAT) is modelled by using a stochastic assignment, as introduced in chapter 5.3. The β-parameters of the choice models estimated in chapter 5 *Choice Models* are based on $\alpha=1$. Computed traffic flows are validated on travel times and traffic counts observed during the survey period.

To model a state of uninformed drivers (UD), α is chosen to be 0.5. This value is based on the assumption that uninformed drivers consider the same choice set as drivers today. A comparison of stochastic assignments with different values of α shows that $\alpha=0.5$ results in a similar choice set to $\alpha=1$.

In the case of perfect information (PI) all drivers are perfectly informed about accurate travel times in the whole network for all times of the day. If they are aware of current network conditions, drivers will choose the best alternative available. This state of

information is modelled with a deterministic assignment which results in a user equilibrium state for the estimated utility functions with *α=inf*.

6.3.2 Modelling Information Devices

Every traffic information device affects driver behaviour differently because of the way information is displayed, the kind of contents provided, and the level of detail that is included. In order to quantify what single traffic information devices could achieve in an optimal case in terms of optimizing traffic flows, for example models are needed to compare the behaviour of drivers using a LOS map to that of drivers who are using navigation systems.

Partly perfect information through LOS (PPI_{LOS})

Drivers using a LOS map are perfectly informed in the sense of being aware of traffic conditions in the whole network at all times of the day. Yet the information provided by a LOS map is condensed to three levels of traffic flows:

- Free flow displayed by green colour-code on link
- Stagnant flow displayed by yellow colour-code on link
- Congested flow displayed by red colour-code on link

This partly perfect information is illustrated in Figure 55. In macroscopic transport models, the relation between traffic volume and travel time on a network element (link or turn) is given by a volume-delay curve. If drivers have perfect information, the current travel time is known for a given traffic volume (or saturation) on a network element.

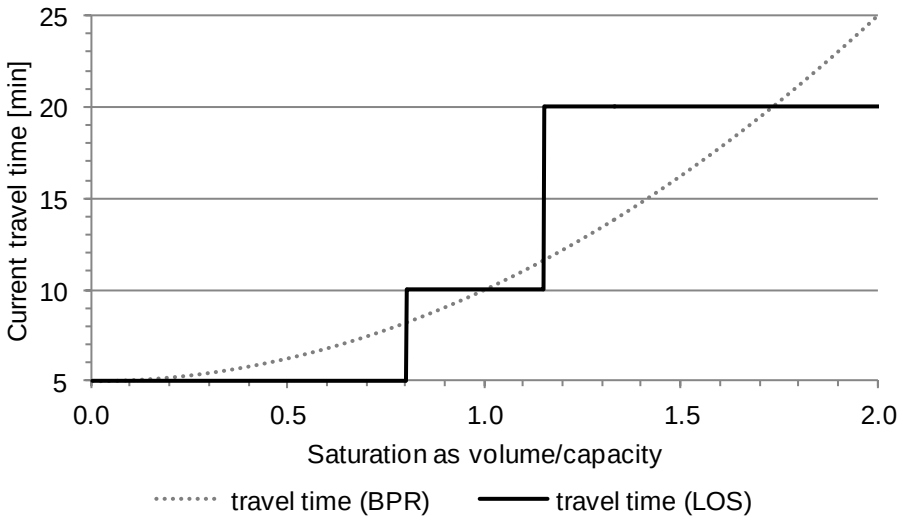

Figure 55: Volume-delay curve for perfect information and LOS map

The dashed line in Figure 55 shows a typical volume-delay curve of type BPR (*a=1*, *b=2*) often used in traffic assignment, see formula 41 taken from U. S. BUREAU OF PUBLIC ROADS (1964):

$$t_{cur} = t_0 \cdot \left(1 + a \cdot \left(\frac{vol}{cap}\right)^b\right) \tag{41}$$

with:	t_{cur}	[min]	Current travel time
	t_0	[min]	Free flow travel time
	vol	[veh]	Traffic volume
	cap	[veh]	Capacity of network element
	a, b		Parameters

The black line in Figure 55 displays the volume-delay curve on which the colour-coding of a standard LOS map is based. Travel times are given as a step function of traffic volume, see formula 42. Stated below is a LOS step function according to the standard threshold values of saturation and speed on a network element:

$$t_{cur} = \begin{Bmatrix} 1 \cdot t_0 \text{ , } if \;\; sat \in [0;0.8] \; and \;\; v_{cur} \in [0.25;1] \\ 2 \cdot t_0 \text{ , } if \;\; sat \in]0.8;1.15] \; and \;\; v_{cur} \in [0;0.25[\\ 4 \cdot t_0 \text{ , } if \;\; sat \in]1.15;\infty] \; and \;\; v_{cur} \in [0;0.25[\end{Bmatrix} \tag{42}$$

with:	t_{cur}	[min]	Current travel time
	t_0	[min]	Free flow travel time
	sat	[-]	Saturation as volume [veh] / capacity [veh]
	v_{cur}	[-]	Current speed / free flow speed

This state of information via a LOS map is modelled with deterministic assignment using the utility function estimated for LOS in chapter 5.1.3 *Route Choice Model* Estimation, page 90:

$$V_j = \beta_{t\_hist} \cdot t_{hist,j} + \beta_l \cdot l_j + \beta_{\text{l\_LOS2}} \cdot l_{\text{LOS2},j} + \beta_{\text{l\_LOS3}} \cdot l_{\text{LOS3},j}$$

The historical travel time is thereby taken from the travel times calculated from the stochastic user equilibrium for state IAT and is set as constant in the utility. Therefore, some alternatives are more attractive than others, due to people's experience. The occurring delays are only represented in the LOS terms of the utility function.

An equilibrium assignment is formulated as a non-linear optimization problem which finds a solution to an objective function (Wardrop's 1st principle) under linear equality and inequality constraints. The problem is usually solved by decomposition algorithms

(FRANK AND WOLFE (1956), LE BLANC ET AL. (1985) and BAR-GERA (2002) among others), column generation algorithms or the method of successive averages which all reduce the user equilibrium problem to a linear programme. Utility functions therefore need to be strictly increasing in order for the assignment to converge to a unique solution.

Assignment algorithms terminate when a certain precision is reached which is defined by a gap criteria. The gap describes the difference between the current value of the objective function and the lower bound estimate of the optimal solution, which is based on the convexity of the problem.

For deterministic user equilibrium using BPR volume-delay functions, Figure 56 illustrates the convergence of the assignment algorithm. The difference in traffic volumes from one assignment step *i* to the next step *i+1* on all links in the network is displayed here. At the beginning of the assignment the traffic volumes differ on a large number of links from one assignment step to the next, as shown by the flat distribution. As the assignment converges to user equilibrium, the number of links on which the difference in traffic volume is zero from one assignment step to the next rises to 100% (4,100 links).

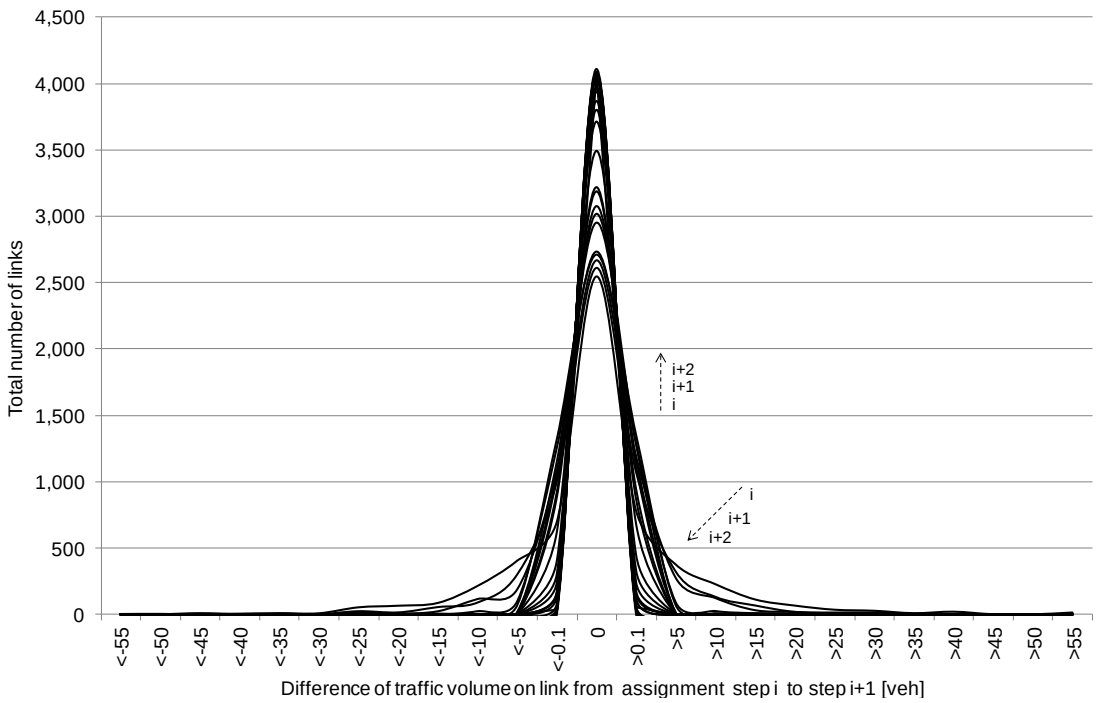

Figure 56: Convergence of deterministic equilibrium assignment for BPR volume-delay function

For an equilibrium assignment using the LOS volume-delay function, the distributions show the same development with ongoing assignment steps (see Figure 57). Although convergence is not reached under the defined gap criteria of 10^{-7} as with the BPR

function, the assignment produces stable results which show that the solution is not a random result depending only on the number of assignment steps performed. As the LOS equilibrium problem is not convex, it does not have a unique equilibrium solution. However, further computational analysis shows that the assignment result depends only marginally on the starting solution. As expected, the closer the starting solution is to user equilibrium, the closer the LOS assignment solution is to user equilibrium. For the following analysis, the starting solution is taken as the assignment result of stochastic user equilibrium (IAT) as the utility function includes historical travel times based on this state of information. Based on this starting solution, the assignment with LOS volume-delay function reaches a steady state faster than in the BPR case. On the whole, the proposed model using a step function for including LOS in the utility provides robust results.

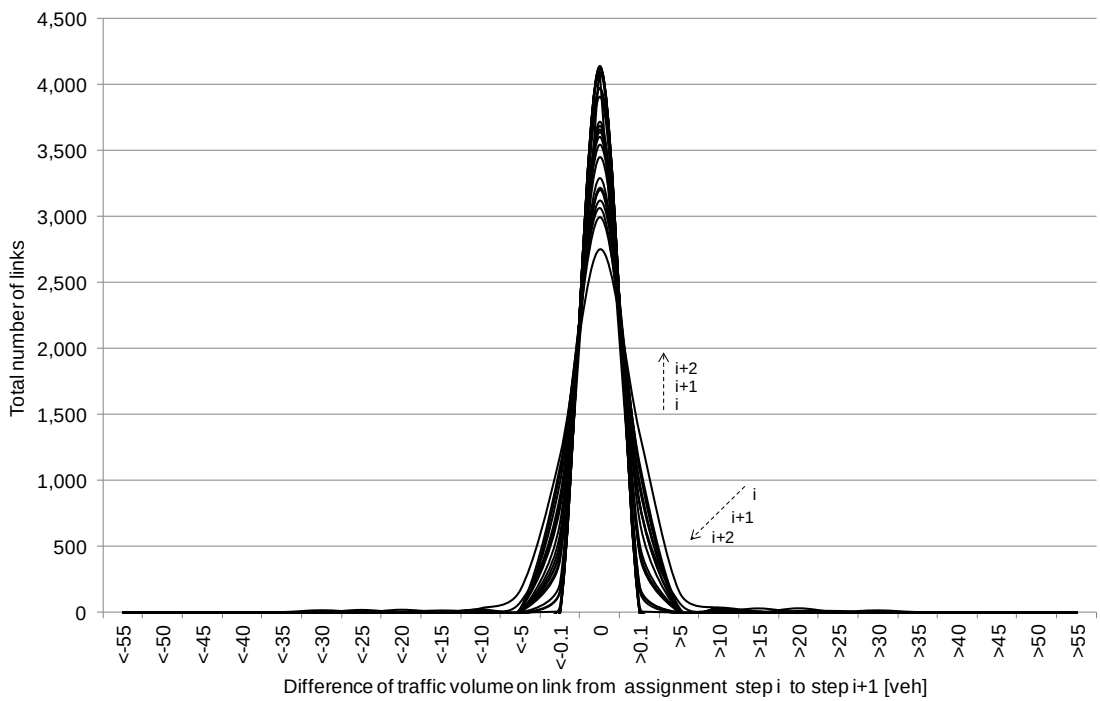

Figure 57: Convergence of deterministic equilibrium assignment for LOS volume-delay function

Partly perfect information through navigation ($PPI_{Navi\_X\%}$)

As a comparison to providing all drivers with LOS information, the effects of information provided to some but not all drivers through a navigation system are modelled in the following. In this model a portion (X%) of drivers are provided with navigations systems and show deterministic behaviour as in PI, whereas a portion of 1-X% of drivers are not provided with navigation systems and show stochastic behaviour, as in IAT. This approach of dividing travel demand into groups with and without navigation systems is used by MATSCHKE (2007) among many others to analyse the effect of market

penetration of navigation systems on traffic flows. As both groups of drivers show different behaviour (stochastic and deterministic) the travel demand needs to be loaded on the network in successive assignment runs. First, all drivers without navigation systems are loaded on the network. Based on the resulting travel times drivers with navigation systems are assigned. This procedure is repeated until both driver groups are in a steady state and assignment results (traffic volumes on links) are stable.

Figure 58 shows the converged state of the combined stochastic and deterministic user equilibrium depending on the market penetration of X% navigation systems. For X=0% the behaviour is almost the same as in IAT. As the portion of X% of drivers equipped with navigation systems increases, the assignment solution gets closer to a deterministic user equilibrium (state PI for X=100%). This is displayed below as the difference in traffic volumes on all links in the network between the converged assignments with X% of drivers with navigation systems and the deterministic user equilibrium solution.

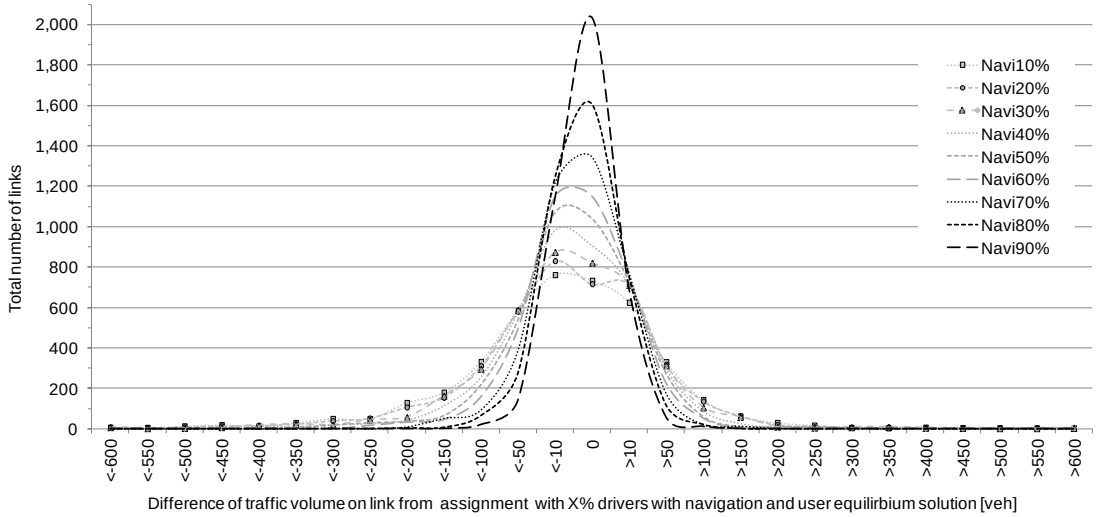

Figure 58: Comparison of assignments with X% drivers with a navigation system and the deterministic user equilibrium solution

In chapter 7 *Results for Munich Case Study* the numbers given for state PPI correspond to 100% of drivers having LOS information or X% of drivers having navigation systems. The height of X% of drivers with navigation systems which results in the same optimization of traffic flows as 100% drivers with LOS (measured in the following in transport time expenditure and fuel consumption) is determined for every demand situation in chapter 7.

6.3.3 Modelling Marginal Travel Costs

To model a benchmark state of a theoretical optimum of traffic flows in which user equilibrium driver behaviour results in system optimal traffic flows, additional costs are introduced. The additional costs, on top of the costs perceived by drivers themselves due to experienced travel time (or impedance in general), account for the costs a driver imposes on all other drivers travelling on the same links in the network. This concept of marginal costs was introduced by SPIESS (1990) (see formula 43) and is widely used to compute system optimal traffic flows with a user equilibrium assignment.

$$c_m(q) = c(q) + q \cdot c'(q) \tag{43}$$

with:	$c_m(q)$	Marginal cost function
	$c(q)$	Cost perceived by each driver due to travel time or impedance
	$q \cdot c'(q)$	Cost imposed by each driver on all other drivers given as derivative of c(q)
	q	Traffic volume q of all driver on a link

For a sample network with two alternative routes for one OD pair this concept can be illustrated graphically, see Figure 59. The dashed grey lines show the cost (travel time with volume-delay function of type BPR, see formula 41) perceived by drivers on route 1 as $c_1(q_1)$ and on route 2 as $c_2(q_2)$. Within this sample network, the total demand of 1,000 drivers is split between the two routes. If 300 drivers travel on route 1, then 700 drivers travel on route 2. The cost functions are displayed over the traffic volume on route 1. For zero drivers on route 1, the cost on route 1 is the free flow travel time of 10 minutes. For 1,000 drivers on route 1 (zero drivers on route 2) the cost on route 2 is the free flow travel time of 14 minutes. User equilibrium (UE) is reached at the intersection point of $c_1(q_1)$ and $c_2(q_2)$ where travel times are equal which is at $q_1=630$ and $q_2=370$. Displayed in the grey dotted line is the total cost within the network given by the transport time expenditure as $c_1(q_1)*q_1 + c_2(q_2)*q_2$. Displayed in the black dashed lines are the marginal costs for route 1 and route 2. The marginal costs functions intersect at $q_1=570$ and $q_2=430$, which is where the total cost in the network is minimal. Thus, a user equilibrium with marginal cost functions is equal to a system optimum with BPR cost functions.

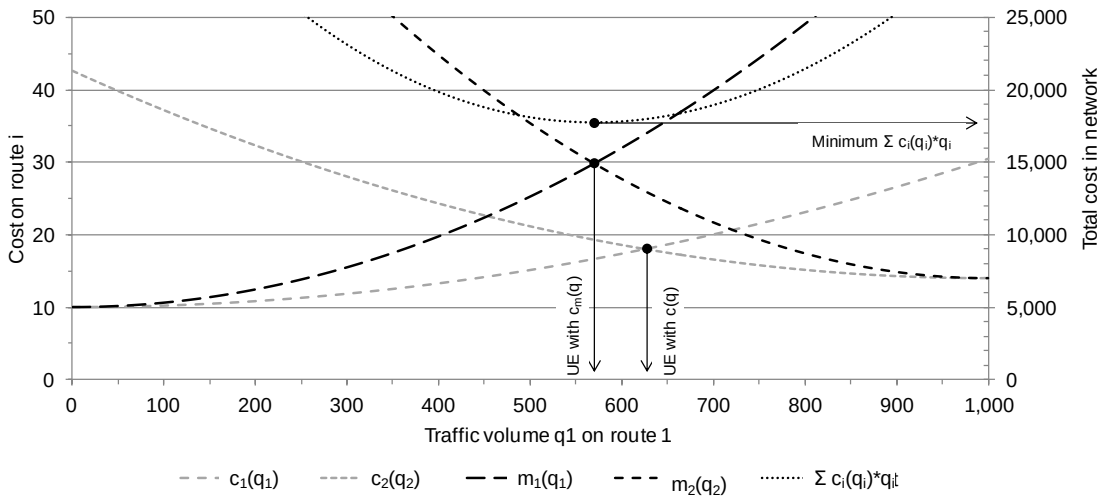

Figure 59: Concept of marginal cost functions on two route network based on BPR volume-delay functions

Mathematically system optimum (Wardrop's 2nd principle) is the optimal solution *f** of the following min-cost multicommodity flow problem, see formula 44.

$$\min \{C(f): f \in X\} \tag{44}$$

$$C(f) := \sum_{r \in R} c_r(f_r) \cdot f_r = \sum_{l \in L} c_l(f_l) \cdot f_l$$

s. t.:

$$\sum_{r \in R_k} f_r = d_k \quad \forall k \in K$$

$$f_l = \sum_{r \in R_l} f_r \quad \forall l \in L, r \in R_l$$

$$f_l \geq 0 \quad \forall l \in L$$

with:

$C(f)$	Total cost in network
f	Feasible solution of traffic flows
X	Set of feasible solutions of traffic flows
f_r	Route flow on route *r*
f_l	Link flow on link *l*
c_r	Cost on route *r*
c_l	Cost on link *l*
d_k	Demand on OD pair *k*
L	Set of links in network
R	Set of routes in network
R_l	Set of routes traversing link *l*
K	Set of OD pairs

To solve the optimal solution *f** the derivative of *C(f*)* is set to zero:

$$\left.\frac{\partial C}{\partial f}\right|_{f^*} \equiv 0$$

$$\frac{\partial C}{\partial f_r} = \sum_{r \in R} c_r + \sum_{r \in R} \frac{dc_r}{df_r} \cdot f_r \equiv 0 \;\; \forall\, f_r \in f$$

For every OD pair *k* this is equal to the user equilibrium formulation with redefined cost functions as marginal costs, see formula 43:

$$c_{r_i} + \frac{dc_{r_i}}{df_{r_i}} \cdot f_{r_i} = c_{r_j} + \frac{dc_{r_j}}{df_{r_j}} \cdot f_{r_j} \quad \forall r \in R_k, \forall k \in K$$

On the example of the BPR function given in formula 41the marginal cost function is:

$$t_{cur} = t_0 \cdot \left(1 + a \cdot (b+1) \cdot \left(\frac{vol}{cap} \right)^b \right)$$

These re-defined cost functions are used in chapter 7 *Results for Munich Case Study* to compute PIC with user equilibrium assignment.

Table 51 gives a concluding overview of the sensitivity parameter *α* and cost function used to compute each of the defined benchmark states of traffic information.

State of information	α-parameter	Cost function
UD	0.5	t_{cur_BPR}
IAT	1.0	t_{cur_BPR}
PPI	inf	t_{cur_LOS}
PI	inf	t_{cur_BPR}
PIC	inf	C_{m_BPR}

Table 51: Overview of sensitivity parameter *α* and cost function used for states of traffic information

6.4 Primary Findings

This chapter introduces modelling approaches to include the effects of traffic information in standard assignment models.

On the basis of hourly trip tables, typical demand situations which represent recurrent spatial and temporal distributions of travel demand are derived for the survey. The defined demand situations are the basis for quantifying the potentials of traffic information to optimize route and departure time choice in chapter 7 *Results for Munich Case Study*.

For this purpose the following benchmark states of traffic information are defined:

- State of uninformed drivers
- State of information available today
- State with perfect information
- State with partly perfect information provided by single information devices
- State of perfect information on marginal costs as a system optimal state

The approaches introduced for modelling traffic information in standard assignments firstly cover the level of driver information and interpret the lack of accuracy of the given information as a sensitivity parameter in the stochastic choice model.

Furthermore, an approach to modelling information devices is provided. Firstly, a cost function for modelling information given by a LOS map is introduced and the stability of assignment results is analysed. Secondly, a method for modelling the share of drivers equipped with navigation systems is discussed and compared to the deterministic user equilibrium solution.

To compute system optimal traffic flows, the concept of marginal costs is applied.

7 Results for Munich Case Study

In the following, the potentials of traffic information to optimise route and departure time choice are quantified for the case study area of greater Munich. Based on the choice models derived in chapter 5, traffic flows in the benchmark states of traffic information introduced in chapter 6 are computed. The potentials of traffic information are derived by a comparison of the global indicators in the network for each state of traffic information. This comparison is done at the level of spatial redistribution of traffic flows in which traffic information only affects route choice. Additionally, spatial and temporal redistribution of traffic flows are examined in which traffic information affects route and departure time choice.

7.1 Sub-network and Indicators

In order to get a better understanding of the resulting traffic flows, all defined states of traffic information are modelled on a sub-network of the survey area. This network includes the strategically interesting motorway network to the north of Munich, as well as the greater city area, see Figure 60.

Figure 60: Sub-network of case study area of greater Munich for analysis of different states of traffic information

To quantify the potentials of traffic information to optimise route and departure time choice, three global indicators are computed for each state of information (see chapter 6.2 *Benchmark States of Traffic Information*).

The transport time expenditure (TTE), often referred to as total time spent, is a suitable global indicator for comparing different states of traffic information with respect to the quality of the transport supply from the driver's point of view. TTE is defined as the product of trip time and number of trips within a time unit *T*, and can be determined directly from the link flows computed in traffic assignment, see formula 45. If the TTE increases despite a constant travel demand, the mean trip time in the network increases.

$$TTE = \sum_{l \in L} t_l(q_l) \cdot q_l \tag{45}$$

with:	TTE	[vehh/T]	Transport time expenditure
	t_l	[h]	Travel time on link *l*
	q_l	[veh]	Traffic flow on link *l*

Transport performance (TP), often referred to as total distance travelled, is defined as the product of trip distance and number of trips within a time unit *T*, see formula 46. As many traffic impacts are linked to the TP, this indicator gives a good quantitative comparison of two states of traffic information. If the TP in the subordinate road networks rises, negative environmental impacts such as pollution or noise emissions will also rise.

$$TP = \sum_{l \in L} l_l \cdot q_l \tag{46}$$

with:	TP	[vehkm/T]	Transport performance
	l_l	[km]	Length of link *l*
	q_l	[veh]	Traffic flow on link *l*

Fuel consumption (FC) is chosen as a global indicator to cover transport related environmental expenditure. Environmental impacts can be analysed on the basis of emission or immission. Governmental guidelines for critical pollutant values are given on immission values. However, immission values for different pollutants depend largely on the external surroundings, such as road-side building developments, etc. For a comparative analysis of different benchmark states, emissions which represent the output values produced by traffic flows are suitable indicators. Primer emission values only include pollutants emitted by vehicles. Secondary emission values furthermore include pollutants emitted for construction of transport infrastructure, etc. Since only traffic flows change from state to state, primer emission values are considered in the

following. Furthermore, most pollutants such as NOX, CO_2 and particulate matter (PM) are directly linked to fuel consumption.

On the basis of link traffic volumes, the FC is calculated for each state of traffic information using the handbook of emission factors (HBEFA). The HBEFA includes emission factors for pre-defined traffic activities built on vehicle composition, macroscopic traffic situations and traffic volumes. Vehicle compositions describe the vehicle fleet in the survey area with different shares of vehicle classes, reference years and countries. A selected vehicle composition varies for different road categories (access roads, collector roads, distribution roads, motorways, etc.) and built-up inner urban or rural areas. A traffic situation is given for each road in the network. It includes a pre-defined part based on infrastructure characteristics (such as road-side building developments or open space, road class, and longitudinal slope) and the given speed limit. Additionally, a traffic volume dependent part is defined by a combination of infrastructure characteristics with the current LOS based on the road's saturation.

The FC on each link in the network is calculated as the product of the HBEFA emission factor and the link length. Thereby, the HBEFA value for the fuel mass in grams [g/km] is given separately for gasoline (with 0.75 kg/l) and diesel (with 0.83 kg/l). For the comparison of the states of information the FC is converted into an energy value in kilowatt hours [kWh], see formula 47.

$$FC = d_e^{gas} \cdot d_m^{gas} \cdot \sum_{l \in L} f_l^{gas}(vc_l, ts_l, q_l) \cdot l_l + d_e^{diesel} \cdot d_m^{diesel} \cdot \sum_{l \in L} f_l^{diesel}(vc_l, ts_l, q_l) \cdot l_l \tag{47}$$

with:

FC	[kWh]	Fuel consumption
vc_l		Vehicle composition on link *l*
ts_l		Traffic situation on link *l*
q_l	[veh]	Traffic flow on link *l*
l_l	[km]	Length of link *l*
f_f^{gas}	[g/km]	Factor for gasoline consumption on link *l*
f_f^{diesel}	[g/km]	Factor for diesel consumption on link *l*
d_m^{gas}	[l/g]	Factor for mass density of gasoline
d_m^{diesel}	[l/g]	Factor for mass density of diesel
d_e^{gas}	[kWh/l]	Factor for energy density of gasoline
d_e^{diesel}	[kWh/l]	Factor for energy density of diesel

In addition to the FC emitted by vehicles travelling through the network, cold start emissions are calculated which consider other FC factors such as engines warm up at the beginning of each trip. The cold start emissions are calculated for link traffic volumes which belong to internal or trips originating in a traffic zone.

7.2 Optimization of Route Choice

The potential of traffic information to optimise route choice by the spatial redistribution of traffic flows are given in Figure 61. Displayed is a comparison of the TTE between the defined benchmark states of traffic information for all eight demand situations. Reductions or increases in TTE compared to the IAT state are displayed by arrows starting at the abscissa, which is the reference value in the IAT state.

The highest potentials to reduce the TTE by spatial redistribution of traffic flows arise in during the rush hours; Tue-Thu 7 - 8 a.m., Tue-Thu 5 - 6 p.m. and Fri 7 - 8 a.m. At these times, the IAT also has the largest benefit compared to UD and reduces the TTE by 2%. The PI state shows a significant potential to reduce the TTE in all demand situations considered by up to 4%. PPI with 100% of drivers provided with LOS information also holds great potentials to reduce the TTE. In the morning peak hours (Tue-Thu 7 - 8 a.m. and Fri 7 - 8 a.m.) PPI decreases the TTE by a margin of 3%. This corresponds to a share of 70% of drivers being equipped with navigation systems for Tue-Thu 7 - 8 a.m., and a share of 80% for Fri 7 - 8 a.m. In all other demand situations LOS information is close to a share of 100% of drivers having navigations systems and therefore close to the PI state. All these potentials are likely to significantly increase in the case of unexpected incidents; however these numbers provide benchmarks for the potentials of traffic information.

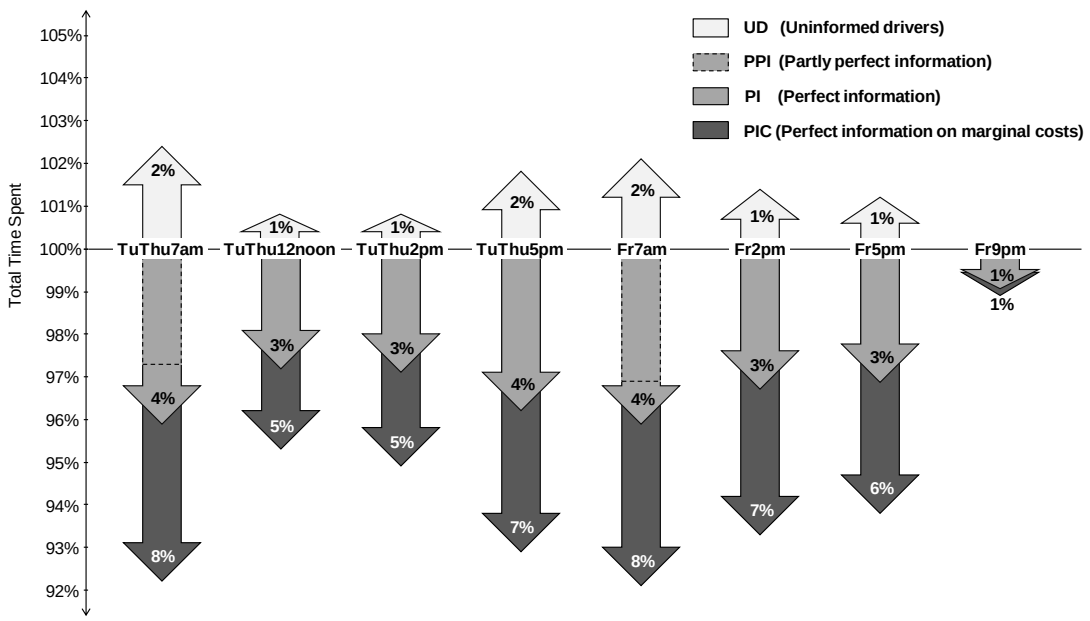

Figure 61: Effects of spatial redistribution of traffic flows as a percentage difference of TTE in relation to the IAT state (information available today)

The PIC state, which results in system optimal redistribution of traffic flows and defines a theoretical optimum, to some extent causes a non-negligible redirection of traffic to

the subordinate road network, see Figure 62. This is displayed as the difference between PIC traffic flows and traffic flows in IAT. In particular, traffic from the A9 motorway is redirected onto the arterial B13.

Figure 62: Difference between traffic flows in a system optimal state (PIC) and the state of traffic information available today (IAT)

Documentation of the absolute TTE numbers for the spatial redistribution of traffic flows is given in Table 52 to Table 59 for each state of information and each demand situation. The numbers show that system optimal redistribution results in an increase in TP in the subordinate road network in all eight demand situations. This stands in direct conflict to the planning aim of concentrating traffic flows on the motorway network. Other indicators for the performance of the transport supply are given by the mean speed, mean travel time, and mean travel distance. The mean speed is calculated as the ratio of TP and TTE, the mean travel time and mean travel distance are both determined as the weighted average over all trips in the network.

In general, the optimal spatial distribution of traffic flows onto free network capacities by introducing marginal costs (PIC) leads to a decrease in saturation and average travel times. This effect is evident by looking at the average speed in the sub-network. Furthermore, today's TP decreases for all eight demand situations for the PI state.

Demand situation	TTE [vehh/h]	TP [vehkm/h]	TP* [vehkm/h]	Mean speed [km/h]	Mean travel time [min]	Mean travel distance [km]
UD	45,000	2,085,000	879,900	46	28	32
IAT	43,900	2,074,000	865,400	47	28	32
PI	42,100	2,046,000	831,200	49	25	30
PPI	42,700	2,040,000	868,900	48	24	30
PIC	40,500	2,058,000	898,400	51	26	31

*only roads in subordinate network

Table 52: Spatial distribution of traffic flows for Tue-Thu 7 - 8 a.m.

Demand situation	TTE [vehh/h]	TP [vehkm/h]	TP* [vehkm/h]	Mean speed [km/h]	Mean travel time [min]	Mean travel distance [km]
UD	19,800	1,341,000	493,100	68	20	30
IAT	19,700	1,339,000	490,800	68	23	33
PI**	19,100	1,328,000	480,800	70	19	30
PIC	18,700	1,322,000	518,700	71	19	30

*only roads in subordinate network
** Same results as with LOS information.

Table 53: Spatial distribution of traffic flows for Tue-Thu noon - 1 p.m.

Demand situation	TTE [vehh/h]	TP [vehkm/h]	TP* [vehkm/h]	Mean speed [km/h]	Mean travel time [min]	Mean travel distance [km]
UD	21,700	1,444,000	528,000	67	23	34
IAT	21,500	1,442,000	525,300	67	22	33
PI**	20,900	1,430,000	513,100	68	20	30
PIC	20,400	1,420,000	560,700	70	22	34

*only roads in subordinate network

** Same results as with LOS information.

Table 54: Spatial distribution of traffic flows for Tue-Thu 2 - 3 p.m.

Demand situation	TTE [vehh/h]	TP [vehkm/h]	TP* [vehkm/h]	Mean speed [km/h]	Mean travel time [min]	Mean travel distance [km]
UD	38,700	2,040,000	831,000	53	26	34
IAT	38,000	2,032,000	819,000	54	25	33
PI**	36,500	2,005,000	792,000	55	24	30
PIC	35,300	2,007,000	854,000	57	25	34

*only roads in subordinate network

** Same results as with LOS information.

Table 55: Spatial distribution of traffic flows for Tue-Thu 5 - 6 p.m

Demand situation	TTE [vehh/h]	TP [vehkm/h]	TP* [vehkm/h]	Mean speed [km/h]	Mean travel time [min]	Mean travel distance [km]
UD	37,900	1,881,000	784,300	50	37	46
IAT	37,100	1,873,000	771,800	50	26	32
PI	35,600	1,848,000	745,000	52	23	30
PPI	36,000	1,848,000	779,700	51	22	30
PIC	34,100	1,860,000	806,600	54	36	47

*only roads in subordinate network

Table 56: Spatial distribution of traffic flows for Fri 7 - 8 a.m.

Demand situation	TTE [vehh/h]	TP [vehkm/h]	TP* [vehkm/h]	Mean speed [km/h]	Mean travel time [min]	Mean travel distance [km]
UD	32,000	1,841,000	714,400	58	25	33
IAT	31,600	1,836,000	705,800	58	25	32
PI**	30,500	1,817,000	681,300	60	23	29
PIC	29,500	1,816,000	747,600	62	22	30

*only roads in subordinate network

** Same results as with LOS information.

Table 57: Spatial distribution of traffic flows for Fri 2 - 3 p.m.

Demand situation	TTE [vehh/h]	TP [vehkm/h]	TP* [vehkm/h]	Mean speed [km/h]	Mean travel time [min]	Mean travel distance [km]
UD	29,200	1,773,000	662,700	61	25	33
IAT	28,900	1,768,000	655,200	61	23	30
PI**	28,000	1,753,000	634,100	63	22	29
PIC	27,100	1,746,000	696,500	64	24	34

*only roads in subordinate network
** Same results as with LOS information.

Table 58: Spatial distribution of traffic flows for Fri 5 - 6 p.m.

Demand situation	TTE [vehh/h]	TP [vehkm/h]	TP* [vehkm/h]	Mean speed [km/h]	Mean travel time [min]	Mean travel distance [km]
UD	7,600	643,000	189,000	84	18	32
IAT	7,600	642,000	188,900	85	18	32
PI**	7,500	641,000	186,600	85	18	32
PIC	7,500	639,000	192,100	85	18	32

*only roads in subordinate network
** Same results as with LOS information.

Table 59: Spatial distribution of traffic flows for Fri 9 - 10 p.m.

A comparison of the fuel consumption between the defined benchmark states of traffic information for all eight demand situations is given in Figure 63.

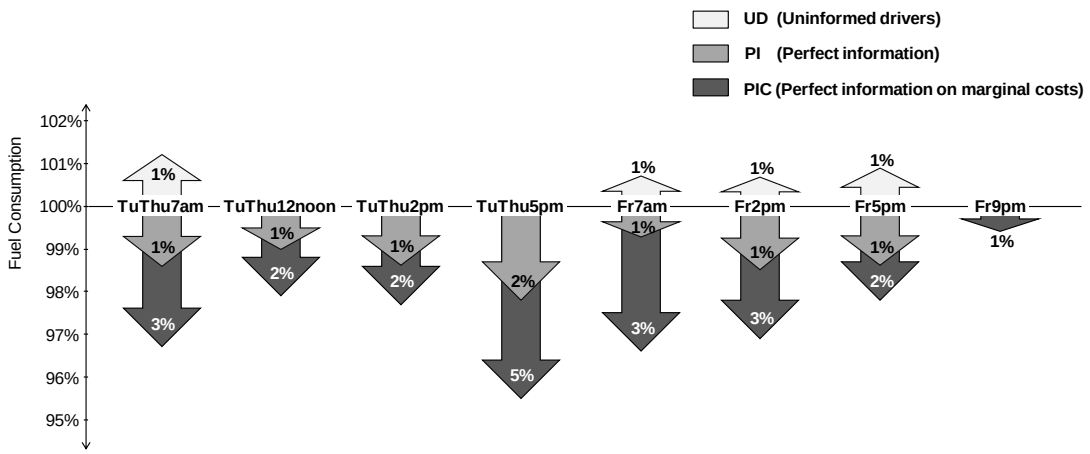

Figure 63: Effects of spatial redistribution of traffic flows as percentage difference of fuel consumption in relation to the IAT state (information available today)

The greatest potentials to reduce FC by spatial redistribution of traffic flows is given in the peak hours Tue-Thu 7 - 8 a.m., Tue-Thu 5 - 6 a.m., and Fri 7 - 8 a.m. During the off-peak hours there are no noteworthy reduction potentials. The differences between

PI and PIC are much smaller than those of the corresponding TTE. This is due to the fact that redirecting traffic flows in the subordinate road network decreases the TTE, however minor roads are generally more emission sensitive than motorways which is accounted for in the HBEFA emission factors. FC values for PPI are not stated in Figure 63 because they barely differ from the PI state and such minor differences are beyond a sensible level of detail that the applied models can account for.

7.3 Optimization of Departure Time Choice

In addition to the mere spatial redistribution of traffic flows, optimisation potentials of traffic information can be analysed at the level of spatial and temporal redistribution of travel demand. In the following, the benchmark PPI state for perfect pre-trip information is compared to IAT and PIC. As online platforms for pre-trip information are not the current state of practice, single information devices delivering partly perfect information are not analysed as no empirical data is available to quantify these effects.

Travel demand observed today, together with the corresponding departure times, largely depends on drivers' trip chains connecting activities with generally fixed starting times as well as on drivers' experience on traffic situations at different times of the day. A theoretical optimum as an equal distribution of travel demand over the entire day is not a sensible benchmark as drivers lack the flexibility needed to shift their departure times accordingly. The PIC state modelled in the following is based on route and departure time decisions including marginal costs within pre-defined time intervals, see chapter 5.3.3 *Joint Route and Departure Time Model*. Figure 64 shows the reduction of TTE for PI and PIC states compared to IAT.

The greatest potentials to reduce the TTE by spatial and temporal redistribution of travel demand is found in the morning peak hours; Tue-Thu 7 - 8 a.m. and Fri 7 - 8 a.m., see Figure 64. In the demand situations; Tue-Thu 7 - 8 a.m., Tue-Thu noon - 1 p.m., Tue-Thu 5 - 6 p.m. and Fri 7 - 8 a.m. an additional reduction in TTE can be achieved by the temporal redistribution of travel demand (displayed in the dashed bars) compared to the mere spatial redistribution of traffic flows (displayed in the corresponding light and dark grey bars). During off-peak hours, temporal redistribution does not provide significant additional potential compared to spatial redistribution. On the one hand, this is due to the fact that network saturation is too low in off-peak hours to cause a departure time shift because travel time savings at other time intervals are small. On the other hand, during the wide-stretched evening peak there are no sufficient capacities available in adjacent time intervals. In all other demand situations no temporal redistribution takes place as travel time savings are too small to provoke a departure time shift. The potential of optimising departure time choice identified are based on the model derived in 5.2.2 *Departure Time Choice* Model Estimation. The β-parameters of the utility function refer to drivers' flexibility on home to work trips.

Therefore, the benchmark PI state very likely underestimates the potential of traffic information to optimise route and departure time choice as drivers' flexibility is very likely to be much higher for other activities such as shopping or leisure trips.

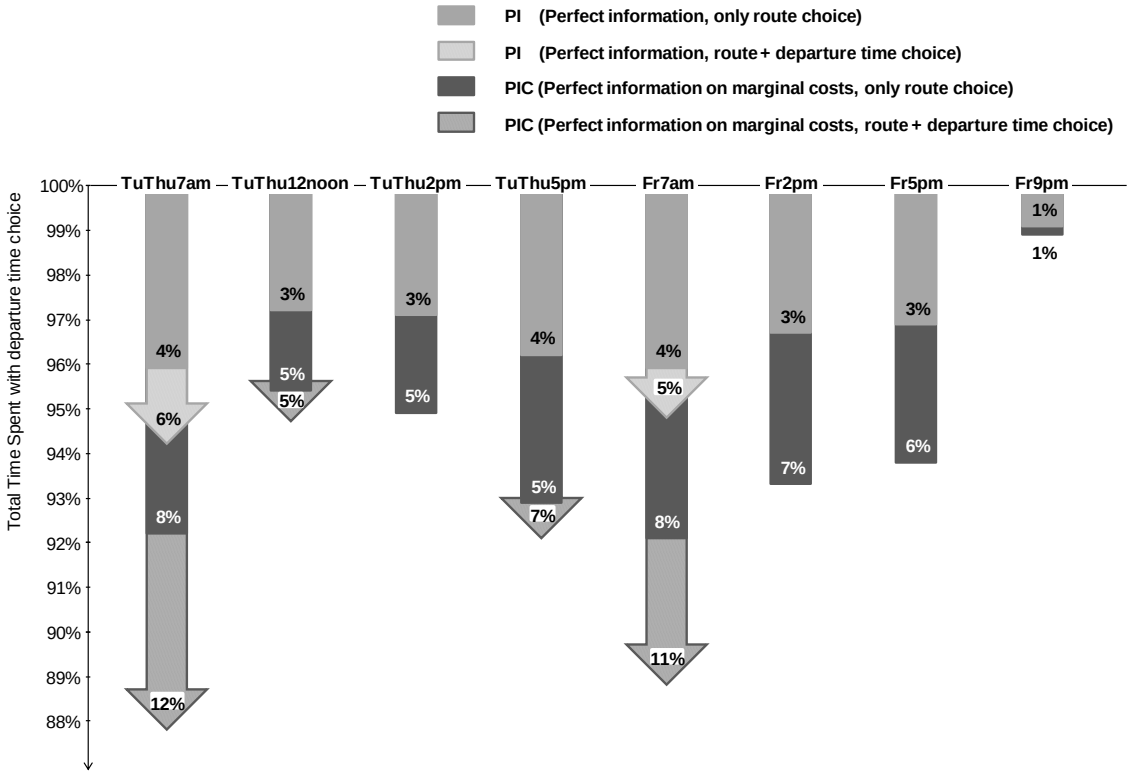

Figure 64: Effects of spatial and temporal redistribution of travel demand as a percentage difference of TTE in relation to the IAT state (information available today)

The assignment result for the analysed sub-network on the example of the demand situation Tue-Thu 7 - 8 a.m. is shown in Figure 65. Thereby, the travel demand of the analysed hour between 7 - 8 a.m. is equally distributed among three time intervals of 20 minutes each. A third of the total demand has a preferred departure time between 7:00 - 7:20 a.m., 7:20 - 7:40 a.m., and 7:40 - 8:00 a.m. respectively. In the adjacent time intervals (6:50 - 7:00 a.m. and 8:00 - 8:10 a.m.) free network capacities exist which can be used with a departure time shift. Travel demand with a preferred departure time in the adjacent hours 6 - 7 a.m. and 8 - 9 a.m. is accounted for by pre-loading the time slices with the according demand. These traffic flows are kept constant as this model calculates benchmark states of traffic information for the analysed hour between 7 - 8 a.m. The top picture in Figure 65 shows the distribution of travel demand if departure times are fixed. The bottom picture of Figure 65 shows the distribution of travel demand if drivers make departure time decisions based on the travel times in different time intervals. In the state PI 0.2% of drivers with a preferred departure time between 7:00 - 7:20 a.m. (displayed in light grey link bars) shift their departure time and start their trips 15 minutes earlier than usual to use existing travel time savings in the

time interval 7:00 - 7:20 a.m. Drivers with a preferred departure time between 7:40 - 8:00 a.m. are displayed in black link bars. Of these, 0.1% delay their departure time by 15 minutes and leave in the time interval 8:00 - 8:10 a.m. In this deterministic user equilibrium the drivers with a preferred departure time between 7:20 - 7:40 a.m. (displayed in the darker grey bars) do not shift their departure time as the demand with preferred departure time between 7:00 - 7:20 a.m. respectively between 7:40 - 8:00 a.m. fills up the free network capacities in the adjacent time intervals. Although this frees up capacities in the time intervals 7:00 - 7:20 a.m. and 7:40 - 8:00 a.m., the advantages are not large enough to cause a departure time shift of the demand with preferred departure time between 7:20 - 7:40 a.m. The numbers of trips which shift their departure time are indicated with arrows coloured according to their preferred departure time.

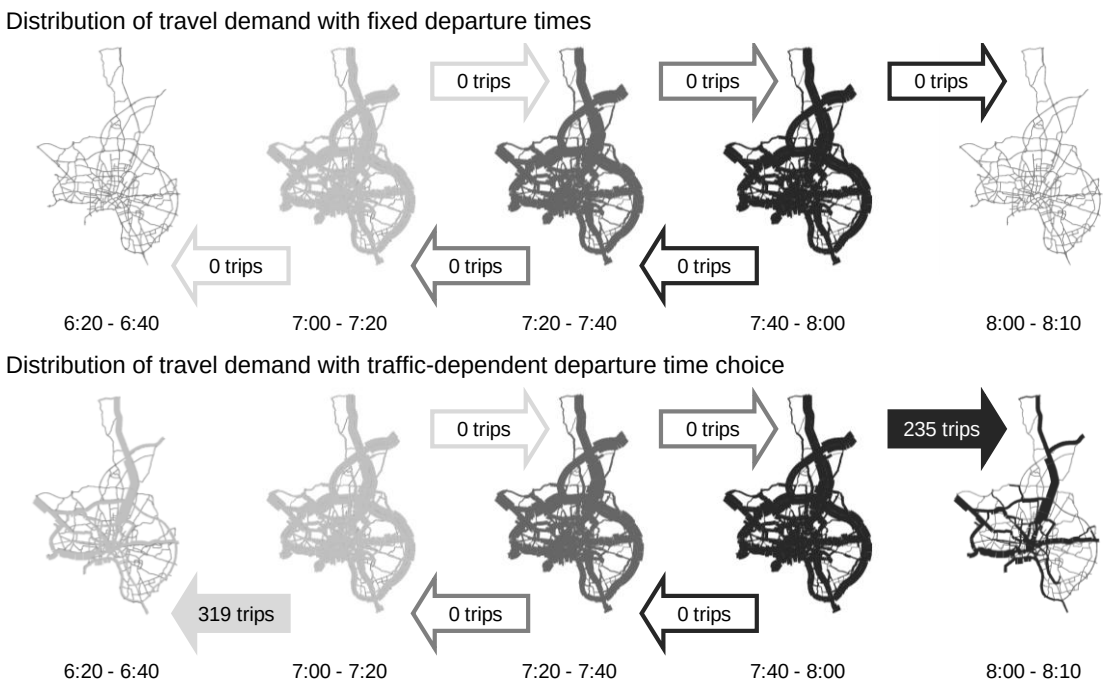

Figure 65: Temporal redistribution of travel demand for departure time shifts between 6:50 - 8:10 a.m. in the case of perfect information for drivers with preferred departure times between 7 - 8 a.m.

A comparison of the absolute numbers of TTE as well as the number of temporal shifted trips to adjacent time intervals for the spatial as well as temporal redistribution of travel demand is given in Tables 60 - 63. If no temporal redistribution of travel demand takes place, the results are the same as the mere spatial redistribution shown in chapter 7.2 *Optimization of Route Choice*. Shifted travel demand is shown by the number of trips departing in adjacent time intervals of 15 minutes earlier or later than the preferred departure time. A departure time shift of more than 15 minutes does not take place in any of the demand situations analysed. The tables clearly show that already a small number of temporal shifted trips can noticeably reduce the TTE in the

whole network. In the morning peak hours, more trips depart 15 minutes earlier due to free capacities in the earlier time intervals before travel demand builds up. The opposite effect shows in the evening peak hours.

Demand situation	TTE [vehh/h]	TP [vehkm/h]	Trips shifted 15 min earlier	Trips shifted 15 min later
PI	41,400	2,042,000	319	235
PIC	38,600	2,051,000	976	566

Table 60: Spatial and temporal distribution of demand for Tue-Thu 7 - 8 a.m. in case of PI (perfect information) and PIC (perfect information on marginal costs)

Demand situation	TTE [vehh/h]	TP [vehkm/h]	Trips shifted 15 min earlier	Trips shifted 15 min later
PI*	19,100	1,328,000	0	0
PIC	18,600	1,318,000	38	15

* no temporal redistribution takes place, results identical to spatial redistribution

Table 61: Spatial and temporal distribution of demand for Tue-Thu 12 - 1 p.m. in case of PI (perfect information) and PIC (perfect information on marginal costs)

Demand situation	TTE [vehh/h]	TP [vehkm/h]	Trips shifted 15 min earlier	Trips shifted 15 min later
PI*	36,500	2,005,000	0	0
PIC	35,000	2,002,000	0	15

* no temporal redistribution takes place, results identical to spatial redistribution

Table 62: Spatial and temporal distribution of demand for Tue-Thu 5 - 6 p.m. in case of PI (perfect information) and PIC (perfect information on marginal costs)

Demand situation	TTE [vehh/h]	TP [vehkm/h]	Trips shifted 15 min earlier	Trips shifted 15 min later
PI	35.200	1.843.000	183	171
PIC	33.000	1.855.000	802	495

Table 63: Spatial and temporal distribution of demand for Fri 7 - 8 a.m. in case of PI (perfect information) and PIC (perfect information on marginal costs)

Figure 66 shows the reduction in FC for the PI and PIC states compared to IAT. The greatest potentials to reduce FC by spatial and temporal redistribution are in the peak hours Tue-Thu 7 - 8 a.m., Tue-Thu 5 - 8 p.m. and Fri 7 - 8 a.m. In the morning peak hours, temporal distribution provides an additional remarkable reduction potential to

mere spatial redistribution. In all other demand situations FC in the PI state is the same as for the mere spatial redistribution of traffic flows. An additional reduction in FC in the PIC state is only given for the demand situation Tue-Thu noon - 1 p.m.

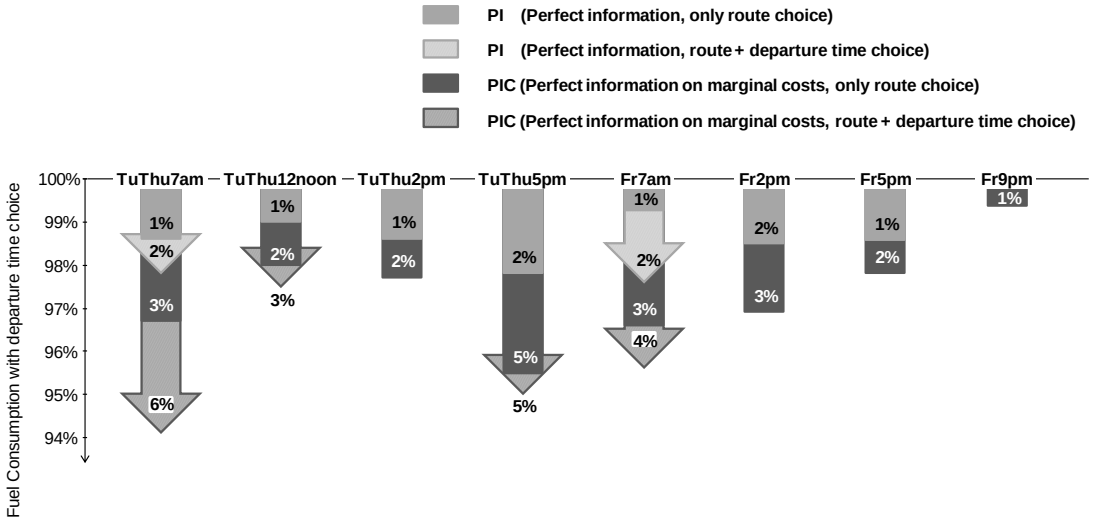

Figure 66: Effects of spatial and temporal redistribution of travel demand as percentage difference of FC in relation to IAT state (information available today)

7.4 Primary Findings

This chapter benchmarks the potentials of traffic information to optimise route and departure time choice in the sense of reducing TTE and FC within the case study area.

The results demonstrate that the theoretically derived modelling approaches of chapter 6 *Optimisation of Traffic Flows* produce reasonable results. Benchmarks for states of traffic information demonstrate the relations expected. The state UD has the highest TTE and FC for all demand situations analysed. Therefore IAT provides a significant benefit to individual drivers as average travel times are lower as well as on a network level as global indicators of traffic impacts are improved. The PPI state further reduces TTE, and FC and comes close to the PI state for off-peak hours. PIC has per definition the lowest TTE but the values show that the potential of traffic information to reduce TTE is at most 8% for the mere spatial redistribution of traffic flows and 12% for temporal and spatial redistribution of travel demand. These potential can be partly accessed by PI with a reduction potential of up to 4% (mere spatial redistribution) and 6% (temporal and spatial redistribution).

The benchmarks determined are derived on the basis of the day-to-day travel behaviour of frequent commuters. Non-recurrent congestion situations are not analysed.

8 Conclusion

In the following chapter, the work carried out in this study is summarized. Firstly, methodological accomplishments such as the developed methods, estimated models and applied algorithms are evaluated for their computational performance and explanatory power as well as their reusability for other applications. Secondly, the major findings of behavioural causalities and the numerical results are summarized and the hypotheses proclaimed in chapter 1.2 *Research Goals* are addressed. Thirdly, recommendations for practitioners in the traffic management field are derived by generalizing findings on the example of a case study of the Munich metropolitan area. Fourthly, an outlook on future prospects is presented as on outlook to researchers in the field of transport modelling.

8.1 Methodological Accomplishments

To address the questions this research has set out to answer, new methods have been developed to derive explanatory behavioural models.

The task of choice set generation is addressed using a Branch and Cut method, which is calibrated on empirical loop detour factors, in order to produce a realistic choice set size with sensible routes in a diverse network structure. An algorithm for automated network simplification makes it possible to reduce high resolution *NAVTEQ* networks to decision relevant structures, which makes Branch and Cut choice set generation computationally feasible for real-size networks of large metropolitan areas. This work has also been partly published in PILLAT ET AL. (2011).

Standard route search procedures in traffic assignments are adapted to produce a similar choice set as Branch and Cut methods by calibrating the number of search iterations, the variance of network impedances as well as the values for global route and loop detour factors. This work is also partly published in MANDIR AND PILLAT (2011).

Discrete choice models for route and departure time behaviour are merged into a joint model which allows for analysis of the trade-off between travel time savings and departure time shifts in standard transport models. Thereby, the representation of time-dependent network capacities as time intervals allows modelling the choice of journeys consisting of a departure time and route within a static assignment.

In order to quantify the potentials of traffic information for reducing total transport time expenditure as well as environmental expenditure, benchmark states of traffic information are defined and an interpretation of user equilibrium assignment methods in respect to driver information and decision behaviour is given.

To address the effect of the level of information quality and single information devices, new modelling approaches are introduced. The lack of information can be interpreted as a degree of stochastic versus deterministic driver behaviour. Information devices are modelled by using a special volume-delay function which accounts for partly perfect information on current travel times. The resulting convergence issues are discussed by examining the stability of the assignment results.

8.2 Major Findings

The relevant parameters which influence route and departure time choice are determined by the use of statistical analysis and choice model estimation. Most importantly, travel time strongly influences route choice and can enhance diversions onto alternative routes. Drivers generally show a strong preference for their usual main route, and alternative routes are usually only considered if travel time on the main route increases beyond a certain threshold. Route recommendations, as well as information on delays, given by different devices such as TMC via radio, VMS and navigation systems, further increase the likelihood of choosing an alternative route. Among these, a LOS map service displayed on navigation devices, as well as standard traffic reports transmitted via radio has the strongest effect on route choice. One reason for this is the comprehensibility of the contents provided by different information devices. If information is hard to interpret, drivers tend to ignore it, along with the recommendations made. Traffic information relayed via LOS maps or radio is the easiest to comprehend. Roadside dynamic message signs require network experience and may be harder to understand. The compliance rates for route recommendations rank between 47%-65% for navigation systems and between 26%-71% for VMS. The compliance rates for complementary recommendations by a navigation system and VMS rank between 76-83% and drop to 37-71% in cases where recommendations are conflicting.

Drivers' departure time choices can be decisively influenced by potential travel time savings. A willingness to shift from a usual departure time to other times of the day is determined by the trade-off between minutes of travel time saving and minutes of departure time shift. Over a typical commuting distance, a departure time of 10 minutes earlier than usual is seen as being acceptable if it brings about a travel time saving of between 6 and 7 minutes. A change of departure time (earlier or later than usual) is generally seen as unattractive. However, later departures have a higher acceptance level than earlier departures. In general, drivers seem to have high expectations about travel time savings if they feel they need to consider changing their daily routine.

On the basis of the derived behavioural causalities, the benchmarks of traffic information can be expressed in numerical results for typical demand situations within the Munich metropolitan area. A state of perfect information on current travel times

causes spatial redistribution of traffic flows, which reduces the TTE by at least 1% and at most 4% and the FC by at least 1% and at most 2%. Theoretically, the TTE can be reduced by 5% to 8% and the FC by 1% to 5% in the case of system optimal distribution of traffic flows.

A state of perfect pre-trip information about travel times for different times of day causes temporal and spatial redistribution of travel demand, which leads to a reduction of TTE of between 3% and 5% and a reduction of FC of between 1% and 2%. At a theoretical optimum, the TTE is reduced by 5% to 12%, and the FC by 2% to 6%. Such significant reductions can be achieved by shifting a marginal number of trips which account for between 0.2% and 0.8% of the total travel demand.

The findings of this research lead to the proving or the disproving of the hypothesis proclaimed in chapter 1.2 *Research Goals*.

Hypothesis I:

Traffic information on current delays based on observed section travel times is more reliable than information based on stationary detectors and flow propagation models.

A comparison between measured and modelled travel times shows that, in total, the travel time predicted by the model differs by less than ±20% from the measured travel time in 95% of all the five minute intervals which are examined. The state-of-the-art short-term travel time forecasts give valuable travel time estimates for motorways if the distance between stationary detectors is around 500 metres. However, an area-wide cover of reliable current travel times in metropolitan networks can only be achieved by using vehicle recognition systems or floating car data, both of which are rapidly emerging technologies. This hypothesis is therefore proved.

Hypothesis II:

Drivers today are relatively well informed about recurrent traffic conditions and choose sensible routes on their daily commute based on their personal experience.

The long-time survey data provides insight in the usage of traffic information devices. Even though the *wiki* smart phone is not high-end equipment, drivers used the navigation system for 8% and the LOS map for 20% of all trips. Navigation systems are used as traffic information tools by 52% of drivers for their daily commute. An analysis of travel times for drivers' daily commutes proves that drivers today are very well informed about their everyday trips. This is not true for trips to unfamiliar destinations where drivers only chose sensible routes in 55% of trips. In the case of unexpected incidents, this value drops further to 43% of trips. This hypothesis is proved in the case of recurrent traffic situations.

Hypothesis III:

Better traffic information can reduce drivers‘ travel times significantly in cases of non-recurrent incidents or when travelling to unfamiliar destinations.

The navigation system used during the survey period guided drivers on routes which are 2% faster than the routes they normally chose. However, this form of route guidance based on historical travel times is far from perfect. Based on the traffic flows observed today, on average each driver could reduce his travel time by 10% if navigation systems always recommended using the route which is currently fastest. This potential can be further increased to a reduction of 4% to 17% if all drivers are equipped with perfect navigation systems and reroute onto the currently fastest route. The effects of self-inflicted traffic jams, in the hypothetical case when navigation systems recommend the same route to all drivers, are not considered. This hypothesis is therefore proved.

Hypothesis IV:

Congested road networks offer a limited number of sensible alternative routes.

On the example of the home to work OD pair of all participants, a network analysis leads to 22 existing alternative routes. Yet almost 65% of all drivers use either only one or two routes from home to work. One reason for this is that the routes partly overlap, so that a driver does not recognize all existing alternatives in his or her mind map. Another reason is that the travel times are not totally independent of partly overlapping alternatives. In situations of congestion when current traffic conditions are hard to evaluate, drivers experienced a travel time reduction in 34% of the cases when they diverted to an alternative route. In the other 66% of trips, the drivers experienced a travel time increase compared with the main route. This hypothesis is therefore only partly proved.

Hypothesis V:

A spatial redistribution of selected trips on alternative routes leads to an overall improvement of traffic flows.

Travel demand and traffic flows can be influenced by traffic information and account for 84% of the delays that occurred in the survey area during 2009. Spatial redistribution of traffic flows decreases the TTE and increases the performance of transport supply as average speed in the network increases by up to 4%. This hypothesis is thus proved.

Hypothesis VI:

A temporal redistribution of selected trips to other times of day is far more effective than a spatial redistribution.

Redistributing only a marginal number of trips to other departure times at which free network capacities exists results in a major reduction of TTE as well as FC. The reduction potentials combining temporal and spatial redistribution compared to mere spatial redistribution are significantly larger, up to the factor of 1.6. This hypothesis is proved.

Hypothesis VII:

Using route guidance measures to minimize the environmental impacts leads to an objectable redistribution of trips to the subordinate road network.

Redistribution of traffic flows in a system optimal way minimizes the TTE as well as the FC. However, making optimal use of existing capacities can lead to a redistribution of traffic into the subordinate road network, which increases the TP on minor roads by up to 7%. If the objective of traffic distribution lies solely in minimizing the FC and thereby minimizing the average trip distance, this effect is even more severe as traffic is redistributed to short cuts along the side roads. This hypothesis is therefore proved.

8.3 Recommendations for Practitioners

The knowledge achieved about the existing potential for route and departure time choice is not only of interest to individual drivers but also to operators in traffic management centres and navigation system developers.

The recommendations for a coordinated and effective use of individual and collective route guidance systems are derived from the extensive empirical and simulative research on the interdependency between traffic information and driver behaviour, in collaboration with the motorway authority of Southern Bavaria (BAKIRCIOGLU AND RIESS (2012)).

Advancement of traffic information quality

High quality information on the current traffic situation can significantly help to reduce travel times. Transport models aim to provide a realistic image of a simplified reality and are an indispensable tool for understanding the interdependencies between travel demand and resulting traffic flows. Furthermore, models are the only tool which can predict future behaviour in changed environments as a reaction to traffic management measures.

For providing high quality traffic information which has real-time accuracy as well as reliable contents, measurements of the current traffic situation are far more instrumental than traffic flow models. To achieve network wide coverage of current travel times, new observation methods should be utilized. Vehicle recognition systems, such as ANPR cameras and Blue-Tooth sensors make it possible for the faster parts of the road infrastructure to be permanently covered by detection systems. The cost of these systems is decreasing steadily. Also, extensive floating car data is becoming increasingly available through navigation service providers such as TomTom. This factor is likely to become even more important in the future.

Standardization of definitions of traffic states and simplification of illustrated traffic information contents

The comprehensiveness of the content being displayed can largely increase the overall effect of traffic information. In order to put drivers in a situation in which they know exactly what the information being provided means in terms of expected travel times, standardized definitions of traffic states are needed. The reported length of congestion or delays and the corresponding LOS should accord with a standard increase in the value of travel times.

Coordination of route guidance for strategy-conform navigation systems

Complementary route guidance provided by individual navigations systems and road-side VMS significantly increases driver compliance as well as trust in the information provided. The coordination of route guidance is thus beneficial not only to public authorities seeking to guide traffic along the major road networks but also to private sector navigation service providers aiming to gain a competitive advantage by guaranteeing to guide their customers along the shortest route. If route guidance by navigation system is based on the authorities' guidance strategies, the driver or customer will directly benefit. This is due to the fact that routing algorithms can be improved if the shortest path search is based on current traffic signal programmes, construction site information, or by-pass recommendations. In order to enable an automated exchange of data between traffic management centres and navigation service providers, data and interface standards need to be agreed on.

Use of measured travel times for traffic guidance systems

Automated vehicle recognition systems deliver real-time travel times which can be used for both traffic guidance strategies and traffic state detection. Implementing traffic state based traffic guidance rules can enhance the reaction time of road-side traffic guidance. However, the overall objectives and traffic management goals need to be carefully considered when defining guidance strategies.

Change of departure time behaviour to utilize free network capacities

The potential for spatial redistribution of traffic flows is limited due to the number of sensible routes which exist in congested situations. Providing time-dependent historical travel times could cultivate a pre-trip decision or trip planning culture among commuters. Online platforms can achieve the necessary publicity for recurrent congestion due high travel demand in rush hours and possibly result in spreading out the volume of demand over longer periods during the day.

8.4 Future Prospects

In this study, the models are kept as simple as possible in order to benchmark the effects of traffic information and determine the interrelationship between drivers' experience of travel times and reports of current delays. Although the presented models are derived from survey data in the Munich metropolitan area, the general set-up can be adapted to analyse the effect of traffic information on other agglomeration areas.

Further research needs to be carried out into other information related influencing parameters within the utility functions of the estimated choice models. Variables of interest could include accuracy of information or fuel consumption. Additionally, the data gathered could be interpreted as panel data of repeated decisions on the daily commute, and this may create the need to use other model structures for parameter estimation.

Some of the estimated variables, such as the main route constant, cannot be modelled in standard assignments because current utility functions are designed on the link level. New assignment procedures considering the utilities of alternatives in the choice set on the route level could overcome this problem. One solution could be new assignment algorithms running on pre-defined choice sets.

The models presented in this study are not appropriate for non-equilibrium situations in cases of non-recurrent congestion. In such situations, drivers tend to react spontaneously to unknown traffic conditions and congestion which dissolves before an equilibrium state can be reached as part of a day-to-day learning process. Extensions to existing models are needed to represent real-time information for on-trip decisions.

To benchmark a theoretical optimum, a marginal costs function can be applied to compute system optimal traffic flows. Future work is needed to develop a method to calculate a mobility pricing policy based on desired traffic flow distributions. This would involve considering different objective functions, such as minimizing the total amount of tolls paid in the network, minimizing the number of toll booths, or maximizing the degree of fairness of the tolls paid by all travelers.

The departure time model is based on parameters estimated for the daily commute from home to work. As it is likely that drivers show different temporal flexibility for different trips, more empirical data is needed in relation to other departure time decision contexts. The applied preferred departure times, on the basis of which departure time shifts are calculated, are taken from the trip tables of the *VALIDATE* demand model. To gain further insight into how daily traffic volume curves are dominated by trip patterns or time-dependent travel times, methods to calibrate departure time models on observed departure times seem to be promising.

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Glossary and Abbreviations

ANPR Automatic Number Plate Recognition (Automatische Kennzeichenerfassung). These systems are used for recording travel time as well as traffic volumes between two detector locations.

App Application software for specific purposes commonly for use on mobile devices

AR Alternative route is a route in the choice set other than the main route (see MR).

ASDA/FOTO Automatische Staudynamikanalyse/Forecasting of Traffic Objects. *ASDA/FOTO* is a traffic forecast model widely used in Germany to estimate the up and downstream propagation of wide moving jams based on stationary detector information to forecast traffic states in real-time traffic management applications.

ATIS Advanced Traveler Information Systems are systems providing information and recommendations to motor vehicle drivers on travel times, and congestion levels and informing public transport users about connections, ticket prices, and delays. In this research, ATIS comprise in-vehicle devices such as navigation systems or LOS maps as well as road-side Variable Message Signs and TMC via radio.

BMBF Bundesministerium für Bildung und Forschung (German Federal Ministry for Education and Research)

BMVBS Bundesministerium für Verkehr, Bau- und Stadtentwicklung (German Federal Ministry of Transport, Building and Urban Development)

BMVBW Bundesministerium für Verkehr, Bau- und Wohnungswesen (German Federal Ministry of Transport, Building and Housing)

BMWi Bundesminsterium für Wirtschaft und Technologie (German Federal Ministry of Economics and Technology)

BASt Bundesanstalt für Straßenwesen (Federal Highway Agency)

Bayern Info An online traffic information platform authorised by the Board of Building and Public Works within the Bavarian Ministry of

	the Interior
CFR	Currently fastest route; the route in the choice set with the current fastest travel time
Choice set	Set of alternatives to choose from in decision making, for example routes, modes of transport, houses, or pizzas
CO_2	Carbon dioxide
ComplexNode-ID	Number identifying all nodes in a NAVTEQ network which belong to the same intersection with multiple nodes and ramps, such as motorway junctions
Compliance	Percentage of drivers (or vehicles) on main route that reroute due to a traffic control device
Connector	An element in a transport model that connects a zone to the transport network, the connector represents the access or egress time from the zone centroid to a node in the network
Cordon zone	A zone in a transport network in which all trips start and end coming from outside and going outside the survey area
CR	Chosen route; the route chosen among all alternatives in the choice set
DGPS	Differential global positioning system is an advanced GPS method to increase the level of accuracy of geographical positioning to centimetres.
dIRA	Dynamische Informationstafel zur Reisezeit-Anzeige. Throughout this research the English term travel time information sign (TTIS) is used (see below).
dWiSta	Dynamische Wegweiser mit integrierten Stauinformationen (dynamic traffic sign with information on traffic jams). dWiSta is the German expression for a special kind of VMS (see below).
ECL	The Event Code List includes traffic incidents such as accidents, congestion, and hazard areas, which are broadcast over TMC (see below).
Elasticity	Elasticity describes the percentage change in choice probability related to a one-percent change of an attribute; it is used in discrete choice modelling for predicting future

	behaviour in the sense of econometric choices on changed attributes of the alternatives in the choice set.
FC	Fuel consumption is used as a global indicator for transport-related environmental expenditure.
FCD	Floating Car Data provide vehicle positions and time stamps from vehicles travelling in the traffic stream.
FGSV	Forschungsgesellschaft für Straßen- und Verkehrswesen (German research society for road and transportation)
FHWA	Federal Highway Administration.
FM	Frequency modulation is a technology providing high-fidelity sound over broadcast radio within a certain frequency band, usually 87.5 to 108.0 MHz.
FPD	Floating Phone Data comprise position and time stamp information from mobile devices, such as mobile phones or other GPS based devices, carried in vehicles while travelling in the traffic stream.
Fundamental diagram	The fundamental diagram displayed the interrelation between traffic flow and density based on macroscopic traffic flow models.
GIS	Geographic information systems store and handle geographically referenced data, such as cartographical and statistical data.
GNSS	Global navigation satellite systems are satellite-based systems for geographical positioning.
Google Maps™	Google Maps™ is mapping service owned by Google Inc. providing digital GIS information and routing
GPS	Global Positioning System is a satellite-based global navigation system that provides time and space information.
GPS log	A data point recorder by a GPS receiver, containing coordinates, time, and date.
GSM	Global System for Mobile communications networks are fully digital networks used for telephony and other data transfers.
HBEFA	Handbook Emission Factors for Road Transport was originally

	developed by the environmental protection agencies of Germany, Switzerland, and Austria and is distributed by INFRAS AG.
HFR	Historical fastest route; the route in the choice set with the historically fastest travel time
IAT	A state of information available today in which drivers make route and departure time choice decisions with traffic information provided today.
Impedance	Often referred to as generalized cost of a network element, impedance is the negative value of the utility.
Intersection-ID	A number which identifies all nodes in a NAVTEQ network that belong to the same intersection with multiple nodes and ramps, such as highway junctions or minor road t-junctions.
LCL	The Location Code List contains the geographic coordinates of TMC locations (see below).
Level-of-Service (LOS)	Level-of-Service is a method to qualitatively interpret the current performance of an element of transport infrastructure, for example by colour (green for good quality, yellow for medium quality, red for poor quality).
Link	Connection of two nodes in a transport network, generally representing a road or lane
Localization network (LN)	A high-resolution digital transport network completely covering all road levels in the survey area; it is used to map-match the recorded GPS trajectories.
Log-likelihood (L)	The Log-likelihood function is the sum of the logarithmic choice probability of each chosen alternative in a data sample and is used as an objective function in Maximum-Likelihood estimation.
Log-likelihood ratio (LR)	The LR is a statistic to test the model fit in discrete choice modelling. The LR tests the goodness of adjustment by determining if the model fit is significantly increased by adding one or more parameters to the utility function.
MAD	The mean absolute deviation is a statistical measure for the variability of a sample of quantitative data.

MAPE	The mean absolute percentage error is a statistical measure of accuracy of a time series of values.
Maximum-Likelihood estimation (MLE)	Maximum-Likelihood estimation is a method for estimating the parameters of a statistical model on a given data set. The parameters are estimated to give the greatest probability to the distribution of the observed data.
Map-matching	A method which locates positions of an object on a digital map
MR	The main route is the route with the highest travel frequency in the choice set.
MiD	Mobilität in Deutschland (Mobility in Germany) is a German wide mobility survey covering mobility patterns of 25,000 households.
MOBINET	*MOBINET* – Mobilität im Ballungsraum München – was a project funded by the BMBF from 1998 to 2003 which addressed sustainable solutions for a socially and economically improved mobility in the Munich agglomeration.
MSA	Method of Successive Averages is an iterative descent method for linear optimisation.
NAVTEQ	*NAVTEQ* is a company providing geographic information systems (GIS) data.
Node	A point in a transport network, generally representing a junction or intersection
NO_X	Term used for mono-nitrogen oxides such as NO (nitric oxide) and NO_2 (nitric dioxide).
OD pair	An origin destination pair is a directed connection of an origin and destination in a transport network. The origin or destination can be nodes or zones.
PI	A state of perfect information in which drivers make route and departure time choices with perfect traffic information.
PIC	A state of perfect information on marginal costs in which drivers make route and departure time choices with perfect information on traffic conditions as well as general journey costs.

PM	Particulate matter suspended in gas or liquid.
PPI	A state of partly perfect information in which drivers make route and departure time choices with partly perfect traffic information provided by single information devices.
Project network (PN)	A project network is a reduction of the localisation network to a strategically important network on which future measures are planned and traffic state data are given.
PTV AG	PTV AG is a provider of traffic software, logistics software, and transport consulting, with headquarters in Karlsruhe.
RDS	Radio Data System is a communications protocol standard that enables receipt of traffic messages via FM radio broadcasts.
Revealed Preference (RP)	RP analyses are surveys on real observed decision or behaviour, ideally recorded without interfering with participants.
Route	Generic term for an ordered sequence of nodes and links in a transport network.
RG	A route group is a group of participants with similar travel patterns using the same main and alternative routes.
Stated Preference (SP)	SP analyses are surveys based on hypothetical decisions or behaviour recorded in designed experiments or interviews.
SIM card	A Subscriber Identity Module card is a chip card for a mobile phone and identifies the user in the phone network.
Simplified project network (SPN)	A simplification of the project network. All complex nodes, meaning junctions and intersections modelled in detail with a link for every lane and allowed turning movement, are reduced to single nodes. The level of detail is much smaller than in the project network, as is the network size. Choice set generation is done on SPN.
Trajectory	Time-space course of a movement
TMC	The Traffic Message Channel provides information on traffic holdups via the non-audible ultra-short-wave frequency range. These messages can be received by radio or contemporary navigation systems.

TMC location	Geographical location of a Traffic Message Channel detector in the road infrastructure
TMC section	Road section between two consecutive TMC locations
TomTom	TomTom (AEX:TOM2) is a provider of in-car location and navigation products and services, with headquarters in Amsterdam.
TP	Transport performance (often referred to as total travelled distance) is the product of the trip distance and the number of trips within a time unit *T*.
TTIS	Travel time information signs are road-side traffic signs showing the current travel time to an important junction downstream (see German expression dIRA).
TTE	The transport time expenditure (often referred to as total time spent) is the product of trip time and the number of trips within a time unit *T*.
Trip	Journey from an origin zone to a destination zone in a transport network
Turn	A turn is an element in a transport model that defines which turning movements are allowed at a node (a junction).
UD	A state of uninformed drivers in which drivers make route and departure time choices without traffic information.
UE	User equilibrium is also known as Wardrop's 1st principle and is an assumption of how travel demand distributes in a network.
Utility	Utility is the general value of an alternative (for example a route). Drivers seek to maximise their personal utility when travelling through a road network by choosing the route with the maximum utility.
VALIDATE	*VALIDATE* is a German wide dynamic transport model owned by PTV AG, which provides hourly travel times for week day categories (Monday, Tuesday to Thursday, Friday, Saturday, Sunday) based on structural data (inhabitants, workplaces, schools, shopping facilities) as well as behavioural data (number of trips to work, shopping, etc.).
VISUM	A transport modelling package; a contemporary product of

	PTV Vision
VMS	Variable Message Sign
Wiki	Wirkungen individueller und kollektiver ontrip Verkehrsbeeinflussung auf den Verkehr in Ballungsräumen. *Wiki* was a project funded by the German Federal Ministry of Economics and Technology which monitored the behaviour of commuters in the Munich metropolitan area to analyse the effect of traffic information on route and departure time choice.
Zone	Area in a transport model which describes land use (residential, commercial, etc.) and structural data (inhabitants, work places, schools, etc.). All trips in a transport network start and end in zones. A zone has a centroid which locates the travel demand in the transport network.

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