Doctoral Thesis

Customer-Centric Travel Planning for Electric Vehicles Unlocking the Full Potential of Personalized and Holistic Decision Support

Author(s): Hoch, Nicklas
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CUSTOMER-CENTRIC TRAVEL PLANNING FOR ELECTRIC VEHICLES

Unlocking the Full Potential of Personalized and Holistic Decision Support

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NICKLAS HOCH
MSc ETH ME, ETH Zurich
born on 02.01.1981
citizen of Germany

accepted on the recommendation of

Prof. Dr. Roland Y. Siegwart
Prof. Dr. Kay W. Axhausen

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Abstract

Decision making in the area of private motorized transport (PMT) generally involves a trade-off between savings in travel time and cost and improvements of travel comfort. Travel decisions are the outcome of economic considerations where travellers evaluate possible travel alternatives and make travel decisions that maximize their personal utility. Many studies have investigated decision making processes in PMT systems [e.g. BAL85, LHSA00]. Some of these studies have analysed the potential benefits and adverse effects of improved information [e.g. BADPI91, EANR95a, EANR95b]. The restrictions that prevent a traveller from making optimal decisions include insufficient information quality, a lack of perfect rationality [Sim57] and a lack of understanding of how other travellers react towards the same information content.

Connected decision support systems (DSSs), embodied by either connected navigation systems or mobile applications, have the potential to overcome these limitations and foster optimal real-time decision making. Findings from travel demand research give an indication as to the critical success factors of these systems where pre-trip and en-route information should take into account personal travel preferences and context [RK08, BADPI91], interrelated choices should be treated as a choice "bundle" [EPPB10, p. 217] and where the integration of additional interaction effects requires approaches that have a "larger scope" [BBA01, p. 2].

In accordance with these findings, this thesis proposes a novel context-aware, holistic and personalized approach for DSSs with a particular focus on electric vehicle (EV) travel. The approach is context-aware insofar as it respects historic, current and predictive information of the driver, the vehicle and the travel environment. It is holistic since all relevant pre-trip and en-route decisions of the traveller are jointly optimized across the trip-chain. It is personalized in view of the fact that the customer’s personal travel preferences govern the choice recommendations of the decision support system.

The DSS presented holistically combines three categories of travel choices: frequently taken choices (e.g. route choice, departure time choice, parking choice), electric vehicle specific choices (e.g. choice of charging strategy) and en-route comfort choices (e.g. choice of driving mode, choice of climatization comfort). It evaluates the interactions between the travel choices across an entire activity-chain and proposes customer-centric travel recommendations. A recommendation (i.e. travel alternative) is described by the following set of performance attributes: travel time, walking time, arrival time, charging induced waiting time, travel cost, parking cost, charging frequency and adherence to both the preferred driving mode and climate comfort.

The DSS proposed is characterized by a high level of modelling detail and both a holistic and personalized treatment of the travel context. This considerably improves the quality of the DSS's travel recommendations when compared with state-of-the-art navigation systems, travel planning services and travel demand models. Moreover, the enlargement of the set of performance attributes addresses new choice trade-offs (e.g. trade-off between en-route travel comfort and travel cost), which are inherent in the real decision making process of an EV traveller and have not been captured before by previous approaches.
This thesis makes multiple contributions to the field of decision support in individual motorized mobility: (1) a contribution to the conceptualization of a context-aware, holistic and personalized DSS for EV travel, (2) a contribution to the modelling of the said DSS, (3) a contribution to the estimation and validation of selected subsystems with real-world data, and (4) a contribution to system evaluation, where potential benefits of the DSS are assessed at the level of trips and trip-chains as well as at the level of the aggregate population and individual customer segments. Selected results are briefly outlined below.

The work introduces a discrete choice model to quantify the choice trade-offs of EV travel. A stated-preference (SP) study consisting of the choice responses of 217 test persons is used to estimate the coefficients of the discrete choice model. The test persons are clustered into distinct customer segments by applying Ward’s method to the individual preference gradients of the test persons, thereby minimizing the heterogeneity of the travel preferences within the customer segments and maximizing it between the customer segments. Four types of customer segments are identified, namely “charge averse”, “safety conscious”, “cost averse” and “balanced” customers.

Moreover, this thesis introduces a black-box\textsuperscript{1} driver model which learns the guiding behaviour of EV drivers with respect to context-classifiers. Seven driver model variants (M1 to M7) are introduced. Among these variants, M1 has the highest level of classification detail while M7 has the lowest level of classification detail. Real-world driving data comprising of 3000km of unsupervised driving data from a manifold of anonymized travellers in the cities of Hamburg, Berlin and Wolfsburg, is used to estimate the coefficients of selected driver model variants and validate the resulting velocity predictions.

A white-box\textsuperscript{2} electric vehicle model is introduced. It is combined with the black-box driver model to form a grey-box EV consumption model. A modular consumption prediction programme is proposed to predict the travel performance (i.e. travel time, energy consumption, comfort adherence) along a route. A comparison between the model variants M1 to M6 shows that the consumption prediction accuracy of the models grows with the level of classification detail. For the vehicle rides analysed, the relative prediction errors of the models when compared with the real-world driving data ranged only from $-8.7\%$ to $7.4\%$.

Furthermore, this thesis introduces a multi-criteria routing approach which jointly optimizes the choice dimensions \{route choice, departure time choice, velocity choice, acceleration choice, choice of comfort settings, choice of driving mode\}. A comprehensive impact assessment\textsuperscript{3} analyses 99 origin-destination pairs in northern Germany with regard to the extent to which the travel performance criteria can be influenced.

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1 A black-box model describes the external response of a system (e.g. driver) without modelling the system’s internal processes.

2 A white-box model describes the external response of a system (e.g. vehicle) in terms of the system’s internal component processes.

3 Refer to chapter 6 for a description of the simulation scenarios, a detailed explanation of the underlying assumptions and a specification of the reference values. The following presentation of the results shows mean absolute values of selected cases.
by the routing approach. Concerning route choice, it is found that choosing the most energy efficient route increases travel time by up to 48% while choosing the fastest route increases energy consumption by up to 36%. A shift of departure time affects travel time by up to 22.2% and energy consumption by up to 11.1% when compared with the reference case (departure time=5am). A choice towards an increased average velocity (\(+20\text{ km} \text{ h}^{-1}\)) reduces travel time by up to 37.5% and increases energy consumption by up to 54.3% when compared with the average velocity choice of the population. The acceleration choices of a slow/fast driver are found to affect travel time by up to 3.3% and energy consumption by up to 4.3% when compared with the mean acceleration choices of the population. Finally, the choice of cabin temperature can influence energy consumption by up to 9.2%, whereby the effect depends on ambient conditions. It is shown that a combined optimization of climate comfort choice and route choice significantly influences travel time. Moreover, it is generally found that the previously mentioned choices influence route choice when jointly optimized.

Lastly, this thesis introduces a routing and scheduling routine, which makes use of the previously described models in order to generate holistic choice combinations and evaluate them taking into account the personal travel preferences of the traveller. An impact assessment analyses the potential benefits of the scheduling approach at the level of trip-chains (i.e. journeys). The characteristics of the choice recommendations are compared between selected customer segments. For the case of the two-trip journey analysed, the mean loss in travel utility resulting from non-personalization ranges from \(-21.3\%\) to \(-0.7\%\) across customer segments. This is likely to worsen for longer activity-chains. In conclusion, a context-aware, holistic and personalized decision support system unlocks the potential for large improvements of electric vehicle travel.

The results shown apply to situations where the DSS market share, with regard to the market of traditional navigation systems and travel planning services, is so low that the recommendations of the DSSs in use do not affect aggregate travel demand. A possible extension of the proposed approach towards a second-stage DSS, denoted by bounded cooperative resource constrained routing and scheduling (BC-RCRS), is outlined in section 8.1.3.

**Keywords**

Electric vehicle, decision support, advanced traveller information, discrete choice modelling, stated preference method, vehicle consumption modelling, driver modelling, range prediction, multi-objective routing, green vehicle routing, resource-constrained scheduling with time windows.
Kurzfassung


Vernetzte Entscheidungsunterstützungssysteme (EUSs), wahlweise umgesetzt als Navigationssysteme oder mobile Apps, haben das Potential diese Hindernisse zu überwinden und optimale Reiseentscheidungen in Echtzeit zu ermöglichen. Aus Untersuchungen der theoretischen Verkehrsplanung lassen sich Hinweise auf kritische Erfolgsfaktoren für EUSs ableiten, so wie die Erkenntnis, dass pre-trip und en-route Informationen die persönlichen Reisepräferenzen und den Reisekontext berücksichtigen sollten [RK08, BAdPI91], dass zusammenhängende Entscheidungen als "bundle" [EPPB10, p. 217] behandelt werden sollten, und dass eine Berücksichtigung zusätzlicher Wechselwirkungen Ansätze mit einem "larger scope" [BBA01, p. 2] erfordert.

Unter Berücksichtigung dieser Erkenntnisse, stellt diese Arbeit einen neuen kontextbewussten, ganzheitlichen und personalisierten Ansatz für EUSs vor, welche insbesondere die Reise mit Elektrofahrzeugen (EVs) unterstützen. Der Ansatz ist insofern kontextbewusst, als dass er historische, aktuelle und prädiktive Informationen des Fahrers, Fahrzeugs und der Umwelt berücksichtigt. Der Ansatz ist ganzheitlich, da er alle relevanten pre-trip und en-route Entscheidungen des Reisenden über die gesamte Tour gekoppelt optimiert. Der Ansatz ist personalisiert, da die persönlichen Reisepräferenzen des Kunden in die Reiseempfehlungen des EUS einfließen.


Das vorgestellte EUS zeichnet sich aus durch eine hohe Modellierungsgenauigkeit und sowohl eine ganzheitliche als auch personalisierte Betrachtung des Reisekontextes. Dies führt zu einer deutlichen Qualitätsverbesserung der EUS Reiseempfehlungen im Vergleich zum aktuellen Stand der Technik von Navigationssystemen, Reisepla-
nungsdiensten und Prognosemodellen der theoretischen Verkehrsplanung. Überdies ermöglichen die neu eingeführten Bewertungskriterien eine Berücksichtigung zusätzlicher Zielkonflikte bei der Entscheidungsfindung (z.B. Zielkonflikt zwischen en-route Reisekomfort und Reisekosten), welche Bestandteil des realen Entscheidungsprozesses eines Elektrofahrzeugnutzers sind aber in bisherigen Ansätzen keine Berücksichtigung gefunden haben.

Die vorliegende Arbeit liefert mehrere Beiträge zum Forschungsgebiet der Entscheidungsunterstützung im motorisierten Individualverkehr: (1) einen Beitrag zur Konzeptualisierung eines kontextbewussten, ganzheitlichen und personalisierten EUS für Elektromobilität, (2) einen Beitrag zur Modellierung des besagten EUS, (3) einen Beitrag zur Parameterschätzung und Validierung ausgewählter Teilsysteme mittels realer Daten, und (4) einen Beitrag zur Systembewertung, welche den potentiellen Nutzen des EUS auf der Ebene von "trips" und "trip-chains" sowie auf der Ebene von Gesamtstichprobe und einzelnen Kundensegmenten bewertet. Ausgewählte Resultate werden im Folgenden kurz skizziert.


Ferner stellt die Arbeit ein Black Box\textsuperscript{1} Fahrermodell vor, welches das Längsführungsverhalten von Elektrofahrzeugnutzern in Bezug auf Kontext-Klassifikatoren beschreibt. Sieben Fahrermodellvarianten (M1 bis M7) werden vorgestellt. Von diesen betrachtet M1 die größte Anzahl von Klassifizierungsmerkmalen und M7 die geringste Anzahl von Klassifizierungsmerkmalen. Anhand von 3000km realen, unüberwachten Fahrdaten von unterschiedlichen anonymisierten Fahrern in den Städten Hamburg, Berlin und Wolfsburg werden die Koeffizienten ausgewählter Fahrermodellvarianten geschätzt und deren Geschwindigkeitsvorhersagen validiert.

Ein White Box\textsuperscript{2} Elektrofahrzeugmodell wird vorgestellt. Aus dem White Box Elektrofahrzeugmodell und dem Black Box Fahrermodell wird ein Grey Box EV Verbrauchsmodell entwickelt. Ferner wird ein modulares Programm zur Vorhersage der Reiseleistung (d.h. Reisezeit, Energieverbrauch, Einhaltung der Komforterwartung) auf einer ausgewählten Route vorgestellt. Ein Vergleich der Modellvarianten M1 bis M6 zeigt, dass die Genauigkeit der Verbrauchsvorhersage mit einer zunehmenden Berücksichtigung von Klassifizierungsmerkmalen steigt. Bei den gezeigten Fahrten liegt der relative

\textsuperscript{1} Ein Black Box Modell beschreibt die Antwort eines Systems, beispielsweise eines Fahrers, ohne dabei die inneren Wirkzusammenhänge dieses Systems zu beschreiben.

\textsuperscript{2} Ein White Box Modell beschreibt die Antwort eines Systems, beispielsweise eines Fahrzeugs, auf Basis der Wirkzusammenhänge der Systemkomponenten.
Prognosefehler der Modelle in Bezug auf die realen Fahrdaten zwischen $-8.7\%$ und $7.4\%$.

Des Weiteren wird in dieser Arbeit ein multikriterieller Routenplanungsansatz einge führt, der eine gekoppelte Optimierung der Entscheidungsdimensionen \{Routenwahl, Abfahrtszeitwahl, Geschwindigkeitswahl, Beschleunigungswahl, Wahl des Klimakonforts, Wahl des Fahrmodus\} ermöglicht. In einer umfangreichen Auswirkungsanalyse\(^1\) werden 99 Start/Ziel Beziehungen in Norddeutschland untersucht hinsichtlich der Beeinflussbarkeit der Leistungsmerkmale durch den Routenplanungsansatz. Bei der Routenwahl zeigt sich, dass die Wahl der ökologischsten Route zu einer Fahrzeiterhöhung um bis zu $48\%$ führt, wohingegen die schnellste Route einen um bis zu $36\%$ erhöhten Energieverbrauch aufweist. Bezogen auf den Referenzfall (Abfahrtszeit=05:00Uhr) kann eine Abfahrtszeitverschiebung die Fahrzeit um bis zu $22.2\%$ und den Energieverbrauch um bis zu $11.1\%$ verändern. Eine Entscheidung zugunsten einer höheren Durchschnittsgeschwindigkeit ($+20\ km/h$) im Vergleich zur Durchschnittsgeschwindigkeit der Bevölkerung reduziert die Fahrzeit um bis zu $37.5\%$ und erhöht den Energieverbrauch um bis zu $54.3\%$. Eine Entscheidung zugunsten moderater/sportlicherer Beschleunigungen im Vergleich zur mittleren Beschleunigungswahl der Bevölkerung hat eine Veränderung der Fahrzeit um bis zu $3.3\%$ und eine Veränderung des Energieverbrauches um bis zu $4.3\%$ zur Folge. Die Wahl der Fahrzeuginnenraumtemperatur kann den Energieverbrauch um bis zu $9.2\%$ verändern, wobei der Einfluss von den Umgebungsbedingungen abhängt. Es wird gezeigt, dass eine gekoppelte Optimierung von Klimakomfortentscheidungen und Routenwahl eine signifikante Auswirkung auf die Fahrzeit hat. Ferner wird gezeigt, dass eine gekoppelte Optimierung der vorgenannten Reiseentscheidungen allgemein die Routenwahl beeinflusst.

Schließlich stellt diese Arbeit eine "Routing and Scheduling Routine" vor, welche die vorgenannten Modelle verwendet um ganzheitliche Entscheidungskombinationen zu generieren und diese unter Berücksichtigung der persönlichen Reisepräferenzen des Fahrers zu bewerten. Eine Auswirkungsanalyse untersucht den potentiellen Nutzen des Planungsansatzes auf der Ebene von "trip-chains". Die Eigenschaften der Entscheidungsannahmen werden verglichen zwischen ausgewählten Kundensegmenten. Im Falle des untersuchten "two-trip journey" führt eine unpersonalisierte Reiseplanung für die Kundensegmente zu einer mittleren Abnahme des generalisierten Reisenutzens von $-21.3\%$ bis $-0.7\%$, wobei der Betrag dieser Werte wahrscheinlich mit zunehmender Länge der Aktivitätskette steigt. Schließlich eröffnet ein konsequent bewusstes, ganzheitliches und personalisiertes Entscheidungsunterstützungssystem Möglichkeiten für eine erhebliche Verbesserung der Elektromobilität.

Die gezeigten Resultate haben Gültigkeit, wenn der Marktanteil von EUS am Markt herkömmlicher Navigationssysteme und Reiseplanungsdienste so gering ist, dass die Reiseempfehlungen der verwendeten EUS keinen signifikanten Effekt auf die Verkehrs-

\(^1\) Siehe Kapitel 6 für eine Beschreibung der Simulationsszenarien, eine detaillierte Erklärung der zugrundeliegenden Annahmen und eine Angabe der Bezugswerte. Die nachfolgende Darstellung der Resultate zeigt mittlere Absolutwerte ausgewählter Fälle.
gesamtnachfrage haben. Eine mögliche Erweiterung des vorgestellten Ansatzes hin zu einem "second-stage" EUS wird in Abschnitt 8.1.3 skizziert, wo der erweiterte Ansatz als "bounded cooperative resource constrained routing and scheduling (BC-RCRS)" bezeichnet wird.

Schlüsselworte
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1 Introduction

1.1 Motivation

For the case of individual motorized mobility, three stakeholder groups can be identified: (1) operators who create and manage the traffic network, (2) original equipment manufacturers that develop and produce vehicles, and (3) travellers that use these vehicles to travel through the traffic network. Sustainable transportation solutions are characterized by their ability to trade-off the conflicting needs of these three stakeholder groups. In the following sections, the stakeholder-specific needs are briefly summarized. These needs give rise to the goals of this thesis, which are presented in section 1.2.

1.1.1 Operator Perspective

Public operators create and manage the transportation network with the aim of balancing transport supply and travel demand. The focus of the operators has been primarily on long-term measures and short-term measures to coordinate the transportation system. Long-term measures include the creation of infrastructure resources (e.g. roads, parking lots), and the development of incentives to influence the travellers' long-term mobility decisions (e.g. choice of residence, choice of workplace). Short-term measures include the provision of travel information and the development of incentives to influence the travellers' short-term travel decisions (e.g. departure time choice, travel mode choice).

The leverage of the existing long-term and short-term measures is insufficient to resolve the supply-demand imbalance of the transportation system. Real-time transport system management provides an opportunity to bridge the gap between supply and demand.

1.1.2 Traveller Perspective

Travel decisions fundamentally result from economic considerations, entailing the trade of personal resources (e.g. time, money), vehicle resources (e.g. fuel) and infrastructure resources (e.g. roads, parking lots). A traveller generally aims to find the set of travel decisions that maximizes his travel utility. In order to achieve this objective, travellers make use of connected services which, amongst others, provide information about the current traffic situation, car parks, petrol stations and petrol prices. In the case of an information overload, also known as oversaturation [BADPI91], travellers tend to fall back to the most primitive decision-making patterns (e.g. nonchoice), and hence, do not make use of any of the opportunities arising from connected information.
Connected decision support systems (DSSs) are able to generate simple high-quality recommendations from large quantities of information. They are capable of exploiting the opportunities arising from connected information, provided that they have the following characteristics: (1) the ability to apply context-aware filters to the large quantities of information in order to extract the subsets of information that are relevant to the traveller in the given situation and at the given time, (2) deductive powers to intelligently combine the relevant pieces of information in order to create choice alternatives, and (3) the ability to assess personal travel preferences in order to tailor the rank order of the choice alternatives to the travellers needs.

1.1.3 OEM Perspective

Automotive Original Equipment Manufacturers (OEMs) continuously try to find ways to increase sales volumes and profits. Recently, OEMs have been rethinking their existing business models, development strategies and products in order to meet new challenges, in particular, the need to address newly arising mobility trends, the necessity to monetize vehicle connectivity and the obligation to meet emission targets.

Newly arising mobility trends shape the customer’s product evaluation. While in the past vehicles have been evaluated on the basis of component characteristics alone, in the future vehicles will also be assessed in terms of their ability to provide carefree travel. The imbalance of travel demand and infrastructure supply is hindering carefree travel, and hence, OEMs need to investigate approaches that not only improve an individual traveller’s journey but also resolve the local supply-demand imbalance.

Vehicle connectivity is an enabler for connected services which have great potential to generate profits. The monetization of connected services requires the control of access points and a clear definition of core software applications that customers are willing to pay for. OEMs need to identify these core applications and develop implementation strategies that guarantee access point control.

Emission targets require new drive train technologies such as battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs). New drive train concepts are perceivably resource constrained, conflict-prone and planning-intensive. In contrast, customers are currently living in times of cheap resources and have shaped their expectations towards a no-think, no-hassle decision making process. This transition has been rather abrupt, and hence, OEMs need to provide solutions to facilitate this transition and make new drive train concepts attractive for the customers.

1.1.4 Motivation Summary

Connected vehicle services have the ability to achieve the objectives of the three mentioned stakeholder groups simultaneously, if they embody DSSs with the following characteristics: (1) enable the customer to optimize his travel performance and save personal resources while avoiding information oversaturation, (2) enable the operator to coordinate infrastructure supply and travel demand in real-time, and (3) enable the
1.2 Goals and Objectives

OEMs to monetize connected services and facilitate the market introduction of new mobility products and new drive train concepts such as HEVs and BEVs.

The author proposes a two-stage development strategy for connected DSSs. In the first-stage, DSSs optimize the customer’s travel decisions with respect to individual travel preferences and personal travel context. In the second-stage, the first-stage DSSs are upgraded in order to allow for a coordination of local decisions and global demand.

1.2 Goals and Objectives

The overall goal of this thesis is to conceptualize and develop a first-stage DSS for electric vehicle travel and to analyse its benefits. A first objective is the conceptualization of a DSS that generates context-aware, holistic and personalized EV travel recommendations. A second objective is the development of the said DSS by creating new models and/or combining existing models, and the estimation (resp. training/calibration) and validation of selected models with real-world data. A third objective is the analysis of the potential effects of the said DSS on travel performance (travel time, energy consumption, travel cost, travel comfort).

1.3 Contributions

This thesis conceptualizes a context-aware, holistic and personalized first-stage DSS for EV travel. (1) The DSS is context-aware insofar as the travel recommendations respect customer activity chains, customer behavioural patterns, current and predicted vehicle states and transport network conditions. (2) The DSS is holistic insofar as all relevant pre-trip and en-route decisions are jointly optimized across the trip-chain, which allows additional choice interactions to be respected and the currently available set of choice trade-offs to be expanded. (3) The DSS is personalized in view of the fact that the choice recommendations are evaluated with respect to learned customer preferences.

The DSS proposed by this study requires several subsystems/models; hence this thesis introduces (1) a discrete choice model capturing the choice trade-offs of EV travel, (2) a black-box driver model, (3) a white-box electric vehicle model, (4) a grey-box EV consumption model, (5) a modular consumption prediction programme, (6) a multi-criteria routing approach, and (7) a routing and scheduling model.

This thesis presents estimation (resp. training/calibration) and validation results for selected subsystems. The choice responses of a stated-preference (SP) study are used to estimate the model coefficients of the discrete choice model. The respondents of the SP study are clustered into customer segments, each of which is used to estimate a separate set of model coefficients. Real-world driving data is used to estimate the coefficients of the black-box driver model. Driver model coefficients are shown for multiple drivers and different road topologies. A separate set of real-world driving data is used to validate the velocity predictions of the black-box driver model and the
1 Introduction

consumption predictions of the modular consumption prediction programme. Validation results are shown for various vehicle rides, multiple drivers and different road topologies.

This thesis analyses the potential effects of the proposed DSS on travel time, energy consumption, travel cost and travel comfort. Effects are assessed at the level of individual trips and at the level of trip-chains (resp. journeys). At the level of individual trips, studies are conducted to analyse the potential effects of route choice, departure time choice, acceleration choice, velocity choice, climate comfort choice and selected interactions thereof. At the level of trip-chains, studies are conducted to analyse the potential effects of holistic and personalized scheduling. The choice recommendations for selected customer segments are compared to the choice recommendations for the aggregate population.

It should be noted that the first-stage DSS proposed by this thesis does not take into consideration the reverse effects of local decisions on aggregate travel demand. Consequently, the results apply to situations where DSS market share, with regard to the market of traditional navigation systems and travel planning services, is so low that the recommendations of the DSSs in use do not affect aggregate travel demand. A possible extension of the proposed approach towards a second-stage DSS, denoted by bounded cooperative resource constrained routing and scheduling (BC-RCRS), is outlined in chapter 8.

1.4 Methodology

The decision support system developed by this thesis involves concepts from various fields of study. This section outlines how these concepts are linked. Detailed discussions on the theories and models can be found in the respective chapters which are summarized in section 1.5.

The objective of the DSS is to provide optimal EV travel recommendations to a traveller. Let \( Y_i \in S \) be a travel recommendation from the set of feasible travel recommendations \( S \). Furthermore, let \( \{y_1i, y_2i, \ldots, y_Li\} \) be the set of related travel choices of the \( i \)-th travel recommendation. The travel choices determine the travel performance (i.e. travel time, travel cost, travel comfort). Let \( U_{in} \) be the travel utility (i.e. generalized travel performance) of the \( i \)-th travel recommendation as perceived by the \( n \)-th traveller. Then, \( Y_{opt} \) is said to be an optimal recommendation if the related travel choices \( \{y_{1opt}, y_{2opt}, \ldots, y_{Lopt}\} \) maximize the travel utility, so that it holds \( U_{optn} \geq U_{in} \), \( \forall Y_i \in S \).

The DSS requires two categories of models in order to provide optimal decision

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1 A recommendation \( Y_i \) is said to be feasible, if it satisfies both the constraints on the individual choice dimensions \( y_{li} \), with \( l = 1, \ldots, L \), and the constraints on the combinations of the individual choice dimensions. For example, consider a simple recommendation \( Y_i \) involving the travel choices \( \{y_{1i} = DT_{Ci}, y_{2i} = RC_{Ci}\} \), where DTC denotes departure time choice and RC refers to route choice. \( Y_i \) is said to be feasible if \( DT_{Ci} \) satisfies the constraint on earliest/latest departure time and if the combination of the choices \( (DT_{Ci} \times RC_{Ci}) \) satisfies the constraint on latest arrival time.
support: (1) "physical models" and (2) "behavioural models". A physical model refers to a function that expresses how a set of travel choices influences the objective travel performance values. A behavioural model refers to a function that expresses how these objective travel performance values are translated into the traveller’s subjective utility evaluation. As a consequence, the design of the DSS involves two parts: (1) the design of physical models which predict the objective travel performance values for a set of travel choices, and (2) the design of behavioural models which subjectify these objective travel performance values and thereby generate a personalized ranking of the recommendations.

Figure 1.1 provides an overview of the life cycle of an operational DSS for holistic and personalized travel planning, denoted by DSSLC. It involves a design loop, where the behavioural models and the physical models are developed, and a runtime loop, where the models are used to provide holistic and personalized decision support for a traveller. During the runtime loop, the system continuously monitors the travel context and the traveller’s decisions. The information is used to update the physical models and to adapt the behavioural models.

Figure 1.1: Overview of the life cycle (DSSLC) of an operational DSS for holistic and personalized decision support in individual motorized mobility for the case of electric vehicle travel.

The behavioural model describes the decision process of the \( n \)-th decision maker (resp. customer segment) with a linear-in-parameter function, which expresses the utility
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The utility \( U_{in} \) of the \( i \)-th alternative as the weighted sum of the attributes \( x_{jin} \), with \( j = 1, \ldots, k \):

\[
U_{in} = \sum_{j=1}^{k} \delta_{jin} x_{jin} + \varepsilon_n \quad \text{with} \quad \delta_{jin} := \beta_{jin} \gamma_{jin}
\]  

(1.1)

where the weights \( \beta_{jin} \) reflect the decision maker’s valuation of the attributes \( x_{jin} \), and where the weights \( \gamma_{jin} \) describe the elasticities of the decision maker’s valuation.

The variables \( \beta_{jin} \) and \( \gamma_{jin} \) can be understood as taste coefficients, which reflect the traveller’s trade-offs between the choice attributes \( x_{jin} \). The random variable \( \varepsilon_n \) captures the deficiencies of the model, that is the deviation of the model from the true process of consideration of the decision maker.

The analyst’s challenge in the design step of the DSSLC is to identify the set of attributes that captures the real process of evaluation of the decision maker. If this real process of evaluation is not accurately captured by the behavioural model, which may be caused by neglected/misinterpreted main/interaction effects or elasticities, the taste coefficient estimates are biased\(^2\). In the runtime step, biased taste coefficients produce a non-optimal rank order of the recommendations \( Y_i \), which results in an inaccurate personalization of the DSS.

The behavioural model determines the structure of \( \beta_{jin}, \gamma_{jin}, \text{and } x_{jin} \) and thereby defines the requirements for the physical models. The physical models express how the travel choices \( \{y_{1i}, y_{2i}, \ldots, y_{Li}\} \) translate into the values of \( x_{jin} \). A physical model can be represented by a transfer function \( f_j \):

\[
x_{jin} = f_j (y_{1i}, y_{2i}, \ldots, y_{Li}, z_{mi})
\]  

(1.2)

where, for the sake of brevity, \( z_{mi} \) is assumed to describe all necessary input values that are not contained in \( \{y_{1i}, y_{2i}, \ldots, y_{Li}\} \). The orchestration of the transfer functions \( f_j \), with \( j = 1, \ldots, k \), forms a cascade of physical control loops. The analyst's challenge in the design step of the DSSLC is to develop a cascade of physical models, respectively transfer functions \( f_j \), that predict \( x_{jin} \) with the highest possible accuracy. If the transfer functions do not accurately capture the real-world effects, including both main and interaction effects, then \( x_{jin} \) are biased. This may lead to the following two deficiencies of the DSS in the runtime step: (1) shift of the rank order of the choice recommendations, and (2) generation of dominated recommendations instead of non-dominated ones, in the sense of Pareto-optimality.

In summary, the quality of the DSS depends on two properties: (1) How accurately the

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1 For the sake of brevity, the attributes \( x_{jin} \) are assumed to be functions of (1) objective travel performance values (e.g. travel cost), (2) socio-economic characteristics of the decision maker (e.g. income), (3) socio-demographic properties of the customer segment (e.g. household type) or any combination thereof.

2 Note, that neglected interaction effects may have an aliasing effect on the estimates of the main effects. However, their contribution is significantly less than that of the main effects. For a more detailed discussion see [LHSA00].
cascade of physical models predicts the values of $x_{jin}$, and (2) how well the behavioural model reproduces the true choice trade-offs of the traveller. Given this context, a major contribution of this thesis, namely the design of a personalized and holistic DSS, can be stated more precisely:

- A DSS is personalized, if ...
  - it involves a behavioural model to evaluate the subjective utility of a feasible travel choice alternative, as perceived by an individual traveller or a customer segment.

- A DSS is holistic, if ...
  - the behavioural model captures the majority of relevant choice trade-offs\(^1\) that are inherent in the true decision making process of a traveller.
  - the set of physical models captures the majority of the cause-effect relationships of $\{y_{1i}, y_{2i}, \ldots, y_{Li}\}$, $z_{mi}$ and $x_{jin}$ that are inherent in the true transfer function $f_j$, thereby guaranteeing non-dominated recommendations and non-distorted $x_{jin}$ values.

State-of-the-art navigation systems, travel planning services and travel demand models are missing some of the relevant choice trade-offs and cause-effect relationships that govern electric vehicle travel. This thesis introduces new choice trade-offs and new cause-effect relationships, which jointly improve the quality of the DSS presented when compared to state-of-the-art methods and up-to-date systems. While a detailed discussion is to follow in the course of the thesis, important extensions of choice trade-offs are listed below:

- Intra-trip choice trade-offs
  - driving dynamics vs. route\(^2\)
  - comfort settings vs. route\(^2\)
  - driving dynamics vs. comfort settings

- Inter-trip choice trade-offs
  - charge frequency vs. all intra-trip trade-offs
  - charge type\(^3\) vs. all intra-trip trade-offs
  - charge frequency vs. charge type\(^3\)
  - charge frequency vs. activity duration\(^4\)

\(^1\) Note, that a property of linear models is that main effects have by far the largest influence on utility.

\(^2\) A route is expressed in terms of geographical position and the travel performance criteria of travel time and travel cost.

\(^3\) A charge type is expressed in terms of charging cost and charge time.

\(^4\) A preference for shorter (resp. longer) activity duration is expressed by $\beta_4$ from table 3.2. An extension towards further activity choice trade-offs is straightforward.
– charge type\(^3\) vs. activity duration\(^4\)
– charge frequency vs. departure time
– charge type\(^3\) vs. departure time

The extension of the choice trade-offs invokes an extension of the physical models, which is detailed in the respective chapters.

1.5 Structure of the Thesis

Chapter 1 provides an introduction to the thesis. Section 1.1 outlines the needs of the major stakeholders of individual motorized mobility which are giving rise to the goals of the thesis. Section 1.2 specifies the goals and objectives of this thesis while section 1.3 describes the contributions of this thesis. Section 1.4 presents the methodology. It gives an overview of the fields of study involved and explains how the concepts are linked.

Chapter 2 presents a structured analysis of the threads and opportunities of individual motorized mobility. Section 2.1 describes the conflicts that arise from global trends and argues that these conflicts entail the need for resource productivity in individual motorized mobility. As far as opportunities are concerned, section 2.2 reviews the potential of existing approaches to increase resource productivity, including long-term transportation planning and active transportation and demand management. Section 2.3 classifies the existing approaches in order to identify the direction of future research, namely, holistic and personalized decision support for individual motorized mobility. Section 2.4 analyses the potential benefits of holistic decision support. It discusses the needs that arise from the approach, including the need for predictive information, the need for interaction models and the need for holistic preference models. These needs give rise to the consecutive chapters.

Chapter 3 develops a discrete choice model and a stated-preference study to estimate the holistic travel preferences of distinct customer segments. Section 3.1 discusses the concepts of discrete choice theory. Section 3.2 reviews discrete choice experiment (DCE) literature, focussing on relevant aspects in theory development and relevant applications thereof. The discussion on DCE theory includes statistical design efficiency, task complexity and taste heterogeneity between individual decision makers. The discussion on DCE applications departs from the studies that investigate activity choice trade-offs, goes on to the studies that assess the trade-offs between activity choices and travel choices, and arrives at the studies that purely investigate travel choice trade-offs. Section 3.3 describes the design of the DCE and the SP study, defining the attributes, attribute levels, estimation model and formatting of the choice experiment. Finally, section 3.4 presents the results, encompassing an analysis of the socio-demographic and socio-economic characteristics of the sample population, an analysis of the aggregate travel preferences of the sample population and an analysis of the disaggregate travel preferences of individual customer segments.

Chapter 4 introduces a context-aware vehicle consumption model. Section 4.1 qualitatively describes the relationship of cause and effect between driver behaviour,
vehicle properties, environment characteristics and vehicle consumption. Section 4.2 presents a behavioural model, denoted by black-box driver model, which learns the behavioural driving patterns (model output) as a function of the driver, vehicle properties and environment characteristics (model input). The model implements an update-prediction loop, which continuously updates the model coefficients on the basis of the driving history, and predicts the future decisions of a driver on the basis of a forecast of the future driving context. The model has a dual use: (1) it serves as input for a vehicle consumption model, and (2) is used as part of a metric to compute the comfort perception of a driver when the vehicle controls acceleration and velocity choices in order to reduce energy consumption. Section 4.3 is the first in a series of sections discussing physical models. It presents a white-box electric vehicle model, which is combined with the black-box driver model to form a grey-box EV consumption model. Section 4.4 analyses the characteristics of the consumption model. It presents a sensitivity analysis that investigates how sensitive the vehicle consumption reacts towards changes in driving behaviour, vehicle properties and environment characteristics.

Chapter 5 presents an approach, denoted by modular consumption prediction programme, to integrate the driver model and the white-box vehicle model with a graph theoretical environment representation in a runtime-efficient manner. Section 5.1 reviews existing consumption prediction approaches. Section 5.2 presents the new modelling approach, including a description of the modularization strategy, a definition of the interfaces and transfer functions of the modules, a graph theoretical environment model and a description of the consumption prediction routine. Section 5.3 provides a performance analysis of the consumption prediction programme suggesting high prediction accuracy and a significant influence of personalization on prediction accuracy.

Chapter 6 presents a multi-criteria routing approach, which expands the consumption prediction programme to include additional choice trade-offs. Section 6.1 discusses existing green vehicle routing approaches. Section 6.2 illustrates multi-criteria routing and Pareto-front analysis. Section 6.3 discusses the routing approach, which enables a combined optimization of the choices \{route choice, departure time choice, velocity choice, acceleration choice, choice of comfort settings, choice of driving mode\} with respect to multiple cost criteria. Section 6.4 analyses the benefits from a combined optimization of the aforementioned choice dimensions. It examines the properties of the Pareto-optimal solutions and how these properties change across road environment topology and choice dimensions. It also analyses the effect of interpersonal taste variations on the properties of the subjective travel optimum.

Chapter 7 presents a scheduling approach that employs the models from the previous chapters. Section 7.1 presents a description of the scheduling problem. It defines the utility function, specifies the hard constraints and discusses the scheduling procedure. Section 7.2 presents the results of a customer survey which are used to construct test scenarios. In section 7.3, selected test scenarios are scheduled. The results are used to determine the benefits from holistic and personalized decision support.

Finally, chapter 8 draws conclusions from and suggests possible extensions of the approach presented. Section 8.1 focuses on theoretical research aspects in human behaviour modelling, vehicle consumption modelling and routing and scheduling. Most
importantly, subsection 8.1.3 presents a possible extension of the first-stage DSS towards a second-stage DSS. Section 8.2 discusses possible impacts of the results of this thesis on applications, in particular, on future navigation systems, driver information systems and mobile online services.
2 Rational for the Study

This chapter presents a structured analysis of the threads and opportunities of individual motorized mobility. Section 2.1 describes the conflicts that arise from global trends and argues that these conflicts entail the need for a higher resource productivity in individual motorized mobility. Section 2.2 reviews the potential of existing approaches to increase resource productivity, including long-term transportation planning and active transportation and demand management. Section 2.3 classifies the existing approaches in order to identify the direction of future research, namely, holistic and personalized decision support for individual motorized mobility, which is further detailed in section 2.4.

2.1 Literature Survey of Values and Resources

The world population today has reached 7 billion people, and is projected to reach 9.3 billion people by 2050 [Uni11]. Population is predicted to peak in Europe by 2020, in China by 2030 and in India by 2060 [Unia]. The entire population growth will be absorbed by urban centres [Uni12]. Additionally, rural population will continue to migrate towards the cities. Today, urban population in the developed world accounts for 78% of the total population and is expected to rise to 86% in 2050; in the developing countries a rise is expected from 47% today to 64% in 2050 [Uni12]. In 2025 more than half of the world urban population will live in urban centres of size greater than 0.5 million inhabitants [Uni12].

At the same time as urban population increases, the level of motorization rises. Between 2009 and 2012 annual growth of vehicle sales has averaged 7% with a predicted annual growth rate of 4% for the years to come [Gom]. According to [SV00], car ownership is correlated with GDP per capita. This is well reflected by today’s realities, where developed countries have a high rate of motorization, with 782 motor vehicles per 1000 capita in the United States, 572 in Germany and an average of 623 in high income OECD countries, and where low and middle income countries have a considerably lower level of motorization, with 58 motor vehicles per 1000 capita in China and 18 in India [The].

[Axh06] describes a relationship between wages and activity spaces. Wealth is found to stimulate travel rate and trip length. The correlation between income and traffic volume is confirmed by [SV00].

A logical consequence of the aforementioned trends (urbanization, rising level of motorization, increasing travel rate) is an increase of congestion rate. Congestion increases travel time and global traffic emissions. Traffic congestion in the U.S. is
responsible for a wasted annual petrol amount of 7.19 billion litres [SLE11]. The annual congestion related delay in travel time averaged 34 hours per commuter in 2010 and accounted for an annual financial loss of 543€ per vehicle commuter; heavy congestion affected on average every fourth trip in the United States [SLE11]. The urban mobility report [SLE11] predicts a further increase of congestion levels in the future. It predicts a further rise of travel delay, wasted energy and congestion related cost. Although commuter delays are particularly severe in larger cities of above 1 million inhabitants, congestion is said to occur in every size of city. Congestion is also cross-influenced by externalities such as non-recurring incidents and parking space availability. [BN] estimates that 30% of urban congestion is induced by park search traffic, which refers to drivers idling in order to find a parking space.

The above stated realities lead to a decline in transportation performance. From the viewpoint of an operator, who assesses the supply side, transportation performance is defined as the effectiveness of infrastructure capacity usage. From the viewpoint of a traveller, who assesses the investment of personal resources, transportation performance is defined in terms of the generalized cost of travel (GCoT), which expresses travel cost as the weighted sum of all monetary and non-monetary expenditures. An important resource is time. [Fos05] shows unit elasticity between personal income and the value of travel time savings (VTTS), meaning that people increase their valuation for travel time savings at the same rate as their net income rises. Income is directly correlated with GDP; consequently, under conditions of economic growth, not only motorization and congestion rate increase, but also customers become more sensitive to the related waste of personal resources, and hence, their perception of travel framework conditions deteriorates disproportionately.

A rising GCoT counteracts economic growth and welfare, and needs to be compensated for by investments into the transportation system. The work of [Axh06] appreciates low GCoT as a prerequisite of welfare and economic growth, and consequently assesses the control loops of travel demand, travel supply and GCoT, namely the loop of investment and the loop of use.

In conclusion, global trends will entail a higher GCoT. Economic growth and prosperity require a lower GCoT. In view of restricted public budgets, the conflict can no longer be solved by infrastructure investments alone; it needs to be solved through an increase in resource productivity, targeting both the operator and the traveller perspective.

2.2 Literature Survey of Measures and Effects

As has been argued in section 2.1, the imbalance of infrastructure supply and travel demand increases GCoT. A higher GCoT hinders economic growth. Global trends are exacerbating the conflict of supply and demand and are therefore threatening economic growth. From this conflict follows the need for coordination actions that increase resource productivity in transportation systems.

This section discusses possible coordination actions and their potential effects on resource productivity. The discussion distinguishes two categories of coordination
actions: A first category, denoted by transportation planning, describes long-term actions to balance supply and demand; a second category, denoted by active transportation and demand management (ATDM) [KGS13], describes short-term and real-time actions to coordinate supply and demand.

Transportation planning covers long-term infrastructure measures and long-term actions of transportation demand management (TDM), which are commonly expressed in transportation plans. Long-term TDM encompasses a set of measures that influence long-term mobility choices, an example of which are incentives for flexible working hours in order to shift departure time and reduce peak traffic. Transportation plans are generated under the involvement of various transportation stakeholders in a lengthy process, which is described in [Tra07].

The effectiveness of transportation plans shall be briefly illustrated from two viewpoints: (1) the traveller's viewpoint, which describes the individual perception of planning effectiveness, and (2) the research perspective, which quantifies the de facto effectiveness of transportation plans independent of personal perception. As to the traveller perception, KPMG's 2012 global automotive survey [KPM12] interviewed a large number of respondents about the potential impact of urban planning on vehicle usage and design. Around 50% of the respondents replied that they think that urban planning considerably shapes the way of travel. As to the research perspective, in [SLE11] a real-world study investigates the effects of infrastructure creation on the level of congestion. The study compares a first set of cities, in which the travel demand has grown 30% faster than the infrastructure supply, to a second set of cities, in which the travel demand has grown 10% faster than the infrastructure supply. As a consequence of the 20 percentage point difference in supply-demand-ratio, the first set of cities has shown a doubling in congestion rate. The two examples illustrate the general importance of long-term planning. Yet, long-term planning does not suffice to resolve the imbalance of supply and demand, which is due to two major shortcomings: firstly, long-term measures are designed on the basis of long-term demand predictions, which rarely match future realities accurately, and secondly, travel demand is varying at a much higher rate than infrastructure supply is created. As to the Federal Highway Administration of the U.S Department of Transportation, "in the 21st century, strategies to manage demand will be more critical to transportation operations than strategies to increase capacity (supply) of facilities." [Unib, p. 1]

ATDM [KGS13] measures target short-term and real-time coordination of capacity supply and travel demand. Enabling technologies such as intelligent transportation systems (ITS) and pervasive connectivity have been leading to a growing importance of this second group of coordination measures.

Many studies have investigated the effects of ATDM, in particular the potential benefit from advanced traveller information systems (ATIS). The approaches largely differ; they address different temporal dimensions of choice (pre-trip, en route, post-trip), different thematic dimensions of choice (e.g. mode choice, departure time choice, route choice), and different fields of transportation demand management (active demand management, active traffic management, active parking management). The following paragraphs provide some examples from literature of how different ATIS approaches improve travel
Levinson [Lev03] discusses ATIS effects on individual travel time savings. He investigates route choice only. Time savings are shown to depend on the penetration rate of ATIS users. At lower penetration rates, ATIS users benefit more; at higher penetration rates, ATIS users benefit less. Generally, the informed choices of ATIS users improve global network conditions. At high penetration rates non-ATIS users also start to benefit from these informed choices. According to [Lev03] advanced travel information systems prove most beneficial for ATIS users in two travel environments: (1) recurring congestion with volume-to-capacity (v/c) ratios of 0.95, where ATIS users can save up to 35% in travel time, and (2) non-recurring congestions at low v/c-ratios. Emmerink et al. investigate the effects from ATIS in situations of non-recurrent congestion [EANR95b] and recurrent congestion [EANR95a]. The analyses focus on route choice; driver behaviour is modelled by boundedly rational principles. In situations of non-recurrent congestion, the authors show that ATIS significantly improves average network travel time and that the benefit of equipped users diminishes at high market penetration rates [EANR95b]. In situations of recurrent congestion, the authors find that the travel time of equipped drivers is reduced by up to 15% in the case of low market penetration rate and en-route information, and that the benefit at high market penetration rates strongly depends on information quality (e.i. update frequency) [EANR95a]. In the case of high market penetration rate, it is found that network travel time can still be reduced by up to 5% if the quality of information is high. More generally, "High quality information allows a high level of market penetration, while low quality information, even when provided at low levels of market penetration, induces overreaction" [EANR95a, p. 21]. These findings are supported by [Mat07].

Research conducted by [SWTL03] quantifies the benefits of pre-trip travel information services. Although aggregate travel time savings are shown to be around 0.3%, ATIS influences route and departure time choice in 60% of the trips and thereby reduces early arrivals of more than 10 minutes by up to 56% and late arrivals by up to 52%. The benefits are found to be correlated with trip length and vary with market penetration rate.

Axhausen et al. [APBP94] conducted several surveys to analyse the effects of parking guidance information systems (PGI) on travellers’ on-trip parking behaviour. It is shown that the usage of PGI systems is around 20%, even though the awareness of PGI systems is 80%. PGI systems are shown to improve the performance for off-street parking in times of heavily-congested traffic. A simulation study by Waterson et al. [WHC01] investigates the potential of PGI systems in Southampton with respect to travel time savings. The reduction potential of total network travel time is found to be 0.1% - 1%. The benefit of individual drivers is larger. The analysis shows that the reduction potential increases when more drivers are informed and parking resources are scarce with respect to parking demand.

Scoot [PST] is an adaptive traffic control system, which optimizes the global network flow through adaptive traffic signal control. [Spr12] also quantifies the improvement potential of adaptive signal timing. It is shown that adaptive signal timing reduces travel time in the Colorado case study by up to 11% and fuel consumption by up to 4%.

Although the list of studies and phenomena is by far not exhaustive, one can already
2.3 Classification of Decision Support Systems in Transportation

ATDM systems, in particular ATIS, are socio-technical systems, involving a human decision maker and a technical device. Human-machine-interaction can be understood as a control loop, where an ATDM/ATIS system and a human decision maker interact in order to perform an information-decision-action activity. Analogously, this activity is called a perception-reasoning-action process in autonomous systems engineering. Stressing this analogy, the author proposes a classification scheme, which categorizes ATDM/ATIS by their degree of autonomy. A system is said to have low autonomy, if it
supports information acquisition, but leaves reasoning processes and actions to the human operator. A system is said to have medium autonomy, if it supports information acquisition and reasoning processes, but leaves the execution of actions to the human operator. A system is said to have full autonomy, if it controls the entire perception-reasoning-action process. Given the classification scheme, up-to-date ATDM/ATIS are categorized as shown in figure 2.2. As can be seen, approaches with low system autonomy exist across all modes of travel (individual motorized mobility, public transport, multi-modal mobility). Approaches with medium system autonomy are confined to public transport and multi-modal mobility. Individual motorized mobility mostly lacks approaches with medium system autonomy. The few existing approaches are confined to route choice and departure time choice, and yet, holistic reasoning support is generally unavailable.

![Figure 2.2: ATDM/ATIS classification by autonomy and mode of travel.](image)

The design of systems with low and medium autonomy requires an understanding of the potential threats arising from the automation of perception and reasoning processes. Potential threats, respectively adverse effects of information provision, are discussed in [BADPI91, p. 254] where they are termed oversaturation, overreaction and concentration. Oversaturation only threatens systems of low autonomy, where a surplus of information easily overstresses the traveller’s reasoning capabilities. Systems of medium and full autonomy computerise the reasoning task and thereby circumvent oversaturation. Overreaction and concentration threaten all levels of autonomy. According to [BADPI91], overreaction may be averted by providing different information content to different groups of drivers. Concentration issues may be resolved by a personalization of the computerised reasoning processes. Ben-Akiva et al. write:

"it is also desirable to generate route directives which are customized in
accordance with individual driver preferences." [BADPI91, p. 254]

From the discussion in section 2.2 and section 2.3 follow the requirements for optimal decision support with medium-autonomy ATDM/ATIS. The criteria are summarized in the following:

- Computerised perception and reasoning, which leaves the execution of actions to the traveller
- Holistic reasoning, which encompasses all temporal and thematic dimensions of travel choice
- Personalized reasoning, which respects individual driver preferences
- Control mechanisms, which allow for a unification or dissociation of information on the group-level
- Highly qualified information, which is provided at a high update frequency
- Open-ended information, which encompasses both historic data, current and predictive information

This thesis implements a medium-autonomy ATDM/ATIS considering the aforementioned criteria. The approach complies with the recommendations of the ministries of transportation, particularly with [RK08], who suggest amongst others:

"The user can make well founded decisions - including environmental, time and cost criteria - both pre-trip and en-route. (...)  
- pre-trip information based on personal profile, journey purpose and preference (...)  
- en-route information support through the journey based on the preference of the traveller and real-time information (traffic, weather, incident, etc)" [RK08, p. 29]

2.4 Conceptualization of Holistic and Personalized Decision Support

Travelling involves a multi-dimensional decision making process, which encompasses many mutually dependent choices. Choice has a time dimension, which is described by the time period from the start of the decision making process to the end of the decision making process – hence, from information acquisition to the execution of a chosen action. If the time period is in the range of seconds, a choice is referred to as manoeuvre choice. If the time period is in the range of minutes, a choice is referred to as tactic choice. Otherwise, it is referred to as strategic choice. Travel choice also has a thematic dimension, which describes what is decided upon. Individual motorized mobility
comprises longitudinal guiding choice, lateral guiding choice, choice of vehicle comfort settings, route choice, departure time choice, parking choice, refuelling choice, mode choice and activity choice. Longitudinal guiding choice (velocity choice, acceleration choice) and choice of comfort settings (e.g. cabin temperature choice) are manoeuvre decisions. Route choice (vehicle route choice, pedestrian route choice), departure time choice and parking choice are tactic decisions. Choice of refuelling strategy and activity choice are strategic decisions. Figure 2.3 groups said travel choices with respect to the aforementioned temporal and thematic dimension and shows how to generate a holistic and personalized ATIS from the combination of choices. ATIS is holistic insofar as it jointly optimizes the temporal and thematic interaction effects of all relevant choice dimensions of the traveller. ATIS is personalized in view of the fact that the customer’s personal travel preferences govern the choice recommendations of the decision support system.

**Figure 2.3:** Grouping of travel choices with respect to a temporal and thematic dimension (cp. [HZWS12]). Hierarchical concept for holistic decision support, which renders non-strategic decisions strategic.

Figure 2.3 shows a hierarchical optimization structure for holistic and personalized decision support. At each hierarchical level, a number of choice dimensions (input) are jointly optimized to produce a set of choice combinations (output). On the lowest hierarchical level, manoeuvre choices, vehicle route choice and departure time choice are jointly optimized to produce an ordered feasible set of stage alternatives. On the next hierarchical level, pedestrian route choice, parking choice and the said stage alternatives are jointly optimized to produce an ordered feasible set of trip alternatives. On the highest hierarchical level, charging choice, activity choice and the said trip alternatives
are jointly optimized to produce an ordered feasible set of journey alternatives, whereby
the elements of the feasible set of journey alternatives are ordered with respect to utility.
The utility follows from the traveller’s travel preferences, and thus, the utility maximizing
element describes the most preferred combination of travel choices.
A holistic and personalized approach taps large improvement potential:

- Strategic potential – manoeuvre choices and tactic choices are evaluated from the
  viewpoint of their strategic effects, thereby expanding the strategic solution space.

- Combinatorial potential – each choice dimension is evaluated under consideration
  of the interaction effects with other choice dimensions, thereby enabling the
  combined maximization of utility; this is generally higher than the sum over the
  maximum utilities of the individual choice dimensions.

- Customer satisfaction potential – the composition of thematic choice dimensions
  better reflects the true decision making process of a traveller, thereby providing
  higher accuracy in predicting the truly preferred option of a traveller in a given
  situation.

The said improvement potential of a holistic and personalized approach comes at the
cost of additional needs.

- Need for predictive information – the evaluation of manoeuvre choices and tactic
  choices from a strategic viewpoint requires prediction models, which forecast the
  choices’ effects in strategic time.

- Need for interaction models – the combinatorial multi-dimensional decision making
  problem requires models that capture the interaction effects of the thematic choice
  dimensions.

- Need for holistic preference – the holistic combination of the choice dimensions
  requires a holistic taste model, which captures the relative valuation of all choice
  criteria in order to enable the computation of the combined utility.

A first set of predictive information is generated from prediction models, which forecast
(i) the effects of manoeuvre decisions on tactic choices and (ii) the effects of manoeuvre
decisions and tactic decisions on strategic choices. A second set of predictive infor-
mation is independent of the traveller’s decisions. Altogether, the following predictive
information is required:

- road properties (traveller independent)
- traffic information (traveller independent)
- ambient conditions (traveller independent)
- charging station and parking lot availability (traveller independent)
• parking and charging prizes (traveller independent)
• charging type (traveller independent)
• effects from activity type, location and duration
• effects on (resp. from) longitudinal guiding choice
• effects on (resp. from) cabin temperature choice
• effects on (resp. from) vehicle route choice
• effects on (resp. from) pedestrian route choice
• effects on (resp. from) departure time choice
• effects on (resp. from) parking choice
• effects on (resp. from) charging choice

The following interaction models are required for the combinatorial decision making problem to optimize the travel performance criteria of travel cost, travel time and travel comfort:

• model capturing the combined effects of longitudinal guiding choice, cabin temperature choice, road properties and ambient conditions
• model capturing the additional effects of route choice and departure time choice
• model capturing the additional effects of pedestrian route choice, parking lot availability and parking cost
• model capturing the additional effects of charging type, charging cost and charging time
• model capturing the additional effects of activity location, activity type and activity duration

The following taste parameters are required to model the holistic travel preferences:

• relative weight for driving time
• relative weight for walking time
• relative weight for deviation from scheduled arrival time
• relative weight for charging induced waiting time
• relative weight for driving cost (consumption equivalent cost)
• relative weight for parking cost
2.4 Conceptualization of Holistic and Personalized Decision Support

- relative weight for the number of charging events
- relative weight for driving dynamics (adherence to preferred driving mode)
- relative weight for cabin temperature

The following chapters present prediction models to generate said predictive information. They introduce interaction models to capture the aforementioned interaction effects. Lastly, they develop a holistic taste model to capture the relative valuation for the cost criteria.
3 Holistic Choice Model for Electric Vehicle Travel

Customer choice is assumed to be rational and follow a deterministic decision process, where a customer evaluates the utility of feasible choice alternatives and chooses the one with highest utility value. The analyst’s perception of the customer’s decision process contains observational errors, which are assumed to be unknown and follow a probability distribution. The assumption about the perception errors gives rise to a probabilistic model of the customer’s decision process. The most widely used approach is a Multinomial Logit (MNL) model, which assumes the random variables to be Gumbel distributed.

This chapter proposes a discrete choice model, more precisely a main effect model, to describe the holistic decision making process of EV travel planning. The model focuses on the short-term and real-time travel decisions described in figure 2.3. It employs a special case of the MNL model, namely the binomial logit approach, to model the decision making process of the customers. The newness of EV travel, and consequently the absence of revealed preference (RP) data, makes necessary a stated-preference (SP) approach. The SP experiment contains 2 blocks, with 16 choice situations per block, 2 choice profiles per choice situation and 9 attributes per profile, where at most 4 of these attributes vary across any two profiles. The sample population comprises 500 test persons, 217 of whom have correctly completed the survey, thereby producing 3472 choice observations.

The coefficients of the main effect model represent the relative preferences of the customers with respect to the profile attributes. The coefficients are computed from maximum likelihood estimation and are determined both at the level of the aggregate population and at the level of individual customer segments. The customer segments are obtained from the aggregate population by the use of Ward’s method [War63], which clusters respondents by taste gradient, so that the consistency of taste is maximized within a segment and minimized across segments. An additional customer segment is clustered from socio-economic data, grouping experienced electric vehicle users with home charging facilities.

This chapter is structured into four sections. Section 3.1 introduces discrete choice theory. Section 3.2 reviews stated-preference approaches in transportation literature. The design of the SP experiment is discussed in section 3.3. Taste coefficient estimates, both at the level of the aggregate population and at the level of individual customer segments, are presented in section 3.4.
3.1 Discrete Choice Theory

Following the presentation in [BAL85, p. 31 et seqq.] and [Hal99, p. 5 et seqq.] discrete choice is described as a sequential process: First, a decision-maker generates a set of discrete choice alternatives; second, he assesses their impact; and third, he determines the most preferred alternative out of the set of feasible alternatives. Here, the decision-maker is assumed to be an individual traveller. He is described by intrinsic preferences, socio-economic context and mobility characteristics. A traveller is believed to have "consistent and transitive preferences" [BAL85, p. 38]. His decision-rule is assumed to be in-line with random utility theory.

In tangible terms, a traveller uses context information to generate a set of discrete travel alternatives, whereby the set contains only those alternatives that satisfy the personal constraints of the traveller. A feasible travel alternative \( Y \) is described by a vector \( X = [x_1, \ldots, x_k] \) of choice attributes, whereby the attribute scale of measure can be nominal, ordinal or continuous. The relative valuation of said attributes is expressed by a vector of coefficients \( \beta = [\beta_1, \ldots, \beta_k] \), which can be understood as the traveller's preference with respect to the attributes. The scalar utility of an alternative follows from said attribute vector \( X \) and said taste vector \( \beta \). The choice of a traveller is governed by utility maximization. In mathematical terms: Given a set of feasible choice alternatives, denoted by \( C_n \), a traveller is assumed to choose travel alternative \( Y_i \), if \( U_{in} \), describing the utility of travel alternative \( Y_i \) as perceived by the \( n \)-th traveller, is larger than any utility \( U_{jn} \), with \( Y_i \neq Y_j \) and \( Y_i, Y_j \in C_n \).

From the viewpoint of a decision-maker, the decision process is deterministic. From the viewpoint of an analyst, the true utility value of a decision-maker is unknown, since observational errors introduce randomness into the model. Sources of randomness are described in [BAL85, Man73]: (1) the true attribute vector \( X'_i \) of a decision-maker may contain more attributes than does the modelled vector \( X_i \), (2) the true taste vector \( \beta' \) of a decision-maker may contain more attributes than does the modelled taste vector \( \beta \) and (3) attributes might be measured incorrectly. To allow for observational errors of the analyst, the utility \( U_{in} \) is defined as a random variable:

\[
U_{in} = V_{in} + \varepsilon_{in} = \beta X_{in} + \varepsilon_{in}
\]  

(3.1)

where \( i \) refers to the \( i \)-th choice alternative, \( n \) denotes the \( n \)-th decision-maker, \( V_{in} \) describes the systematic components such as the systematic taste vector \( \beta \) and the systematic attribute vector \( X_{in} \), and \( \varepsilon_{in} \) represents disturbances as induced by the perception of the analyst of the decision process. The utility function is linear in the parameters of \( X \), whereby \( x_1, \ldots, x_k \) can be generated from non-linear combinations of product characteristics and socio-economic variables.

Following the analysis of [BAL85, p. 75 et seqq.], three categories of taste variables are distinguished. A first category, whose variables are denoted by "alternative-specific constant", explains differences in utility between two choice alternatives when attribute values are identical. A second category, whose variables are denoted by "alternative-specific socioeconomic", explains differences in utility between groups of
decision-makers with different socio-economic characteristics. A third category, whose variables are denoted by "generic", describes taste variables that are equal across choice alternatives and socio-economic properties.

Different approaches exist to model the disturbance terms of the utility function. Multinomial logit (MNL) is the most extensively studied closed-form model. It assumes the disturbances to be Gumbel distributed, and hence, the difference in disturbance between any two choice alternatives to be logistically distributed. This chapter employs a special case of MNL, termed binomial logit, where the \( n \)-th decision-maker is forced to choose among two alternatives, that is alternative \( Y_i \) and alternative \( Y_j \), with \( C_n = \{ Y_i, Y_j \} \) [BAL85, p. 59 et seqq.]. In binary logit, the probability that choice alternative \( Y_i \) is preferred over choice alternative \( Y_j \) is described by [BAL85, p. 71]:

\[
P_n(i) = Pr(U_{in} \geq U_{jn}) = \frac{1}{1 + e^{-\mu \beta (x_{in} - x_{jn})}}
\]

where \( \mu \) is a scaling parameter and \( \beta \) is to be estimated. A number of approaches exist to estimate the \( \beta \) parameters. Feasible estimators are required to be unbiased, efficient with respect to the variance and asymptotically consistent with the true taste vector. The most frequently used estimator in linear regression analysis is the maximum likelihood estimator, whereby "a maximum likelihood estimator is the value of the parameters for which the observed sample is most likely to have occurred" [BAL85, p. 20]. The maximum likelihood is defined as the extreme value of the log likelihood function. For a set of \( n = 1, \ldots N \) observations, the log likelihood function of binary logit is defined as [BAL85, p. 84]

\[
L = \sum_{n=1}^{N} \{ y_{in} \log(P_n(i)) + y_{jn} \log(P_n(j)) \} \quad \text{with} \quad y \in \{0,1\}
\]

satisfying the constraint \( y_{in} + y_{jn} = 1 \), where \( y = 1 \) if the respective alternative is chosen. The maximum likelihood value is commonly computed with the Newton-Raphson method. For a detailed discussion on maximum likelihood estimation refer to [LHSA00, LM12, BAL85].

### 3.2 Literature Review of Discrete Choice Theory

This section reviews discrete choice experiment (DCE) literature. Advances have been made both in theory development and applications thereof. While subsection 3.2.1 discusses relevant aspects in the domain of theory development, subsection 3.2.2 revisits the findings from transport applications.
3.2.1 Relevant Aspects of Theory Development

Comprehensive reference books [e.g. BAL85, LHSA00] and a number of publications [e.g. SBL05, Kuh10, FW88] exist that discuss the design and analysis of DCEs, both involving theoretical concepts and practical considerations. The following paragraphs refer to the theoretical concepts that are most relevant for this thesis.

Generally, the regression coefficients of a DCE model can be estimated from stated-preference (SP) data, revealed preference (RP) data or both. In [LSB04], the authors comment on the fact that the results from well-designed SP experiments are generally in-line with RP results. The congruence of SP and RP approaches gives rise to the question for when an SP approach should be favoured over an RP approach. In [Hen94], it is argued that SP experiments should be favoured in situations where new products are assessed, or as Hensher writes:

“Stated preference (SP) methods are widely used in travel behaviour research and practice to identify behavioural responses to choice situations which are not revealed in the market (...) .” [Hen94, p. 107]

All DCE models assume a linear-in-the-parameter utility function. This implies that the behavioural pattern of a human decision maker can be represented by a linear relationship between the attribute vector $X$ and the taste vector $\beta$. The general applicability of this assumption, and hence, the suitability of linear models to represent human decision making is discussed in [DC74], who write:

“Linear models work because the situations in which they have been investigated are those in which: (a) The predictor variables have conditionally monotone relationships to criteria (or may easily be rescaled to have such a relationship); (b) there is error in the dependent variable; (c) there is error in the independent variables; and (d) deviations from optimal weighting do not make much practical difference.”[DC74, p. 105].

Given the general applicability of linear models, it still holds that the better results are obtained (1) the better the model reflects the true decision making process of the decision maker and (2) the higher is the statistical efficiency of the DCE design.

Statistical design efficiency is motivated by the fact that restrictions from both the decision maker (e.g. task complexity restriction) and the analyst (e.g. sample size restriction) require fractional factorial designs, and that these fractional factorials lose statistical significance when compared to the respective full factorial design. The design goal is thus to find the fractional factorial that minimizes the loss of statistical significance under the given constraints. While literature provides a vast number of design approaches for various models, it generally lacks an extensive comparison of the statistical significance of the existing approaches from the perspective of applied research.

A valuable contribution to the comparison of design approaches is found in [SBL05],
where Louviere et al. discuss multiple DCE design strategies\(^1\) and compare them with respect to statistical efficiency. Most relevant for this thesis is strategy\(^5\) (S5), which employs SAS software to construct an orthogonal main effect plan (OMEP) and a search algorithm to find efficient profile combinations. Louviere et al. show that S5 has superior statistical properties for the design of main effects and two-factor interactions when compared to the alternative design strategies S1-S4.

In [SB07], Street and Burgess present methods to construct statistically optimal designs for the class of DCEs, where variables are generic, choice situations are unlabelled and the analysis employs MNL models. Moreover, they provide a discussion on optimal DCE design in view of asymmetric attributes and present a theorem to determine an upper bound on the optimal choice set size for the case of asymmetric attributes and main effect models. This thesis develops a DCE of this very class of DCEs discussed in [SB07], namely, a model with all-generic variables, asymmetric attributes, unlabelled profiles and an estimation of main effects with an MNL model.

In [LSB04], the authors provide a review of DCE approaches, discussing theoretical advances in the development of the strategies to improve statistical efficiency of SP designs. Louviere et al. critically remark (1) the absence of theoretical concepts to address the heterogeneity in decision making processes and taste preferences across individuals, and (2) the lack of understanding of how task complexity affects statistical efficiency.

In [FW88], Fowkes and Wardman examine taste heterogeneity between individual decision makers and propose an approach to include interpersonal taste variations into the design and evaluation of DCEs. They address "The 'ratio of means' problem" [FW88, p. 30], which arises when taste ratios are aggregately estimated at the level of the sample population, although they vary between the individuals of the sample. Amongst others, they write:

"(...) one should perform logit analysis only on segments of the sample that can be taken to have reasonably uniform values of the relative valuation of interest." [FW88, p. 42]

Task complexity is analysed in [SA01], where Swait and Adamowicz present an approach to model task complexity and estimate its effect on the decision making strategy of a customer. The complexity definition comprises criteria such as the number of attributes per profile, the number of profiles per choice situation and the utility-equivalence of the profiles in a choice situation. The authors present a metric to capture said influences and estimate their effect on the subject's decision strategy. The results of [SA01] underpin previous findings from the judgement and decision making domain, including:

\(^{1}\) For a detailed description of the design strategies refer to [SBL05].

\(^{2}\) In line with S5, this thesis uses SAS software, concretely the choice modelling package of JMP (JMP®), Version 11. SAS Institute Inc., Cary, NC, 1989-2014) to infer an efficient design for the estimation of main effects.
"(...) increasing complexity produces more nonchoice or adherence to the status quo." [SA01, p. 143]

"As task order increases, respondents move from the apparently rich, attribute-based strategy, to a simpler one. (...) Also, it seems that respondents take on the challenge of the higher entropy early in the sequence by choosing the richer strategy (with increased probability) (...)." [SA01, p. 146].

The work presented in [LPC11] discusses undervalued issues of DCE design for real-world applications, some of which have been sketched in the previous paragraphs. The authors raise awareness of the fact that, from the perspective of applied research, theoretical DCE design approaches lack a clear statement of the implications of the underlying set of assumptions.

In [Kuh06], Kuhfeld discusses the construction of DCEs from a more applied perspective. He discusses the design of DCEs for all-generic attributes and alternative-specific attributes. In particular, he addresses the construction of blocked designs and partial profiles, where only subsets of the attribute levels are varied across the profiles of a choice set. In [Kuh10], Kuhfeld provides a more comprehensive discussion on DCE design, again from the applied perspective, where he focuses on the implementation of the respective methods in SAS software.

Tool support for the design and analysis of DCEs encompasses, amongst others, the open source software Biogeme [Bie03] and the commercial software JMP1.

Finally, the aforementioned DCE design considerations can be structured in a multi-level process. As to [Hen94], the first six steps of the DCE design process encompass the identification of relevant attributes, specification of attribute types, definition of attribute levels, choice of statistical design, choice of format and the choice of estimation procedure.

### 3.2.2 Relevant Findings from DCE Applications

In transportation literature, a vast number of applications exist that use DCE theory to estimate the behavioural characteristics of a sample population. The studies address different choice trade-offs, such as activity choice and mode choice, and have different underlying assumptions. The following paragraphs present a selection of these studies. The discussion departs from the studies that investigate activity choice trade-offs, goes on to the studies that assess the trade-offs between activity choices and travel choices, and arrives at the studies that purely investigate travel choice trade-offs.

In [CA10], an activity-type choice model is presented, which uses past information to infer future decisions. Cirillo and Axhausen express the past choices in terms of three primary variables, namely a variable describing the within-day time period that

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is yet unaffected from past activity choices, denoted by "time budget" [CA10, p. 23], a variable describing a minimum within-week occurrence of a particular activity purpose, denoted by "high week episode" [CA10, p. 23], and a variable describing the temporal gap between the current activity choice and the last one of its kind, denoted by "last time" [CA10, p. 23]. These variables are shown to be statistically significant, particularly, if analysed at the level of individuals.

In [BBA01], Bowman and Ben-Akiva present a discrete choice model, which expresses the choice of a within-day activity pattern in form of a hierarchy of interconnected subtour choices. The subtour choices comprise time-of-day choice, destination choice and mode choice. The interconnectedness of the model allows for trade-offs in activity choice, which are otherwise ignored.

In [EPPB10], a choice model is presented that holistically combines activity choices and travel decisions, namely the choices of travel mode, activity type, activity location, activity time and activity duration. Eluru et al. argue that these choices are made in a "bundle" [EPPB10, p. 217], which requires a holistic approach rather than a sequential approach. The data obtained supports their assumption. Eluru et al. use the presented model to quantify changes in activity choice as caused by variations in travel conditions such as an increase in travel time or travel cost.

In [WASZ10], mode choice characteristics are investigated. Two DCEs are designed, which pay particular attention to the effects of fuel prices. Amongst others, it is shown at a statistically significant level that travel time and fuel cost influence mode choice, whereby the valuation of these attributes changes with activity purpose and varies between motorized travel and public transport.

In [VSEA10], Vritic et al. conduct three DCEs in order to investigate the behavioural characteristics of route choice, departure time choice and mode choice and how these characteristics change with the choice of road pricing scheme. One of the DCEs is most relevant for the objectives of this thesis. It investigates the combined choice of route and departure time in motorized travel; a first choice model analyses the behavioural characteristics without road pricing and a second choice model assesses the behavioural characteristics with road pricing. The DCE involves the set of generic attributes \{vehicle fuel cost with/without road pricing, late departure, early departure, vehicle travel time\}. The model encloses elasticities of both travel cost and travel time. The DCE shows an average trip length of 55.6km, respectively 40.1km in the earlier SBB study, which compares well to the trip length of 40km in this thesis. A total of 3,927 observations are obtained for the DCE on route and departure time choice, as compared to 3,472 in this thesis. The valuation for fuel cost is shown to be elastic with travel time, while the valuation for travel time is proven to be elastic with travel cost.

Finally, in [WVWA11], SP experiments are used to analyse a traveller’s valuation for parking type, parking cost and parking search time. Weis et al. investigate the traveller’s relative valuation, amongst others, for the case of parking space choice, choice of destination and mode choice.
3.2.3 Discussion

Concerning the theoretical foundation, this thesis follows the DCE design process described in [Hen94]. It employs a DCE design with all-generic variables, asymmetric attributes, unlabelled profiles and an estimation of main effects with an MNL model; where possible it follows the recommendations from [SB07] and [SBL05], as well as [Kuh06, Kuh10]. The design of the DCE considers the findings from the task complexity analysis of [SA01]. Particular attention is paid to interpersonal taste variations. In contrast to [FW88], who estimate interpersonal taste variations on the basis of socio-economic properties of the sample population, this thesis uses the gradients of the taste coefficients in order to cluster segments of respondents with similar travel preferences. Concerning tool support, this thesis uses Biogeme [Bie03] and JMP\textsuperscript{1} to design the SP experiments, compute the customer segments and estimate the values of the taste coefficients.

Concerning the applied perspective, SP experiments in transportation literature investigate activity choices (e.g. activity type, activity location, activity time), travel choices (e.g. mode choice, departure time choice, route choice) and the combination thereof.

Literature lacks approaches that connect in-vehicle comfort choices (e.g. driving mode, air conditioning choice) with the remaining travel choices and activity choices, although these choices are certainly intertwined. Moreover, literature is missing a fine grasp of the choice mechanisms of electric vehicle travel.

With regard to state-of-the art literature, this thesis introduces new choice dimensions and most importantly new choice trade-offs, which describe the connection between choice dimensions as discussed in greater detail in section 1.4 and section 3.3.1. This chapter presents an SP study that allows for the quantification of the choice trade-offs both at the level of the aggregate population and at the level of population subsets, denoted by customer segments.

3.3 Experimental Setup and Procedure

This section describes the DCE design using widely accepted choice experiment terminology [e.g. LHSA00, BAL85]. Briefly, a choice experiment describes a set of choice situations, each of which is given to one or many test persons producing a set of choice responses. A choice situation contains a finite number of choice alternatives, denoted by profiles. A profile is described by a set of attributes, where each attribute is defined over a set of attribute levels, whereby the scale of measure can be nominal, ordinal or continuous. A full-factorial design contains all possible combinations of attribute levels (resp. treatment combinations). A fractional factorial design contains a subset of the full-factorial set. A nested design addresses interdependencies between selected attribute levels. A block design groups subsets of choice situations, denoted by blocks, where each block is exclusively assigned to a subset of the test persons.

Generally, a design of a stated-preference experiment is the result of a balancing act, where requirements from statistics must be reconciled with psychological considerations and monetary constraints. In particular, it needs to compromise the conflicting criteria of (1) choice realism, (2) choice complexity, (3) statistical coverage of the effects under consideration and (4) constraints on budget, respectively sample size. As to (1), realism follows from several mostly soft criteria, the first among them being the extent to which attributes reflect the respondent’s real process of consideration, along with the comprehensibility of choice situations and the justifiability of choice situations by the customer’s current market experience. As to (2), choice complexity is correlated with the number of choice experiments per respondent, the number of profiles per choice experiment and the number of varied attribute-levels per profile. Regarding (3), statistical coverage has to be evaluated with respect to the modelling objectives. Generally, a full-factorial set allows for a complete analysis of all main effects and interaction effects. Yet, full-factorial designs are likely to violate either the constraint on maximum sample size or the requirements from choice realism and choice complexity, which gives rise to fractional-factorial designs, which however compromise statistical coverage.

The design objective of an SP experiment is best described as follows: given a constraint on maximum sample size and an upper bound on choice complexity, find the fractional-factorial that maximizes choice realism and statistical efficiency for the effects under consideration. Given the design objective, the SP experiment is developed in six steps, following the presentation of [Hen94]: (1) identification of relevant attributes, (2) specification of attribute types, (3) definition of attribute levels, (4) statistical design, (5) formatting and (6) the choice of estimation procedure. The structure of this section follows from these development steps. Subsection 3.3.1 describes the decision problem of EV travel, which serves as the basis for attribute inference. Subsection 3.3.2 describes attribute types and attribute levels. Subsection 3.3.3 presents the formatting of the choice experiment. Subsection 3.3.4 discusses the statistical model of the choice experiment, followed by a critical discussion on perception bias and error terms.

3.3.1 The Decision Problem of EV Travel

At first glance, there seems to be a substantial matching in the specific decision problem of EV travel and the general decision problem of motorized travel. On closer inspection, the EV decision problem reveals several anomalies, namely (1) additional travel choice dimensions, (2) changes in choice interaction characteristics and (3) the need for dovetailing of travel decisions and range restrictions. The following paragraphs delve into the anomalies of the EV decision problem. The full EV decision problem, combining anomalies and general characteristics, is then shown in figure 3.2.

Additional travel choice dimensions

Additional travel choice dimensions complicate the existing decision problem of motorized travel. Examples include the choice of charging strategy and the choice of driving mode, both of which shall be briefly discussed.
The choice of driving mode is not to be confused with the choice of travel mode; while the latter relates to the medium of transportation, the former refers to the settings of a driver assistance system (DAS) that controls vehicle dynamics. Driving mode levels can be selected via a head unit control dial. In this thesis, five levels are distinguished: Level_1 defines a driving mode, where vehicle dynamics are fully driver-controlled without system intervention. Level_2 enforces light restrictions on maximum acceleration and maximum vehicle velocity. Level_3 enforces severe restrictions on maximum acceleration and maximum vehicle velocity. Level_4 defines a semi-automatic driving mode, where longitudinal velocity control is fully-automated and steering is driver-controlled. Level_5 defines a fully-automated driving mode, respectively autonomous driving. The choice of driving mode level influences travel cost, travel time and travel comfort, whereby the benefits are highly dependent on the context such as the natural driving style of a driver and the road environment. Generally, higher levels of intervention reduce travel cost, and at the same time, increase the reliability of both energy consumption and travel time prediction. The more similar the natural driving style of the driver is to driving mode level_5, the smaller are the monetary benefit and the travel time savings from the DAS. Concerning travel comfort, higher driving mode levels (e.g. level_4, level_5) are perceived as helpful assistance in tedious driving situations, while being perceived as patronizing in pleasant ones. Examples of tedious driving situations include traffic jams, situations of driver fatigue and range critical situations.

A charging strategy defines a chain of charging events, whereby a charging event is defined by a charging location, a charging start time, a charging duration, an energy intake and a unit energy cost. The choice of charging strategy therefore reflects a set of coupled decisions, encompassing the choice of charging frequency (i.e. number of charging events), the choice of charging type (e.g. 11 kW at 32 c/ kWh), the choice of charging station (e.g. distance to destination = 500 m and provider = RWE) and the choice of timing (e.g. synchronized with activity duration). When a driver chooses a charging station, he thereby defines a destination, respectively an intermediate destination, which has implications on route choice and potentially influences driving time, energy consumption and walking time. The choice of charging station also predefines a set of possible charging types. A charging type determines the maximum charging power, whereby the maximum charging power defines a lower bound on charge time for a given energy intake, respectively an upper bound on energy intake for a given charge time. Maximum charging power and unit energy cost are generally proportional, and hence, charge time and charging cost are inversely proportional. Charge time has implications on waiting time, while energy intake has implications on charging frequency.

Changes in choice interaction characteristics

Changes in choice interaction characteristics may be caused by new component characteristics (e.g. HVAC system), new choice dimensions (e.g. choice of charging strategy) or leveraged choice dimensions (e.g. driving behaviour). The following paragraphs should be understood as a very brief account. They intend to highlight and explain only the most significant anomalies of EV travel when compared to internal combustion.
3.3 Experimental Setup and Procedure

engine (ICE) vehicle travel.

**Choice of charging type:** Its equivalent in ICE vehicle travel is the choice of petrol station. Petrol station choice assumes a constant refuelling time, with an average duration of 12 min per refuelling event. It assumes a variable petrol price, with price variations in the range of 20 cent (resp. 15%). In contrast, the choice of charging type assumes both variable charge time and variable energy price. Charge time and energy price are inversely proportional. Energy price variations are in the range of 30 cent/kWh (resp. 150%) across charging types. Charge time varies in the range of 20 min – 7 hours. Hence, the choice of charging type has a pronounced influence on travel cost and a leveraged impact on timing decisions (e.g. departure time, driving time). The impact is significantly larger than the one of petrol station choice in ICE vehicle travel.

**Choice of charging frequency:** While ICE vehicles refuel every 400 km to 800 km, EVs are required to recharge every 80 km to 200 km. Charging frequency has an implication on waiting time. Whilst a higher charging frequency tends to reduce charge time and therefore tends to reduce the magnitude of waiting time periods, it also increases the frequency of waiting time occurrence. Whether a higher charging frequency acts against or in favour of waiting time, greatly depends on activity frequency and activity duration. Hence, a systematic approach requires a joint optimization of charging frequency, charge time and activity choice.

**Walking time:** In ICE vehicle travel, walking time purely relates to parking choice. In EV travel, walking time also relates to charging choice. Assume, a charging event starts upon arrival at a charging station and terminates upon departure from the said charging station. Then, zero waiting time requires the charge time to be equal to the activity duration plus the forward and backward walking time. Excess charge time produces waiting time, thereby creating a link between waiting time, walking time, activity duration and charge time.

**Energy intake:** In ICE vehicle travel, fuel intake follows from simple cost considerations. In EV travel, energy intake follows from a complex evaluation process. Energy intake is governed by pre-trip choices, encompassing, amongst others, the choice of charging frequency, charge time and activity. The energy intake determines the energy budget for the trips ahead and thereby affects all on-trip travel decisions that are related to vehicle consumption. The said on-trip decisions encompass, amongst others, the choice of driving mode and comfort settings.

**Choice of comfort settings:** In ICE vehicle travel, the influence of auxiliary consumers on overall vehicle consumption is often neglected. Engine waste heat is used to control the cabin temperature. Engine excess energy is used to supply auxiliary consumers. In EV travel, waste heat and excess energy are not available, and hence, heating power directly affects vehicle consumption. Under extreme conditions, the contribution of auxiliary consumers to overall vehicle consumption may be as large as 50%. The consumption of auxiliary consumers grows linearly with driving time, and hence, a strong link is established between the choice of comfort settings and the choice of route.

**Driving mode choice and longitudinal guiding choices:** For a given route, the longitudinal guiding behaviour and the choice of driving mode considerably influence vehicle consumption. The influence strongly varies with road environment, and hence, these
choices are strongly related to route choice. The said interdependencies also exist in ICE vehicle travel. Yet, due to EV consumption characteristics, in particular their ability to recuperate energy, the characteristics are considerably different.

**Route choice**: As has been stated before, EV route choice is closely related to driving mode choice, longitudinal guiding decisions and the choice of comfort settings. While route choice, longitudinal guiding decisions and driving mode choice mainly interact in the spatial domain, the choices of route and comfort settings mainly interact in the temporal domain.

Dovetailing of travel decisions and range restrictions

In the presence of range restrictions, the decision making process of a traveller has to obey additional constraints. The additional constraints from the range restrictions apply only to those choice dimensions that influence vehicle consumption. Examples of these dimensions are route choice, driving mode choice and the choice of comfort settings. Vehicle consumption is a result of the joint effect of said choice dimensions rather than the sum of the individual effects. Thus, range restrictions constrain choice combinations, respectively attribute-level combinations in SP experiment terminology.

In mathematical terms, let $c_i$ be a set of feasible choices of the $i$-th choice dimension. Let $C_k \subseteq c_1 \times \ldots \times c_k$ be a set of feasible choice combinations containing $k$ different choice dimensions. Let a function $f$ map a choice combination to the residual range of the vehicle, $f : C_k \rightarrow \mathbb{R}$. Then, a range restriction can be defined as a constraint on the co-domain of $f$, and thus, as a restriction on the feasible set of choice combinations. $C_k^+ \subset C_k$ is said to be the subset of choice combinations that obey the range constraint, while $C_k^- \subset C_k$ is said to be the subset of choice combinations that violate the range constraint.

For example, let $c_1 = \{\text{fast}, \text{eco}, \text{normal}\}$ be the set of feasible route choices, $c_2 = \{17^\circ \text{C}, 19^\circ \text{C}, 22^\circ \text{C}\}$ be the set of feasible cabin temperature choices and $c_3 = \{\text{level}_1, \text{level}_3, \text{level}_5\}$ be the set of feasible driving mode choices. Furthermore, assume a mean route distance of 40km between an origin and a destination location and an ambient temperature of $0^\circ \text{C}$. Assume $C_3^+ = c_1 \times c_2 \times c_3$. Then, all elements of $C_3^+$ satisfy residual range $\geq 40$km and all elements of $C_3^-$ cause residual range $< 40$km. An example of a feasible choice combination of $C_3^+$ is the limit case, where a traveller chooses the most energy efficient combination $\{\text{eco}, 17^\circ \text{C}, \text{level}_3\}$, thereby provoking residual range $= 50$km. An example of an infeasible choice combination of $C_3^-$ is $\{\text{fast}, 17^\circ \text{C}, \text{level}_1\}$, producing residual range $= 35$km. Yet, this infeasible combination is rendered a feasible combination, if $\{17^\circ \text{C}, \text{level}_1\}$ is combined with a route choice from the set $\{\text{eco}, \text{normal}\}$ instead of $\{\text{fast}\}$.

As can be seen, range restrictions introduce a nesting of attribute levels, whereby the nesting depends on the range value and the driving context. A context dependent nesting has proven to be too complex for a respondent to fathom. Nesting is therefore circumvented by an appropriate choice of attribute levels, as will be seen later.
3.3 Experimental Setup and Procedure

Holistic decision problem of EV travel

Figure 3.1 illustrates the holistic decision problem of EV travel. It shows a two-trip segment of a trip-chain. The activity frame is given by an activity pattern \(<\text{home, work, secondary purpose}>\). The set of travel decisions encompasses widely-accepted choices (vehicle route choice, pedestrian route choice, departure time choice, parking choice), electric vehicle specific choices (choice of charging strategy) and in-vehicle/en-route comfort choices (driving mode choice, longitudinal guiding choices, choice of comfort settings). The choice dimensions are combined both across the stages of a trip and across the trips of the activity-chain, thereby producing a set of feasible choice combinations, denoted by $C_k^+$, with $k = 7$ in the case of figure 3.1. A choice combination is described in terms of travel performance attributes, which encompass departure time, driving time, walking time, arrival time, energy consumption, adherence to preferred climate-comfort, adherence to preferred driving mode, parking cost, charging frequency, charging induced waiting time and travel cost, whereby the travel cost is obtained from energy consumption and charge price (resp. unit energy price).

In conclusion, EV anomalies change the traveller’s decision making process significantly. This is due to additional choice dimensions and a pronounced interdependency of choice dimensions, where residual range acts as a context dependent constraint on the choice combinations. EV travel preferences are likely to differ from ICE vehicle travel preferences. In particular, they must reflect the relative valuation of widely accepted choice dimensions, EV specific choice dimensions, en-route comfort choices and their mutually dependencies across the trips of a trip-chain. Current SP approaches fall short in capturing most of these EV anomalies.

Due to the low market penetration of EVs, travellers mostly do not have a sound understanding of the decision problem of EV travel. A design of a holistic SP experiment therefore needs to pay particular attention to choice realism. The design target of the choice experiment is therefore two-fold: create choice situations that are compliant with current experience, on the one hand, and integrate the underlying constraints of EV travel, on the other hand.

![Figure 3.1: Holistic decision problem of EV travel, exemplified for a two-trip segment of a trip-chain. Refer to the author’s publication [HZWS12] for an earlier version.](image-url)
3.3.2 Attributes and Attribute Levels

A stated preference experiment must reflect the real process of consideration of a consumer, which requires attributes to reflect his real decision criteria and attribute levels to reflect his real market experience or, in the case of new products, a justifiable assumption. Attribute inference thus requires a precise description of the characteristics of the underlying decision problem. While the general decision problem of motorized travel is subject to an extensive amount of studies [e.g. BAL85, Hal99], section 3.3.1 has provided an extension towards the specific anomalies of EV travel. Based upon the specific description of the EV decision problem, this section discusses attribute selection and the definition of attribute types and levels.

As described in [Hen94] attributes can be employed in two different ways. Either an attribute is included in the context-setting part of a choice experiment or in the attribute set of a product profile. The product profile may either represent an unranked (resp. unlabelled) alternative or a ranked (resp. labelled) one. The following paragraphs discuss the attribute selection, starting with the specification of the attributes that go into the product profile of the choice experiment, denoted by profile attributes, followed by the specification of the attributes that go into the context-setting part of the choice experiment, denoted by context attributes.

The set of profile attributes encompasses two subsets. A first subset reflects the general decision problem of motorised travel, comprising the attributes of driving time, walking time, late arrival time (denoted by "deviation from scheduled arrival time"), parking cost (denoted by "parking fee") and driving cost. A second subset models EV specifics, namely charging frequency (denoted by "number of charging events"), comfort settings (denoted by "cabin temperature"), waiting time (denoted by "charging induced waiting time at the car") and driving mode (denoted by "driving dynamics"). The profile set omits a number of attributes, among them departure time, charge time, charging type, energy consumption and residual range. Said attributes are either integrated with existing profile attributes or left out completely, which shall be briefly justified.

Concerning departure time and charge time, it is argued that a respondent jointly assesses time related attributes if they form a closed temporal sequence, thereby threatening an independent treatment of the profile attributes. A closed temporal sequence requires the time related attributes – i.e. departure time, driving time, walking time, arrival time, charge time and waiting time – to be concerted, in order to avoid implausible combinations. This requires a nesting approach, which increases mathematical design complexity. Without a nesting approach, test persons have reported implausible choice situations during preparatory studies. The exclusion of departure time and charge time from the set of profile attributes generates an open temporal sequence, making it impossible to generate implausible temporal combinations, and thus, avoiding attribute nesting. In the face of an open temporal sequence, test persons have shown a naturally independent assessment of timing attributes, which has been confirmed by a reduction in the correlation values of the coefficient estimates and by a thinking-aloud test, where test persons have commented on their decision process.

Concerning the charging type attribute, it is found that test persons have little under-
standing of the implications of charging type and therefore disrespect the said attribute altogether. Concerning the attributes of energy consumption and residual range, it is argued that, in the face of little or no EV experience, test persons are strongly biased by the significant press attention directed towards EV consumption and range. Preparatory studies also suggest a particular bias from political opinion (e.g. ecological) and human personality (e.g. anxiety). Given the previous discussion, an explicit integration of departure time, charge time, charging type, energy consumption and range may not be advisable, which is due to nesting constraints, attribute comprehensibility and attribute bias. As a corrective measure, the dependency of charge time, charging type and energy consumption is exploited in order to jointly integrate said attributes in the driving cost attribute, thereby providing an implicit but meaningful representation, which is in line with customer experience. Departure time and range are omitted completely.

The context-setting part of the choice experiment encompasses three attributes, namely activity purpose, trip length and ambient conditions. The selection of these attributes shall be briefly justified.

Research has described a strong connection between activity choice and travel choice [e.g. Cas09]. Activity choice is a complex process, whose output is an activity chain, where each activity is described by location, purpose (e.g. work, leisure) and timing characteristics (e.g. start time, duration). EV travel establishes a particularly close connection between the number of activities and the choice of charging frequency. It also establishes a particularly strong link between activity duration, charge time and waiting time, and thus, the universally recognized connection between activity choice and travel choice is particularly pronounced in EV travel, which suggests that activity purpose is integrated into the context-setting part of the choice experiment.

Research has investigated the valuation of time [e.g. MJDF01]. Criteria have been analysed which influence the individual value of travel time savings. As described in [MJDF01], trip length has a considerable influence on the valuation of travel time savings. To account for the said dependency, trip length is added to the context-setting part of the choice experiment.

Concerning ambient conditions, a clinical trial has been conducted to analyse the customer’s sensitivity towards changes in cabin temperature. It has been found that ambient temperature has a significant influence on the assessment of interior cabin temperature. To account for the impact of ambient temperature on the valuation of interior cabin temperature, ambient temperature is added to the context-setting part of the choice experiment.

Table 3.1 summarizes both the profile attributes and the context attributes of the choice experiment. The attributes are defined by attribute name, unit of measure (e.g. min, €), scale of measure (e.g. continuous, ordinal) and over a set of attribute levels, which will be discussed in the following paragraphs.

Following the description in [Hen94], the definition of attribute levels follows realism considerations, that is, conformity to experience in the case of existing alternatives and a high degree of believability in the case of new alternatives. This thesis employs a three step procedure to guarantee the realism of the attribute levels.

The first step involves an analysis of the travel context in the sample region. Departure
time shifts and waiting time shifts are chosen in accordance with SP experiments in transportation literature. A clinical trial is conducted in order to analyse the customer’s sensitivity towards changes in cabin temperature. Route alternatives are computed\(^1\) for a set of travel choices (departure time choice, driving mode choice, cabin temperature choice) and a set of origin-destination (OD) pairs from the sample region (Braunschweig, Wolfsburg). The route alternatives are evaluated with respect to driving time and energy consumption. Online sources are consulted for parking fees and charging rates. The charging rates and energy consumption values are combined in order to derive the driving cost. Charging frequency is obtained from an assessment of real-world EV fleet data, where the mean and maximum charging frequency are evaluated for a reference day. As a result of the first step, objective ranges are obtained for possible attribute level values.

In a second step, these objective ranges are presented for discussion in an expert group, whereby the range of attribute levels is described by a tuple \{minimum, mean, maximum\}. The objective attribute level range may greatly differ from what a test person perceives as a realistic range. In order to capture perception bias, test persons are asked to add subjective values to the attribute ranges. Each test person provides a subjective minimum value, denoted by awareness threshold, and a subjective maximum value, denoted by dominance threshold. The awareness threshold defines a value, below which an attribute is perceived insignificantly small and is thus disrespected during the process of consideration. The dominance threshold defines a value, above which an attribute dominates all remaining attributes and thus distorts the true process of consideration. Undershooting the awareness threshold and exceeding the dominance threshold renders a choice situation statistically meaningless. The awareness and dominance thresholds of the first expert group are used to subjectify the impartial ranges from the first step. It should be noted that response data produces distributions of awareness and dominance values. The awareness distribution overlaps with the dominance distribution, meaning that attribute level values exist that are insignificantly small for some test persons while being dominantly large for others. Moreover, it should be noted that the distribution characteristics of the driving mode values propose a two-level design of the "driving dynamics" attribute. Test persons distinguish only the unlimited case, respectively driving mode \textit{level}_{1}, and the perceivably limited cases, covering the set of driving mode levels \{level_{3}, level_{4}, level_{5}\}. The distinction is likely to be caused by a lack of experience and may therefore change in the near future when drivers gain experience with electric vehicles and automatic driving.

In a third step, choice profiles are generated. The profiles employ the subjectified attribute levels from the second step. All profile attributes, except for driving mode, are defined as three level attributes, thereby allowing for an analysis of potential non-linearities. In the absence of nesting, many choice situations are reported implausible. For example, consider "number of charging events" to be a three level attribute defined over the values \(x_{num} = \{0,1,2\}\) and "charging induced waiting time at the car" to be a

\[^{1}\] Route alternatives are computed with the method described in chapter 5 and chapter 6.
three level attribute defined over the values $x_{WTch} = \{0, 8, 15\}$. Then, any combination of $x_{num} = \{0\}$ and $x_{WTch} = \{8, 15\}$ is implausible. To avoid implausibility, attribute levels can be adjusted in one of two ways: reducing the number of attribute levels or shifting the attribute values. Given the above example, one may reduce the number of attribute levels, so that $x_{num} = \{1, 2\}$, or shift the attribute level values, so that $x_{num} = \{1, 2, 3\}$. A value of $x_{num} = \{3\}$ would exceed the dominance threshold of the choice experiment, which is why a decision is made in favour of two attribute levels rather than shifted attribute level values. A plausibility check is performed for all attribute level combinations. The final selection is shown in table 3.1.

<table>
<thead>
<tr>
<th>Attribute Name</th>
<th>Variable</th>
<th>Unit of measure</th>
<th>Scale of Measure</th>
<th>Attribute Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>driving time</td>
<td>$X_{Tdrive}$</td>
<td>min</td>
<td>continuous</td>
<td>[25, 36, 45]</td>
</tr>
<tr>
<td>walking time</td>
<td>$X_{Twalk}$</td>
<td>min</td>
<td>continuous</td>
<td>[1, 8, 15]</td>
</tr>
<tr>
<td>deviation from scheduled arrival time</td>
<td>$X_{WTarr}$</td>
<td>min</td>
<td>continuous</td>
<td>[0, 10, 15]</td>
</tr>
<tr>
<td>charging induced waiting time at the car</td>
<td>$X_{WTch}$</td>
<td>min</td>
<td>continuous</td>
<td>[0, 8, 15]</td>
</tr>
<tr>
<td>driving cost</td>
<td>$X_{Cdrive}$</td>
<td>€</td>
<td>continuous</td>
<td>[2, 3, 4]</td>
</tr>
<tr>
<td>parking fee</td>
<td>$X_{Cpark}$</td>
<td>€</td>
<td>continuous</td>
<td>[0, 1, 2]</td>
</tr>
<tr>
<td>number of charging events</td>
<td>$X_{num}$</td>
<td>–</td>
<td>ordinal</td>
<td>[1, 2]</td>
</tr>
<tr>
<td>driving dynamics</td>
<td>$X_{dyn}$</td>
<td>mode</td>
<td>ordinal</td>
<td>[unlimited, limited]</td>
</tr>
<tr>
<td>cabin temperature</td>
<td>$X_{temp}$</td>
<td>°C</td>
<td>continuous</td>
<td>[17, 19, 22]</td>
</tr>
<tr>
<td>Activity purpose</td>
<td>$X_{act}$</td>
<td>–</td>
<td>ordinal</td>
<td>[work]</td>
</tr>
<tr>
<td>Trip distance</td>
<td>$X_{dist}$</td>
<td>km</td>
<td>continuous</td>
<td>[40]</td>
</tr>
<tr>
<td>Ambient temperature</td>
<td>$X_{amb}$</td>
<td>°C</td>
<td>continuous</td>
<td>[0]</td>
</tr>
</tbody>
</table>

Table 3.1: Specification of attributes and attribute levels of the choice experiment, encompassing the attributes from the profile set (1-9) and the attributes from the context-setting part (10-12).

3.3.3 Choice Set Generation and Formatting

The choice experiment is embedded into a three part online survey. Part one contains questions on socio-demographic and socio-economic characteristics. Part two asks for a travel diary of a reference day. Part three contains the choice experiment. Part three is divided into two sections. The first section introduces the specifics of EV travel. The
second section presents a number of choice sets.

As has been stated earlier, the perceived complexity of survey completion is a subjective measure. No clear set of rules exists to assess complexity other than asking respondents. If an SP experiment is embedded into a larger survey, two complexity analyses are required. One analysis evaluates aggregate survey complexity, which describes the perceived load when completing all three parts of the online survey. A second analysis assesses SP complexity, which describes the perceived load when completing the choice experiment part of the survey separately. Aggregate survey complexity and SP complexity must adhere to the respondents’ load thresholds. To test this, the load perception of 16 test persons is rated. The test persons are asked to complete the three-part online survey as a thinking aloud test. They are asked to judge aggregate survey complexity and SP complexity, in particular, to define an upper bound on the number of choice situations and on the number of attribute levels that are allowed to vary across the profiles of a choice situation. It is found that respondents accept a maximum of 16 choice situations containing two profiles each and at most 4 attribute levels that vary across the profiles.

Inversely, the choice model defines a lower bound on the number of choice profiles, respectively the factorial of the choice experiment. From a purely statistical viewpoint, a full factorial design achieves maximum efficiency. Yet, a full factorial design scales exponentially with the number of attributes and attribute levels, for which reason it is unusable in most practical cases. An alternative to a full factorial design is a fractional factorial design, which employs a portion of the full factorial treatment combinations. The design challenge of a fractional factorial is to reduce the number of treatment combinations at the smallest possible loss of statistical efficiency. Many researchers have addressed the design challenges of fractional factorials [e.g. SBL05, LHSA00]. For the herein discussed model (see section 3.3.4), the fractional factorial must allow for an efficient estimation of all main effects.

The three-part survey is provided as an online survey, which is hosted on a server. Authentication information and a link are emailed to the test persons. Organisational restrictions constrain the maximum sample size to 500 test persons. With an expected return rate of 50% – 80%, the predicted sample size is around 300 test persons. Monetary restrictions allow for at most two surveys, and hence, at most two blocks. Given both the upper bound from the complexity analysis, the lower bound from the model and the constraints on sample size and blocking, it is preferable to design an SP experiment, which comprises two blocks with 16 choice situations per block and two profiles per choice situation producing a total of 64 choice profiles, allowing for at most four attribute levels to vary across the profiles of a choice situation. With an expected sample size of 300 test persons, this produces 4,800 choice responses, from which the modelled effects are estimated.

A choice experiment is designed, which obeys all of the aforementioned boundary conditions. It is generated under the assumption that all prior estimates are zero. This choice experiment is presented to a third expert group of 32 test persons. Response data is used to compute prior-estimates. Prior estimates represent a priori knowledge about the means and variances of the coefficients and assist the construction of plausible
and efficient choice situations. The final SP experiment is computed on the basis of the said prior-estimates. As expected, the final SP experiment shows superior mathematical efficiency when compared to the earlier SP versions. The mathematical design is performed using the choice modelling package of JMP\textsuperscript{1}. Refer to [JMPa, JMPb] for a technical documentation of JMP. Many text books and articles address the mathematical concepts of choice experiment design, among them [SB07, SBL05, LHSA00]. A comprehensive technical report on the concepts of choice design is provided by [Kuh10].

Given the final design, figure 3.2 shows the formatting of the SP experiment. A two-part layout is chosen. Figure 3.2(a) depicts the context-setting part of the choice experiment. Figure 3.2(b) shows the profile attributes. The context setting part encompasses activity purpose, trip distance and ambient temperature, all of which are modelled as one-level attributes. The profile set comprises nine attributes, whose specification follows from table 3.1. Meta-attributes – time, cost and comfort – are used to cluster the profile attributes. The choice profiles are unlabelled. They are named option 1 and option 2.

3.3.4 Model Description

As described in section 3.1, a choice model contains a deterministic part and a stochastic part. The deterministic part defines the coefficients $\beta$ and the variable attributes $X$ of the linear-in-parameter utility function. The stochastic part defines the distribution of the random term $\varepsilon$, which accounts for the modelling uncertainty of the deterministic part when compared to the real process of consideration of a customer. Attributes $X$ may represent socio-economic characteristics, profile attributes, dummy variables or a combination of them. They may be continuous or discrete-valued (e.g. ordinal). Attributes may reflect a linear relationship or a non-linear one. Coefficients $\beta$ represent the relative travel preferences of a customer. They may be alternative-specific constant, alternative-specific socio-economic or generic. Additional coefficients $\gamma$ may be introduced to model parameter elasticities. The terms of the model capture either one of the following effects: main effects, first-order interaction effects, higher-order interaction effects or parameter elasticities. The modelled effects determine the minimum number of choice profiles that are required to estimate the coefficients, namely the taste parameters $\beta$ and the elasticities $\gamma$.

This thesis confines itself to the estimation of main effects. The main effect model is shown in table 3.2. Main effects are estimated from a fractional factorial SP experiment. The minimum size of the fractional factorial follows from the modelled effects and the attribute characteristics. In the case where all three-level attributes of table 3.1 are continuous and linear, the smallest fractional to estimate all main effects contains 9 choice situations. In the case where all three-level attributes of table 3.1 are either discrete-valued or continuous and non-linear, the smallest fractional to estimate all main

Figure 3.2: Holistic choice situation of electric vehicle travel, with (a) describing the context-setting part and (b) depicting the profile attributes of the holistic choice situation. The SP experiment is unlabelled, distinguishing option 1 and option 2. It is translated from the German language.

Effects contains 16 choice situations.

Transportation studies have suggested several interaction effects between attributes. The estimation of first-level or higher-level interaction effects requires significantly larger fractional factorials than does the estimation of main effects only. For the study at hand, the smallest fractional factorial to estimate the degrees of freedom of all first-level interaction effects, respectively two-level interactions, comprises of 113 choice situations. For the study at hand, the estimation of interaction effects likely fails to produce significant results, given the minimum size of the fractional factorial, on the one hand, and the constraints on choice complexity and sample size, on the other hand. This is particularly true for the customer segment analysis. Errors are introduced, when interaction effects are present in the actual decision process of the traveller but neglected by the model. Said errors dominate at the limits of the utility space and diminish elsewhere [LHSA00, p. 88]. Hence, the herein presented main effect model should be most comprehensive in the region of interest, while predictions should be considered with care at the limits of the utility space.

A large number of the modelling approaches of section 3.2 are motivated by travel-
3.3 Experimental Setup and Procedure

demand prediction, where choice models frequently include main effects, interaction effects and elasticities of socio-economic attributes. In contrast, this thesis focuses on real-time decision support, where travellers receive holistic and personalized recommendations both pre-trip and en-route. Although the influence of socio-economic characteristics on travel decisions is well-justified, socio-economic data is unavailable to the decision support system during operation. Consequently, the herein presented model omits socio-economic main effects (e.g. gender, age), socio-economic interaction effects (e.g. gender and walking time, gender and cabin temperature) and socio-economic elasticities (e.g. income elasticity of travel cost). Neglecting the effects from socio-economic attributes is a source of estimation error, and yet, it is inevitable to omit these effects in real-time decision support systems, if travellers are not willing to provide socio-economic information.

Ideally, the attributes from table 3.1 should be relevant and exhaustive. De facto, exhaustiveness only holds within the previously discussed limits. It cannot be tested and is a potential source of error, whereby only a rough estimate can be made about the magnitude of error. Relevance can be investigated with statistical tests. The likelihood ratio test evaluates the null hypothesis that a restricted model performs equally good as a non-restricted model, whereby a model is said to be restricted if the marginal effect of two or more attributes is equal, and hence, the dimension of the taste vector is reduced by the number of independent restrictions. The likelihood ratio test computes the difference of log-likelihood values of the restricted and the non-restricted model. As to [LHSA00, pp. 114] said approach can also be used to test parameter genericness, where the log-likelihood of an alternative-specific approach is compared to the one of a generic approach. For the herein discussed model, a generic approach can also be logically justified. Consider a first case, where all attribute values are equal but different from zero. There is no plausible explanation for a difference in utility between the unlabelled choice options, and hence, alternative specific taste preferences are unlikely to be present. Consider a second case, where all attributes are zero. Again, there is no plausible explanation for a difference in utility between the unlabelled choice options, and hence, alternative specific constant taste preferences are also unlikely to be present.

3.3.5 Discussion

SP approaches in transportation commonly aim at one of the following three objectives: (1) predict travel demand of a population in order to assist policy decisions, (2) analyse the willingness to pay for transportation measures and infer market shares, (3) help design attractive transportation products. The main objective of this chapter is somewhat different from the common objectives of transportation planning. It aims at the personalization of real-time decision support systems, thereby producing travel recommendations that are in line with the driver’s personal travel preferences. From the objective of this chapter follow three implications: First, an interest in particular customer groups, namely drivers with privately owned vehicles and either a distinguished number
Main effect model, involving option $Y_i$ and option $Y_j$, and a travel context as described by the context-setting part of the choice experiment (i.e. home-work trip, 40km travel distance, 0°C ambient temperature)

$$U_{ni} = \beta_1 X_{Tdrive_i} + \beta_2 X_{Twalk_i} + \beta_3 X_{WTarr_i} + \beta_4 X_{WTch_i} + \beta_5 X_{Cdrive_i} + \beta_6 X_{Cpark_i} + \beta_7 X_{num_i} + \beta_8 X_{dyn_i} + \beta_9 X_{temp_i}$$

$$U_{nj} = \beta_1 X_{Tdrive_j} + \beta_2 X_{Twalk_j} + \beta_3 X_{WTarr_j} + \beta_4 X_{WTch_j} + \beta_5 X_{Cdrive_j} + \beta_6 X_{Cpark_j} + \beta_7 X_{num_j} + \beta_8 X_{dyn_j} + \beta_9 X_{temp_j}$$

**Table 3.2:** Main effect model of holistic EV travel choice, with generic coefficients and attributes as defined in table 3.1.

of daily trips or a high sensitivity towards personal resource savings; second, a choice model that is independent of socio-economic data, which is not available in navigation systems and is likely to be absent in the future due to privacy regulations; third, a main effect model, which produces significant estimates with a relatively small number of choice situations and a limited sample size.

The aforementioned characteristics of the herein taken approach are a possible source of error. The absence of socio-economic variables in the model and the homogeneity of the sample population are likely to introduce estimation bias. As to [LHSA00, p. 105 et seqq.], successive responses of the same individual and non-modelled preference heterogeneity across respondents violate the IID assumption, rendering parameter estimates inefficient, yet consistent across the sample. Additionally, the neglect of interaction effects may produce an aliasing effect, which distorts the estimates of the main effects, for a detailed discussion refer to [LHSA00, p. 94 et seqq.].

EVs have been gaining significant press attention and are subject to controversial debates. In public, EVs are seen as a disruptive technology. Customers have little or no real EV experience. The opinion of respondents is therefore likely to be manipulated by the current mood and influenced by political opinion and personality. Consequently, the behaviour of respondents in an artificial choice situation is likely to be biased. Concerning the influence of personality, an investigative study has been performed by the author. The study analyses the effect of human personality on the acceptance of holistic and personalized EV travel planning systems. A standard acceptance test is used. Human personality is modelled by the well-known five factor model (FFM). A prototype travel planning system is presented to the test persons. Correlating the two data sets, a statistically significant correlation is found between system acceptance and the personality factor of openness to experience. No significant correlation is found for the remaining personality traits. This suggests that the behavioural bias, when conducting the SP experiment, may be particularly large if people show an extreme value of openness to experience. Logically, this trend may apply to all disruptive technologies, which however, requires further investigation.
In conclusion, the first paragraph suggests that parameter estimates are meaningful for the herein presented purpose, and yet, due to sampling characteristics and the absence of socio-economic variables in the model, should be treated with care when estimating population demand and inferring policy decisions. The second paragraph suggests that EV travel preference is likely to be biased by political conviction and human personality, whereby the magnitude and particular characteristics will need to be investigated in greater detail.

3.4 Discrete Choice Experiment Results

A total of 500 test persons in northern Germany were asked to complete the three-part online survey. Within a four weeks test period, 217 respondents successfully completed the online survey, which amounts to a return rate of 43.4%. A number of 117 respondents (54%) completed survey1, containing the first block of choice experiments. A number of 100 respondents (46%) completed survey2, containing the second block of choice experiments. The remaining 283 respondents had either not started the survey, started but aborted the survey or completed but incorrectly answered the survey.

Given the response data, this section has a threefold objective: (1) to analyse the socio-demographic and socio-economic characteristics of the sample, (2) to estimate the aggregate travel preferences of the sample and (3) to analyse the disaggregate travel preferences of customer segments, which are clustered from the sample.

The socio-demographic and socio-economic characteristics are presented in section 3.4.1. Similarities and differences are discussed between the sample group and the German population mean. Section 3.4.2 presents aggregate estimation results, which are based on the full sample of 3472 observations. The results comprise taste estimates, parameter ratios and willingness to pay values. Statistical tests are used to test for parameter relevance (e.g. log-likelihood ratio test) and the significance of the estimated values (e.g. t-test). Section 3.4.3 presents the disaggregate estimation results of the customer segments, whereby the customer segments are obtained from the aggregate population by the use of Ward’s method, which clusters respondents by taste gradient, so that the consistency of taste is maximized within a segment and minimized across segments. Again, parameter estimates are statistically tested for relevance and significance.

3.4.1 Evaluation of Respondent Statistics

It has been argued that the particular objective of the SP experiment, namely the personalization of real-time decision support systems, requires some respondent characteristics to be oversampled (e.g. proportion of drivers), while other characteristics (e.g. age distribution) should be in line with the German population mean in order to satisfy large sample characteristics. The socio-demographic and socio-economic characteristics of the said 217 respondents are presented in table 3.3 and are discussed in the following.
The employment rate of the sample is 100%. When applying the naming convention of the international standard classification of occupations, the sample encompasses mostly professionals and managers. 86% of the test persons are pay-scale workers, while 14% hold non-pay-scale management positions. 96% of the sample have flexible working arrangements, which define either a fully flexible arrangement, where workers have genuine control over start time and duration, or a partially flexible arrangement, where workers are given a two hour start time window and a three hour duration time window.

The proportion of men in the sample is 81%. When comparing this value to the gender distribution of the Braunschweig-Gifhorn-Wolfsburg area, given in [Stab], male population is considerably overrepresented (+32%). Yet, the proportion of men in the sample matches the said distribution, when the data is adjusted by occupational field as available from [Stad].

The German age distribution is given in [Staa]. A comparison of the German age distribution with the sample reveals an undersampling at the extremes of the age scale: 18-25 years (−8.6%) and 56-65 years (−12.8%). The remaining age groups are slightly oversampled, with 26-35 (+0.2%), 36-45 (+11.9%) and 46-55 (+11.3%).

Private households are usually classified by household type, distinguishing "single-person", "single parent", "couples without child" and "couples with child". The distribution of household types in Germany is given in [Stac]. When comparing the sample to the German population mean, "couples without child" and "single parent" households are in line with the German household characteristics, while "couples with child" (+27%) are overrepresented and "single-person" households (−27%) are underrepresented.

The car availability of the German population is given in [Ins13, FGJ+10]. Alternatively, it can be computed from the German level of motorization, given in [The], and the German household characteristics, given in [Stac]. The car availability of the sample amounts to 99%. This significantly exceeds the German population mean. It also exceeds car availability of reference studies, such as [AZS+02]. Motorization is known to be positively correlated with household net income, which may partially explain the overrepresentation of households with one or many cars.

In the sample, the proportion of EV drivers is 17.5%. This significantly exceeds EV market share. All EV drivers report private parking spaces with home charging facilities. Concerning the ICE vehicle owners, 58.5% of the sample have access to a private parking space with a retrofitting option, while 12% of the sample rely on public parking.

The sample shows an average of 3.8 trips per person and day. This is in line with the German population mean, as given in [FGJ+10], where the average number of trips per day and person is 3.4, respectively 3.6 when averaged over "couples with child". Note, that the data is sampled for a Friday workday, justifying the surplus of 0.4 (resp. 0.2) trips per person and day.

The sample’s average home-work travel distance is around 30km. As a reference, mean daily travel distance of the German population is 39km [FGJ+10]. It is shown to be positively correlated with net household income and car availability. When compared with one vehicle households, two vehicle households show an increase in daily mileage by +18.5%, while two and more vehicle households show a plus of +37%, see [FGJ+10]. In
it is also shown, that daily mileage is generally larger for males (+39.5%), age groups between 18 years and 55 years, employed persons, non-urban population and motorists, all of which are overrepresented in the herein presented sample, explaining all or at least some of the differences in travel distance.

In conclusion, the sample fulfills the aforementioned objectives of this chapter. It provides a reasonable gender distribution, when adjusted by occupation. Its age distribution shows similar mean and slightly smaller variance than the German population. The sample shows justifiable values of trip distance and a good distribution of trip frequency. Car availability is deliberately oversampled and so are EV drivers. The sample’s income distribution is shifted towards higher income levels when compared to the German net income distribution, as given in [FGJ+10]. The only flaw in the study is the distribution of household type. “Couples with child” are oversampled while “single-person” households are underrepresented.

3.4.2 Evaluation of Aggregate Population Estimates

This section presents the results of the SP study at the aggregate level of the sample population. The results are computed from the entire set of observations (3472). They comprise taste coefficient estimates, coefficient ratios and willingness to pay values. Statistical tests are used to evaluate the relevance of the coefficients (e.g. log-likelihood ratio test) and the significance of the estimated values (e.g. t-test). The coefficient estimates for the main effect model of table 3.2 are computed with Biogeme [Bie03] and are shown in table 3.4(a).

For a structured discussion of the results, let $\beta_{\text{exp}} = \{\beta_1, \beta_2, \beta_3, \beta_5, \beta_6\}$ be the subset of widely accepted taste coefficients, which have been examined by numerous SP experiments in transportation literature, and for which exists an expectancy of sign and value. Let $\beta_{\text{nov}} = \{\beta_4, \beta_7, \beta_8, \beta_9\}$ be the subset of novel taste coefficients, which have not been examined in literature before and therefore require justification of value and sign.

All elements of $\beta_{\text{exp}}$ have negative sign, which agrees with the findings from literature. The time related coefficients $\{\beta_1, \beta_2, \beta_3\}$ have similar magnitude. They are in the range of $[-0.155, -0.113]$. Among them, $\beta_2$ has highest absolute value, implying a stronger preference for a reduction in walking time than driving time or late arrival. The cost related coefficients $\beta_5 (-0.717)$ and $\beta_6 (-0.696)$ show similar values at the aggregate level of the population, while the expected difference in the valuation of cost components becomes apparent at the disaggregate level of the customer segments, as will be seen later. When comparing cost and time related coefficients, it is important to note that time related coefficients are given in $[u_{\text{min}}]$ and cost related coefficients are given in $[\bar{u}]$.

The elements of $\beta_{\text{nov}}$ are discussed in two parts: first, a logical justification is given for the sign of $\{\beta_4, \beta_9\}$, and second, a nuanced discussion is provided on $\{\beta_7, \beta_8\}$, for which both signs are possible and no expectancy value exists. Concerning the preference for charging induced waiting time ($\beta_4$), it is logical to expect a decrease in utility from an increase in waiting time. This agrees with waiting time studies, and thus, a negative
<table>
<thead>
<tr>
<th>Attribute</th>
<th>Level</th>
<th>Absolute Occurrence</th>
<th>Relative Occurrence [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Male</td>
<td>176</td>
<td>81.12</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>41</td>
<td>18.89</td>
</tr>
<tr>
<td>Age</td>
<td>18 – 25</td>
<td>13</td>
<td>5.99</td>
</tr>
<tr>
<td></td>
<td>26 – 35</td>
<td>41</td>
<td>18.89</td>
</tr>
<tr>
<td></td>
<td>36 – 45</td>
<td>75</td>
<td>34.56</td>
</tr>
<tr>
<td></td>
<td>&gt; 65</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>Household type</td>
<td>Single-person</td>
<td>24</td>
<td>11.06</td>
</tr>
<tr>
<td></td>
<td>Single parent</td>
<td>13</td>
<td>5.99</td>
</tr>
<tr>
<td></td>
<td>Couple without child</td>
<td>66</td>
<td>30.41</td>
</tr>
<tr>
<td></td>
<td>Couple with child</td>
<td>114</td>
<td>52.53</td>
</tr>
<tr>
<td>Net household income²</td>
<td>&lt; 2000€</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>2001€– 3000€</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>3001€– 4000€</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>4001€– 5000€</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>5001€– 6000€</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>6001€– 7000€</td>
<td>–</td>
<td>–</td>
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<tr>
<td></td>
<td>7001€– 8000€</td>
<td>–</td>
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</tr>
<tr>
<td></td>
<td>&gt; 8000€</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Employment</td>
<td>Flexible work time</td>
<td>179</td>
<td>82.49</td>
</tr>
<tr>
<td></td>
<td>Non-pay scale</td>
<td>30</td>
<td>13.82</td>
</tr>
<tr>
<td></td>
<td>Always</td>
<td>215</td>
<td>99.08</td>
</tr>
<tr>
<td>Car availability</td>
<td>Occasionally</td>
<td>2</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>Never</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>Public parking (NP)</td>
<td>26</td>
<td>11.98</td>
</tr>
<tr>
<td></td>
<td>Private parking (PP)</td>
<td>26</td>
<td>11.98</td>
</tr>
<tr>
<td></td>
<td>PP with charging station</td>
<td>38</td>
<td>17.51</td>
</tr>
<tr>
<td></td>
<td>PP with retrofitting option</td>
<td>127</td>
<td>58.53</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>55</td>
<td>25.35</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>50</td>
<td>23.04</td>
</tr>
<tr>
<td>Average number of trips per weekday</td>
<td>4</td>
<td>61</td>
<td>28.11</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>17</td>
<td>7.83</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>17</td>
<td>7.83</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>2</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>&gt; 7</td>
<td>14</td>
<td>6.45</td>
</tr>
<tr>
<td></td>
<td>0km – 10km</td>
<td>13</td>
<td>5.99</td>
</tr>
<tr>
<td></td>
<td>11km – 20km</td>
<td>54</td>
<td>24.88</td>
</tr>
<tr>
<td></td>
<td>21km – 30km</td>
<td>65</td>
<td>29.95</td>
</tr>
<tr>
<td></td>
<td>31km – 40km</td>
<td>49</td>
<td>22.58</td>
</tr>
<tr>
<td></td>
<td>41km – 50km</td>
<td>19</td>
<td>8.76</td>
</tr>
<tr>
<td></td>
<td>51km – 60km</td>
<td>3</td>
<td>1.38</td>
</tr>
<tr>
<td></td>
<td>61km – 70km</td>
<td>3</td>
<td>1.38</td>
</tr>
<tr>
<td></td>
<td>&gt; 70km</td>
<td>11</td>
<td>5.07</td>
</tr>
</tbody>
</table>

Table 3.3: Socio-demographic characteristics of a sample of 217 respondents.

¹ Collected data is expunged for data privacy reasons.
### 3.4 Discrete Choice Experiment Results

<table>
<thead>
<tr>
<th>Taste Parameter</th>
<th>Unit</th>
<th>Description</th>
<th>Coefficient estimate</th>
<th>Robust Asympt. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>[min]</td>
<td>driving time</td>
<td>-0.113</td>
<td>0.00745</td>
<td>-15.21</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>[min]</td>
<td>walking time</td>
<td>-0.155</td>
<td>0.0132</td>
<td>-11.77</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>[min]</td>
<td>late arrival</td>
<td>-0.115</td>
<td>0.00885</td>
<td>-13.03</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>[min]</td>
<td>charging induced waiting</td>
<td>-0.143</td>
<td>0.00829</td>
<td>-17.27</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>[e$^{-1}$</td>
<td>driving cost</td>
<td>-0.717</td>
<td>0.0626</td>
<td>-11.46</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_6$</td>
<td>[e$^{-1}$</td>
<td>parking fee</td>
<td>-0.696</td>
<td>0.0579</td>
<td>-12.02</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_7$</td>
<td>[stop]</td>
<td>number of charging stops</td>
<td>-0.261</td>
<td>0.0773</td>
<td>-3.38</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_8$</td>
<td>[mode]</td>
<td>driving dynamics</td>
<td>-0.0958</td>
<td>0.0817</td>
<td>-1.17</td>
<td>0.24</td>
</tr>
<tr>
<td>$\beta_9$</td>
<td>[°C]</td>
<td>cabin temperature</td>
<td>0.260</td>
<td>0.0274</td>
<td>9.49</td>
<td>0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Taste Parameter ratio</th>
<th>Unit</th>
<th>Absolute value</th>
</tr>
</thead>
<tbody>
<tr>
<td>driving cost vs. parking fee</td>
<td>[-]</td>
<td>1.03</td>
</tr>
<tr>
<td>walking time vs. parking fee</td>
<td>[sec]</td>
<td>269.42</td>
</tr>
<tr>
<td>charging induced waiting vs. charging stops</td>
<td>[sec]</td>
<td>109.51</td>
</tr>
<tr>
<td>cabin temperature vs. driving dynamics</td>
<td>[°C]</td>
<td>0.37</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Willingness to pay</th>
<th>Unit</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>driving cost vs. driving time</td>
<td>[e]</td>
<td>9.46</td>
</tr>
<tr>
<td>driving cost vs. charging induced waiting</td>
<td>[e]</td>
<td>11.97</td>
</tr>
<tr>
<td>parking cost vs. walking time</td>
<td>[e]</td>
<td>13.36</td>
</tr>
<tr>
<td>driving cost vs. charging stops</td>
<td>[e]</td>
<td>0.36</td>
</tr>
<tr>
<td>driving cost vs. cabin temperature</td>
<td>[°C]</td>
<td>0.36</td>
</tr>
</tbody>
</table>

Number of observations = 3471

\[
\mathcal{L}(0) = -2405.914 \\
\mathcal{L}(\hat{\beta}) = -2399.251 \\
-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})] = 1470.993 \\
\rho^2 = 0.306 \\
\hat{\rho}^2 = 0.302
\]

**Table 3.4:** Coefficient estimates at the aggregate level of the sample population. 
(a) Logistic regression estimates of the coefficients, whereby \{\beta_7, \beta_8\} are ordinal and \{\beta_1, ..., \beta_6, \beta_9\} are continuous. (b) Selected coefficient ratios. (c) Willingness to pay for time savings and comfort improvements. (d) Summary of estimation statistics. Results are computed with Biogeme [Bie03].
sign of $\beta_4$ meets the expectation. A discussion on cabin temperature preference ($\beta_9$) is slightly more complex. Let $T_{\text{amb}}$ be the ambient temperature, respectively outside temperature, and $T_{\text{opt}}(T_{\text{amb}})$ be the most preferred cabin temperature, given $T_{\text{amb}}$. Let $T_{\text{cab}}$ be the cabin temperature at the time. In a case, where $T_{\text{cab}} < T_{\text{opt}}$, the taste coefficient $\beta_9$ is expected to have a positive sign, expressing a preference for a higher cabin temperature. In a case, where $T_{\text{cab}} > T_{\text{opt}}$, the taste coefficient $\beta_9$ is expected to have a negative sign, expressing a preference for a lower cabin temperature. The coefficient $\beta_9$ represents a context dependent, non-linear relationship, which however, can be expressed by a context independent, linear relationship, if ambient temperature is assumed to be invariant and $T_{\text{cab}}$ is defined either entirely below or entirely above $T_{\text{opt}}$.

The SP experiment defines $T_{\text{amb}} = 0^\circ\text{C}$, $T_{\text{opt}} = 22^\circ\text{C}$ and $T_{\text{cab}}$ in the range $[17^\circ\text{C}, 22^\circ\text{C}]$. Hence, a positive sign of $\beta_9$ is in accordance with the expectation. Concerning the taste coefficients $\{\beta_7, \beta_8\}$, both a positive and a negative sign can be justified. A negative sign of $\beta_7$ implies a preference for fewer charging events. A positive sign of $\beta_7$ implies a preference for a higher charging frequency, which may be justified by a pronounced range anxiety. A negative sign of $\beta_8$ implies a preference for a less restricted driving mode. A positive sign of $\beta_8$ implies a preference for a more restricted driving mode, which may be justified by either a preference for automated driving, a pronounced ecological-awareness or a pronounced safety need.

Table 3.4(b) shows selected ratios of the taste coefficients, reflecting specific trade-offs. The ratio of driving cost and parking fee is close to one, implying that customers assign similar importance to said categories. This raises reasonable doubt as to the customers independent evaluation of driving cost and parking fee. Yet, when assessing the cross-correlation value and the p-values, both of which are small, and the log-likelihood ratio, which is large, the doubt can be dispelled at high probability. Another interesting trade-off is expressed by the ratio of charging frequency and charging induced waiting time. The ratio is $109.5$, when expressing waiting time in seconds, and $1.83$, when expressing waiting time in minutes. Another ratio relates the comfort preferences of cabin temperature and driving dynamics. It manifests a high sensitivity towards cabin temperature when compared to driving dynamics. Yet, this result must be treated with care, since it may be biased by a lack of experience of the test persons as described in section 3.3.2.

Table 3.4(c) analyses the willingness to pay for time savings and comfort improvements. Customers valuate driving time savings at $9.46\text{\$}_h$. They valuate savings in charging induced waiting time at $11.97\text{\$}_h$, which exceeds the valuation for driving time savings. The highest valuation for time savings is shown for walking time, with $13.36\text{\$}_h$. Both the ranking of said categories and the willingness to pay values agree with literature. Concerning comfort savings, a reduction of the charging frequency by one stop is valuated by the customers at $0.36\text{\$}$. An increase in cabin temperature by $1^\circ\text{C}$ is valuated at the same amount. Note, that said relations only apply to the specific set of definitions.

Given the plausibility of the coefficient values and signs, it remains the need for an assessment of the goodness-of-fit of the model, in tangible terms, an assessment of the significance of the coefficients. Three statistical tests are conducted. The t-test
assesses the significance of individual coefficients. The likelihood ratio test and the
rho-squared value evaluate the global quality-of-fit of the model.

For a comprehensive discussion on goodness-of-fit tests refer to statistics text books
[e.g. LM12] and SP literature [e.g. BAL85, LHSAO0]. Briefly, from [BAL85, LM12], the
t-test in linear regression analysis evaluates $H_0 : \beta_i = 0$, where $H_0$ is the null hypothesis
that the estimated coefficient $\beta_i$ is zero. The null hypothesis is evaluated for a given
level of statistical significance, which is denoted $\alpha$. Commonly, $H_0$ is tested at $\alpha = 0.05$. If $H_0$ is rejected, the term $\beta_i x_i$ is said to contribute to the utility of the choice model at
the $\alpha$ significance level. Conversely, the p-value describes the probability to obtain the
estimated $\beta$-values, if $H_0$ is true. Hence, “the P-value is the smallest $\alpha$ at which we
can reject $H_0$” [LM12, p. 359]. Table 3.4(a) presents the t-test results and p-values of
the coefficient estimates. As to the t-test results, $H_0$ can be rejected at the 5% level of
significance for all coefficients, except $\beta_8$. P-values indicate even smaller significance
levels, meaning that the null hypothesis can be rejected at sub-percent significance with
$\alpha \ll 0.01$. As to the exception, $\beta_8$ shows a p-value of 0.24. The reasons for $\beta_8$ not being
statistically significant at the 5% level can be manifold, including a lack of experience
with driving modes, a non-normal distributed random variable and an aliasing of said
main effect with one or many non-modelled effects.

Table 3.4(d) presents global test statistics, namely the log-likelihood ratio test and the
$\rho^2$ value. A detailed discussion on said test statistics can be found in [LM12, BAL85,
LHSAO0]. The likelihood function is a measure of the probability of the estimates
explaining the data. It is defined in the interval $[0,1]$. The closer is the value to one,
the higher the probability that the coefficient estimates explain the data. The logarithm
maps the likelihood function from the interval $[0,1]$ to the interval $[-\infty,0]$, with values
close to zero indicating high probability. The log-likelihood function is denoted $L$. Table
3.4(d) evaluates the log-likelihood function for three cases, namely $L(0)$, $L(c)$ and
$L(\beta)$. Following the interpretation of [BAL85, p. 90 et seqq.], case $L(0)$ evaluates
the hypothesis that choosing alternative1 is equally likely as choosing alternative2,
independent of the attribute values. Case $L(c)$ evaluates the hypothesis that the
probability of choosing alternative1 equals the proportion of respondents choosing
alternative1 over alternative2. Case $L(\beta)$ evaluates the hypothesis that response data
is best explained by the estimated $\beta$-values of the model. Note, that the difference of
any two values of $\{L(0), L(c), L(\beta)\}$ is distributed $\chi^2$.

A first log likelihood ratio test (LLR) evaluates the null hypothesis that an alternative
specific constant variable is zero. From table 3.4(d) follows $-2[L(0) - L(c)] = 13.326$.
Given the model’s degrees of freedom, the null hypothesis cannot be rejected at the
5 percent significance level. This justifies the decision to remove alternative-specific
constants from the model. A second LLR evaluates the hypothesis that all modelled
coefficients are zero. From table 3.4(d) follows $-2[L(0) - L(\beta)] = 1470.993$, and hence,
said hypothesis can be rejected at a sub-percent level of significance. For completeness,
the goodness-of-fit parameter $\rho^2 = 1 - \frac{L(\beta)}{L(0)}$ is provided. Yet, the explanatory power of
$\rho^2$ is limited, which is why a discussion is omitted.

Summarizing the findings of the analysis: Concerning the signs and values of the
coefficient estimates, $\beta_{exp}$ agrees with the findings from existing SP studies in transportation literature and $\beta_{nov}$ is well justified. Concerning the statistical significance of the individual coefficient estimates, it is shown that all estimates are statistically significant at the sub-percent level, except driving dynamics, which is significant at the 24% level. As to the relevance of the terms of the choice model, a first LLR provides a justification to neglect alternative-specific constant variables. A second LLR approves the relevance of the modelled terms, by rejecting the null hypothesis that the modelled coefficients are zero at a sub-percent significance level.

3.4.3 Evaluation of Customer Segment Estimates

The coefficient estimates from table 3.4 describe the preference characteristics of the total sample. They do not necessarily express the preference characteristics of customer groups or individuals, and yet, precisely these preference characteristics are required to provide personalized decision support. Consequently, this section analyses the travel preferences at the disaggregate level of customer segments, whereby the customer segments are clustered from the total sample population. This section is structured into four parts: First, the clustering method is described; second, the clustering method is applied to the total sample to compute customer segments; third, taste coefficients are estimated for the said customer segments; and last, taste similarities and differences between the customer segments are discussed.

Ward’s method [War63] is used to cluster the sample population into customer segments. It is an agglomerative hierarchical clustering approach. At the first clustering step, each subject of the sample population is assigned to a separate cluster. During consecutive steps, clusters are merged in pairs. Clustering terminates once all clusters are merged, that is, all clusters are aggregated into a single cluster comprising all subjects of the sample population. The clustering process is controlled by an optimization routine. A pairing (resp. merging) of two clusters has an associated cost. Here, the cost of pairing is given by the dissimilarity in partial taste gradient between the clusters, as will be explained later. An objective function computes said cost for all possible cluster pairings. The orchestration of the clusters follows from the minimization of said objective function. The result is a hierarchy of clusters, which is represented by a recursive tree, whose nodes represent the clusters. Each cluster contains a subset of the subjects of the total population, whereby a subject is described in terms of partial taste gradient. While clusters are created in a bottom-up process, the resulting tree presents the clusters in a top-down view. The root node cluster contains the total sample population. Leaf node clusters contain single subjects. The number of leaf node clusters equals the number of subjects in the sample. Edges define how smaller clusters are combined into a larger cluster, respectively how a larger cluster is disaggregated into smaller clusters. As an example, let $G = (V,E)$ be the maximum recursive tree of a sample population. Let $G' = (V',E')$ be an induced subgraph of $G$, which again is a recursive tree. Let $V' = \{n_i, n_{i+1}, n_{i+2}\}$ be the set of nodes, with $n_i$ denoting the root node of the induced subgraph. Let $E' = \{e_{i,i+1}, e_{i,i+2}\}$ be the set of induced edges. Let
be a function, which assigns a cluster of subjects to a node. Assume that the child node assignments are given by $w_{i+1}$ and $w_{i+2}$. Then, the assignment of subjects to the parent node $n_i$ follows from:

$$w_i = w(n_i) = \bigcup_{j=i+1}^{k} w_j \quad \text{with} \quad w_j = \begin{cases} w_j & \text{if } e_{i,j} \in E \\ \emptyset & \text{else} \end{cases}$$

with $k = i + 2$ in this simple example. Given the clustering approach and the result structure, it remains the discussion of how the pairing cost is calculated. The approach is presented in [JMPa, p. 423 et seq.] and is explained in the following. Recall from section 3.1, that the coefficients of the herein presented logit model are evaluated at the extreme point of a log-likelihood function, respectively at the null of its total gradient. The Newton-Raphson method is used to iteratively compute the said extreme point. At each iteration, the partial gradient of the Newton-Raphson method is computed, with the partial gradient referring to a subject specific and coefficient specific gradient. When a partial gradient is averaged over the number of iterations, one obtains a mean gradient value per subject and coefficient. Mean gradient values can be used as a measure of taste dissimilarity between subjects. The pairing cost follows from the difference in mean gradient value between the paired clusters. As a result of this approach, one obtains maximum similarity of taste within a cluster and maximum dissimilarity of taste between clusters.

The total sample of 217 subjects is clustered with the method described above. The computation is done with JMP\textsuperscript{1}. Small clusters are unlikely to produce statistically significant coefficient estimates. Consequently, taste coefficients are only evaluated for those clusters that exceed a minimum size of 25 subjects. Biogeme [Bie03] is used to estimate the taste coefficients of the said clusters. Figure 3.3 shows an induced subgraph $G_0$ of the result graph $G$, whereby $G_0 = G[S]$ is defined by the subset of nodes $S \subset V$, whose cluster size exceeds 25 subjects. Cluster names uniquely identify the nodes, whereby a name has the form "CS clusterLevel - clusterNumber". Below the names, cluster size is given. If the taste coefficients of a cluster are estimated, the respective cluster is highlighted in blue, otherwise, it is coloured grey. The coefficient estimates of the blue clusters are presented in Table 3.6, Table 3.5 and Table 3.7.

The clustering process uses partial gradients, which are coefficient specific and subject specific. These partial gradients allow for both a clustering by coefficient and a clustering by coefficient and subject. An evaluation of the said clusterings makes the following possible: (1) an identification of common trends, (2) an identification of the specific dissimilarities between the customer segments and (3) an understanding of how the specific dissimilarities diminish when clusters are merged.

The presentation of the results departs from the identification of common trends. An analysis of the cost related travel preferences of the customer segments reveals that savings in driving cost ($\beta_5$) are mostly higher valued than savings in parking cost.

---

Among the time-related coefficients \( \{\beta_1, \beta_2, \beta_3, \beta_4\} \), savings in walking time are usually valued the highest. An examination of the comfort related coefficients \( \{\beta_7, \beta_8, \beta_9\} \) shows large dissimilarities between the customer segments. Among the comfort related coefficients, charging frequency \( \beta_7 \) exhibits the largest taste variations; as an example, customer segment (3-4) shows an extreme aversion towards charging stops \( \beta_7 = -2.16 \pm 0.166 \), while customer segment (4-4) has a pronounced affinity for a higher charging frequency \( \beta_7 = +0.715 \pm 0.262 \). Generally, the taste estimates of the driving dynamics coefficient \( \beta_8 \) have limited statistical significance. Yet, values imply that people belong to either one of two groups, namely, a group with an aversion towards controlled driving dynamics or a group with an affinity for controlled driving dynamics. In contrast to the largely varying coefficients \( \{\beta_7, \beta_8\} \), climate comfort preference \( \beta_9 \) is always positive and rather homogeneous across customer segments.

The presentation of the results shall now continue on to the specific dissimilarities between the customer segments and how these dissimilarities diminish along the merging process. Table 3.5 presents the coefficient estimates of the customer segments (3-4) and (4-4). The customer segments largely differ in how they value cost savings and comfort improvements. Main effects of customer segment (3-4) show an extreme aversion towards charging events. Consequently, customer segment (3-4) is termed "charge averse". In contrast, main effects of customer segment (4-4) show an extreme affinity for higher charging frequencies. At the same time, they exhibit a high valuation for cost savings and a particularly pronounced valuation for both controlled driving dynamics and higher cabin temperature. Consequently, customer segment (4-4) is

---

1 When comparing the cost and time related coefficients, it is important to note that time related coefficients are given in \( [\frac{u}{min}] \) and cost related coefficients are given in \( [\frac{u}{e}] \).
labelled "cost and safety conscious"\textsuperscript{1}. Table 3.6 presents the coefficient estimates of the customer segments (4-5) and (2-2). The main effects of customer segment (4-5) show an extreme valuation for cost savings, while the valuation for time savings and comfort improvements is moderate. Cost is the predominant criterion, which is why the customer segment is named "cost averse". Customer segment (2-2) represents a cluster from a higher level of aggregation. It is composed of the aforementioned customer segments \{(3-4), (4-4), (4-5)\}. Child segment (3-4) is charge averse, child segment (4-4) is cost and safety conscious and child segment (4-5) is cost averse. The said dissimilarities are considerably smoothed in the parent cluster (2-2), where the aversion towards charging events is not as pronounced as in (3-4), where the safety consciousness from (4-4) is compensated, and where the cost aversion from (4-5) is significantly reduced. Finally, table 3.7 presents the coefficient estimates of the customer segments (3-1) and (EV). The main effects of customer segment (3-1) show a particularly balanced valuation for all taste categories. Consequently, the segment is termed "balanced". The characteristics of (3-1) largely differ from the characteristics of the aforementioned customer segments \{(3-4), (4-4), (4-5), (2-2)\}. The differentness of the travel preference is well reflected by the recursive cluster tree from figure 3.3, where (3-1) and \{(3-4), (4-4), (4-5)\} are from opposing branches. Customer segment (EV) is not clustered from the partial gradients. Instead, it is clustered from socio-economic characteristics. The customer segment contains individuals that have access to an electric vehicle and a private parking space with a charging option. The coefficient estimates $\beta_7$ and $\beta_8$ are statistically not significant at the 5\% level, showing a relatively large asymptotic standard error. Excluding said uncertainty from the discussion, it can be stated that experienced EV users show distinct taste ratios for $\frac{\beta_7}{\beta_4}$ and $\frac{\beta_8}{\beta_9}$. The distinct ratios may imply that EV users have built an understanding of the particular trade-offs of electric vehicles. Yet, this argument will need to be confirmed in the future, when higher market shares allow for drawing larger samples.

In conclusion, the data reveals distinct valuations for time and cost savings and large differences in comfort perception between the customer segments. The data implies at least four customer segments, denoted by "charge averse", "safety conscious", "cost averse" and "balanced". Dissimilarities between the customer segments are shown to be smoothed by the merging process. A specific analysis of EV users suggests that a daily use of EVs provokes a shift in travel preferences, indicating an increased awareness of EV mechanisms. The findings suggest that personalization, be it on the level of individuals or customer segments, has a large potential to increase customer satisfaction.

\textsuperscript{1} A safety conscious customer prefers vehicle-controlled driving and a higher safety margin with respect to residual driving range.
### Table 3.5: Coefficient estimates at the disaggregate level of the sample population.

The main effects of customer segment (3-4) show an average valuation for time and cost but an extreme aversion towards charging events. The main effects of customer segment (4-4) show a strong aversion towards cost and a pronounced affinity for higher charging frequencies, controlled driving dynamics and higher cabin temperature. Results are computed with Biogeme [Bie03].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Rob. A. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>driving time</td>
<td>-0.163</td>
<td>0.0189</td>
<td>-8.60</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>walking time</td>
<td>-0.268</td>
<td>0.0341</td>
<td>-7.87</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>late arrival</td>
<td>-0.140</td>
<td>0.0159</td>
<td>-8.79</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>charging induced waiting</td>
<td>-0.189</td>
<td>0.0242</td>
<td>-7.84</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>driving cost</td>
<td>-1.03</td>
<td>0.151</td>
<td>-6.81</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_6$</td>
<td>parking fee</td>
<td>-0.460</td>
<td>0.107</td>
<td>-4.30</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_7$</td>
<td>number of charging stops</td>
<td>-2.16</td>
<td>0.166</td>
<td>-13.00</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_8$</td>
<td>driving dynamics</td>
<td>-0.352</td>
<td>0.171</td>
<td>-2.06</td>
<td>0.04</td>
</tr>
<tr>
<td>$\beta_9$</td>
<td>cabin temperature</td>
<td>0.532</td>
<td>0.0826</td>
<td>6.44</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Summary Statistics**

- Number of observations = 736
- $\mathcal{L}(0) = -509.463$
- $\mathcal{L}(c) = -507.093$
- $\mathcal{L}(\hat{\beta}) = -273.262$
- $-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})] = 472.403$
- $\hat{\rho}^2 = 0.464$
- $\bar{\rho}^2 = 0.446$

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Rob. A. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>driving time</td>
<td>-0.125</td>
<td>0.0267</td>
<td>-4.69</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>walking time</td>
<td>-0.317</td>
<td>0.0843</td>
<td>-3.76</td>
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<tr>
<td>$\beta_3$</td>
<td>late arrival</td>
<td>-0.117</td>
<td>0.0264</td>
<td>-4.43</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>charging induced waiting</td>
<td>-0.124</td>
<td>0.0296</td>
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<td>$\beta_5$</td>
<td>driving cost</td>
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<td>0.260</td>
<td>-7.58</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_6$</td>
<td>parking fee</td>
<td>-1.25</td>
<td>0.242</td>
<td>-5.17</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_7$</td>
<td>number of charging stops</td>
<td>0.715</td>
<td>0.262</td>
<td>2.73</td>
<td>0.01</td>
</tr>
<tr>
<td>$\beta_8$</td>
<td>driving dynamics</td>
<td>0.667</td>
<td>0.282</td>
<td>2.37</td>
<td>0.02</td>
</tr>
<tr>
<td>$\beta_9$</td>
<td>cabin temperature</td>
<td>0.636</td>
<td>0.0881</td>
<td>7.22</td>
<td>0.00</td>
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</tbody>
</table>

**Summary Statistics**

- Number of observations = 432
- $\mathcal{L}(0) = -298.746$
- $\mathcal{L}(c) = -291.090$
- $\mathcal{L}(\hat{\beta}) = -145.575$
- $-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})] = 306.343$
- $\hat{\rho}^2 = 0.513$
- $\bar{\rho}^2 = 0.483$
### 3.4 Discrete Choice Experiment Results

<table>
<thead>
<tr>
<th>Taste Parameter</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Rob. A. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>driving time</td>
<td>-0.187</td>
<td>0.0181</td>
<td>-10.32</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>walking time</td>
<td>-0.297</td>
<td>0.0477</td>
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<td>0.00</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>late arrival</td>
<td>-0.202</td>
<td>0.0232</td>
<td>-8.71</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>charging induced waiting</td>
<td>-0.191</td>
<td>0.0162</td>
<td>-11.80</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>driving cost</td>
<td>-2.10</td>
<td>0.186</td>
<td>-11.28</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_6$</td>
<td>parking fee</td>
<td>-2.15</td>
<td>0.146</td>
<td>-14.77</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_7$</td>
<td>number of charging stops</td>
<td>-0.358</td>
<td>0.119</td>
<td>-3.00</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_8$</td>
<td>driving dynamics</td>
<td>0.116</td>
<td>0.184</td>
<td>0.63</td>
<td>0.53</td>
</tr>
<tr>
<td>$\beta_9$</td>
<td>cabin temperature</td>
<td>0.269</td>
<td>0.0776</td>
<td>3.47</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Customer Segment 4-5**

Number of observations = 960

\[
\mathcal{L}(0) = -664.728
\]

\[
\mathcal{L}(\hat{\beta}) = -324.221
\]

\[
-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})] = 681.015
\]

\[
\rho^2 = 0.512
\]

\[
\bar{\rho}^2 = 0.499
\]

**Customer Segment 2-2**

Number of observations = 2128

\[
\mathcal{L}(0) = -1474.324
\]

\[
\mathcal{L}(\hat{\beta}) = -861.822
\]

\[
-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})] = 1225.003
\]

\[
\rho^2 = 0.415
\]

\[
\bar{\rho}^2 = 0.409
\]

**Table 3.6:** Coefficient estimates at the disaggregate level of the sample population. The main effects of customer segment (4-5) show an extreme aversion towards cost. Customer segment (2-2) is aggregated from the child segments (3-4), (4-4), (4-5) and shows the extreme characteristics of these child segments to be smoothed. Results are computed with Biogeme [Bie03].
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Rob. A. std. error</th>
<th>$t$-stat</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>driving time</td>
<td>-0.0853</td>
<td>0.0131</td>
<td>-6.52</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>walking time</td>
<td>-0.114</td>
<td>0.0197</td>
<td>-5.78</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>late arrival</td>
<td>-0.144</td>
<td>0.0218</td>
<td>-6.60</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>charging induced waiting</td>
<td>-0.156</td>
<td>0.0172</td>
<td>-9.08</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>driving cost</td>
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<td>0.0693</td>
<td>-3.26</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_6$</td>
<td>parking fee</td>
<td>-0.140</td>
<td>0.101</td>
<td>-1.39</td>
<td>0.16</td>
</tr>
<tr>
<td>$\beta_7$</td>
<td>number of charging stops</td>
<td>-0.292</td>
<td>0.0772</td>
<td>-3.79</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_8$</td>
<td>driving dynamics</td>
<td>-0.326</td>
<td>0.124</td>
<td>-2.62</td>
<td>0.01</td>
</tr>
<tr>
<td>$\beta_9$</td>
<td>cabin temperature</td>
<td>0.212</td>
<td>0.0509</td>
<td>4.17</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Customer Segment EV

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Rob. A. std. error</th>
<th>$t$-stat</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>driving time</td>
<td>-0.126</td>
<td>0.0157</td>
<td>-8.00</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>walking time</td>
<td>-0.204</td>
<td>0.0327</td>
<td>-6.24</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>late arrival</td>
<td>-0.140</td>
<td>0.0236</td>
<td>-5.92</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>charging induced waiting</td>
<td>-0.160</td>
<td>0.0220</td>
<td>-7.29</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>driving cost</td>
<td>-0.955</td>
<td>0.155</td>
<td>-6.17</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_6$</td>
<td>parking fee</td>
<td>-0.923</td>
<td>0.148</td>
<td>-6.26</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_7$</td>
<td>number of charging stops</td>
<td>-0.193</td>
<td>0.186</td>
<td>-1.03</td>
<td>0.30</td>
</tr>
<tr>
<td>$\beta_8$</td>
<td>driving dynamics</td>
<td>0.238</td>
<td>0.167</td>
<td>1.43</td>
<td>0.15</td>
</tr>
<tr>
<td>$\beta_9$</td>
<td>cabin temperature</td>
<td>0.295</td>
<td>0.0853</td>
<td>3.46</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Summary Statistics

Customer Segment 3-1

- $L(0) = -609.276$
- $L(c) = -606.565$
- $L(\hat{\beta}) = -450.843$
- $-2[L(0) - L(\hat{\beta})] = 316.866$
- $\rho^2 = 0.260$
- $\bar{\rho}^2 = 0.245$

Customer Segment EV

- $L(0) = -409.650$
- $L(c) = -409.581$
- $L(\hat{\beta}) = -264.408$
- $-2[L(0) - L(\hat{\beta})] = 290.484$
- $\rho^2 = 0.355$
- $\bar{\rho}^2 = 0.333$

Table 3.7: Coefficient estimates at the disaggregate level of the sample population. The main effects of customer segment (3-1) show a very balanced valuation for all categories. Customer segment (EV) encompasses experienced electric vehicle users with a private parking space and access to a private charging station. When compared to the remaining customer segments, the main effects suggest a shift in travel preference through experience. Results are computed with Biogeme [Bie03].
4 Context-aware Electric Vehicle Consumption Model

As has been discussed in section 1.4, a decision support system requires two categories of models in order to provide optimal decision support: (1) *physical models* and (2) *behavioural models*. So far, chapter 3 has presented a behavioural model that captures the holistic travel preferences of a driver. This chapter presents a second behavioural model that captures the personal driving behaviour. Moreover, it is the first in a series of chapters discussing physical models.

Driving behaviour is expressed in terms of velocity choice and acceleration choice, omitting lateral guiding decisions. It can be understood as the personal response of a driver to vehicle properties (e.g. throttle response profile, driving mode level) and environment characteristics (e.g. speed limits, traffic lights). A vehicle can continuously learn the behavioural patterns of acceleration choice and velocity choice from real-world driving data where context information is available from vehicle sensors, road maps and connected services. These learned patterns have a dual use: (1) they serve as input parameter for the vehicle consumption model, and (2) they are used as part of a metric to compute the value of the profile attribute *adherence to preferred driving mode*\(^1\), which is defined as the difference in driving behaviour between driving mode levels.

Section 4.2 discusses the development of this behavioural model, denoted by black-box driver model, which learns the behavioural patterns of a driver (model output) as a function of vehicle properties and environment characteristics (model input). The model implements an update-prediction loop, which continuously updates the model parameters on the basis of revealed preference data (past driving context), and predicts the future decisions of a driver on the basis of a forecast of the future driving context. The black-box model distinguishes multiple model variants that implement different degrees of context-awareness where model \(M_1\) has maximum context awareness and model \(M_7\) has minimum context-awareness. Selected model variants are both calibrated and validated with an extensive amount of real-world driving data.

Section 4.3 discusses the development of a physical model, denoted by white-box electric vehicle model, which captures the characteristics and interactions of the vehicle components. The white-box model is combined with the black-box driver model to form a grey-box vehicle consumption model. The grey-box vehicle consumption model expresses vehicle consumption (model output) as a function of driving behaviour, vehicle

\(^1\) *Adherence to preferred driving mode* is also referred to as *driving dynamics*.
properties and environment characteristics (model input). It is used to predict the value of the attribute \textit{'energy consumption'\footnote{The attribute ’energy consumption’ serves as input for a function that calculates the value of the profile attribute ’travel cost’.}} when given a prediction of the travel choices \{velocity choice, acceleration choice, choice of comfort settings\} and a prediction of the future road environment context (e.g. road inclination, ambient temperature).

Finally, section 4.4 presents a sensitivity analysis of the grey-box vehicle consumption model, which investigates how sensitive vehicle consumption reacts towards changes in the said input parameters (driving behaviour, vehicle properties, environment characteristics).

### 4.1 Qualitative Analysis of Driver-Vehicle-Environment Interaction

Road environment characteristics, vehicle properties and on-trip choices of the driver jointly influence vehicle consumption. The development of a consumption prediction method therefore requires an understanding of the cause-effect relationships of the aforementioned factors, in particular, how

1. cues of the environment influence driving decisions
2. vehicle properties influence driving decision
3. environment characteristics influence vehicle consumption
4. driving decisions influences vehicle consumption

Concerning environment characteristics, two categories can be distinguished, namely, a category called \textit{Class}_{envRoad} and a category termed \textit{Class}_{envAmb}. \textit{Class}_{envRoad} encompasses environment characteristics that are related to the road network, such as speed limits, road gradient, road curvature and traffic. \textit{Class}_{envAmb} relates to ambient characteristics that are independent of the road network, such as temperature and humidity.

Concerning en-route driving decisions, the category \textit{Class}_{driverDyn} comprises decisions that influence vehicle dynamics, such as acceleration choice, velocity choice, steering angle choice and driving mode choice (for a definition of driving mode choice revisit section 3.3.1); the category \textit{Class}_{driverComf} encompasses comfort decisions of the driver that are related to the air conditioning system, seat heating, rear window heating, front window heating, lights and the infotainment system.

Regarding vehicle properties, two classes of components can be distinguished, namely the class of propulsion related components, termed \textit{Class}_{vehicleDyn}, and the class of comfort related components, called \textit{Class}_{vehicleComf}. While the consumption of
the propulsion related components\(^1\) follows from the interaction between Class\(_{envRoad}\) and Class\(_{driverDyn}\), the consumption of the comfort related components follows from the interplay of Class\(_{envAmb}\) and Class\(_{driverComf}\).

The sum of power requests over Class\(_{vehicleDyn}\) and Class\(_{vehicleComf}\) determines the load on the vehicle traction battery, the power output of which is limited. The power output depends on the battery state-of-charge, battery state-of-health, temperature and the requested current. In most cases, the sum of component power requests satisfies the traction battery constraints, and hence, the driver wishes are met. In some cases, the sum of component power requests exceeds the maximum battery power, in which case driver requests cannot be fully satisfied. In those cases, the battery management system (BMS) distributes energy portions according to priority, with safety critical and propulsion-related components being favoured.

Figure 4.1 summarizes the relationships between the vehicle components, environment characteristics and driver decisions. A driver generally aims to achieve the vehicle operating characteristics that are most desirable from his personal perspective. Yet, the interaction of vehicle constraints and environment characteristics imposes restrictions on driver decisions. In many cases the driver’s most desirable decisions are feasible. As explained before, in some cases driver wishes cannot be met, leading to a sacrifice of comfort for propulsion and safety.

Environment information is available through digital road maps, floating car data and web services. Current vehicle states are captured by vehicle sensors and are made available on the vehicle CANbus.

Given the high-level description of the vehicle consumption characteristics, the following sections provide the modelling details. Section 4.2 presents a driver model, whose inputs are environment characteristics and vehicle states and whose outputs are the driving decisions of the driver. Section 4.3 presents a vehicle model, whose inputs are driving decisions, vehicle states and environment characteristics and whose output is vehicle consumption.

\(^1\) For the sake of ease of presentation, the effect of Class\(_{envAmb}\) on propulsion related components is acknowledged but neglected.
Figure 4.1: Overview diagram describing how environment characteristics, driver decisions and vehicle properties qualitatively influence vehicle consumption.
4.2 Context-aware Driver Model

The driver model detailed below is a black-box abstraction of the longitudinal driving decisions. It comprises a learning process and a prediction routine.

During the learning process, longitudinal vehicle velocity is continuously classified into constant phases and acceleration phases. A discrete valued function captures the phases in terms of polynomial coefficients and context categories. Depending on the modelling objective, the function may capture the behavioural characteristics of a single driver (personalization), a group of drivers (customer segmentation) or all drivers jointly (driver-generic).

During the prediction routine, the route segments ahead are classified into categories, to which polynomial driver model coefficients are assigned by the use of the discrete valued function. The polynomial coefficients are then used to construct a velocity profile over the sequence of route segments ahead.

Section 4.2.1 details the learning process and the prediction routine. A number of model variants are calibrated with extensive amounts of real-world data and validated with a number of real-world rides. Model calibration is shown in section 4.2.2. The validation results are discussed in section 4.2.3.

4.2.1 Modelling Approach

This section describes a piecewise polynomial model to capture velocity profiles in terms of polynomial coefficients. It shows how to learn these coefficients in a context-aware manner and how to apply them to the route ahead in order to predict the future velocity profile of a driver. Moreover, it presents a set of driver model variants that implement different degrees of context-awareness where model \( M_1 \) has maximum context awareness and model \( M_7 \) has minimum context-awareness.

Piecewise polynomial model

A driving stage is defined by the time interval \([t_{\text{engine on}}, t_{\text{engine off}}]\). The vehicle velocity profile of a driving stage is continuous in both the time domain and the spatial domain.

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2 Routines use vehicle and environment data of the group research.
3 The classification employs velocity profile characteristics and context parameters.
4 Route segments are a result of a clustering process, which uses the same context parameters as the learning routine, thereby assuring an unambiguous assignment of the polynomial coefficients to the route segments.
5 The model has been used and written down (full or in parts) by the supervised theses (also see Appendix A.3) of S. Habermann [Hab12], B. J. Manning [Man13], S. Schinke [Sch11] and K. Zemmer [Zem12].
The continuous velocity profile is measured by a sensor in $n$ discrete sampling intervals $\Delta t$. In the discrete time domain (resp. spatial domain) the velocity profile function becomes a countable, totally ordered set $S_n$. The discrete velocity profile of a driving stage is defined as a sequence of discrete velocities, denoted by $(v_k)_{k=1}^n$, with $v_1 = v(t_{\text{engine on}})$ and $v_n = v(t_{\text{engine off}})$. The discrete velocity profile is segmented into $m$ disjoint phases so that it holds: $S_1 \cup S_2 \cup ... S_m = S_n$ and $S_1 \cap S_2 \cap ... S_m = \emptyset$, where a phase is defined as a sequence of velocity measurements $(v_k)_{k=i}^j$, with $(v_k)_{k=i}^j \subset S_n$. The set $(v_k)_{k=1}^n$ is bounded from above by the maximum speed of the vehicle $v_{\text{max}}$ and is bounded from below by zero, since reversing is neglected.

Two categories of velocity phases exist: constant phases and acceleration phases. These phases are approximated by polynomial functions. Constant phases are approximated by zero-order polynomials and acceleration phases are approximated by linear or cubic polynomials. The polynomials are estimated for free-flow conditions, where the longitudinal guiding decisions follow the natural behavioural pattern of the driver and are not imposed by the surrounding vehicles. In the congested case, the driver behaviour should preferably be modelled in accordance with microscopic traffic simulations, adopting the aggregate population characteristics of following models at high v/c ratios.

While cubic polynomials reflect real-world acceleration phases best, linear approximations are easier to integrate into routing routines. Both approaches are implemented and compared with respect to prediction accuracy. In the linear case, regression is straightforward. The cubic case is described in the following. Let

$$v(t_k) = \alpha_0 + \alpha_1 t_k + \alpha_2 t_k^2 + \alpha_3 t_k^3$$

be a cubic polynomial with $\vec{\alpha} \in \mathbb{R}^4$. Let $(v_k)_{k=i}^j$ be an acceleration phase, with the first velocity element $v(t_i) = v_i$ and the last velocity element $v(t_j) = v_j$. Given the condition that phases are determined so that no two acceleration phases exist, which are consecutive and have the same sign, it holds:

$$v'(t_i) = v'(t_j) = 0$$

where $v'$ denotes the central difference quotient. The coefficients of the polynomial can be uniquely determined, given

$$\Delta t_{\text{phase}} = t_j - t_i$$

Alternatively, a boundary condition can be defined in terms of the maximum acceleration $a_{\text{max}}$ at the respective time stamp $t_{\text{max}}$, with $t_i < t_{\text{max}} < t_j$, or equivalently at the respective distance $s(t_{\text{max}})$. In summary, the piecewise polynomial model captures velocity profiles in a parametric form.
4.2 Context-aware Driver Model

Learning context-dependent driver model coefficients

The driver model becomes context-aware, if the phases \( (v_k)_{k=1}^j \subset S_n \) are segmented on the grounds of a context representation, as defined by the context parameters of table 4.1, and if the polynomial coefficients \( \vec{\alpha} \) are classified with respect to these context parameters. This is achieved in a multi-step process. In a first step, both the longitudinal velocity profile of the vehicle and the context parameters are monitored. In a second step, the velocity profile is synchronized with the context parameters in the temporal and spatial domain. In a third step, a classification routine uses the context parameters in order to segment the velocity profile into constant phases and acceleration phases. In a fourth step, these phases are categorized with respect to the context parameters from table 4.1, namely driver properties\(^1\), vehicle properties and environment cues. In a fifth step, polynomial functions are fitted to the categorized velocity phases. In a sixth step, the polynomial coefficients are stored in a lookup table, respectively captured by a discrete valued function expressing the coefficients in terms of the context parameters.

The driver model coefficients can depend on any combination of the context parameters of table 4.1. The more parameters are combined, the higher the dimensionality of the model. The learning routine of the driver model is described in listing 4.1.

Listing 4.1: Learning routine of a black-box context-aware driver model, which captures driver decisions as a function of context cues without modelling the underlying psychological or behavioural mechanisms of the driver.

Predicting a velocity profile on the basis of context-dependent driver model coefficients

The discrete valued function, which is continuously updated by the learning routine, is used in conjunction with the context information of the road ahead to predict the future velocity profile of a driver. This is achieved in a multi-step process. In a first step, the route ahead is classified so that each resulting route segment matches one of the context categories of the driver model. In a second step, the discrete valued function is applied to the context categories of the route segments to obtain the respective driver model coefficients. In a third step, the driver model coefficients are used to construct a velocity profile along the route segments. The prediction routine of the driver model is described in listing 4.2.

Listing 4.2: Prediction routine of a black-box context-aware driver model, which predicts the future velocity profile of a driver in real-time based on context cues.

\(^1\) Note, that driver mood and driver ability are neglected for the sake of simplification.
<table>
<thead>
<tr>
<th>Category</th>
<th>Context parameter</th>
<th>Parameter level</th>
</tr>
</thead>
<tbody>
<tr>
<td>driver</td>
<td>driving phase</td>
<td>acceleration phase, constant velocity phase</td>
</tr>
<tr>
<td></td>
<td>operator</td>
<td>driver-specific (personalization), customer-segment-specific, driver-generic</td>
</tr>
<tr>
<td>vehicle</td>
<td>driving mode</td>
<td>level(_1), \ldots, level(_5)</td>
</tr>
<tr>
<td></td>
<td>propulsion</td>
<td>config(_1), \ldots, config(_n)</td>
</tr>
<tr>
<td></td>
<td>throttle response profile</td>
<td>mapping-function from pedal angle to power output</td>
</tr>
<tr>
<td>environment</td>
<td>street class</td>
<td>classification of road type w.r.t the degree of mobility and the degree of land access. Here, a distinction is made between rural, urban and highway topology. Alternatively, a distinction can be made between roadClass(_1), \ldots, roadClass(_n)</td>
</tr>
<tr>
<td></td>
<td>speed band</td>
<td>relaxation of legal speed limits into speed intervals, which are defined by: ([0,20], (20,40], (40,60], (60,90], (90,110], (110,130], (130,v_{\text{max}}])</td>
</tr>
<tr>
<td></td>
<td>access type</td>
<td>cross-traffic intersection left turn, cross-traffic intersection right turn, left turn, right turn, round-about</td>
</tr>
<tr>
<td></td>
<td>road curvature</td>
<td>0°, \ldots, 180°</td>
</tr>
<tr>
<td></td>
<td>road gradient</td>
<td>(-22%, \ldots, +22%)</td>
</tr>
<tr>
<td></td>
<td>road slipperiness</td>
<td>high slip danger, medium slip danger, low slip danger</td>
</tr>
<tr>
<td></td>
<td>traffic flow</td>
<td>0 km/h, \ldots, free-flow speed</td>
</tr>
<tr>
<td></td>
<td>traffic lights</td>
<td>pass, single-stop, multi-stop</td>
</tr>
</tbody>
</table>

Table 4.1: Context parameters of the driver model.
compute a velocity profile over a sequence of segments, whereby the profile is based on segment attributes and driver model coefficients.

Listing 4.2: Prediction routine of a black-box context-aware driver model, which forecasts the velocity profile on the basis of driver coefficients and route context.

In summary, the black-box driver model implements an update-prediction-loop. The update step segments a past velocity trace into subtraces and assigns these subtraces to categories. Locally, a subtrace is transformed to a set of polynomial coefficients, which are globally captured by a discrete valued function expressing polynomial coefficients with respect to context categories. The prediction step classifies the route ahead into segments, to which the discrete valued function is applied in order to predict the future velocity profile of the vehicle. Note, that a predicted velocity profile can be compared with an actual velocity profile of the driver to compute performance criteria of the model and trigger adaptation mechanisms.

Driver model variants

The accuracy of the driver model rises with the level of classification detail. In other words, the more context parameters are respected, the higher will be the model accuracy. Table 4.2 lists the most important combinations of context parameters, thereby defining the most important driver models. The definitions of the classification sets are provided in table 4.3.

<table>
<thead>
<tr>
<th>Driver Model</th>
<th>Classification detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>maximum driver set, maximum environment set</td>
</tr>
<tr>
<td>M2</td>
<td>maximum driver set, medium environment set</td>
</tr>
<tr>
<td>M3</td>
<td>maximum driver set, minimum environment set</td>
</tr>
<tr>
<td>M4</td>
<td>medium driver set, maximum environment set</td>
</tr>
<tr>
<td>M5</td>
<td>medium driver set, medium environment set</td>
</tr>
<tr>
<td>M6</td>
<td>medium driver set, minimum environment set</td>
</tr>
<tr>
<td>M7</td>
<td>minimum driver set, minimum environment set</td>
</tr>
</tbody>
</table>

Table 4.2: Level of classification detail of the driver model variants. The classification sets are defined in table 4.3.

The calibration results described later are based on the driving data of a homogeneous vehicle fleet, where all vehicles are the same model and have the same configuration, and hence, the vehicle context does not change across fleet vehicles. Consequently, the context parameters of the vehicle category are omitted in the course of this section.
4.2.2 Driver Model Calibration

This section discusses the calibration of the driver models with real-world driving data. It uses the M2, M3 and M5 models of table 4.2 as an example. The calibration results are presented in three parts. In the first part, selected real-world velocity profiles of a single driver are shown. More specifically, two representative categories of acceleration phases are presented: (1) urban street class and speed band transition \([0,20] \leftrightarrow (40,60]\), and (2) rural street class and speed band transition \((40,60] \leftrightarrow (90,110]\). Using the M2 model as an example, the driver model coefficients are calibrated for these phases. They are then used to predict velocity profiles which are compared with the original driving data in order to provide an indication of the prediction accuracy. In the second part, M2 model coefficients are calibrated for all combinations of speed bands and street classes. In the third part, M3 and M5 model coefficients are calibrated for several drivers travelling in the cities of Hamburg, Berlin and Wolfsburg. The M3 model is used to emphasize the differences between drivers, thereby justifying the need for a personalization of driving behaviour. The M5 model is used to demonstrate the differences between street classes, thereby suggesting a regional distinction of driving behaviour.

Training data

The models with high classification detail, such as the M1 model, require beyond state-of-the art data-resolution, data-correctness and data-freshness. In order to attain meaningful calibration results, two sets of real-world rides are therefore recorded. A first set of driving data, denoted by \(S_{\text{high}}\), is used to calibrate the models with high classification detail. It represents conditions as they will be, if the technological capabilities are fully exploited. A second set of driving data, denoted by \(S_{\text{low}}\), is used to calibrate the models with medium and low classification detail. It represents the status quo, given up-to-date vehicle telematics, connected environment information and the resolution of

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>maximum environment set</td>
<td>street class, speed band, access type, traffic flow, traffic lights</td>
</tr>
<tr>
<td>medium environment set</td>
<td>street class, speed band</td>
</tr>
<tr>
<td>minimum environment set</td>
<td>speed band</td>
</tr>
<tr>
<td>maximum driver set</td>
<td>operator, driving phase</td>
</tr>
<tr>
<td>medium driver set</td>
<td>driving phase</td>
</tr>
<tr>
<td>minimum driver set</td>
<td>constant velocity phase</td>
</tr>
</tbody>
</table>

| Table 4.3: Classification sets are defined in terms of the context parameters from table 4.1. Note, that instead of speed bands, one could use legal speed limits or historic average speeds as a context reference. |
4.2 Context-aware Driver Model

the vehicle sensors.

$S_{\text{high}}$ comprises real-world rides of a single driver and several hundred kilometres of driving distance. The rides are conducted in homogeneous environments, where routes are chosen so that they are entirely located in either one of the three topologies: urban, rural or highway. $S_{\text{high}}$ has optimal data quality, meaning that context information, such as traffic flow and traffic lights, is captured at the highest possible resolution and accuracy. Vehicle data is acquired from highly resolved vehicle CANbus information and additional GPS positioning equipment. Vehicle and context data are perfectly synchronized in the time (resp. spatial) domain. In summary, the data quality of $S_{\text{high}}$ provides optimal conditions for the calibration of the driver model coefficients.

$S_{\text{low}}$ comprises real-world rides of multiple drivers and a fleet of vehicles. The rides are conducted in inhomogeneous environments, where a ride may either be entirely located in one of the three road topologies or span multiple road topologies. $S_{\text{low}}$ has non-optimal data quality, which is due to three reasons. First, information about speed limits is erroneous; both weather and traffic conditions are only partially known and have low resolution; traffic light information is unavailable and positioning data is of lower resolution than $S_{\text{high}}$, which is due to the frequency and transfer format of the inbuilt GPS device. Second, vehicle information is streamed wirelessly to a vehicle backend server, throughout which process data packets are lost. Third, both the data transfer outages and the low resolution of vehicle and environment information produce erroneous data synchronization. In summary, $S_{\text{low}}$ provides non-optimal conditions for the calibration of the driver model coefficients.

M2 model calibration on $S_{\text{high}}$ data for the case of urban street class and selected speed band transitions

Figure 4.2 shows 78 real-world velocity curves of an acceleration phase which is defined by the following characteristics: velocity curves start within the speed band $[0 - 20] \text{ km/h}$, denoted $\text{band}_1$, and end in the speed band $(40 - 60] \text{ km/h}$, denoted $\text{band}_3$; velocity curves are personalized and street class specific (street class = urban). The velocity curves are used to calibrate both the linear and the cubic driver model coefficients. The coefficient of the linear model is found to be $1.034 \frac{m}{s^2}$ ($\sigma = 0.247 \frac{m}{s^2}$). The maximum linear coefficient is found to be $2.899 \frac{m}{s^2}$. The coefficients of the cubic model are $\alpha_0 = 0.5382 \frac{m}{s^3}$, $\alpha_1 = 0$, $\alpha_2 = 0.2422 \frac{m}{s^4}$ and $\alpha_3 = -0.0124 \frac{m}{s^5}$.

The learned coefficients are used to predict a velocity profile for a representative road segment. The 78 real-world velocity curves of figure 4.2 are overlaid with the predicted velocity profiles. The error between the real-world velocity curves and the predicted velocity profiles is quantified. The error statistics are shown in the figure for both the linear and the cubic case. Qualitatively, the cubic model seems to better reflect the acceleration behaviour of a driver. Quantitatively, the linear prediction curve shows a
smaller mean error\(^1\) and a slightly smaller standard deviation\(^2\). The acceleration phase presented is most representative for urban environments. An analysis of a number of real-world rides reveals that the said acceleration phase (band\(_1\)-band\(_3\)) accounts for 33.5\% of the acceleration phases in urban environments. The respective deceleration phase, denoted by band\(_3\)-band\(_1\), is shown in figure 4.3. It accounts for 29.6\% of the deceleration phases in urban environments. For the band\(_3\)-band\(_1\) deceleration phase, the coefficient of the linear prediction model is found to be \(-1.094 \frac{m}{s^2}\) (\(\sigma = 0.302 \frac{m}{s^2}\)). The maximum linear coefficient is found to be \(-3.726 \frac{m}{s^2}\). The coefficients of the cubic model are \(\alpha_0 = 14.418 \frac{m}{s^2}\), \(\alpha_1 = 0\), \(\alpha_2 = -0.2956 \frac{m}{s^2}\) and \(\alpha_3 = 0.0164 \frac{m}{s^2}\). The error statistics are shown in the respective figure for both the linear and the cubic case.

**Figure 4.2:** Predicted velocity profiles (linear, cubic) are compared with 78 real-world velocity curves for the case of a single driver, urban street class and an acceleration phase band\(_1\)-band\(_3\), respectively \([0 - 20] \rightarrow [40 - 60]\).

**M2 model calibration on \(S_{\text{high}}\) data for the case of rural street class and selected speed band transitions**

Most representative in rural environments are band\(_3\)-band\(_5\) acceleration phases, with an occurrence of 33\%, and band\(_5\)-band\(_3\) deceleration phases, with an occurrence of 27.4\%. Figure 4.4 shows 41 real-world velocity curves (personalized, street class = rural) of a band\(_3\)-band\(_5\) acceleration phase. The coefficient of the linear prediction model is found to be \(0.922 \frac{m}{s^2}\) (\(\sigma = 0.242 \frac{m}{s^2}\)). The maximum linear coefficient is found to be \(2.559 \frac{m}{s^2}\). The coefficients of the cubic model are \(\alpha_0 = 14.0933 \frac{m}{s^2}\), \(\alpha_1 = 0\), \(\alpha_2 = 0.2017 \frac{m}{s^2}\) and \(\alpha_3 = -0.0096 \frac{m}{s^2}\). Error statistics are shown in the figure. Figure 4.5 shows 34

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\(^1\) The mean error refers to the mean of a set of mean errors, where each element of the set of real-world velocity curves is compared with the predicted profile (linear, cubic).

\(^2\) The standard deviation refers to the mean of a set of standard deviations, where each element of the set of real-world velocity curves is compared with the predicted profile (linear, cubic).
4.2 Context-aware Driver Model

Figure 4.3: Predicted velocity profiles (linear, cubic) are compared with 69 real-world velocity curves for the case of a single driver, urban street class and a deceleration phase band $3$-band $1$, respectively $(40 - 60) \rightarrow [0 - 20]$.

The real-world velocity curves of a band $3$-band $3$ deceleration phase. The linear coefficient is $-0.8905 \frac{\text{m}}{\text{s}^2}$ ($\sigma = 0.2877 \frac{\text{m}}{\text{s}^2}$). The maximum linear coefficient is $-2.9 \frac{\text{m}}{\text{s}^2}$. The cubic coefficients are $\alpha_0 = 27.3938 \frac{\text{m}}{\text{s}^4}$, $\alpha_1 = 0$, $\alpha_2 = -0.1791 \frac{\text{m}}{\text{s}^3}$ and $\alpha_3 = 0.008 \frac{\text{m}}{\text{s}^4}$.

Note, that in urban environments, the prediction accuracy of the acceleration/deceleration phases has a significant effect on the cumulative velocity prediction error of a ride. The effect is smaller in environments where acceleration/deceleration phases have a low share in driving time.

Figure 4.4: Predicted velocity profiles (linear, cubic) are compared with 41 real-world velocity curves for the case of a single driver, rural street class and an acceleration phase band $3$-band $5$, respectively $(40 - 60) \rightarrow (90 - 110)$.
Figure 4.5: Predicted velocity profiles (linear, cubic) are compared with 34 real-world velocity curves for the case of a single driver, rural street class and a deceleration phase band5-band3, respectively \((90 - 110) \rightarrow (40 - 60)\).

M2 model calibration on \(S_{\text{high}}\) data for all combinations of speed bands and street classes

Following the previously presented procedure, the M2 model is now calibrated for all combinations of speed bands and street classes. Recall from table 4.1 that the street class parameter has three levels \{urban, rural, highway\} and that seven speed band levels exist, producing 147 possible labels \{street class, band\(_i\), band\(_j\)\}, which makes impossible a simple visualization of the results. The label size is reduced in two steps: (1) accelerations within a speed band are omitted, thereby reducing 49 speed band combinations to 42 combinations, and (2) order is neglected\(^1\), thereby reducing the 42 combinations to 21 band-to-band transitions. Figure 4.6 shows the magnitude of the mean linear coefficients of the M2 model as a function of the \(21 \times 3\) band-to-band transitions\(^2\).

The characteristics of urban street class are presented in figure 4.6(a) where the following band-to-band transitions exceed the minimum threshold: \{\(b_{1}, b_{2}\), \(b_{1}, b_{3}\), \(b_{1}, b_{4}\), \(b_{2}, b_{3}\) and \(b_{2}, b_{4}\). It can be seen that the magnitude of both the acceleration and the deceleration coefficients rises with an increasing velocity delta between the speed bands. For example, a driver accelerates harder from 0\(\text{km}/\text{h}\) to 50\(\text{km}/\text{h}\) than from 30\(\text{km}/\text{h}\) to 50\(\text{km}/\text{h}\). A comparison between the acceleration and the deceleration coefficients reveals that the deceleration coefficients have lower magnitude than the respective acceleration coefficients. For example, the driver accelerates harder from 30\(\text{km}/\text{h}\) to 50\(\text{km}/\text{h}\)

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\(^1\) The same label \((b_{i}, b_{j})\) is used for an acceleration from a lower speed band \(b_{i}\) to a higher speed band \(b_{j}\) as for a deceleration from the higher speed band \(b_{j}\) to the lower speed band \(b_{i}\).

\(^2\) Note, that the coefficients are shown only if the occurrence of the respective velocity phases in \(S_{\text{high}}\) exceeds a minimum threshold.
Figure 4.6: Linear coefficients of the M2 model for all combinations of speed bands and street classes (medium environment set). Note, that \( \{b_i, b_j\} \) defines the transition from band \( i \) to band \( j \) and inversely, the transition from band \( j \) to band \( i \) (red).
than he would brake from $50 \frac{\text{km}}{\text{h}}$ to $30 \frac{\text{km}}{\text{h}}$.

The characteristics of rural street class are presented in figure 4.6(b). Rural acceleration characteristics resemble urban characteristics in that acceleration magnitude rises with an increasing velocity delta between the speed bands. Rural characteristics differ from urban characteristics in that deceleration magnitude exceeds acceleration magnitude for almost all band-to-band transitions.

Finally, figure 4.6(c) compares the urban, rural and highway case. Urban acceleration coefficients show highest magnitude for all band-to-band transitions. Rural acceleration coefficients exceed highway coefficients.

**M3 model calibration on $S_{\text{low}}$ data with special reference to personalization**

The following paragraphs calibrate the M3 model. Specific attention is given to personalization and regional distinction. The analysis is based on $S_{\text{low}}$ data. The lack of data quality requires multiple information pre-processing steps. Only those subsets of $S_{\text{low}}$ are used for driver model calibration that fulfil certain fitness criteria. The qualified data sets cover multiple drivers in the cities of Hamburg, Berlin and Wolfsburg and around 90 rides of around 3000 km of driving distance.

The M3 model is used to evaluate the differences in driving behaviour between individuals. This is achieved, when the learning algorithm of the M3 model is applied once to the driving data of individual drivers (driver-specific) and once to the driving data of all drivers aggregately (driver-generic). The driver model coefficients can then be compared between drivers and between drivers and the aggregate population. The results of these comparisons are shown in figure 4.7 for the case of linear acceleration coefficients.

Figure 4.7(a) compares the driver-specific coefficients between the drivers from the urban regions of Hamburg, Berlin and Wolfsburg. It can be seen that the coefficients vary significantly between the drivers and across the band-to-band transitions. The Wolfsburg driver shows much higher linear coefficients than both the Berlin and Hamburg driver, while the Berlin driver shows generally higher coefficients than the Hamburg driver. One could argue that the driver characteristics of figure 4.7(a) are induced by regional properties rather than being an inherent characteristic of the driver himself. While this is certainly true to some extent, figure 4.7(b) analyses four different drivers from the Wolfsburg region, and despite equal conditions, the driver coefficients still differ, with the variations being of similar magnitude as figure 4.7(a).

Moreover, a comparison between the driver-specific coefficients and the driver-generic coefficients shows significant differences in the patterns. This suggests that non-personalized driver behaviour modelling introduces prediction errors. The error statistics are computed for various drivers (see figure 4.7).

**M5 model calibration on $S_{\text{low}}$ data with special reference to regional distinction**

The M5 model is used to evaluate the differences in driving behaviour between street classes. This is achieved, when the learning algorithm of the M5 model is applied
Figure 4.7: Linear M3 model coefficients, calibrated on pre-processed $S_{low}$ data, with special reference to the differences between drivers (personalization) from the cities of Hamburg, Berlin and Wolfsburg. Note, that coefficients are street class generic.
once to the street class specific driving phases (urban-specific, rural-specific, highway-specific) and once to the driving phases aggregately (street class generic). Street classes are extracted from synchronized map data. Each constant phase and each acceleration phase is mapped to a street class. If a driving phase spans multiple street classes, it is mapped to the predominant street class.

The street class specific coefficients are compared with the street class generic coefficients for all band-to-band transitions. The results are shown in figure 4.8. Figure 4.8(a) compares urban-specific linear coefficients with street class generic coefficients; it is shown that the use of street class generic coefficients induces a prediction error in urban environments for both acceleration phases and deceleration phases. The mean prediction error for acceleration phases (per transition) is $0.036 \, \text{m}^2/\text{s}^2$ with a standard deviation of $0.074 \, \text{m}^2/\text{s}^2$. The mean prediction error for deceleration phases (per transition) is $-0.0096 \, \text{m}^2/\text{s}^2$ with a standard deviation of $0.0693 \, \text{m}^2/\text{s}^2$. Figure 4.8(b) compares rural-specific coefficients with street class generic coefficients. Figure 4.8(c) compares highway-specific coefficients with street class generic coefficients. The mean error and the standard deviation are computed for each street class comparison. Error statistics are shown in the respective figures.

The real-world relevance of a transition-specific error depends on the real-world occurrence of the said transition. Figure 4.9 shows the relative occurrence of the speed band transitions by street class. When correlating the error statistics with the band-to-band occurrences, it can be seen that band-to-band transitions show a comparatively small error if they occur either exclusively in one street class (e.g. $\{b_5, b_6\}, \{b_5, b_7\}$) or particularly often (e.g. $\{b_1, b_2\}, \{b_1, b_5\}$).

In conclusion, driver coefficients vary significantly with operator and street class. A driver generic and street class generic modelling approach induces significant error. Hence, a highly accurate prediction of the longitudinal velocity decisions of the drivers requires a learning approach that is driver-specific and street class specific. The coefficients have been presented for multiple drivers and street classes. The next section uses these coefficients in order to predict a velocity profile on the basis of context information.

### 4.2.3 Driver Model Validation Results

Section 4.2.1 has proposed an update-prediction-loop, which learns behavioural patterns of a driver on the basis of past (resp. historic) driving data and applies these patterns to the predicted driving context in order to forecast driver behaviour. It has presented a number of driver model variants, which capture different levels of classification detail of the driving context.

Section 4.2.2 has presented the calibration results of the $M_2$, $M_3$ and $M_5$ model. The $M_3$ model has been used to quantify the effects of personalization. The $M_5$ model has been used to investigate the potential benefits from regional distinction.

This section focuses on the prediction step, applying the calibration results to the future driving context. The validation of the model variants encompasses: (1) a comparison
Figure 4.8: Linear M5 model coefficients, calibrated on pre-processed $S_{low}$ data, with special reference to the differences between street classes (regional distinction). Note, that coefficients are driver generic.
between the predicted velocity profiles of the model variants and the drivers’ real-world velocity profiles, and (2) a benchmark between the model variants. The benchmark is performed for different driving contexts, which are shown to influence the relative performance of the driver model variants.

Recall from table 4.2 and table 4.3, that the driver model variants have different levels of classification detail, which are defined by the driver set and the environment set. The driver set determines, amongst other things, whether the driver model is operator-generic or operator-specific (personalized). The environment set defines, amongst others, whether the driver model is street class generic or street class specific (regional distinction). When comparing the driver model variants at the level of the \{operator, street class\} parameter, it follows:

- M1, M2 $\rightarrow \{\text{operator specific, street class specific}\}$
- M3 $\rightarrow \{\text{operator specific, street class generic}\}$
- M4, M5 $\rightarrow \{\text{operator generic, street class specific}\}$
- M6, M7 $\rightarrow \{\text{operator generic, street class generic}\}$

The M1 model and the M4 model contain the so-called additional environment parameters (access type, traffic flow, traffic lights), which are only contained in the $S_{\text{high}}$ data set. The M2 model and the M5 model do not contain said additional environment parameters. In order to compare the M1, M2, M4 and M5 model, rides from the $S_{\text{high}}$ data set are.
chosen. The additional environment parameters are once considered \((M_1, M_4)\) and once neglected \((M_2, M_5)\).

Several studies are conducted to analyse the performance of the driver model variants: (1) the predictions from first-order and third-order polynomials are compared with real-world rides in the temporal and spatial domain; (2) the velocity predictions of the \(M_1\) model are compared with urban and rural real-world rides of a single driver; (3) the velocity predictions of the \(M_2\) model are compared with the real-world rides of multiple drivers from mixed-environments; (4) the velocity predictions of the \(M_1\) model are compared with the velocity predictions of the \(M_2\) model in urban environments; (5) a benchmark is performed between the models \(M_1 - M_6\).

Validation of acceleration phase predictions of first-order and third-order polynomials against real-world rides in the temporal and spatial domain

While constant driving phases are expressed in terms of zero-order polynomials, acceleration phases can either be captured by first-order polynomials or third-order polynomials. Section 4.2.2 has presented calibration results for both the linear and the cubic case. This paragraph validates the prediction accuracy of the two approaches against urban real-world rides. The reason for choosing urban rides is the high occurrence of acceleration phases per travel distance. Figure 4.10 shows the linear, cubic and real-world velocity profile of a 5 km ride in the city of Wolfsburg. The ride encompasses the following band-to-band transitions: \(\{b_1, b_2\},\ \{b_2, b_1\},\ \{b_1, b_3\},\ \{b_3, b_1\},\ \{b_2, b_3\},\ \{b_3, b_2\}\). The difference between the linear and the cubic profile prediction in the velocity domain is shown to be comparatively small, which is due to the fact that the linear model compensates the overestimation (resp. underestimation) at the beginning of an acceleration phase (resp. deceleration phase) with an underestimation (resp. overestimation) at the end of the respective phase. The impact in the energy domain remains to be discussed in this work.

Figure 4.10 also makes the reader acquainted with the analogy of time and space. Figure 4.10(a) shows the said 5 km urban ride in the time domain. Figure 4.10(b) shows the same ride in the spatial domain. Figure 4.10(c) visualizes the ride on a road map. The prediction model has maximum classification detail, comprising the context parameters of operator, street class, speed band, access type, traffic flow and traffic lights. Changes of these context parameters (i.e. context cues) throughout the ride are indicated in the figures. The ride originates from location1 and ends at location13, passing through:

- location2 → \{traffic light = single-stop, access type = right turn\}
- location3 → \{traffic light = pass\}
- location4 → \{traffic light = multi-stop\}
- location5 → \{traffic light = multi-stop\}
- location6 → \{access type = cross-traffic intersection left turn\}
• location7 $\rightarrow \{\text{traffic light = single-stop, access type = right turn}\}$

• location8 $\rightarrow \{\text{traffic light = multi-stop, traffic flow = } 20 \text{ km/h}\}$

• location9 $\rightarrow \{\text{traffic light = single-stop, access type = left turn}\}$

• location10 $\rightarrow \{\text{traffic light = single-stop, access type = left turn}\}$

• location11 $\rightarrow \{\text{traffic light = single-stop}\}$

• location12 $\rightarrow \{\text{access type = right turn}\}$

As can be seen, time domain properties, such as idle times at traffic lights and crossings, are lost when mapping the velocity profile from the time domain to the spatial domain. Also, the typical linear and cubic shapes of the velocity curve are transformed by the mapping from the time domain to the spatial domain. It is beyond the scope of this thesis to predict idle times at traffic lights and crossings. In the course of this section, validation results are therefore presented in the spatial domain. Moreover, only cubic profiles are shown.

Validation of M1 model predictions against a single driver’s real-world rides from urban and rural environments

In accordance with the definition from table 4.2, the M1 model encompasses the context parameters of operator, street class, speed band, access type, traffic flow and traffic lights. The M1 model is validated against an urban and a rural ride of driver1\(^1\). Figure 4.11(a) shows a 6km urban ride, where acceleration phases are dominated by the band-to-band transitions \((b_1, b_3)\) and \((b_3, b_1)\), which are mostly induced by traffic lights. Figure 4.11(b) shows a 74km rural ride, where acceleration phases are dominated by the band-to-band transitions \((b_3, b_5)\) and \((b_5, b_3)\), which are mostly induced by speed limit changes instead of being induced by access type or traffic lights.

Validation of M2 model predictions against real-world rides from mixed-environments and multiple drivers

The performance of the M2 model is now analysed for mixed-topologies and different drivers. The M2 model is validated against a 24km rural-urban ride of driver4 and a 43km highway-urban ride of driver2. Figure 4.12 compares the real-world velocity profiles with the predicted velocity profiles of the M2 model. It can be seen, that prediction accuracy is high in rural and highway environments and relatively low in urban environments. The reasons for this include: (1) urban environments show a large fluctuation of the context parameters that are not captured by the M2 model, namely, the context parameters of access type, traffic flow and traffic lights, and (2)

\(^1\) Calibration results of driver1 are shown in figure 4.7
Figure 4.10: (a) Time domain comparison between a real-world velocity profile of a 5km urban ride and the respective linear and cubic velocity profile predictions. (b) Mapping of the said velocity profiles from the time domain to the spatial domain. (c) Indication of context cues on the road map along the 5km urban ride.
Figure 4.11: (a) Comparison between a real-world velocity profile of a 6km urban ride and the predicted cubic velocity profile of the M1 model. (b) Comparison between a real-world velocity profile of a 74km rural ride and the predicted cubic velocity profile of the M1 model. The real-world velocity profiles are generated by driver1 (compare figure 4.7). Note, that the set of rides that is used for driver model calibration does not contain the rides that are used to validate the prediction routine.
rural and highway environments show a low fluctuation of these context parameters. In other words, the M2 model captures the majority of context changes in rural and highway environments, while missing a significant number of context changes in urban environments.

**Figure 4.12:** (a) Comparison between a real-world velocity profile of a 24km mixed-rural-urban ride of driver4 and the predicted velocity profile of the M2 model. (b) Comparison between a real-world velocity profile of a 43km mixed-highway-urban ride of driver2 and the predicted velocity profile of the M2 model. The real-world velocity profiles are generated by driver2 and driver4 (compare figure 4.7). Note, that the set of rides that is used for driver model calibration does not contain the rides that are used to validate the prediction routine.
Comparison between M1 model predictions and M2 model predictions in urban environments

Figure 4.13 compares the velocity profile prediction of the M1 model with the prediction of the M2 model for the previously shown 6km urban ride. As can be seen, the reduction of classification detail of the M2 model leads to a significant deterioration of the prediction accuracy when compared with the M1 model. As stated before, the prediction error is caused by the M2 model’s inability to capture the most prominent context changes in urban environments (e.g. access type, traffic lights). The adverse effects of the reduced classification set of the M2 model are worsened owing to a high occurrence of these context changes in urban environments. The occurrence (per driving distance) of these context changes in urban environments may exceed the one in rural environments by a factor of seven. Consequently, the difference in prediction accuracy between the M1 model and the M2 model mitigates in rural and highway environments.

![Figure 4.13: Comparison of the M1 velocity profile prediction with the M2 velocity profile prediction for the 6km urban ride from figure 4.11.](image)

Benchmark between the models M1 – M6

The M1 model has maximum classification detail. It shows high prediction accuracy across all rides. In contrast, the prediction accuracy of the M2 model depends on the properties of the ride; the prediction accuracy is high, if the non-modelled context parameters change rarely along the ride (e.g. rural environment) and it is low, if the non-modelled context parameters change frequently along the ride (e.g. urban environment). This section now compares the remaining models.

Figure 4.14 compares all possible combinations of the context parameters \{operator, street class\}. Figure 4.14(a) shows the results under the assumption that the model’s classification set includes the additional context parameters. Figure 4.14(b) depicts the results under the assumption that the model’s classification set omits the additional context parameters.

It can be seen that the prediction accuracy rises if a model is operator-specific
4.2 Context-aware Driver Model

(personalization). This trend is independent of the additional context parameters. The benefit of personalization is particularly large, if the behaviour of an individual driver strongly deviates from the mean behaviour of the population; the benefit is zero, if the behaviour of an individual driver equals the mean population characteristics. For the case of personalization, street class specific prediction further improves the prediction accuracy of a model. Lastly, it can be observed that the gain in prediction accuracy from an operator-specific and street class specific model is more pronounced, if the model has high classification detail.

Figure 4.14: Comparison between all possible combinations of the context parameters \{operator, street class\}. (a) Making the assumption that the model’s classification set includes the additional context parameters; this is the case for the M1 and M4 model. (b) Making the assumption that the model’s classification set omits the additional context parameters; this is the case for the M2, M3, M5 and M6 model.
4.3 Grey-box Electric Vehicle Consumption Model

EV consumption modelling involves a number of physical models. A first set of equations describes the relationship between external vehicle forces and wheel traction force. A second set of equations describes how wheel traction force and angular wheel speed translate into mechanical motor torque and angular motor speed. A third set of equations describes electrical motor power as a function of mechanical motor torque and angular motor speed. Finally, a fourth set of equations describes how electrical motor power and the electrical power requirements of the auxiliary components translate into battery consumption.

In [GS13], Guzzella and Sciarretta distinguish three approaches of consumption modelling: (1) an average operating point approach, (2) a quasi-static approach, and (3) a dynamic approach. The average operating point approach projects a driving cycle onto a single operating point; vehicle consumption is computed for that operating point only. A quasi-static approach to consumption modelling represents a driving cycle by a piecewise constant function. Piecewise constant input parameters (acceleration, velocity, inclination) are used to determine the tractive forces and the power train efficiencies, from which vehicle consumption is computed. In a dynamic modelling approach a driving cycle is represented by a continuous velocity function. This function serves as input to a set of differential equations, which model driver and vehicle behaviour in a closed-loop form.

This thesis develops an operational EV consumption model. The selection of the modelling approach is based on three conditions: (1) a driving cycle is not entirely known a-priori; (2) the acceleration behaviour of the driver is not computed by a feedback controller, but results from the context-aware driver model of section 4.2; (3) an optimal trade-off is to be reached between high modelling accuracy and low computational effort.

The lack of a-priori driving cycle information renders the average operating point approach unfit for consumption modelling. The absence of a feedback controller and the need for computational efficiency suggest the selection of the quasi-static approach.

4.3.1 Component Model

This section models the consumption characteristics of a state-of-the-art battery electric vehicle. It uses a quasi-static approach for EV consumption modelling. The methodology applied in this section is based upon the methodology used by Guzzella and Sciarretta [GS13].

Figure 4.15 presents a component diagram of the herein developed EV consumption model. It illustrates the interplay of environment characteristics, driver behaviour and both mechanical and electrical vehicle properties. A white-box model describes the

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1 The supervised theses (also see Appendix A.3) of B. J. Manning [Man13], S. Habermann [Hab12] and S. Schinke [Sch11] have contributed to model refinement and software development.
physical properties of the vehicle components and the mutual interactions between them. The driver behaviour is represented by a black-box model. The white-box model and the black-box model are combined to form a grey-box consumption model.

An environment component (E) contains extended predictive road data, denoted xPSD, and methods to modify xPSD fields. xPSD is modelled in the form of an extended road graph as described in chapter 5. Amongst others, xPSD contains information about speed limits, road gradient, road curvature, traffic lights, crossings, current traffic, street class, temperature and sun intensity. xPSD fields serve as input for several components.

Vector $\vec{u}_{DC}$ contains xPSD fields, which are relevant to driver comfort choice. A comfort choice component (DC) contains methods to compute driver comfort settings $\vec{x}_{DC}$ as a function of $\vec{u}_{DC}$. Amongst others, $\vec{x}_{DC}$ describes settings of the air conditioning system, seat heating, front window heating and infotainment system. Vector $\vec{u}_{DD}$ contains xPSD fields, which are relevant to the driver’s longitudinal guiding decisions. A longitudinal guiding choice component (DD) computes the driver’s velocity and acceleration choice, which are captured by vector $\vec{x}_{DD}$ as a function of $\vec{u}_{DD}$, as has been exhaustively discussed in section 4.2. Vector $\vec{u}_{V}$ contains xPSD information relevant to the calculation of the vehicle dynamics, including but not limited to road inclination and rolling friction. Vector $\vec{u}_{AC}$ contains xPSD information that is relevant to the consumption calculation of auxiliary consumers (AC$^1$). It contains information such as sun intensity and ambient temperature.

The vehicle component (V) contains a model of the vehicle dynamics as described in

---

1 The HVAC model of the AC component also requires velocity information from $\vec{x}_{DD}$. For the sake of visual simplicity, the connector has been neglected in the above figure. Yet, vehicle velocity is respected by the HVAC simulation.
4.3.2 A set of equations is used to compute wheel torque $T_v$ and angular wheel speed $\omega_v$ from xPSD information $\vec{u}_v$ and longitudinal driving choice $\vec{x}_{DD}$. Recall, that $\vec{x}_{DD}$ describes a piecewise constant velocity and acceleration set point. The gear box component (G) models the transmission of the mechanical power factors from the wheel to the electric motor. $T_v$ and $\omega_v$ are mapped to motor torque $T_G$ and angular motor speed $\omega_G$ under consideration of transmission ratios and mechanical losses. The motor component (EM) contains a motor transfer function that maps mechanical power factors to electrical power factors $P_{EM}$. The transfer functions of the gear box and the electric motor are described in section 4.3.3.

Auxiliary components (AC) have rather simple transfer functions, except for the heating, ventilation and air conditioning (HVAC) system, whose transfer function is the outcome of cascaded control loops. It takes as inputs the wheel speed ($\omega_v$), the driver desired cabin temperature (from $\vec{x}_{DC}$), the sun intensity and ambient temperature (from $\vec{u}_{AC}$). It returns HVAC\(^1\) power $P_{AC1}$. The power requests of all auxiliary consumers are collected in the vector $\vec{P}_{AC}$.

The electric motor and the auxiliary components have local controllers. Hence, the electrical power factors of the electric motor ($P_{EM}$) and the auxiliary components ($\vec{P}_{AC}$) are the outcome of local control loops. Note, that power factors may either reflect the current values or forecast values. The combined power requirements of $\vec{P}_{AC}$ and $P_{EM}$ are input to the battery management system (BMS), which serves as a supervisory controller. The BMS employs rule-based control algorithms. It monitors the traction battery (B) and computes component individual power limits ($P_{DD}^{BMS}$, $\vec{P}_{AC}^{BMS}$). The local controllers of the components guarantee adherence to these power limits, as indicated by the feedback loops.

4.3.2 Tractive Force Model

Mathematical models of vehicle dynamics can be found in [e.g. SHB10, MW04, HEG13]. A discussion about driving performance and vehicle consumption is provided by [GS13, MW04, HEG13]. Literature distinguishes longitudinal, vertical and lateral dynamics. Consumption modelling mainly involves longitudinal dynamics. The methodology applied in this section is based upon the methodology used by [HEG13].

An instance $i$ is described by a time $t_i$ and a vehicle location $s_i$. The longitudinal guiding choice of a driver at instance $i$ is specified by the vector $\vec{x}_{iDD} = [a_{iDD}, v_{iDD}]$. Environment properties at location $s_i$ and time $t_i$ are expressed by the vector $\vec{u}_{iV}$. Vehicle physics introduce acceleration constraints. The maximum positive acceleration $a_{iDD}^{max+}$ is restricted by maximum drive train power ($P_i^{max}$), maximum motor current ($I_{EM}^{max}$), respectively current induced thermal limitations, lateral vehicle forces ($F_{ilat}$) and the maximum traction coefficient ($F_{i\mu}^{max}$), respectively adhesion coefficient, not to be confused with the static friction coefficient or the rolling loss coefficient. Maximum

\(^1\) For the sake of simplicity, the HVAC system is also referred to as air conditioning system.
4.3 Grey-box Electric Vehicle Consumption Model

braking acceleration $a_{iDD}^{max^-}$ is restricted by lateral dynamics and the maximum traction coefficient. Hence, acceleration is defined in the limits $a_{iDD}^{max^-} \leq a_{iDD} \leq a_{iDD}^{max^+}$.

The maximum vehicle velocity $v_{iDD}^{max}$ is restricted by maximum drive train power $P_{i}^{max}$ and maximum angular motor speed $\omega_{EM}^{max}$. Hence, velocity is defined in the limits $0 \leq v_{iDD} \leq v_{iDD}^{max}$, reverse driving neglected. Maximum drive train power ($P_{i}^{max}$) is a function of maximum electric motor power ($P_{EM}^{max}$), maximum traction battery power ($P_{B}^{max}$) and BMS provided power ($P_{BMS}^{DD}$), which will be described in later sections. For the sake of simplicity, the index $i$ is omitted in the remainder of this chapter.

$$a_{iDD}^{max^+} = f_1 (P_{i}^{max}, P_{EM}^{max}, F_{\mu}, F_{lat})$$

$$a_{iDD}^{max^-} = f_2 (F_{\mu}^{max}, F_{lat})$$

$$v_{iDD}^{max} = f_3 (P_{EM}^{max}, \omega_{EM}^{max})$$

$$P_{i}^{max} = f_4 (P_{EM}^{max}, P_{B}^{max}, P_{BMS}^{DD})$$

Given these constraints, the tractive resistance $F_T$ of a vehicle follows from Newton’s third law, with wheel resistance $F_r$, drag resistance $F_d$, climbing resistance $F_g$ and acceleration resistance $F_a$.

$$F_T = F_r + F_d + F_g + F_a$$

The cumulative wheel resistance $F_r$ comprises rolling resistance, bearing resistance and skew force. A detailed tire/wheel model can be found in [e.g. PB12, HEG13]. During a straight-line drive on a dry and paved road, bearing resistance and skew force can be neglected. From rolling resistance follows

$$F_r = \mu_r F_z$$

$$\mu_r = f_5 (F_z, p, T_{amb,v}, v_{DD}, t)$$

with the coefficient of rolling resistance $\mu_r$, the normal force of the vehicle $F_z$, tire pressure $p$, tire temperature $T_{amb,v}$, driving velocity $v_{DD}$ and driving time $t$ (resp. driving distance $s$). Rolling resistance varies significantly. It cannot be measured directly. A software service has therefore been developed (see supervised master thesis [Man13]) that estimates a rolling resistance coefficient on-line and on-board a vehicle by the use of an Extended Kalman Filter (EKF) approach.

The aerodynamic drag resistance $F_d$ can be formulated in accordance with [HEG13, p. 47]:

$$F_d = \frac{p_{amb}}{2 R_a T_{amb}} c_w A (v_{DD} - v_{w})^2$$

with the ambient air pressure $p_{amb}$, the gas constant of air $R_a$, the ambient temperature $T_{amb}$, the drag coefficient of the vehicle $c_w$, the projected reference area of the vehicle $A$, the vehicle ground speed in driving direction $v_{DD}$ and the wind speed projected in
driving direction $v_w$.  

The climbing resistance $F_g$ is described in terms of the downhill force:

$$ F_g = m g \sin(\alpha) $$

with the vehicle mass $m$, the gravitational acceleration of earth $g$ and the road inclination $\alpha$.

Acceleration resistance $F_a$ results from translational and rotatory acceleration resistance. Rotatory acceleration resistance is governed by the inertia of the rotating masses of the drive train such as wheel and cardan shaft inertia ($\theta_w$), drive shaft inertia ($\theta_v$), gearbox inertia ($\theta_G$) and rotor inertia of the electric motor ($\theta_{EM}$). Gear transmission increases inertia by the square of the transmission ratio $i_G$. The reduced mass inertia $\theta_{red}$ of the drive train is described by [MW04, p. 72 et seqq.]:

$$ \theta_{red} = \theta_w + i_G^2 (\theta_v + \theta_G + \theta_{EM}) $$

From the reduced mass inertia and the translational resistance $F_{at} = m a_{DD}$ follows the acceleration resistance $F_a$ [HEG13, p. 49]:

$$ F_a = \left(m + \frac{\theta_{red}}{r_w^2}\right) a_{DD} = \kappa m a_{DD} $$

with the dynamic wheel radius $r_w$. The summand $\frac{\theta_{red}}{r_w^2}$ can be interpreted as the rotatory part of translational mass, which can be represented by a positive additive factor of mass termed $\kappa$. Note, that electric vehicles generally have a constant transmission ratio $i_G$, which is in contrast to conventional ICE vehicles with up to ten reduction stages.

The output parameters of the vehicle component (V) of figure 4.15 follow from the tractive vehicle resistance $F_T$ and the velocity $v_{DD}$:

$$ T_v = F_T r_w $$

$$ \omega_v = \frac{v_{DD}}{r_w} $$

### 4.3.3 Motor and Gearbox Model

Generally, a gearbox transforms mechanical power factors; here, it converts the torque $T_G$ and angular velocity $\omega_G$ into wheel torque $T_v$ and angular wheel velocity $\omega_v$. The research field of gearbox modelling comprises many aspects and a multitude of different modelling approaches. A review of models can be found in [ÖH88].

In the view of vehicle consumption modelling, it is particularly important to model gearbox transmission efficiency. Most electric vehicles feature single-gear transmission,
where $i_G$ denotes the single-gear transmission ratio and $\eta_G$ denotes the single-gear transmission efficiency, which is defined by the quotient of gearbox power loss $P_G^{\text{loss}}$ and gearbox power input $P_G$:

$$
\eta_G = 1 - \frac{P_G^{\text{loss}}}{P_G}
$$

Power loss is governed by friction, which is composed of coulomb friction between gear teeth and viscous friction of the lubricant. Amongst others, friction depends on gearbox power, angular speed, temperature $T_{\text{amb},G}$ and lubricant immersion depth $r_g$. A friction and efficiency model can be found in [RM75].

$$
P_G^{\text{loss}} = f_6(P_G, \omega_G, T_{\text{amb},G}, r_g)
$$

From the gearbox transmission ratio and gearbox transmission efficiency, the gearbox transfer function is obtained:

$$
T_G = \begin{cases} 
\frac{T_v}{\xi_G \eta_G} & \text{for } T_v \geq 0 \\
\frac{T_v}{\xi_G \eta_G} & \text{for } T_v < 0 
\end{cases}
$$

$$
\omega_G = \omega_v i_G
$$

Note, that the definition of torque $T_v$, as given in section 4.3.2, takes into account the inertia of the rotating masses of the drive train, and that a separate discussion at the level of the gearbox is omitted.

Electric vehicles mostly use permanent-magnet synchronous AC motors. Both electrical and mechanical motor design as well as motor controller design are well understood and can be found in standard text books [e.g. Tol04]. Consumption modelling of electric vehicles is mostly concerned with the power loss characteristics of the electric motor at the various operating points.

In generator mode, an electric motor transforms mechanical power into electrical power. In motor mode, it transforms electrical power into mechanical power. Mechanical power is described in terms of the product of gear torque $T_G$ and angular gear velocity $\omega_G$. Electrical power is described in terms of the product of motor voltage and motor current, $P_{EM} = U_{EM} I_{EM}$. A quasi-static model of the electric motor expresses electrical power as a function of motor efficiency $\eta_{EM}$ and said mechanical power factors [GS13, p. 87/88]:

$$
P_{EM} = \begin{cases} 
\frac{T_G \omega_G}{\eta_{EM}(T_G, \omega_G)} & \text{for } T_G \geq 0 \\
T_G \cdot \omega_G \cdot \eta_{EM}(T_G, \omega_G) & \text{for } T_G < 0 
\end{cases}
$$

where $\eta_{EM}(T_G, \omega_G)$ is represented by a piecewise linear function and has been obtained from measurement data. The variables of the model are restricted, whereby only one
constraint is active at a time.

\[ T_G \leq T_G^{\text{max}}, \quad \omega_G \leq \omega_G^{\text{max}}, \quad P_{\text{EL}} \leq P_{\text{EL}}^{\text{max}} \]

A brief discussion can be found in [GS13, p. 88/89], where constraints on the variables are explained in terms of current limitations of the electric motor and power limitations of the power electronics.

4.3.4 Auxiliary Consumer Model

In the context of this thesis, auxiliary consumers are defined as EV components that contribute to driving comfort and safety but are not part of the vehicle drive train. Amongst others, the category of auxiliary consumers encompasses the HVAC system, seat heating, window heating, infotainment system and lights. The power consumption of said category has not been much of a concern in ICE vehicle consumption analysis. Yet, it is of crucial importance in the consumption analysis of BEVs and PHEVs.

In [LS06], Lange and Schimanski investigate measures to improve PHEV energy management and present a simple model of a heating system (cabin air conditioning, seat heating, window heating). The rate of heat flow is modelled as electrical power loss of a temperature dependent ohmic resistance. The model disregards a number of important aspects such as the influence of radiation and the dependence of the heat-transfer coefficient on vehicle velocity. Moreover, the model lacks a detailed component description. For example, the HVAC system requires component transfer functions of the compressor, condenser, evaporator, PTC-heater, valves and fans.

A detailed analysis of electric vehicle climatization (heating, cooling) can be found in [KLFE11]. The report investigates all major thermal transport mechanisms (solar irradiance, heat radiation of cabin components, convection). It analyses vehicle range with respect to climatization measures and quantifies the range improvement potential from recirculated-air operation, heat pump operation and insulation of the auto body [KLFE11, p. 59 et seqq.]. Yet, the air conditioning system is not treated in full component detail.

In the E-Komfort project [Vol11], funded by the German Federal Ministry of Education and Research, Konz, Bader, Menzel and the author have developed a power consumption model for electric vehicle climatization. The power consumption model features full component detail and models all major thermal transport mechanisms. It encompasses climatization component models, a thermal 3D cabin model\(^1\) and a human thermal comfort model\(^2\). For ease-of-integration in the herein presented operational vehicle consumption model, the climatization consumption is represented by a consumption map. The consumption map can be understood as a piecewise constant transfer func-

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\(^1\) The thermal 3D cabin model has been developed by M. Konz, S. Menzel and V. Bader of the Volkswagen corporate research department.

\(^2\) The human thermal comfort model has been developed by C. Thomschke and V. Bader of the Volkswagen corporate research department.
tion that models the effect of a set of input parameters on the electrical HVAC power $P_{AC1}$. The set of input parameters encompasses the driver-desired cabin temperature $T_{cabin}$, the ambient temperature $T_a$, the sun intensity $Irr$, the driving velocity $v_{DD}$ and the recirculated-air operation $Rec$.

$$P_{AC1} = f_7(T_{cabin}, T_a, Irr, v_{DD}, Rec)$$

Generally, the remaining auxiliary components (e.g. seat heating, window heating) show less responsive behaviour to changes in the environment than does the HVAC system. Moreover, they require on average less power than the HVAC system, making $P_{AC1}$ the dominating component of the collection of auxiliary components $P_{AC}$. The power consumption of the $j$-th component of $P_{AC}$, with $j \geq 2$, can be modelled as a function $f_8$ of state $x_j$:

$$f_8: P_{ACj} = \begin{cases} c_j & \text{for } x_j = 1 \\ 0 & \text{for } x_j = 0 \end{cases} \text{ for } x_j \in \{0,1\}, j = 2, \ldots, n$$

with the piecewise constant power consumption $c_j$ and the states $[on = 1]$ and $[off = 0]$.

### 4.3.5 Battery Model

An ideal battery is entirely described by the time-invariant parameters of nominal capacity and voltage. Ideally, terminal voltage remains constant independent of the battery load and until battery capacity is zero.

"Reality is different, though: the voltage drops during discharge and the effectively perceived capacity is lower under a higher load. This phenomenon is termed the rate capacity effect." [JH09, p. 446].

The relation can be described by Peukert’s equation. The rate capacity effect is the most dominant short-term characteristic of a battery cell. To some extent the diminished capacity can be recovered during load dwell times, which is described by the so-called recovery effect. For relaxation phenomena refer to [FDN94a]. In [JH09], Jongerden and Haverkort present battery models that consider the recovery effect and show that the benefit of these models greatly depends on the load frequency. Hence, the benefit for EV consumption prediction from an integration of the said recovery effect models would need to be investigated for real-world driving profiles and the respective load frequencies, which is not in the scope of this thesis. Consequently, the hereafter presented battery model respects the rate capacity effect and omits the recovery effect.

A review of battery models is presented in [JH09]. A highly accurate electrochemical model that is often used as a reference model for lithium and lithium-ion batteries is presented in [DFN93, FDN94b]. A simulation tool for electrochemical systems can be found in [New]. Battery models for electric vehicles and hybrid electric vehicles are described in [GS13].
This thesis employs an electrical circuit model. A piecewise constant function describes the battery terminal voltage $U_B$ with respect to the battery terminal power $P_B$ (resp. current $I_B$), battery state-of-charge $SoC_B$ and the battery temperature $T_B^1$.

$$U_B = f_9(P_B, SoC_B, T_B)$$

It is then straightforward to compute the local battery efficiency $\eta_B$. The local battery efficiency is not to be confused with the global battery efficiency, which follows from an energy comparison and depends on discharge and charge cycles [GS13]. Let $U_{B0}$ be the open circuit voltage of the battery. Then, the local battery efficiency $\eta_B$ can be described by the quotient of the terminal voltage and the open circuit voltage [GS13, p. 120]:

$$\eta_B = \begin{cases} 
\frac{U_B}{U_{B0}}, & \text{discharge case} \\
\frac{U_{B0}}{U_B}, & \text{charge case}
\end{cases}$$

Power limits of the battery are given by $P_{B}^{\text{max,dis}}$ for the consumption case and $P_{B}^{\text{max,ch}}$ for the recuperation case. Power limits of the battery depend on the battery state-of-charge and the battery temperature and are defined as piecewise linear functions.

$$P_{B}^{\text{max,dis}} = f_{10}(SoC_B, T_B)$$
$$P_{B}^{\text{max,ch}} = f_{11}(SoC_B, T_B)$$

Note, that the battery model does not respect long-term effects such as state-of-health (SoH). Long-term effects depend on the power load collective, state-of-charge, delta state-of-charge, temperature and time. No operational model is known to the author that considers both long-term and short-term effects at reasonable computational time.

### 4.3.6 Calculation Routine

The algorithm of the grey-box consumption model from figure 4.15 is described from a high-level perspective in listing 4.3. It employs the naming conventions of figure 4.15, with the respective modelling detail presented in section 4.2 and section 4.3.

1. %xPSD contains the predicted environment information of the road ahead
2. while (xPSD != empty)
3. %get environment information
4. read $\vec{u}_{DC}$, $\vec{u}_{DD}$, $\vec{u}_{AC}$, $\vec{u}_{V}$
5. %get current vehicle information
6. read vehicle CANbus data

---

1 The following discussion assumes the battery to be always preconditioned and therefore omits battery temperature.
%invoke driver model
compute \( T_{DD} \) from driver model
compute \( T_{DC} \) from driver model

while (vehicleStatus.v != \( v_{DD} \))
%compute the load collective
compute \( P_{AC} \)
compute \( P_{EM} \)

%high-level control loops
if (electric motor limits are violated)
  control \( a_{DD}, v_{DD} \)
end
if (battery limits are violated)
  control \( P_{BMS}^{AC}, P_{BMS}^{DD} \)
end

%low-level control loops
control \( a_{DD} \) and \( v \) satisfying \( P_{BMS}^{DD} \)
control auxiliary consumers satisfying \( P_{AC2} \)
control \( T_{cabin} \) satisfying \( P_{AC1} \)

%update vehicle status
compute vehicle states
vehicleStatus = concatenate \(( a_{DD}, v, T_G, \omega_G, P_{EM}, P_{AC}, T_{cabin}, U_B, P_B, \text{SoC} )\)
outputFile = concatenate ( outputFile, vehicleStatus )
end

%advance to next PSD element
xPSD = xPSD(2:EOF)
end

Listing 4.3: High-level algorithm of a grey-box consumption model predicting the EV consumption on the basis of a given xPSD.

4.4 Results of Sensitivity Analysis of Electric Vehicle Consumption Model

This section examines the characteristics of the grey-box consumption model presented. In particular, it analyses how vehicle consumption reacts towards changes in input parameters, namely longitudinal guiding decisions of the driver, environment characteristics and vehicle properties. For that purpose, several studies are conducted: (1) A one-at-a-time sensitivity analysis investigates how vehicle consumption reacts towards changes in a single input parameter if all the remaining parameters are kept constant around an operating point, and (2) several interaction analyses investigate how vehicle

---

1 Routines use vehicle and environment data of the group research.
consumption reacts towards simultaneous changes in multiple input parameters.

4.4.1 One-at-a-time Sensitivity Analysis

Generally, a one-at-a-time sensitivity analysis is used to investigate how sensitive a model output reacts towards changes in a single parameter if all remaining parameters are kept constant around an operating point. Here, it is used to examine how sensitive vehicle power reacts towards a change in value of a single parameter from the parameter set \{velocity, rolling resistance, road gradient, ambient temperature, combined vehicle mass, combined drag area, state-of-charge\}, given the following operating point:

- velocity = 50 km/h
- combined vehicle mass = 1780 kg
- rolling resistance = 0.015
- road gradient = 1%
- combined drag area = 0.686 m²
- state-of-charge = 30%
- ambient temperature = 20 °C

The parameters represent different context categories. Velocity values follow from driver decisions. The road gradient and the ambient temperature are environment specific and independent of both the driver and the vehicle. The vehicle mass and the combined drag area are vehicle specific and mostly independent of the driver and the environment. The rolling resistance is the result of a vehicle-environment-interaction. The state-of-charge follows from the combination of driver decisions, vehicle properties and environment characteristics over a period of time. Figure 4.16 presents the results of the one-at-a-time sensitivity analysis, plotting the relative increase in vehicle power against the relative increase in parameter value\(^1\). It can be seen that velocity, vehicle mass, rolling resistance, road gradient and combined drag area have a considerable influence on vehicle power; velocity plays a dominant role. The effects of the ambient temperature and the state-of-charge are rather small.

4.4.2 Sensitivity Analysis with Interaction Effects

A one-at-a-time sensitivity analysis quantifies the relative importance of the parameters around the specific operating point. It makes no indication as to how the relative

\(^1\) The relative increase in parameter value is measured with respect to the operating point value.
4.4 Results of Sensitivity Analysis of Electric Vehicle Consumption Model

importance of the parameters changes across operating conditions. Real-world operation causes large changes in the parameter values and therefore large shifts of the operating point, where in most cases the operating point shifts in multiple dimensions simultaneously.

This section evaluates the effect on the vehicle power output when multiple parameters\(^1\) are varied simultaneously. Three studies are conducted to analyse the interaction effects of (1) driver decisions (acceleration choice, velocity choice) on vehicle power output, (2) driver decisions and environment characteristics (road gradient) on vehicle power output, and (3) driver decisions, environment characteristics and vehicle properties (state-of-charge) on vehicle power output.

Analysis of the interaction effects of the driver decisions on the vehicle power output

The interaction effects of the driver decisions (acceleration choice, velocity choice) on the vehicle power output are shown in figure 4.17 where vehicle power output\(^2\) is plotted against vehicle velocity and vehicle acceleration. The vehicle power surface is shown to have non-linear and non-convex properties. The boundary\(^3\) of the power surface defines the operating limits of the vehicle. It follows from a constraint on either a single vehicle component or the interaction of multiple vehicle components and imposes restrictions

---

1 The range of values is given by the parameter’s set of definitions.
2 The vehicle power output captures the vehicle component interactions as described by the white-box vehicle model from section 4.3, given the operating point parameters from section 4.4.1.
3 The resolution of the simulation distorts the boundary of the power surface in the region of high acceleration values and low velocity values.
Figure 4.17: Vehicle power-surface describing the interaction effects of the driver decisions \{acceleration choice, velocity choice\} on the vehicle power output. Driver decisions of a real-world ride are superimposed on the power-surface: (a) urban ride, (b) rural ride, (c) highway ride.
on the acceleration choice and velocity choice of the driver.

Figure 4.17(a) superimposes on the vehicle power surface the driver decisions of a real-world urban ride. Figure 4.17(b) superimposes on the vehicle power surface the driver decisions of a real-world rural ride, while figure 4.17(c) superimposes on the vehicle power surface the driver decisions of a real-world highway ride. The acceleration choices and velocity choices of a driver are captured in discrete time intervals of one second. The so-obtained acceleration-velocity-tuples, denoted by a-v-tuples, are projected onto the power surface of the vehicle.

It can be seen that a-v-tuples exist outside the boundary of the power surface. Mechanical braking is the reason for which the a-v-tuples in figure 4.17(b) exceed the lower boundary of the power surface. If a braking manoeuvre of a driver\textsuperscript{1} requires a breaking power larger than the maximum recuperation power, mechanical brakes exert the required excess breaking power. A negative road slope is the reason for which the a-v-tuples in figure 4.17(c) exceed the upper boundary of the power surface. A negative road slope allows the acceleration and velocity values to exceed the propulsion limits of the drive-train.

Analysis of the interaction effects of driver decisions and environment characteristics on the vehicle power output

The second study analyses the interaction effects of driver decisions (acceleration choice, velocity choice) and environment characteristics \{road gradient\} on the vehicle power output. The results of the interaction analysis are shown in figure 4.18(a) where the vehicle power output is plotted against vehicle velocity, vehicle acceleration and road gradient. The power output is visualized by means of isosurfaces of the volume at the sampling points \{-25\,\text{kW}, -15\,\text{kW}, 0\,\text{kW}, 20\,\text{kW}, 40\,\text{kW}, 60\,\text{kW}, 75\,\text{kW}\}.

The power volume is shown to have non-linear and non-convex properties. A comparison between figure 4.18(a) and figure 4.17 reveals that the additional environment parameter \{road gradient\} shifts the boundary of the power volume, and hence, shifts the restrictions on the acceleration choices and velocity choices of the driver. It can therefore be stated that environment properties not only influence the preference for a longitudinal guiding choice, as described in section 4.2, but also impose constraints on choice options, respectively restrict the set of feasible choices.

Analysis of the interaction effects of driver decisions, environment characteristics and vehicle properties on the vehicle power output

The third study analyses the interaction effects of driver decisions (acceleration choice, velocity choice), environment characteristics \{road gradient\} and vehicle properties \{state-of-charge\} on the vehicle power output. The results of the interaction analysis

\textsuperscript{1} Refer to figure 4.6 for mean deceleration values in rural environments when braking from the speed band (60-90] to the speed band (40-60).
Figure 4.18: (a) Iso-power-surfaces describing the interaction effects of driver decisions \{acceleration choice, velocity choice\} and environment parameters \{road gradient\} on the vehicle power output. (b) Iso-power-surfaces describing the interaction effects of driver decisions \{acceleration choice, velocity choice\}, environment parameters \{road gradient\} and vehicle properties \{state-of-charge\} on the vehicle power output.
are shown in figure 4.18(b). The power output is visualized by means of isosurfaces of the five-dimensional space at the sampling tuples: \{-10\text{ kW}, 24.8\%\}, \{-10\text{ kW}, 80.2\%\}, \{70\text{ kW}, 24.8\%\}, \{70\text{ kW}, 80.2\%\} where the sampling tuples have the format \{\text{power}, \text{SoC}\}. The isosurfaces visualize the interaction characteristics during recuperation mode \((-10\text{ kW})\) and motor mode \((70\text{ kW})\) for the case of full recuperation ability \((24.8\%)\) and limited recuperation ability \((80.2\%)\).

It can be seen that the vehicle state-of-charge has a negligibly small influence on the surface characteristics and a significantly large effect on the boundary properties. Consequently, the vehicle state-of-charge imposes restrictions on the driver’s choice options, whereby the restrictions increase when the state-of-charge approaches 0\%. At the same time, the state-of-charge influences the characteristics of the power surface, whereby these influences are generally small, except for the extreme case when the state-of-charge is close to 0\%.

---

1 The influence on the surface characteristics increases when the state-of-charge approaches 0\%, whereby the effects greatly depend on battery technology.
5 Travel Performance Prediction along a Route\textsuperscript{1, 2, 3}

Section 4.2 has presented a black-box driver model to learn the patterns of acceleration choice and velocity choice as a function of driving context. The black-box driver model has a dual use: on the one hand, it is part of a metric to determine the profile attribute ‘adherence to preferred driving mode’\textsuperscript{4} and, on the other hand, it is used to personalize vehicle consumption in respect of driving behaviour.

Section 4.3 has presented a white-box vehicle model, which describes the physical interactions between the vehicle components by means of quasi-static transfer functions. Moreover, it has proposed a grey-box consumption model, which describes the effects of driver behaviour (acceleration choice, velocity choice, driving mode choice, choice of comfort settings), vehicle properties and road environment characteristics on vehicle consumption.

This section presents an approach, denoted by modular consumption prediction programme, to integrate the driver model from section 4.2 and the white-box vehicle model from section 4.3 with a graph theoretical environment representation in a runtime-efficient manner. For a given route and the set of choices \{velocity choice, acceleration choice, choice of driving mode, choice of comfort settings\}, the consumption prediction programme quantifies the set of profile attributes \{energy consumption, driving time, adherence to preferred driving mode, adherence to comfort settings\}.

Section 5.1 reviews existing consumption prediction approaches. Section 5.2 presents the new modelling approach. Section 5.3 provides a two-part performance analysis of the consumption prediction programme: (1) The predicted values are compared with the true values of several real-world drives, thereby giving an indication of the prediction accuracy; (2) the model variants \{M\textsubscript{1}, M\textsubscript{2}, M\textsubscript{3}, M\textsubscript{4}, M\textsubscript{5}, M\textsubscript{6}\} are compared in different driving situations, thereby giving an indication of the effect of the driving context on the relative performance of the models. General findings are presented, including (1) a high prediction accuracy of the models, (2) a significant influence of personalization on consumption prediction accuracy, and (3) the general principle that the prediction accuracy of a model is directly related to (i) the frequency of the context parameter

\textsuperscript{1} The supervised theses (also see Appendix A.3) of B. J. Manning [Man13], S. Habermann [Hab12] and S. Schinke [Sch11] have contributed to model refinement and software development.
\textsuperscript{2} Note, that selected concepts presented are the basis for and shown in parts in selected patents and/or patent applications listed in Appendix A.1.
\textsuperscript{3} Routines use vehicle and environment data of the group research.
\textsuperscript{4} ‘Adherence to preferred driving mode’ is also referred to as ‘driving dynamics’. 
changes along a route, and (ii) the ability of the model’s classification set to capture these changes. Thus, the prediction accuracy largely depends on the congruence between the model and the specific context characteristics of the route.

5.1 Review and Discussion of Consumption Prediction Approaches

Vehicle consumption prediction is discussed in various contexts. Guzzella and Sciarretta [GS13] present a comprehensive discussion on vehicle consumption modelling in view of vehicle design and control strategies. Lange and Schimanski [LS06] analyse energy management strategies for vehicle propulsion using alternative means. Konz et al. [KLFE11] elaborate on HVAC systems for electric vehicles and investigate their influences on vehicle range. Barth et al. [BAY+00] present a comprehensive modal emissions model for internal combustion engine vehicles, investigating a large number of vehicle models and different operating characteristics. In [BMS01], possible strategies are proposed to integrate the modal emissions models of internal combustion engine vehicles into microscopic traffic simulations. Bartsch [Bar10] proposes a routing approach which employs a consumption prediction model of an internal combustion engine vehicle in order to find ecological routes, making a number of simplifying assumptions.

The approach presented in this chapter builds on the existing theoretical framework of consumption prediction. It extends individual aspects of consumption models and proposes a new composition thereof. More precisely, the approach presented...

• extends the level of detail of the context representation, enabling the vehicle model and the driver model to respond to new context dimensions and new combinations of context dimensions.

• extends and adapts the classifiers of the driver models, distinguishing between different levels of aggregation (personalized, customer segment, aggregately) and between different types of drivers, where each type of driver responds to a unique set of cues in the environment.

• decomposes the context representation into different categories, encompassing (1) a category that influences the longitudinal guiding decisions of a driver, (2) a category that affects the comfort decisions of a driver, and (3) a category that serves as input for the white-box vehicle consumption model.

• decomposes the driver model and the vehicle model into different modules, encompassing (1) a module capturing location-dependent stationary vehicle characteristics, (2) a module expressing location-dependent transient vehicle characteristics, (3) a module describing time-dependent vehicle characteristics, (4) a module capturing velocity decisions of a driver, (5) a module describing the combined choices of acceleration and velocity of a driver, and (6) a module specifying the comfort choices of a driver.
• models the combined effects of auxiliary consumers and drive train components.

• extends the modules towards real-time adaptation, incorporating learning routines.

• proposes a paradigm shift, away from the classical distinction of model types by temporal properties, where consumption prediction approaches are classified by means of time discretization (e.g. $\Delta t \leq 1\text{sec}$, $1 < \Delta t \leq 15\text{sec}$, stationary), towards a thematic distinction, where consumption prediction approaches are distinguished by means of classification detail (e.g. context parameter set, transient characteristics, stationary characteristics, location-dependent characteristics).

As stated before, the approach enables a joint prediction of driving time, vehicle consumption and comfort adherence on the basis of individual driver decisions and highly accurate environment information. Also, the approach addresses the shortcoming of existing approaches to compromise the performance criteria of (1) real-time adaptability, (2) prediction accuracy, (3) computational efficiency, and (4) memory requirements. Existing approaches often perform well in one of the aforementioned performance criteria while moderately in another.

Before proceeding to the modelling section, a simple justification of the proposed procedure is provided. Let a route $r$ at time-of-day $t$ be entirely described by the set of context parameters $C = C_d \cup C_v$ where the $i$-th context parameter is denoted by $p_i \in C$ with $i=1,\ldots,n$. Let the driver model respect the context parameters $p_i \in C_d$ with $i=1,\ldots,l$ and let the vehicle model respect the context parameters $p_i \in C_v$ with $i=1,\ldots,m$. Some context parameters may be used exclusively by either the driver model (e.g. traffic lights) or the vehicle model (e.g. sun irradiance) whereas others may be common to both models (e.g. road gradient), and hence it holds $C_d \cap C_v \neq \emptyset$.

Moreover, let $f_{p_i,r}$ describe the frequency of the context switches of the $i$-th context parameter along route $r$ at a given time. Let $g_{p_i,d_j}$ define the influence of the $i$-th context parameter on the behaviour of the $j$-th driver and let $g_{p_i,v_j}$ define the influence of the $i$-th context parameter on the consumption of the $j$-th vehicle. Then, the accuracy of a vehicle consumption prediction model grows with the value of

$$\sum_{i=1}^{m} (f_{p_i,r} \times g_{p_i,d_j}) + \sum_{i=1}^{m} (f_{p_i,r} \times g_{p_i,v_j})$$

where the first term describes the extent to which the classifier of the driver model captures the relevant environment parameters and where the second term describes the extent to which the vehicle consumption model captures the relevant environment parameters. Since $f_{p_i,r}$ depends on the route, $g_{p_i,d_j}$ depends on the behavioural characteristics of the driver and $g_{p_i,v_j}$ depends on the vehicle characteristics, the consumption prediction model must be adaptive with respect to the driver, vehicle and environment. A lack of adaptation capabilities can be compensated for by a model, which encompasses all possible driver, vehicle and environment characteristics. This however leads either to a high computational effort or, in the case of precomputed maps, to extensive memory requirements, both of which are impractical for real-time decision support. Most existing approaches use non-adaptive reduced models, which however
leads to a significant decline in prediction accuracy for particular combinations of routes, drivers and vehicle models.

### 5.2 Modular Prediction Model

This section presents an approach to integrate the driver model from section 4.2 and the white-box vehicle model from section 4.3 with a graph theoretical environment representation. The modelling approach is presented in four parts: (1) Section 5.2.1 presents a modularization strategy which enables an efficient decomposition of the grey-box consumption model into separate modules; (2) section 5.2.2 describes the interfaces and the transfer functions of the modules; (3) section 5.2.3 discusses the graph theoretical environment representation of the road network; (4) finally, section 5.2.4 presents the modularized consumption prediction procedure which embeds the road environment representation and the aforementioned modules capturing the driver behaviour and the vehicle characteristics.

#### 5.2.1 Modularization Strategy

The grey-box consumption routine is decomposed into separate software modules. In particular, the modularization allows for (1) a distributed system, where modules are either distributed within the vehicle or between the vehicle and a backend server, (2) parallel computation, and (3) precomputation of selected processes, all of which measures considerably improve runtime performance without any loss of prediction accuracy. This section proposes a strategy to modularize the grey-box consumption routine by means of decomposition, employing the following decomposition criteria:

- **Location- vs. time-dependent process**: A location-dependent process predominantly depends on the characteristics of the geographical space (see below module 5 and module 6) and is therefore closely linked to the environment representation of the route. A time-dependent process primarily depends on driving time (see below module 4) and is mostly independent of the specific route properties. A time-dependent process is preferably invoked during post-processing, as will be seen in section 5.2.4.

- **Invariant vs. adaptive process**: An invariant process provides the same output for a given input throughout the entire life cycle (see below module 4, \ldots, module 6). Invariant processes are preferably implemented as precomputed maps. An adaptive process invokes a learning routine; throughout the course of system operation, it may provide different outputs for the same input depending on the learning state (see below module 1, \ldots, module 3).

- **Steady-state vs. transient process**: A steady-state process assumes that the process variables do not change as a function of time (see below module 1 and module 5). A transient process assumes that the process variables change over
time, that is describe a trajectory in the state space. The output of the process holds only for the specific trajectory and the respective boundary conditions (see below module\textsubscript{2} and module\textsubscript{6}).

When applying the decomposition criteria to the grey-box consumption routine, the following modules are obtained: (1) module\textsubscript{1} captures the driver’s velocity choice during cruising phases as an adaptive, steady-state process, (2) module\textsubscript{2} expresses the driver’s acceleration choice and velocity choice during acceleration phases as an adaptive, transient process, (3) module\textsubscript{3} describes the driver’s choice of comfort settings as an adaptive process, (4) module\textsubscript{4} captures the consumption of the auxiliary components of the vehicle as an invariant, steady-state process, (5) module\textsubscript{5} specifies the drive train consumption of the vehicle during cruising phases as an invariant, steady-state process, and finally (6) module\textsubscript{6} describes the drive train consumption of the vehicle during acceleration phases as an invariant, transient process. Module\textsubscript{3} and module\textsubscript{4} mostly depend on time, while the remaining modules mainly depend on geographical space. Given this decomposition, the following paragraphs present a brief discussion on the embodiments of the modules.

Concerning the embodiment of module\textsubscript{4},...,, module\textsubscript{6}, both an invariant and an adaptive design are possible. An invariant design allows for a pre-computation of the processes, which makes the approach runtime efficient but only applicable to the vehicle model and vehicle configuration considered. An adaptive design makes the approach independent of the vehicle model and the vehicle configuration\textsuperscript{1}. An adaptive white-box approach considerably increases computational effort. An adaptive black-box approach is only advisable for driver models with a small classification set (e.g. M5, M6) since otherwise, self-calibration requires an unacceptably large amount of driving data before producing accurate predictions.

Concerning the consumption of the auxiliary components, it is advisable to divide module\textsubscript{4} into two modules where module\textsubscript{4a} captures the consumption characteristics of the HVAC system and module\textsubscript{4b} describes the consumption characteristics of the remaining auxiliary components. The HVAC system has specific consumption characteristics and dependencies (e.g. velocity-dependence) and a significantly larger influence on vehicle consumption than the remaining auxiliary components. The physical model of the HVAC system is highly complex and should not be captured by a learning algorithm. In contrast, the remaining auxiliary components have simple transfer functions, which can easily be captured by a learning algorithm and are purely time-dependent.

The modules can be described in terms of mathematical transfer functions, as is shown in the next section. Note, that for the case of invariant modules, the values of the transfer functions are only exact at the supporting points and interpolated elsewhere. The resolution of the supporting points should be determined from a sensitivity analysis. The interpolation method should be chosen in accordance with the true system characteristics between the supporting points.

\textsuperscript{1} Self-calibrating models are particularly attractive for series production.
5.2.2 Module Interface Parameters and Transfer Functions

This section describes the interfaces of the modules in terms of input and output parameters. It also presents a high-level description of the mathematical transfer functions that map input values to output values. The description employs the vehicle modelling notation from chapter 4 and the graph notation that will be introduced in section 5.2.3, in particular table 5.1.

Module 1 describes the driver’s velocity choice during cruising phases as captured by the driver model from chapter 4 and expressed by \( f_{12} \). The module outputs constant velocity choice, denoted \( v_{DD}(e_i,t) \), as a function of the operator parameter \( op_{id} \) (cp. table 4.1) and the edge weights \( w_j(e_i,t) \) of the mathematical road graph. The classification set of the driver model variant determines the scope of the operator parameter and the edge weights. The operator parameter may refer to a single driver, a set of drivers representing a customer segment, or the aggregate population of drivers. Edge weights may comprise all context parameters from table 4.1. The output \( v_{DD}(e_i,t) \) is generated from the input \( u_{vDD} = \{ op_{id}, w_j(e_i,t) \} \) as follows:

\[
v_{DD}(e_i,t) = \begin{cases} 
  f_{12}(u_{vDD}) & \text{in case of free-flow situation} \\
  w_5(e_i,t) & \text{in case of high density traffic situation} \\
  v_{max} & \text{if } \min(f_{12}(u_{vDD}), w_5(e_i,t)) > v_{max} 
\end{cases}
\]

In free-flow situations, the cruising speed follows from the driver model. In high density traffic situations, the guiding decisions are imposed by the surrounding vehicles. Then, the cruising speed is described macroscopically by the traffic flow speed. Generally, the cruising speed is constrained by the maximum vehicle speed \( v_{max} \), as obtained from manufacturer information. \( v_{max} \) is not to be confused with \( v_{DD}^{max} \), which describes the maximum vehicle speed with respect to the operating conditions of the vehicle.

Module 2 expresses the driver’s acceleration choice during acceleration phases as captured by the driver model from chapter 4 and expressed by \( f_{13} \). The module outputs acceleration choice in the form of one/many polynomial coefficients, denoted by \( a_{DD}(e_i,t) \), as a function of \( op_{id} \), initial velocity \( v_{a}(e_i,t) \), target velocity \( v_{DD}(e_i,t) \) and the edge weights \( w_j(e_i,t) \). The classification set of the driver model variant determines the scope of the operator parameter and the edge weights. The output \( a_{DD}(e_i,t) \) is generated from the input \( u_{aDD} = \{ op_{id}, v_{a}(e_i,t), v_{DD}(e_i,t), w_j(e_i,t) \} \) as follows:

\[
a_{DD}(e_i,t) = \begin{cases} 
  a_{max}^+ & \text{if } f_{13}(u_{aDD}) > a_{max}^+ \\
  a_{max}^- & \text{if } f_{13}(u_{aDD}) < a_{max}^- \\
  f_{13}(u_{aDD}) & \text{otherwise} 
\end{cases}
\]

The positive acceleration is constrained by the maximum vehicle acceleration \( a_{max}^+ \), as obtained from manufacturer information. \( a_{max}^+ \) is not to be confused with \( a_{DD}^{max} \), which describes the maximum vehicle acceleration with respect to the operating conditions of the vehicle. The negative acceleration is constrained by the traction coefficient. Recall, that some of the driver model variants of chapter 4 omit acceleration choice.

Module 3 describes the driver’s choice of comfort settings which is expressed by \( f_{14} \).
The module outputs the choice of comfort settings, denoted by \( x_{DC_k} \), as a function of \( op_{id} \) and the edge weights \( w_j(e_i,t) \). HVAC choice is expressed by \( x_{DC_1} \). Generally, the k-th comfort choice is described by:

\[
x_{DC_k}(e_i,t) = f_{14}^k(op_{id},w_j(e_i,t)) \quad \text{for } k = 1, \ldots, m
\]

Module 4 describes the consumption of the auxiliary components of the vehicle as modelled by the white-box vehicle model from chapter 4. Module 4 describes the consumption characteristics of the HVAC system, which are expressed by \( f_{15} \). The module outputs the HVAC power, denoted by \( P_{AC_1} \), as a function of \( x_{DC_1}(e_i,t), v_{DD}(e_i,t), w_7(e_i,t) \), mean sun irradiance \( w_7(e_i,t) \) and mean ambient temperature \( w_8(e_i,t) \). The output \( P_{AC_1} \) is generated from the input \( u_{ADC_1} = \{ x_{DC_1}(e_i,t), v_{DD}(e_i,t), w_7(e_i,t), w_8(e_i,t) \} \) as follows:

\[
P_{AC_1}(e_i,t) = f_{15}(u_{ADC_1})
\]

Module 5 describes the drive train consumption of the vehicle during cruising phases, denoted by \( P_{EM} \). The consumption characteristics are captured by \( f_{16} \) (motor mode) and \( f_{17} \) (generator mode) as modelled by the white-box vehicle model from chapter 4. The module provides the output tuple \( \{ P_{EM_1}, P_r \} \) as a function of \( v_{DD}(e_i,t) \), linearly interpolated road gradient \( w_2(e_i,t) \) and vehicle state-of-charge \( SoC(e_i,t) \). A violation of the vehicle component constraints or component interaction constraints is indicated by \( P_{EM_c} = \emptyset \). The residual power \( P_r \) quantifies the excess power of the vehicle traction battery at the respective vehicle operating point. As previously defined in chapter 4, \( P_B^{max_{dis}} \) describes the maximum discharge power of the vehicle traction battery. The output values are obtained from the input \( u_{VDD} = \{ v_{DD}(e_i,t), w_2(e_i,t), SoC(e_i,t) \} \) as follows:

\[
P_{EM_c}(e_i,t) = \begin{cases} 
0 & \text{if } v_{DD}(e_i,t) > v_{DD}^{max} \\
0 & \text{if } |f_{16}(u_{VDD})| > |P_{max}^{dis}| \\
f_{16}(u_{VDD}) & \text{in case of motor mode} \\
f_{17}(u_{VDD}) & \text{in case of generator mode}
\end{cases}
\]

\[
P_r(e_i,t) = \begin{cases} 
|P_B^{max_{dis}}| - |P_{EM_c}(e_i,t)| & \text{if } |f_{16}(u_{VDD})| > |P_B^{max_{dis}}| \\
|P_B^{max_{dis}}| + |P_{EM_c}(e_i,t)| & \text{in case of generator mode}
\end{cases}
\]

Lastly, module 6 describes the drive train consumption of the vehicle during acceleration phases, denoted by \( P_{EM_a} \). The consumption characteristics are captured by \( f_{18} \) (motor mode) and \( f_{19} \) (generator mode) as modelled by the white-box vehicle model from chapter 4. The module provides the output tuple \( \{ P_{EM_a}, P_{ra} \} \) as a function of \( v_6(e_i,t), v_{DD}(e_i,t), a_{DD}(e_i,t) \), linearly interpolated road gradient \( w_2(e_i,t) \) and vehicle state-of-charge \( SoC(e_i,t) \). The residual power \( P_{ra} \) quantifies the mean excess power of the vehicle traction battery as averaged over the driving time of the acceleration manoeuvre. The output values are obtained from the input \( u_{ADD} = \)
\{v_a(e_i,t), v_{DD}(e_i,t), a_{DD}(e_i,t), w_2(e_i,t), SoC(e_i,t)\} as follows:

\[
P_{EM_e}(e_i,t) = \begin{cases} 
0 & \text{if } a_{DD}(e_i,t) > a_{DD}^{max} \\
0 & \text{if } |f_{18}(u_{ADD})| > |P_{max}| \\
f_{18}(u_{ADD}) & \text{in case of motor mode} \\
f_{19}(u_{ADD}) & \text{in case of generator mode}
\end{cases}
\]

\[
P_{r_e}(e_i,t) = \begin{cases} 
0 & \text{if } |f_{18}(u_{ADD})| > |P_{B}^{max_{dis}}| \\
|P_{B}^{max_{dis}}| - |P_{EM_e}(e_i,t)| & \text{in case of motor mode} \\
|P_{B}^{max_{dis}}| + |P_{EM_e}(e_i,t)| & \text{in case of generator mode}
\end{cases}
\]

Note, that the interface descriptions presented omit vehicle parameters (e.g. rolling friction), since they are assumed to be globally updated before the modules are called.

### 5.2.3 Graph Theoretical Environment Model

The previous section has used the notion of edge weights for the description of the interfaces and transfer functions of the modules. This section now presents a graph theoretical environment model, which captures the connectivity of a road network in terms of nodes and edges and represents both the location- and time-dependent environment properties as edge weights. The graph theoretical environment model is termed ‘extended predictive road graph’ (xPG).

The term ‘extended’ refers to the enrichment of the graph with additional context information. The term ‘predictive’ refers to the temporal validity of the information, which covers the past and current driving context as well as a forecast of the future conditions. This thesis distinguishes two types of extended predictive road graphs: (1) a weighted, connected linear digraph (xPLG) that captures a single path of the road network, and (2) a weighted, connected digraph (xPCG) that captures the entire road network. Let \(G_C = (V_C,A_C)\) be an xPCG and \(G_L = (V_L,A_L)\) be an xPLG, then, roughly speaking, \(G_L\) can be understood as an induced subgraph of \(G_C\) which contains a single directed path \(n_1, n_2, \ldots, n_{m-1}, n_m\) connecting a departure location \(n_1 \in V_C\) and a destination location \(n_m \in V_C\).

Specifically, \(G_L = (V_L,A_L)\) is a weighted, connected linear digraph with a finite set of nodes \(V_L\) and a finite set of edges \(A_L\). The terminal vertices are denoted by \(n_1\) and \(n_m\), with \(deg(n_1) = deg(n_m) = 1\) and \(deg^{-}(n_1) = deg^{+}(n_m) = 0\). All non-terminal vertices \(n_i\) have \(deg^{-}(n_i) = deg^{+}(n_i) = 1\). The given definition of \(G_L\) allows for a simplified notation, where in the following, \(A_L\) is defined as the set of ordered pairs of vertices \(e_i = \{n_i, n_{i+1}\}\), with \(e_i \in A_L\), \(n_i, n_{i+1} \in V_L\) and \(i = 1, \ldots, m - 1\).

Each edge \(e_i \in A_L\) has associated with it a \(k\)-tuple of weights \(w_l(e_i)\), with \(l = 1, \ldots, k\). This \(k\)-tuple contains all environment parameters that are defined by the interfaces of the driver modules (\(\text{module}_1, \ldots, \text{module}_3\)) and the vehicle modules (\(\text{module}_4, \ldots, \text{module}_6\)). The interface parameters of \(\text{module}_1, \ldots, \text{module}_3\) vary across the driver model variants (cp. table 4.2). The driver model variants with high classification detail (e.g. M1) have a larger set of interface parameters than the driver model...
variants with low classification detail (e.g. M6). Exemplary, table 5.1 shows the k-tuple of the M1 driver model variant. The elements of the k-tuple are by definition edge-dependent. It can be seen that the elements may additionally depend on time-of-day.

| $w_1(e_i)$ | length of edge $e_i$ |
| $w_2(e_i)$ | linearly interpolated road gradient of edge $e_i$ |
| $w_3(e_i)$ | street class of edge $e_i$ |
| $w_4(e_i)$ | access type at location $s(e_i)$ |
| $w_5(e_i,t)$ | reference velocity of edge $e_i$ at time $t$ |
| $w_6(e_i,t)$ | state of traffic light at location $s(e_i)$ at time $t$ |
| $w_7(e_i,t)$ | mean sun irradiance of edge $e_i$ at time $t$ |
| $w_8(e_i,t)$ | mean ambient temperature of edge $e_i$ at time $t$ |

Table 5.1: Edge weight tuple of $G_L$ as required for the driver model variant M1.

The reference velocity $\omega_5(e_i,t)$ is defined in terms of the real-time traffic-flow $v^{RT}$, historic velocity data $v^{HT}$ and the legal speed limit of the road $v^{LT}$, with $v^{RT}, v^{HT}, v^{LT} \in \mathbb{N}$. The unavailability of the respective data is indicated by a parameter value of zero.

$$\omega_5(e_i,t) = \begin{cases} v^{LT}(e_i,t) & \text{if } v^{RT}(e_i,t) = v^{HT}(e_i,t) = 0 \\ v^{HT}(e_i,t) & \text{if } v^{RT}(e_i,t) = 0 \\ v^{RT}(e_i,t) & \text{otherwise} \end{cases}$$

The cumulative driving distance $s$ from a node $n_i \in V_L$ to a node $n_j \in V_L$ with $j > i$ is defined by $s$: $s_{ij} = \sum_{k=i}^{j-1} w_1(e_k)$. Note, that the spatial resolution of the extended predictive road graph is context dependent. The minimum edge length is in the range of meters (e.g. round-about) and the maximum edge length is in the range of kilometres (e.g. highway section). Also note, that $G_L$ is obtained from $G_C$ through a graph transformation which depends on the classification set of the driver model variant and the vehicle model.

5.2.4 Calculation Routine

This section presents the high-level procedure of the modular consumption prediction programme. The procedure is presented in listing 5.1 and is briefly summarized in the following. In a first step, the extended predictive road graph $G_L$ is generated. In a second step, both the vehicle states and the vehicle settings are updated by means of CANbus data. Then, given $G_L$ and the updated vehicle states, module$_1, \ldots, \text{module}_3$ are invoked$^1$ to predict the driver behaviour for the route ahead. Given the aforementioned information (route context, vehicle characteristics, driver behaviour), the

$^1$ The specifics of the module-calls depend on the characteristics of the driver model variant. Vehicle parameters (e.g. rolling friction) are assumed to be globally updated before the modules are called.
route performance factors \{energy consumption, driving time, comfort satisfaction\} are computed in a loop, which iterates over the edges of \(G_L\) and encompasses multiple steps: (1) the type of the current driving phase is determined from a comparison between the vehicle velocity and the velocity trajectory of the driver model; (2) in the case of an acceleration phase, the manoeuvre distance is evaluated with regard to the edge length, thereby dividing the edge into an acceleration part and a cruising part; (3) the set of drive train performance factors \{drive train consumption, driving time\} is computed for each driving phase separately by means of the respective modules (module\(_5\), module\(_6\)); (4) on the basis of the drive train consumption, the battery management system defines the power constraints on the auxiliary components; (6) the set of performance factors \{auxiliary component consumption, comfort satisfaction\} is computed by means of module\(_4\) respecting the power constraints imposed by the battery management system; (7) the vehicle status (e.g. SoC, temperature, rolling friction) and the set of cumulative performance factors \{energy consumption, driving time, comfort satisfactions\} are updated. The algorithm terminates once all edges have been visited or once the state-of-charge of the vehicle either reaches 0% SoC or some predefined threshold.

Note, that for the sake of simplicity the time parameter \(t\) refers to either the ‘elapsed time on the current edge’, the ‘elapsed time on the route’ as accumulated over the past set of edges or the ‘time-of-day’. Also note, that \(P_{EM}, P_r,\) and \(P_{AC}\) may either refer to ‘power’ or ‘energy consumption per manoeuvre’. It is also of merit to know that selected special cases are presented, including the violation of vehicle power constraints, acceleration phases that span multiple edges and constraints on auxiliary component consumption, while many other special cases are omitted for reasons of ease-of-presentation\(^1\). One example of a special case not mentioned is the satisfaction of driving comfort, which describes the degree to which the vehicle satisfies the acceleration and velocity choices of the driver. If the driver model is vehicle specific, the learned driving behaviour complies with the vehicle constraints. Yet, a vehicle generic driver model, which is trained across a fleet of vehicles, may produce driver decisions that violate the vehicle constraints in a number of cases. Then, a metric must be computed, similar to the metric capturing comfort satisfaction, which expresses these violations.

\(^1\) The algorithm that is used to compute the validation results respects special cases.
5.2 Modular Prediction Model

\[ v_a = w_5(e_i,t_0) \]

\[ \text{drivingTime} = 0 \]

\[ \text{comfortSatisfaction} = 0 \]

\[ \text{energyConsumption} = 0 \]

%predict vehicle consumption, driving time and comfort satisfaction for the route ahead by

\[ \text{invoking module}_4, \text{module}_5 \text{ and module}_6 \]

\[ \text{for } i = 1 : (m-1) \]

\[ P_{EM} = 0; P_r = 0; t_d = 0; s_d = 0 \]

\[ v_b = v_{DD}(e_i,t) \]

\[ a = a_{DD}(e_i,t) \]

while \( s_d < \omega_1(e_i,t) \)

%predict drive train consumption and driving time by \invoking \text{module}_5 \text{ and module}_6

if \( v_b > v_a \)

compute acceleration phase parameters \{\( t_i, s_i, v_i, P_{EM_i}, P_{r_i} \}\)

while constraints violated

adapt \( a \) and \( v_b \) to satisfy constraints

compute acceleration phase parameters \{\( t_i, s_i, v_i, P_{EM_i}, P_{r_i} \}\)

end

if \( s_i \leq \omega_1(e_i,t) \)

\[ v_a = v_i \]

\[ t_d += t_i; s_d += s_i; P_{EM} += P_{EM_i}; P_r += P_{r_i} \]

else if \( s_i > \omega_1(e_i,t) \)

compute partial acceleration phase parameters \{\( t_i, s_i, v_i, P_{EM_i}, P_{r_i} \}\)

\[ v_a = v_i \]

\[ t_d += t_i; s_d += s_i; P_{EM} += P_{EM_i}; P_r += P_{r_i} \]

end

else

\[ s_c = \omega_1(e_i,t) - s_d \]

compute for \( s_c \) the constant phase parameters \{\( t_i, s_i, P_{EM_i}, P_{r_i} \}\)

if constraints violated

adapt \( v_b \) to satisfy constraints

else

\[ t_d += t_i; s_d += s_i; P_{EM} += P_{EM_i}; P_r += P_{r_i} \]

end

end

%predict auxiliary component consumption and comfort satisfaction by invoking \text{module}_4

request \( P_{AC}(e_i,t) \) from \text{module}_4

while \( P_r < P_{AC}(e_i,t) \)

adapt \( x_{DC} \) to meet power limits

compute partial auxiliary component consumption \( P_{AC} \) and partial comfort satisfaction \( c_d \)

end

%accumulate performance factors for \( e_i \) and update vehicle state

\[ \text{drivingTime} += t_d \]

\[ \text{comfortSatisfaction} += c_d \]
energyConsumption += (P_{EM} + P_{AC})

update vehicleState
end

Listing 5.1: High-level procedure of the modular consumption prediction programme involving driver modules, vehicle modules and a graph theoretical environment representation.

5.3 Validation Results and Model Benchmark

Section 5.2 has presented a modular consumption prediction programme, whose adaptive driver modules implement the driver models from section 4.2 and whose vehicle modules implement the white-box vehicle models from section 4.3 in a runtime efficient manner. In particular, section 5.2.1 has discussed the modularization strategy, section 5.2.2 has presented the interface descriptions and transfer functions of the modules, section 5.2.3 has introduced a graph theoretical environment representation of the road network and section 5.2.4 has elaborated on the prediction procedure.

This section now analyses the consumption prediction accuracy of the modular consumption prediction programme by comparing the real-world SoC curves of a set of test drives with the predicted SoC curves of the modular consumption prediction programme. In order to be consistent with the previous chapter, the validation results are shown for the test drives that have been used for the driver model validation in section 4.2.3.

5.3.1 Comparative Analysis of M1 and M2 Prediction Accuracy in Urban Environments

Given a 6km urban ride of driver1, this section compares the measured real-world vehicle consumption with the predicted consumption of the M1 model and the predicted consumption of the M2 model. The consumption prediction is based on two sets of context parameters: (1) the context parameters of the driver model, as defined in table 4.2, and (2) the context parameters of the vehicle model, as defined in section 4.3. The context parameters of the vehicle model encompass the parameters that are internal to the vehicle such as the vehicle payload and the parameters that are external to the vehicle such as the road gradient and the rolling loss coefficient.

By definition, the M2 driver model uses a smaller set of context parameters than the M1 driver model. More precisely, the M2 driver model omits the set of context parameters \{access type, traffic flow, traffic light\}. Consequently, the M2 model misses a number of context switches that occur frequently in urban environments. While the effect on the velocity prediction accuracy has previously been shown in figure 4.13, figure 5.1 depicts the influence on the energy consumption prediction accuracy. The M1 model overestimates the real-world vehicle consumption by 2.5%. The M2 model underestimates the real-world vehicle consumption by −8.7%. The underestimation is
a result of the missed acceleration phases, which is due to the M2 model’s inability to capture the respective context changes. And yet, the prediction error remains relatively small, since the influence of the acceleration phases on overall vehicle consumption is moderately low in the presence of energy recuperation. Note, that the recuperation ability decreases when the vehicle SoC increases, and hence, the prediction error of the M2 model is expected to rise at higher SoC values, when SoC > 60% and SoC → 100%.

![Graph showing consumption prediction vs. driving distance](image)

**Figure 5.1:** Comparison between the real-world vehicle consumption of a 6km urban ride, the predicted vehicle consumption of the M1 driver model and the predicted vehicle consumption of the M2 driver model.

### 5.3.2 Analysis of the M2 Prediction Accuracy for Mixed-topologies and Different Drivers

The performance of the M2 model is analysed for mixed-topologies and different drivers. The M2 model is validated against a 24km rural-urban ride of driver4 and a 43km highway-urban ride of driver2. The consumption of the vehicle, as measured during the real-world drive, is compared with the predicted consumption, as computed from the modular consumption prediction programme.

The 24km rural-urban ride of driver4 is presented in figure 5.2(a). The 43km highway-urban ride of driver2 is presented in figure 5.2(b). As can be seen, the accuracy of the consumption prediction of the M2 model varies across the road topologies. It is highest in highway environments, moderately high in rural environments and moderate in urban environments. The mixed rural-urban ride shows a relative prediction error of 2.7%, while the mixed highway-urban ride shows a relative prediction error of 7.4%, both of which errors are smaller than in purely urban environments.
Figure 5.2: (a) Comparison between the real-world vehicle consumption of a 24km mixed-rural-urban ride of driver 4 and the predicted vehicle consumption of the M2 model. (b) Comparison between the real-world vehicle consumption of a 43km mixed-highway-urban ride of driver 2 and the predicted vehicle consumption of the M2 model. Note, that the consumption prediction is based on the velocity profile of figure 4.12.
5.3.3 Comparative Analysis of M1-M6 Prediction Accuracy in Rural Environments

This section compares the performance of all models on the basis of a 74km rural ride. The ride is obtained from the $S_{\text{high}}$ data set, as described in section 4.2.2. The difference between the models can be described in terms of the context parameters \{operator, street class\} and the so-called additional context parameters \{access type, traffic flow, traffic lights\}. Figure 5.3(a) compares four possible combinations of \{operator, street class\} under the assumption that the classification sets of the models contain the additional context parameters, thereby describing the models M1 and M4. Figure 5.3(b) compares four possible combinations of \{operator, street class\} under the assumption that the classification sets of the models exclude the additional context parameters, thereby describing the models M2, M3, M5, and M6.

The error statistics of figure 5.3(a) imply that a model containing a larger number of context parameters has generally a higher prediction accuracy. It is also indicated that the effect of an operator-specific prediction (personalized) is larger than the effect of a street-class specific prediction.

When comparing the qualitative course of the SoC curves, the models with lower classification detail seem to match the real-world curve better throughout the first 50km of the vehicle drive than the models with higher classification detail. This characteristic is not a general property of the models. It is caused by abnormalities of the driver which falsify the prediction of the velocity profile, as shown in figure 4.14. These abnormalities decrease the prediction error of the models in that they counteract the general tendency of the models to overestimate vehicle consumption. When adjusting the real-world consumption for these abnormalities, the prediction error of the models increases while the rank order of the models remains constant.

The models in figure 5.3(b) show the same rank order as the models in figure 5.3(a). The error analysis of the graphs reveals two properties, the discussion of which requires definitions: (1) Let $\text{err}_a$ denote the difference in prediction error between two consecutive models in figure 5.3(a); (2) let $\text{err}_b$ denote the difference in prediction error between two consecutive models in figure 5.3(b); (3) let $\text{err}_{ab}$ denote the difference in prediction error between equally ranked models in figure 5.3(a) and figure 5.3(b).

The prediction error of a model in figure 5.3(a) is generally larger than the prediction error of the equally ranked model in figure 5.3(b), and hence, $\text{err}_{ab} > 0$. The prediction error between the models in figure 5.3(a) is generally larger than the prediction error between the models in figure 5.3(b), and hence, $\text{err}_a > \text{err}_b$. While the first observed property is not generalizable, the second one is.

As to the first property, it shall be shown that $\text{err}_{ab} > 0$ does not generally hold. All models in figure 5.3(a) and figure 5.3(b) overestimate the real-world consumption. The models M1 and M4 contain the context parameters \{access type, traffic flow, traffic lights\}, while the models M2, M3, M5, and M6 omit these context parameters, which causes the latter models to miss several acceleration phases. Each missed acceleration phase causes an underestimation of the real-world consumption, which compensates for the general overestimation of the real-world consumption. Consider
a case where all models generally underestimate real-world consumption. Then, the characteristics of the models $M_2, M_3, M_5$ and $M_6$ would amplify the prediction error, and hence $\text{err}_{ab} < 0$.

As to the second property, it shall be shown that $\text{err}_a > \text{err}_b$ generally holds. The models $M_2, M_3, M_5$ and $M_6$ omit the so-called additional context parameters and therefore ignore several acceleration phases. Each acceleration phase increases the difference in prediction error between the models. For example, an operator-specific model usually adds a smaller prediction error than an operator-generic model. Consequently, the less acceleration phases are considered the smaller the difference in the prediction error between the models, and hence, $\text{err}_a > \text{err}_b$. This property is less pronounced in environments where the occurrence of the said context parameters is low. This property is more pronounced in environments that are rich in the said context parameters, such as urban environments.

This section ends with a couple of remarks: (1) The benefit of personalization is particularly large, if the behaviour of an individual driver strongly deviates from the mean behaviour of the population; (2) the benefit of a street-class specific prediction is generally large, if the road properties alter significantly between the street classes, which mainly depends on the map provider’s definition of the street classes; (3) the benefit of the street-class specific prediction is also large, if a specific driver is very sensitive towards changes in road topology; (4) all of the latter influences depend on the general occurrence of the context changes along the route. Thus, the choice of the driver model variant is likely to influence the route choice as computed by a shortest path algorithm.

Note, that a rural ride generally has a medium number of context changes, a highway ride has a low number of context changes and an urban ride has a large number of context changes. Hence, the difference between the models diminishes in highway environments and significantly increases in urban environments. Mixed-environments will show a combination of the aforementioned characteristics.
5.3 Validation Results and Model Benchmark

Figure 5.3: Comparative analysis of the consumption prediction accuracy of the models M1, ..., M6 for a 74km rural ride. (a) Comparison between driver model variants with different combinations of the parameters {operator, street class} under the assumption that each model’s classification set contains the additional context parameters, thereby describing the models M1 and M4. (b) Same as (a) under the assumption that each model’s classification set excludes the additional context parameters, thereby describing the models M2, M3, M5 and M6. Note, that the respective velocity profile predictions are shown in figure 4.14 and that the models opt1 and opt4 are just slight modifications of M1 and M4.
6 Multi-criteria Green Vehicle Routing Problem with Constraints\textsuperscript{1, 2, 3, 4}

Chapter 5 has presented a modular consumption prediction programme to integrate the driver model from section 4.2 and the white-box vehicle model from section 4.3 with a graph theoretical environment representation in a runtime efficient manner. The approach has employed a weighted linear digraph $G_L$, which represents a single path of the road network. The road network has been modelled as an 'extended predictive road graph' described by the weighted digraph $G_C$.

This chapter presents a routing approach that uses the modular consumption prediction programme designed for $G_L$ and extends it towards $G_C$. It thereby adds 'route choice' to the existing set of choice trade-offs captured by the modular consumption prediction programme.

The routing approach considers the travel choices \{acceleration choice, velocity choice, choice of driving mode, choice of comfort settings, departure time choice, vehicle route choice\} and the travel performance criteria \{energy consumption, driving time, adherence to comfort settings, adherence to preferred driving mode\}.

This chapter is structured as follows: Section 6.1 presents a brief review of green vehicle routing approaches; section 6.2 discusses an extension towards multi-criteria routing and introduces the terminology required to analyse the properties of the non-dominated solutions, which are generated if multiple criteria are conflicting as is the case with travel time, energy consumption and travel comfort; section 6.3 briefly discusses selected aspects of the routing model, whereas the implementation details are not part of this thesis; section 6.4 thoroughly analyses the benefits from a combined optimization of multiple choice dimensions with respect to multiple performance criteria.

\textsuperscript{1} The software package that implements the electric vehicle routing approach on a digital road map and that is used in this thesis, has been developed in a joint development work between Volkswagen AG, namely N. Hoch and B. Werther, and Fraunhofer FOKUS in Berlin (Germany), namely K. Isakovic, H. W. Pohl and A. Hoheisel, and is property of Volkswagen AG.
\textsuperscript{2} Note, that selected concepts presented are the basis for and shown in parts in selected patents and/or patent applications listed in Appendix A.1.
\textsuperscript{3} Routines use vehicle and environment data of the group research.
\textsuperscript{4} Note, that the implementation of the routing approach makes simplifying assumptions where necessary to achieve reasonable routing performance. This comes at the cost of prediction accuracy when compared with chapter 5. An example is the simplifying assumption that the drive train consumption of a vehicle during an acceleration phase, as output of module $\delta$, is linearly distributed over the driving distance if the acceleration manoeuvre spans several edges. The implementation details are not part of this thesis.
6.1 Review and Discussion of Green Vehicle Routing Approaches

Lin et al. [LCH⁺14] present "an extensive literature review of Green Vehicle Routing Problems (GVRP)" [LCH⁺14, p. 1118]. They describe the category of Green-VRP (G-VRP) as a class of VRPs whose routing approaches consider energy consumption and/or whose scheduling approaches incorporate refuelling or recharging strategies due to range limitations. They write:

"The existing research on VRP with the aim of minimizing the fuel consumption seems rare." [LCH⁺14, p. 1128]

"To the best of our knowledge, there are only 2 research papers in the literature that address refueling or recharging problems." [LCH⁺14, p. 1129]

The author adds to the aforementioned review of Lin et al. the contributions of Bartsch [Bar10] and Artmeier et al. [AHLS10]. Bartsch [Bar10] presents a green vehicle routing approach for internal combustion engine vehicles where an ICE vehicle model is used to capture the consumption characteristics and where an algorithm based on ant colony optimization is applied to find the shortest path under the assumption that energy consumption is always larger than zero. Artmeier et al. [AHLS10] address energy optimal routing for electric vehicles. They present an approach that is based on "the shortest route problem with constraints" [Jok66] and consider the cost of acceleration/deceleration by the use of graph transformation. They critically remark that they use an "overly simplistic vehicle model" [AHLS10, p. 7]. Although their approach is mathematically viable, it has a number of shortcomings, including:

- the absence of (i) vehicle consumption characteristics comprising the drive train and the auxiliary components, (ii) specific component related constraints such as the power limitations of the electric motor, (iii) interaction constraints resulting from the interaction of the drive train components and the auxiliary components.

- the absence of (i) a driver model, (ii) a comprehensive environment model including location- and time-dependent context parameters, (iii) a differentiation between the environment cues that influence driver behaviour and vehicle consumption.

- the graph transformation depends on the static speed limits of the road and neither on dynamic environment information, on driver characteristics nor on vehicle consumption characteristics, which may produce non-optimal solutions.

- the graph transformation approach misses the acceleration/deceleration manoeuvres that span more than two edges.

1 Page number is given with reference to the paper.
6.2 Analysis of Multi-criteria Routing and Pareto-front Characteristics

The graph transformation becomes largely inefficient in the face of detailed vehicle models, detailed driver models and both time-dependent and extensive environment information.

In addition to the specific weaknesses listed above, most existing green vehicle routing approaches have general shortcomings: (1) They optimize the route choice independent of \{velocity choice, acceleration choice, choice of driving mode, choice of comfort settings, departure time choice\}, and (2) they do not model the multi-criteria routing problem addressing the trade-offs between energy consumption, travel time and travel comfort. This chapter presents a routing approach that models interactions between choice dimensions and trade-offs between choice criteria.

6.2 Analysis of Multi-criteria Routing and Pareto-front Characteristics

The trade-offs of the multi-criteria routing approach are illustrated in figure 6.1. The following paragraphs provide a detailed explanation of the concepts and terminology used. Note, that for ease of presentation, the comfort related performance criteria ‘adherence to preferred driving mode’ and ‘adherence to comfort settings’ are hereinafter collectively referred to as ‘travel comfort’.

![Figure 6.1: Effects of travel choice on travel performance in the time-energy-comfort domain: (a) choice vector from the set $X^{par^+}_{\text{inv}}$ given the comfort choices $\overrightarrow{c}_{\text{inv}}$; the comfort specific spectrum is not visualized; (b) choice vector from the set $X^{par^+}_{\text{inv}}$ given the route choice $r_{\text{inv}}$; the travel performance vector is constrained by the route-specific spectrum $\Delta T^{r_{\text{inv}}}$, $\Delta E^{r_{\text{inv}}}$, $\Delta C^{r_{\text{inv}}}$; (c) combined spectrum $\Delta T^{\text{var}}$, $\Delta E^{\text{var}}$ and $\Delta C^{\text{var}}$; (d) fastest route as computed by an up-to-date navigation system using a single-criterion optimization and omitting the driver comfort choices $c_{\text{inv}}$; the values of energy consumption and travel comfort can be obtained from post-processing. Note, that (a) dominates (d). Also note, that depending on the formulation of the optimization problem, travel comfort may be interpreted as travel discomfort.](image-url)
A multi-criteria optimization problem comprising multiple conflicting objective functions generally produces a set of non-dominated solutions. The reader may refer to operations research text books for an in depth treatment of Pareto optimization. Attention is drawn here to the application of the Pareto concepts to the specific routing problem rather than revisiting multi-criteria optimization theory.

Let $\vec{x}_i = \{\text{velocity choice}_i, \text{acceleration choice}_i, \text{choice of driving mode}_i, \text{choice of comfort settings}_i, \text{vehicle route choice}_i, \text{departure time choice}_i\}$ be a feasible choice vector obeying the set of constraints $\vec{h} (\vec{x}) \geq 0$. Let $\vec{y}_i = \{\text{energy consumption}_i, \text{driving time}_i, \text{travel comfort}_i\}$ be the respective travel performance vector. It follows from $\vec{y}_i = \vec{r} (\vec{x}_i)$ where $\vec{r}$ is a vector of objective functions mapping the choice vector to the travel performance vector. The objective functions are conflicting, and hence, a minimization (resp. maximization) of the objective functions does not lead to a unique optimum but to a set of non-dominated solutions.

The collection of feasible non-dominated choice vectors is termed Pareto-set, denoted by $X_{\text{par}}^+$. The collection of the respective co-domain vectors, respectively feasible non-dominated travel performance vectors, is termed Pareto-front and is denoted by $Y_{\text{par}}^+$. The vector $\vec{x}_{\text{min}} \in X_{\text{par}}^+$ describes a choice vector whose travel performance vector $\vec{y}_{\text{min}} \in Y_{\text{par}}^+$ minimizes the $k$-th dimension of the Pareto-front, with $k = 1$ referring to travel time, $k = 2$ referring to energy consumption and $k = 3$ referring to travel (dis-)comfort. Analogously, the vector $\vec{x}_{\text{max}} \in X_{\text{par}}^+$ describes a choice vector whose travel performance vector $\vec{y}_{\text{max}} \in Y_{\text{par}}^+$ maximizes the $k$-th dimension of the Pareto-front.

The elements of $Y_{\text{par}}^+$ are hereinafter referred to as 'effective travel performance tuples' comprising the real-valued elements <driving time, energy consumption, comfort adherence>. As long as no relative valuation of the real-valued elements is given, all effective travel performance tuples are equally good. Once a relative valuation (trade-off) is given, the tuples can be mapped to utility values. When ranked by utility, the highest ranking tuple is termed 'subjective travel optimum' or 'optimal travel performance tuple'. The trade-offs, also denoted by 'travel preference' or 'taste vector' (cp. chapter 3), reflect the driver’s perception of the travel performance criteria.

Given these conventions, the terminology of 'comfort-specific spectrum', 'route-specific spectrum' and 'combined spectrum' is introduced (cp. figure 6.1). Note, that the spectrum defines the range of values in each single travel performance dimension, when not yet confined to a specific value in any of the other dimensions. Moreover, it is noteworthy to mention that the spectrum is only valid for a specific origin-destination pair and the respective environment properties.

- The 'comfort-specific spectrum' describes the effect of route choice on driving time and energy consumption when given the remaining choices. Specifically, let $X_{\text{inv}}^+ \subseteq X_{\text{par}}^+$ be a subset of the Pareto-set and let the elements of the subset $\vec{x}_{\text{inv}}^+ \in X_{\text{par}}^+$ have different route choices and equal remaining choices $\vec{c}_{\text{inv}}$. Then, the comfort-specific range of the travel time values is defined as $\Delta T_{\text{inv}} = \vec{y}_{\text{max}}^+ - \vec{y}_{\text{min}}^+$, with $\vec{y}_{\text{min}}^+, \vec{y}_{\text{max}}^+ \in Y_{\text{par}}^+$. Analogously, the comfort-specific
range of the energy consumption values is defined as 
\[
\Delta E_{cinv}^{par} = \bar{y}_{inv}^{par+} - \bar{y}_{min}^{par+},
\]
with \( \bar{y}_{min}^{par+}, \bar{y}_{max}^{par+} \in Y_{cinv}^{par+} \). Note, that the comfort-specific spectrum is computed with reference to a single origin-destination pair (OD-pair) and may be averaged over a number of OD-pairs in a post-processing step.

- The 'route-specific spectrum' describes the effect of the remaining choices on driving time, energy consumption and travel comfort when given the choice of route \( r_{inv} \). In analogy to the previous paragraph, the route-specific range of the travel time values is defined as 
\[
\Delta T_{rinv}^{rinv} = \bar{y}_{par}^{par+} - \bar{y}_{min}^{par+}, \quad \text{with} \quad \bar{y}_{min}^{par+}, \bar{y}_{max}^{par+} \in Y_{rinv}^{par+} \]; the route-specific range of the energy consumption values is defined as 
\[
\Delta E_{rinv}^{rinv} = \bar{y}_{par}^{par+} - \bar{y}_{min}^{par+}, \quad \text{with} \quad \bar{y}_{min}^{par+}, \bar{y}_{max}^{par+} \in Y_{rinv}^{par+}. \]
Additionally, since the comfort related choices are allowed to vary, the route-specific range of the travel comfort values is defined as 
\[
\Delta C_{rinv}^{rinv} = \bar{y}_{par}^{par+} - \bar{y}_{min}^{par+}, \quad \text{with} \quad \bar{y}_{min}^{par+}, \bar{y}_{max}^{par+} \in Y_{rinv}^{par+} \]
where index 3 refers to travel comfort. The route-specific spectrum is computed with reference to a single origin-destination pair and may be averaged over a number of OD-pairs in a post-processing step.

- The 'combined spectrum' describes the combined effect of all choice dimensions on driving time, energy consumption and travel comfort. It thereby defines the maximum improvement potential in each single travel performance dimension. The combined range of the travel time values is defined as 
\[
\Delta T_{var}^{var} = \bar{y}_{max}^{par+} - \bar{y}_{min}^{par+}, \quad \text{the combined range of the energy consumption values is defined as} \quad \Delta E_{var}^{var} = \bar{y}_{max}^{par+} - \bar{y}_{min}^{par+}, \quad \text{and the combined range of the travel comfort values is defined as} \quad \Delta C_{var}^{var} = \bar{y}_{max}^{par+} - \bar{y}_{min}^{par+} \]
where \( \bar{y}_{max}^{par+}, \bar{y}_{min}^{par+} \in Y_{var}^{par+} \) with \( k = 1, \ldots, 3 \) as previously defined.

For a given origin-destination pair, figure 6.1 visualizes the newly introduced terminology. The axes of the figure describe the travel performance criteria. The combined spectrum is indicated by a dotted line. It depicts the range of values of the Pareto-front. In addition to the combined spectrum, the route-specific spectrum is shown.

Figure 6.1 visualizes an effective travel performance tuple of the set \( Y_{cinv}^{par+} \) whose values lie within the comfort-specific spectrum. It also shows an effective travel performance tuple of the set \( Y_{rinv}^{par+} \) whose values lie within the route-specific spectrum. Lastly, it depicts a fastest route as computed by an up-to-date navigation system. While a detailed analysis will be provided in the remainder of this chapter, the reader’s attention should be drawn here to the fact that a multi-criteria routing approach, which jointly optimizes multiple choice dimensions, may simultaneously improve all travel performance dimensions when compared to an up-to-date navigation system. Note, that a minimization problem, where searching for the element with the lowest generalized cost of travel, can equivalently be formulated as a maximization problem, where searching for the element with the highest travel utility. Depending on the formulation of the optimization problem, travel comfort may be interpreted as travel discomfort.
6.3 Multi-criteria Green Vehicle Routing Model\(^1,\,^2\)

This section describes a strategy to find an optimal path from an origin node to a terminal node. It discusses three aspects: (1) the modelling of the hard constraints, (2) the modelling of the objective function, and (3) a shortest path algorithm to find the path that minimizes the objective function and obeys the hard constraints.

Hard constraints

As previously discussed in section 3.3.1, electric vehicles have a considerably shorter driving range and a significantly longer recharging time than internal combustion engine vehicles. It is a desirable property of EV routing and scheduling approaches to avoid unintended waiting times due to range or charge limitations. Section 7 addresses this property at the scheduling level. At the routing level, the property can be modelled as a constraint satisfaction problem where a feasible path \( P \) connecting an origin node with a terminal node satisfies the hard constraint \( \text{SoC}_B(e_i) > 0, \forall e_i \in P \). For a detailed discussion on the shortest route problem with constraints refer to [Jok66]. The aforementioned hard constraint applies to discharging phases in motor mode where it represents a lower bound on the state-of-charge of the EV’s traction battery.

A second constraint may be introduced to capture charging restrictions in generator mode. A detailed discussion on battery physics has previously been presented in section 4.3.5 where the maximum charge power \( P_{\text{max, ch}}^B \) has been defined as a function of the state-of-charge \( \text{SoC}_B \) and the temperature \( T_B \). Generally, the maximum charge power decreases as the state-of-charge of the battery increases; in the limit, \( P_{\text{max, ch}}^B(\text{SoC}_B, T_B) \rightarrow 0 \text{kW} \) when \( \text{SoC}_B \rightarrow 100\% \). In order to avoid situations where the electric motor generates power that exceeds the charge limitation of the traction battery, the routing algorithm may penalize inefficient recuperation. One possible approach is proposed by Artmeier et al. [AHLS10], who model the charge limitations as a soft constraint, thereby favouring paths that avoid these situations. Besides the fact that the approach does not capture the true physical battery characteristics of a vehicle, it misses the point, that in view of consumption minimization the recuperation efficiency is irrelevant as long as the respective path remains non-dominated with respect to energy consumption.

The approach\(^3\) used hereinafter captures charge limitations during generator mode at full physical detail by invoking \( \text{module}_5 \) and \( \text{module}_6 \) of section 5.2. It finds an energy optimal path by penalizing consumption but not explicitly penalizing inefficient

---

1 In the supervised thesis of K. Zemmer [Zem12] (also see Appendix A.3) a description of a time-energy optimal routing approach for EVs is written down.

2 Also refer to: EP 00 0002 669 632A2, Verfahren zum Berechnen einer Route und Navigationsgerät, Patentee: Volkswagen Aktiengesellschaft, Inventor: N. Hoch, K. Zemmer, Priority date: 31.05.2012.

3 The approach allows for a consideration of (i) recuperation restrictions such as the power limitations of the electric motor in generator mode, and (ii) the redistribution of recuperation energy to auxiliary consumers, if the battery’s charge limitations are exceeded.
6.3 Multi-criteria Green Vehicle Routing Model

Recuperation. Note, that a previously non-dominated path may become dominated as a result of wasted recuperation energy. Also note, that recuperation restrictions depend on the state-of-charge of the vehicle, and hence, the initial state-of-charge $\text{SoC}_B(n_0)$ at the origin node $n_0$ codetermines the optimal path connecting the origin with the terminal.

In addition to the aforementioned constraints, the routing approach must capture further constraints, denoted by $\overrightarrow{h}_a(\overrightarrow{u}) \geq 0$, including (i) driver related constraints such as minimum cabin temperature and minimum acceleration, (ii) vehicle component related constraints such as maximum electric motor power and maximum deceleration, and (iii) component interaction constraints such as a restriction on the combined power consumption of the drive train components and the auxiliary components. These constraints are mostly captured by the modules described in chapter 5. They are not explicitly modelled by the routing routine but mostly implicitly satisfied by the modular consumption prediction programme.

In the remainder of this chapter, $\overrightarrow{h}_z(\overrightarrow{u}) \geq 0$ collectively refers to all hard constraints including the choice vector constraints $\overrightarrow{h}_i(\overrightarrow{x}_i) \geq 0$, the state-of-charge constraint $\text{SoC}_B > 0$ and the additional constraints $\overrightarrow{h}_a(\overrightarrow{u}) \geq 0$.

Objective function

In accordance with section 5.2.3, the road network is described by a weighted digraph $G_C = (V_C, A_C)$ where $A_C$ defines the set of edges and $V_C$ the set of nodes. An edge is defined as $e_{ij} = \{n_i, n_j\}$, with $e_{ij} \in A_C$ and $\{n_i, n_j\} \in V_C \times V_C$. In accordance with section 6.2, $\overrightarrow{x}_i$ describes the $i$-th choice vector of a driver; $T(e_{ij}, t)$ describes the driving time along edge $e_{ij}$ at time-stamp $t$; $E(e_{ij}, t)$ describes the respective energy consumption and $C(e_{ij}, t)$ describes the respective comfort adherence. The vehicle parameters defined in section 4.3 are hereinafter denoted by $\overrightarrow{u}_v$.

The modular consumption prediction programme presented in chapter 5 computes from the set of inputs $\{G_C, \overrightarrow{x}_i, \overrightarrow{u}_v\}$ the real-valued output parameters $\{T(e_{ij}, t), E(e_{ij}, t), C(e_{ij}, t)\}$. An objective function $g : \mathbb{R}^3 \rightarrow \mathbb{R}$ maps the set of output parameters to the generalized edge cost $w_{gc}(e_{ij}, t)$ as follows:

$$g : w_{gc}(e_{ij}, t) = \beta_T T(e_{ij}, t) + \beta_E E(e_{ij}, t) + \beta_C C(e_{ij}, t)$$ (6.1)

where $\overrightarrow{\beta} = [\beta_T, \beta_E, \beta_C]$ is the traveller’s taste vector. An extension towards the generalized cost of a path is straightforward. Given a path $P = \{n_1, n_2, \ldots, n_{m-1}, n_m\}$ starting at the origin node $n_1$ at time-stamp $t$ and ending at the terminal node $n_m$, the generalized cost $p_{gc}(P, t)$ of the path follows from:

$$p_{gc}(P, t) = \sum_{i=1}^{m-1} w_{gc}(e_{i,i+1}, t)$$ (6.2)

1 The time-stamp $t$ denotes the time of day when the vehicle passes node $n_1$. 
Note, that the objective function \( g \) can be understood as the sum of three soft constraints: ‘driving time’, ‘energy consumption’ and ‘comfort adherence’. These soft constraints generate different optimum values when minimized independently, and hence, can be interpreted as a set of conflicting objective functions of a multi-criteria optimization problem.

Also note, that driving time \( T \in \mathbb{N} \) is given in seconds, energy consumption \( E \in \mathbb{Z} \) is given in Joules and travel comfort \( C \in \mathbb{N} \) is given as the relative deviation from the most preferred comfort setting/behaviour. The taste vector is defined as \( \overrightarrow{\beta} \in \mathbb{R}^3 \), and hence, \( w_{gc} \in \mathbb{R} \).

**Algorithm**

The routing routine executes a sequence of high-level steps: (1) It reads the weighted digraph \( G_C \); (2) it reads the vehicle parameters \( \overrightarrow{u} \); (3) it initializes the choice vectors \( \overrightarrow{x} \), with \( i = 1, \ldots, n \); (4) it invokes the modules of section 5.2 which output the edge specific values of driving time, energy consumption and comfort adherence and give an indication of the constraint satisfaction; (5) it uses a shortest path algorithm to evaluate the objective function and the hard constraints \( \overrightarrow{h} (\overrightarrow{z}) \geq 0 \) (implicitly and explicitly); (6) it outputs the subjective travel optimum, given the traveller’s taste vector.

Step 5 can be implemented in different ways. The non-dominated solutions can be computed by means of soft constraint logic programming (SCLP) or by means of taste variation. The two options are briefly discussed in the following.

**Non-dominated solutions by means of SCLP:** Given the hard constraints \( \overrightarrow{h} (\overrightarrow{z}) \geq 0 \) and the edge weights \( \langle T(e_{ij},t), E(e_{ij},t), C(e_{ij},t) \rangle \), an SCLP approach can be used to model and solve the multi-criteria routing problem. The result of the SCLP routine is a set of non-dominated paths connecting an origin node with a terminal node. The approach is described in [MMH12a, MMH12b] (a contribution of the author of this thesis). The paper focuses on the bi-objective optimization of the tuple \( \langle T(e_{ij},t), E(e_{ij},t) \rangle \). It is not revisited here. Instead, the reader may refer to [MMH12a, MMH12b] for a detailed description. Note, that the SCLP approach computes the set of non-dominated paths (expressed in terms of effective travel performance tuples) for a given choice vector. These non-dominated solutions are evaluated by means of the objective function in order to determine the subjective travel optimum.

**Non-dominated solutions by means of taste variation:** Given the hard constraints \( \overrightarrow{h} (\overrightarrow{z}) \geq 0 \), the edge weights \( \langle T(e_{ij},t), E(e_{ij},t), C(e_{ij},t) \rangle \) and a taste vector \( \overrightarrow{\beta} \), the objective function \( g \) is applied to the edge weights of the road network. A standard shortest path algorithm is used to find the optimal path \( P_{opt} \) which minimizes \( p_{ge} \), thereby obtaining the subjective travel optimum for the given taste vector. This procedure is repeated for all possible taste vectors \( \overrightarrow{\beta} \), thereby obtaining the set of non-dominated solutions for the given choice vector. The Pareto-front is thus obtained from the variation of the coefficients of the objective function.
The Bellman-Ford algorithm [Bel58] is a well-known shortest path algorithm able to find the optimal path $P_{opt}$ in the presence of both positive and non-positive edge weights. A necessary condition is the non-existence of negative cycles. Given the law of conservation of energy and the strictly positive values of time, the condition is satisfied. Then, given the set of feasible paths $P^+$, connecting an origin node $n_0$ with a terminal node $n_t$, the optimal path $P_{opt}$ minimizes the generalized cost, so that

$$P_{opt}(t) = \min_{W \in P^+} p_{gc}(W,t)$$  \hspace{1cm} (6.3)

The reader may refer to operations research text books for a detailed discussion on shortest path algorithms in general and the Bellman-Ford algorithm in particular. Note, that the edge values can either be generated on runtime or can be precomputed.

### 6.4 Results of Impact Assessment of Travel Choices on Travel Performance

This section conducts several studies to analyse the effects of travel choices on travel performance. The objective of the studies is threefold: (1) to assess the effects of the choice dimensions on the properties of the Pareto-front, (2) to evaluate the effects of the environment characteristics on the Pareto-front, and (3) to analyse the effects of interpersonal taste variations on the characteristics of the subjective travel optimum.

Several studies are conducted to evaluate the effects of the choice dimensions on the properties of the Pareto-front. In particular, section 6.4.1 investigates the influence of route choice, section 6.4.2 analyses the effect of departure time choice, section 6.4.3 evaluates the impact of acceleration choice and velocity choice, and section 6.4.4 assesses the influence of climate comfort choice.

The studies are conducted for a large number of origin-destination pairs from different road environment topologies. This allows for an analysis of the combined effects of the choice dimensions and the environment characteristics on the properties of the Pareto-front.

The Pareto-front is evaluated at selected points that represent particular travel preferences of the drivers. The Pareto optimal elements obtained are compared. This allows for an assessment of the effects of interpersonal taste variations on the characteristics of the subjective travel optimum.

Note, that for the sake of ease of presentation, the one-sided Pareto-front is presented, which represents the one-sided travel preferences as discussed in section 6.4.1. Also

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2 The shortest path is computed on the basis of the terms $E$ and $T$. The influences of the comfort choices on $E$ and $T$ are respected. The term $C$ is disrespected during the shortest path search. The focus is on the visualization of the E-T-domain as a function of the comfort choices. The non-dominated solutions are obtained by means of taste variation.
note, that the non-dominated solutions are computed by means of taste variation.

6.4.1 Effects of Route Choice

The collection of choice vectors $X$ follows from the set of definitions given in table 6.1. The Pareto-set $X^{\text{par}+} \subset X$ contains all feasible and non-dominated choice vectors. The Pareto-front describes the effect of the Pareto-set in terms of effective travel performance tuples. The ‘subjective travel optimum’ is the element of the Pareto-front that minimizes\(^1\) the generalized cost of travel, when given the driver’s taste vector $\beta \ (\text{cp. section 6.3})$. A driver always chooses the subjective travel optimum.

The effects of route choice are analysed in three parts: (1) The properties of the elements of the Pareto-front are analysed; (2) it is investigated how these properties vary across road environment characteristics; (3) the properties of the subjective travel optimum are evaluated as a function of travel preference.

The first part of this section compares the effective travel performance tuples of the Pareto-front with each other and across road environment topologies. In particular, it quantifies the characteristics of the ‘comfort-specific spectrum’ (cp. section 6.2). The second part of this section analyses the characteristics of the subjective travel optimum. Specifically, it quantifies the energy consumption and driving time of the optimal travel performance tuple as a function of travel preference.

Study procedure

Given the set of definitions of table 6.1, Pareto-sets are computed for 99 origin-destination pairs. The OD-pairs represent four different road environment topologies (‘road topologies’):

- **intra-urban** topology, where the origin and the destination location are located in the same city.
- **ruralurban** topology, where the origin is located in an urban centre and the destination is located in an outlying area, and vice versa.
- **rural** topology, where the origin and the destination are both located in a rural region.
- **inter-urban** topology, where the origin and the destination are located in different cities.

The properties of the elements of the Pareto-front are described in terms of the 2-tuple $<\text{energy consumption, driving time}>$. The Pareto-front is evaluated at selected points

---

\(^1\) Note, that a minimization problem, where searching for the element with the lowest generalized cost of travel, can equivalently be formulated as a maximization problem, where searching for the element with the highest travel utility.
representing the interpersonal taste variations of the drivers. More specifically, the relative change in driving time and energy consumption is quantified as a function of travel preference and road topology.

<table>
<thead>
<tr>
<th>Choice dimension</th>
<th>Type</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>route choice</td>
<td>variable</td>
<td>{route_1, \ldots, route_n}</td>
</tr>
<tr>
<td>travel preference</td>
<td>variable</td>
<td>{&lt;1,0&gt;, &lt;1,250&gt;, &lt;1,750&gt;, &lt;1,1250&gt;, &lt;1,1750&gt;, &lt;1,2250&gt;, &lt;1,2750&gt;, &lt;1,3250&gt;, &lt;1,3750&gt;, &lt;1,4250&gt;, &lt;1,4750&gt;, &lt;0,1&gt;}</td>
</tr>
<tr>
<td>departure time choice</td>
<td>invariant</td>
<td>8am</td>
</tr>
<tr>
<td>choice of comfort settings</td>
<td>invariant</td>
<td>auxiliary consumers turned off</td>
</tr>
<tr>
<td>choice of driving mode</td>
<td>invariant</td>
<td>level_1 (cp. chapter 3)</td>
</tr>
<tr>
<td>constant velocity choice</td>
<td>invariant</td>
<td>(v^{HT}) (cp. chapter 5)</td>
</tr>
<tr>
<td>acceleration choice</td>
<td>invariant</td>
<td>driver-generic and street-class generic (cp. section 4.2.2)</td>
</tr>
</tbody>
</table>

Table 6.1: Sets of definitions of the parameters used to analyse the effects of route choice.

Characteristics of the Pareto-front\(^1\) across road topologies

Let \(N_{i}^{\text{inv}}\) be the cardinality of the Pareto-front \(Y_{i}^{\text{par}+}\) of the \(i\)-th OD-pair. Let \(T_{i}^{\text{inv}}(j)\) be the driving time and let \(E_{i}^{\text{inv}}(j)\) be the energy consumption of the \(j\)-th non-dominated route alternative of the \(i\)-th OD-pair. Let \(T_{i}^{\text{inv}}_{\text{min}}\) be the driving time of the fastest route and let \(E_{i}^{\text{inv}}_{\text{min}}\) be the energy consumption of the most ecological route of the set of non-dominated route alternatives of the \(i\)-th OD-pair.

Let \(\delta T_{i}^{\text{inv}}(j,k)\) express the magnitude of the relative change in driving time when choosing the \(k\)-th route alternative instead of the \(j\)-th route alternative. Analogously, let \(\delta E_{i}^{\text{inv}}(j,k)\) express the magnitude of the relative change in energy consumption.

\[
\delta T_{i}^{\text{inv}}(j,k) = \frac{|T_{i}^{\text{inv}}(k) - T_{i}^{\text{inv}}(j)|}{T_{i}^{\text{inv}}_{\text{min,i}}}, \text{ with } j,k \leq N_{i}^{\text{inv}} \quad (6.4)
\]

\[
\delta E_{i}^{\text{inv}}(j,k) = \frac{|E_{i}^{\text{inv}}(k) - E_{i}^{\text{inv}}(j)|}{E_{i}^{\text{inv}}_{\text{min,i}}}, \text{ with } j,k \leq N_{i}^{\text{inv}} \quad (6.5)
\]

where \(\delta T_{i}^{\text{inv}}(j,k)\) is denoted disaggregate comfort-specific spectrum of driving time and \(\delta E_{i}^{\text{inv}}(j,k)\) is denoted disaggregate comfort-specific spectrum of energy consumption. The comfort-specific spectrum \(\triangle T_{i}^{\text{inv}}\), and \(\triangle E_{i}^{\text{inv}}\) respectively, can be expressed in

\(^{1}\) It is noteworthy to mention that a Pareto-front contains many non-dominated elements with small differences in driving time and energy consumption. The travel performance tuples presented hereinafter are selected elements of a Pareto-front.
terms of the disaggregate comfort-specific spectrum\(^1\) as follows:

\[
\Delta T_{i}^{\text{inv}} = \sum_{j=1}^{N_{i}^{\text{inv}}-1} \delta T_{i}^{\text{inv}}(j,j+1), \text{ for } N_{i}^{\text{inv}} \geq 2 \tag{6.6}
\]

\[
\Delta E_{i}^{\text{inv}} = \sum_{j=1}^{N_{i}^{\text{inv}}-1} \delta E_{i}^{\text{inv}}(j,j+1), \text{ for } N_{i}^{\text{inv}} \geq 2 \tag{6.7}
\]

Given the set of definitions of table 6.1, the one-sided set of non-dominated route alternatives is computed for \(i = 1, \ldots, 99\) origin-destination pairs. Figure 6.2 shows the results of 20 inter-urban OD-pairs. Figure 6.2(a) presents both the disaggregate and the aggregate comfort-specific spectrum. The \(i\)-th bar relates to the \(i\)-th OD-pair. The length of the \(i\)-th bar specifies the comfort-specific spectrum \(\Delta T_{i}^{\text{inv}}\), and \(\Delta E_{i}^{\text{inv}}\) respectively. The \(j\)-th segment of the \(i\)-th bar represents element \(j+1\) of the \(i\)-th set of Pareto optimal route alternatives, when elements are ordered with respect to driving time, and energy consumption respectively. The length of the segment specifies the disaggregate comfort-specific spectrum \(\delta T_{i}^{\text{inv}}(j,j+1)\), and \(\delta E_{i}^{\text{inv}}(j,j+1)\) respectively, with \(j = 1, \ldots, N_{i}^{\text{inv}}-1\). Each value of \(j\) is associated with a colour uniquely identifying the pair \(<\delta T_{i}^{\text{inv}}(j,j+1), \delta E_{i}^{\text{inv}}(j,j+1)\>\). Figure 6.2(b) plots the cardinality \(N_{i}^{\text{inv}}\) of the \(i\)-th Pareto-front against the shortest route distance between the origin and the destination of the \(i\)-th OD-pair. Analogously, the remaining road topologies are analysed. Figure 6.3 shows the simulation results of 42 intra-urban OD-pairs. Figure 6.4 depicts the simulation results of 7 rural2urban OD-pairs. Figure 6.5 presents the simulation results of 30 rural OD-pairs.

It can generally be seen that route choice has a major influence on driving time and energy consumption. Both the disaggregate and the aggregate comfort-specific spectrum vary significantly across the OD-pairs of the same road topology and across the road topologies.

When evaluating rural and inter-urban OD-pairs, the cardinality \(N_{i}^{\text{inv}}\) is shown to rise with an increasing distance between the origin and the destination location. This trend does not apply to intra-urban and rural2urban OD-pairs.

Inter-urban route choice has on average the largest effect on travel performance; the effects on driving time and energy consumption are comparable. Intra-urban route choice has a smaller effect on travel performance than inter-urban route choice; the effect on energy consumption is larger than the effect on driving time.

\(^1\) It is assumed that route alternatives are ordered with respect to driving time, and energy consumption respectively.
Figure 6.2: Comfort-specific spectrum shown for 20 inter-urban OD-pairs.
Figure 6.3: Comfort-specific spectrum shown for 42 intra-urban OD-pairs.
Figure 6.4: Comfort-specific spectrum shown for 7 rural2urban OD-pairs.
Figure 6.5: Comfort-specific spectrum shown for 30 rural OD-pairs.
Characteristics of the subjective travel optimum across road topologies and travel preferences

A comfort-specific travel preference is expressed by a 2-tuple $\langle \beta_1, \beta_2 \rangle$, where $\beta_1$ describes the driver’s relative valuation for energy consumption and $\beta_2$ reflects the driver’s relative valuation for driving time. Let $S$ be a tupleset containing different preferences: $S = \{ \langle 1,0 \rangle, \langle 1,1250 \rangle, \langle 1,1750 \rangle, \langle 1,1750 \rangle, \langle 1,2250 \rangle, \langle 1,2750 \rangle, \langle 1,3250 \rangle, \langle 1,3750 \rangle, \langle 1,4250 \rangle, \langle 1,4750 \rangle, <0,1> \}$, where $<1,0>$ describes the preference for the most energy efficient (resp. ecological) route and $<0,1>$ reflects the well-known preference for the fastest route. The tupleset\(^1\) is defined for the case where energy consumption is measured in Watts and travel time is measured in seconds.

Let $p_{gc,i}(j,t)$ be the generalized cost of the $j$-th non-dominated route alternative of the $i$-th OD-pair, given a preference tuple $\langle \beta_1, \beta_2 \rangle$. Let $p_{gc,opt,i}(t)$ be the generalized cost of the subjective travel optimum of the $i$-th OD-pair and let $x_{r,opt,i}(t)$ be the respective optimal route choice.

$$
p_{gc,opt,i}(t) = \min_{j=1}^{N_{i}^{\text{env}}(t)} p_{gc,i}(j,t), \text{ given } \langle \beta_1, \beta_2 \rangle \in S
$$

$$
x_{r,opt,i}(t) = \arg \min_{j=1}^{N_{i}^{\text{env}}(t)} p_{gc,i}(j,t), \text{ given } \langle \beta_1, \beta_2 \rangle \in S
$$

Two studies are conducted to analyse the characteristics of the subjective travel optimum: The first study evaluates the standardized consumption, defined as the quotient of energy consumption and route distance $[\text{kWh/km}]$, of the subjective travel optimum across road topologies and travel preferences $\langle \beta_1, \beta_2 \rangle \in S$; the second study analyses the difference between the subjective travel optimum and the time optimal (resp. energy optimal) route alternative across the road topologies and travel preferences $\langle \beta_1, \beta_2 \rangle \in S$.

Figure 6.6 presents the results of the first study, showing the distribution of the standardized consumption values with respect to the travel preferences and road topologies. The travel preferences $\langle \beta_1, \beta_2 \rangle \in S$ are plotted on the x-axis. The distribution of the standardized consumption is plotted on the y-axis. A separate plot is presented for each road topology.

It can generally be seen that the travel preferences have a significant influence on the standardized energy consumption and that the effects vary across road topology.

A comparison between the road topologies shows that rural OD-pairs have larger median values of standardized consumption than intra-urban OD-pairs across the entire one-sided preference range. When comparing rural OD-pairs with inter-urban OD-pairs it can be seen that rural OD-pairs have larger median values of standardized consumption in the preference range $[<1,0>, <1,3250>]$ and smaller values in the preference range $[<1,0>, <1,1250>]$.\(^1\) For the sake of ease of presentation, the elements of the tupleset $\{<1,0>, \ldots, <1,4750>\}$ reflect the one-sided travel preferences.
An analysis of the course of the median values over the range of travel preferences reveals that the standardized consumption values of intra-urban topology and rural topology are rather insensitive towards changes in travel preference, while the standardized consumption values of inter-urban topology and rural2urban topology react rather sensitively towards changes in travel preference.

A comparison between the extreme preferences \(<1,0>\) and \(<0,1>\) shows an increase of the median standardized consumption of +10.7\% (intra-urban topology), +11.5\% (rural topology), +20.9\% (rural2urban topology) and +27.3\% (inter-urban topology).

An evaluation of the standard deviation reveals a general increase towards \(<0,1>\) preference. Inter-urban topology and rural topology show a comparatively small standard deviation. Intra-urban topology shows constantly high values of standard deviation.

Figure 6.7 presents the results of the second study, showing the mean relative deviation between the subjective travel optimum and the time optimal route (resp. energy optimal route) across the travel preferences and road topologies. The relative deviation from the time optimal route is defined as the difference in driving time between the subjective travel optimum and the time optimal (fastest) route divided by the driving time of the fastest route. The relative deviation from the energy optimal route is defined as the difference in energy consumption between the subjective travel optimum and the energy optimal route divided by the consumption of the energy optimal route. The relative deviations are averaged over the OD-pairs of the road topology, thereby obtaining the mean relative deviation. The mean relative deviation is computed for the travel preferences \(<\beta_1,\beta_2> \in S>.

When comparing the extreme values of the mean relative deviation of driving time, inter-urban topology and rural2urban topology have significantly larger values than intra-urban topology and rural topology. A comparison between the extreme values of driving time and energy consumption reveals significant differences between the road topologies. The extreme values of driving time and energy consumption have similar magnitude in rural regions. Intra-urban topology exhibits a larger extreme value of energy consumption than driving time. Inter-urban topology and particularly rural2urban topology show larger extreme values of driving time than energy consumption.

A correlation of the mean relative deviation of driving time with the mean relative deviation of energy consumption over the range of travel preferences reveals that intra-urban topology has the highest correlation coefficient (according to amount) and rural2urban topology has the smallest correlation coefficient (according to amount).

Note, that the first study uses standardized consumption values in order to make the absolute values comparable, thereby disregarding the differences in consumption between the route alternatives due to different route length; the second study uses absolute consumption values and absolute driving time values; it thereby respects the differences between the route alternatives that are due to different route length.
Figure 6.6: Distribution of the standardized energy consumption [kWh/km] across road topologies and travel preferences. The central mark of a box refers to the median value and the box edges describe the 25th percentile, and the 75th percentile respectively.
Figure 6.7: Mean relative deviation between the subjective travel optimum and the time optimal route (resp. energy optimal route) across road topologies and travel preferences.
6.4.2 Effects of Departure Time Choice

This section investigates the effects of departure time choice on travel performance. It analyses the influence of departure time choice on the 2-tuple <energy consumption, driving time> at the representative travel preference <1,750> and assesses how the influence changes with road topology.

Study procedure

The collection of choice vectors $X$ follows from the set of definitions given in table 6.2. The previously introduced 99 origin-destination pairs are used to represent the four road topologies inter-urban, intra-urban, rural and rural2urban. The departure time choice is varied in 15min intervals between 5:00am and 22:00pm. The choice of route follows from the travel preference <1,750>. Due to the joint optimization of the choice dimensions, a shift in departure time may provoke a change of route.

<table>
<thead>
<tr>
<th>Choice dimension</th>
<th>Type</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>departure time choice</td>
<td>variable</td>
<td>[05:00, 05:15, ..., 21:45, 22:00]</td>
</tr>
<tr>
<td>travel preference</td>
<td>invariant</td>
<td>&lt;1,750&gt;</td>
</tr>
<tr>
<td>choice of comfort settings</td>
<td>invariant</td>
<td>auxiliary consumers turned off</td>
</tr>
<tr>
<td>choice of driving mode</td>
<td>invariant</td>
<td>level_1 (cp. chapter 3)</td>
</tr>
<tr>
<td>constant velocity choice</td>
<td>invariant</td>
<td>$v^{HT}$ (cp. chapter 5)</td>
</tr>
<tr>
<td>acceleration choice</td>
<td>invariant</td>
<td>driver-generic and street-class generic (cp. section 4.2.2)</td>
</tr>
</tbody>
</table>

Table 6.2: Sets of definitions of the parameters used to analyse the effects of departure time choice on travel performance.

Effects of departure time choice on travel performance across road topologies

Since a shift in departure time may provoke a change of route, the analysis of the effect of departure time choice must distinguish between two cases: (1) the case where the reference route remains unchanged, and (2) the case where the reference route changes when departure time is shifted.

Formally, let $t_{dep}$ be the departure time and $x_{r,opt,i}(t_{dep})$ be the optimal route choice where $T_{r,opt,i}(t_{dep})$ is the driving time and $E_{r,opt,i}(t_{dep})$ is the energy consumption of the route. Moreover, let $T_{r,min,i}(t_{dep})$ be the minimum driving time of the said route across departure times $[05:00, 05:15, \ldots, 21:45, 22:00]$ and let $E_{r,min,i}(t_{dep})$ be the respective

1 Recall, that the standard deviation of the travel performance values has shown to be small at <1,750>.
2 The driving time (resp. energy consumption) is evaluated only in the cases where the respective route represents the optimal route choice.
energy consumption. Then, the two cases can be expressed by the variables $\delta T_{i}^{\text{inv}}(t_{\text{dep}})$, termed route-specific spectrum, and $\delta T_{i}^{\text{var}}(t_{\text{dep}})$ as follows:

$$\delta T_{i}^{\text{inv}}(t_{\text{dep}}) = \frac{T_{i}^{\text{opt}}(t_{\text{dep}}) - T_{\text{min},i}(t_{\text{dep}})}{T_{\text{min},i}(05:00)}$$

$$\delta T_{i}^{\text{var}}(t_{\text{dep}}) = \frac{T_{\text{min},i}(t_{\text{dep}}) - T_{\text{opt},i}(05:00)}{T_{\text{opt},i}(05:00)}$$

where $\delta T_{i}^{\text{inv}}(t_{\text{dep}})$ captures the change in driving time resulting from a shift in departure time when the route remains unchanged, and where $\delta T_{i}^{\text{var}}(t_{\text{dep}})$ expresses the change in driving time resulting from the change of route. Driving time and energy consumption are associated. Hence, the variables $\delta E_{i}^{\text{inv}}(t_{\text{dep}})$ and $\delta E_{i}^{\text{var}}(t_{\text{dep}})$ follow from $\delta T_{i}^{\text{inv}}(t_{\text{dep}})$ and $\delta T_{i}^{\text{var}}(t_{\text{dep}})$.

The effect of departure time choice on travel performance is illustrated for the set of definitions of table 6.2 and the previously presented origin-destination pairs. Inter-urban results are shown in figure 6.8. Intra-urban results are presented in figure 6.9. Rural results are shown in figure 6.10. Rural2urban results are presented in figure 6.11. Finally, figure 6.12 compares the cumulative effects of departure time choice between the road topologies. Departure time choice is plotted on the y-axis. The mean relative deviation of travel time and the mean relative deviation of energy consumption are plotted on the x-axis. The mean is obtained from averaging over the OD-pairs of the same road topology.

It can generally be seen that the effect on travel time is significantly larger than the effect on energy consumption. This property holds true for all road topologies except for rural road topology where the effects on travel time and energy consumption have similar magnitude (according to amount). The mean relative deviation of travel time shows a morning peak and an afternoon peak. The mean relative deviation of energy consumption also shows these peaks except for intra-urban road topology.

A comparison between $\delta T_{i}^{\text{inv}}$ (route-specific spectrum) and $\delta T_{i}^{\text{var}}$ (effect of route change) across the road topologies reveals that $\delta T_{i}^{\text{inv}}$ dominates in intra-urban environments while $\delta T_{i}^{\text{inv}} \approx \delta T_{i}^{\text{var}}$ for the remaining road topologies.

When comparing the cumulative effect of $\delta T_{i}^{\text{inv}}$ and $\delta T_{i}^{\text{var}}$ between the road topologies, intra-urban road topology shows the largest extreme value of the mean relative deviation of travel time (22.2%) and the largest extreme value (according to amount) of the mean relative deviation of energy consumption (−11.1%). In contrast, rural road topology shows the smallest cumulative effects.

In a real-world situation, the driver’s ability to shift the departure time depends on the temporal constraints of the daily activity chain; the time flexibility is usually in the range of several minutes up to one hour. The derivatives of the mean relative deviation of travel time and energy consumption give an indication of the potential benefit from a

1 Note, that the property holds true for the travel preference $<1,750>$ and is likely to change across travel preferences.
6.4 Results of Impact Assessment of Travel Choices on Travel Performance

departure time shift. A large value indicates a great benefit, while a small value indicates a small benefit. An analysis of the derivatives reveals that intra-urban road topology and rural2urban road topology show significantly larger values than inter-urban road topology and rural road topology. Hence, the driver’s benefit from a departure time shift is pronounced in intra-urban road environments and rural2urban road environments. This holds particularly true for the departure times ranges $[06:30, 07:45]$ and $[17:45, 19:45]$.

As a final note, it can be seen across the figures that the energy consumption decreases in times of peak traffic where the average driving speed is reduced. This is in contrast to ICE vehicle experience where the higher frequency of acceleration cycles during peak traffic has adverse effects on consumption. However, electric vehicles have (i) the ability to recuperate energy during deceleration manoeuvres and (ii) a very low idle consumption during standstill. These characteristics make EVs efficient in peak traffic situations. Yet, it is critically remarked that the frequency and magnitude of acceleration cycles cannot be modelled with high confidence in peak traffic situations and that the quantitative values should therefore be treated with care. The real-world consumption prediction error is much larger in high traffic density situations than it is in free-flow situations.
Figure 6.8: Effect of departure time choice on travel performance for inter-urban road topology.
Figure 6.9: Effect of departure time choice on travel performance for intra-urban road topology.
Figure 6.10: Effect of departure time choice on travel performance for rural road topology.
Figure 6.11: Effect of departure time choice on travel performance for rural2urban road topology.
6.4.3 Effects of Acceleration Choice and Velocity Choice

This section investigates the effects of acceleration choice and velocity choice on travel performance. It analyses the influence of acceleration choice and velocity choice on the 2-tuple \(<\text{energy consumption}, \text{driving time}\>) at the representative travel preference \(<1,750>\) and assesses how the influence changes with road topology.

Study procedure

The collection of choice vectors \(X\) follows from the set of definitions given in table 6.3. The previously introduced 99 origin-destination pairs are used to represent the four road topologies inter-urban, intra-urban, rural and rural2urban. The velocity choice alternatives are defined by the set \(\{v_{HT}, v_{HT} + 10, v_{HT} + 20\}\) where \(v_{HT}\) describes the average velocity choice of the population as defined in chapter 5. The acceleration choice alternatives are defined by the set \(\{\text{avg}, \text{fast}, \text{slow}\}\) where \(\text{avg}\) describes the driver-generic and street-class generic acceleration behaviour as defined in section 4.2.2. The choice of route follows from the travel preference \(<1,750>\). Due to the joint optimization of the choice dimensions, a change of acceleration choice and/or velocity choice may provoke a change of route choice.

Effects of acceleration choice and velocity choice on travel performance across road topologies

The effects of acceleration choice and velocity choice on travel performance are analysed by means of a comparison between alternative cases and a reference case. The
6.4 Results of Impact Assessment of Travel Choices on Travel Performance

<table>
<thead>
<tr>
<th>Choice dimension</th>
<th>Type</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant velocity choice</td>
<td>variable</td>
<td>( {v^\text{HT}, v^\text{HT} + 10, v^\text{HT} + 20} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(cp. chapter 5)</td>
</tr>
<tr>
<td>acceleration choice</td>
<td>variable</td>
<td>( \text{avg} = \text{driver-generic street-class generic} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \text{fast} = \text{driver}_1 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \text{slow} = \text{driver}_4 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(cp. section 4.2.2)</td>
</tr>
<tr>
<td>choice of driving mode</td>
<td>invariant</td>
<td>level(_1) (cp. chapter 3)</td>
</tr>
<tr>
<td>travel preference</td>
<td>invariant</td>
<td>( &lt;1,750&gt; )</td>
</tr>
<tr>
<td>departure time choice</td>
<td>invariant</td>
<td>8:00am</td>
</tr>
<tr>
<td>choice of comfort settings</td>
<td>invariant</td>
<td>auxiliary consumers turned off</td>
</tr>
</tbody>
</table>

Table 6.3: Sets of definitions of the parameters used to analyse the effects of acceleration choice and velocity choice on travel performance.

The reference case is defined as the acceleration-velocity-tuple \( <\text{avg}, v^\text{HT}> \), where \( \text{avg} \) describes the driver-generic and street-class generic acceleration behaviour as previously defined in section 4.2.2 and, where \( v^\text{HT} \) describes the average velocity choice of the population as previously defined in chapter 5. The alternative cases are defined as the acceleration-velocity-tuples \( \{<\text{slow}, v^\text{HT}>, <\text{fast}, v^\text{HT}>, <\text{avg}, v^\text{HT} + 10>, <\text{avg}, v^\text{HT} + 20>\} \), where \( \text{slow} \) and \( \text{fast} \) describe the alternative acceleration choices and, where \( v^\text{HT} + 10 \) and \( v^\text{HT} + 20 \) describe the alternative velocity choices.

The alternative cases are compared with the reference case. The relative deviations of travel time, energy consumption and route distance\(^1\) are analysed. The relative deviations are averaged over the OD-pairs of the road topology in order to obtain the mean relative deviations of travel time, energy consumption and travel distance. The results are presented in figure 6.13(a) where acceleration choice and velocity choice are plotted on the y-axis and where the mean relative deviations of travel time and energy consumption are plotted on the x-axis.

It can generally be seen that the effect of velocity choice on travel time and energy consumption is significantly larger than the effect of acceleration choice. A comparison between the road topologies reveals that the larger the velocity offset and the smaller \( v^\text{HT} \) are, the larger the relative effect on travel time and energy consumption will be. Consequently, the velocity choice \( v^\text{HT} + 20 \) has the largest relative effect in urban and rural2urban road topology where \( v^\text{HT} \) is comparatively small.

Concerning acceleration choice, it is shown that a change from "\( \text{avg} \)" to "\( \text{slow} \)" causes an increase in travel time across all road topologies. It also increases the energy consumption in rural and inter-urban road environments but reduces the energy consumption.

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\(^1\) Note, that the relative deviation of route distance is zero if the optimal route of the reference case equals the optimal route of the alternative case.
consumption in urban and rural-urban road environments. A change from "avg" to "fast" reduces the travel time across all road topologies except for inter-urban road topology\(^1\). Counter-intuitively, it also reduces the energy consumption across all road topologies. Hence, moderately high acceleration values may reduce both the mean travel time and the mean energy consumption, at least in this simulation.

The choice dimensions are jointly optimized. Thus, a change of acceleration choice and/or velocity choice may provoke a change of route choice. The mutual dependencies of the choice dimensions are expressed by two parameters: (1) The 'frequency of occurrence' of a change of route, and (2) the 'extra distance' of the alternative route. The former parameter describes the likelihood that the optimal route changes when switching from the reference case to the alternative case. The latter parameter describes the mean relative change in route distance when the optimal route changes.

The effects of the alternative acceleration-velocity-tuples on the choice of route are shown in figure 6.13(b) where the frequency of occurrence is plotted on the x-axis, the acceleration-velocity-tuples are plotted on the y-axis and the extra distance is indicated by data tips.

The velocity choice has a larger influence than the acceleration choice on both the frequency of occurrence and the extra distance. The velocity choice \(v_{HT}+20\) causes the highest frequency of occurrence and the largest extra distance across the road topologies.

Although the acceleration choice "fast" shows small values of 'frequency of occurrence' across the road topologies, it shows relatively large values of 'extra distance' in urban and rural-urban road topologies. Inversely, the acceleration choice "slow" shows relatively large values of 'frequency of occurrence' but comparatively small values of 'extra distance' in urban and rural-urban road topologies.

As a final remark, note that figure 6.13 shows average values, and hence, the characteristics may considerably differ between individual OD-pairs of the same road topology.

---

\(^1\) An in-depth analysis of the 20 OD-pairs of inter-urban road topology reveals that two OD-pairs show an unexpected increase in travel time, which distorts the mean value. The two OD-pairs may represent a special case, which however requires further justification.
Figure 6.13: Effects of acceleration choice and velocity choice on travel performance across road topologies.
6.4.4 Effects of Climate Comfort Choice

This section investigates the effects of climate comfort choice on travel performance. It analyses the influence of climate comfort choice on the 2-tuple \(<\text{energy consumption}, \text{driving time}\>\) at the representative travel preference \(<1,750>\) and assesses how the influence changes across road topologies and ambient conditions (e.g. ambient temperature, sun irradiance).

Study procedure

The collection of choice vectors \(X\) follows from the set of definitions given in table 6.4. The previously introduced 99 origin-destination pairs are used to represent the four road topologies inter-urban, intra-urban, rural and rural2urban. The driver can choose among the cabin temperatures \([17°C, 19°C, 22°C, 24°C, 26°C]\) and between fresh air operation [air recirculation choice=off] and recirculating air operation [air recirculation choice=on]. The ambient temperature values are defined in accordance with the German weather characteristics where winter \(\approx 0°C\), spring \(\approx\) autumn \(\approx 8°C\), summer \(\approx 16°C\) and where \([-10°C, -5°C, 24°C, 30°C]\) represent extreme conditions. Sun irradiance distinguishes between night-time \(\approx 0\frac{W}{m^2}\), cloudy days \(\approx 500\frac{W}{m^2}\) and sunny days \(\approx 1000\frac{W}{m^2}\). The choice of route follows from the travel preference \(<1,750>\). Due to the joint optimization of the choice dimensions, a change of cabin temperature choice and/or air recirculation choice may provoke a change of route choice. Since departure time choice, travel preference, driving mode choice, velocity choice and acceleration choice are not altered throughout the study, only a change of route may influence travel time.

The consumption of the heating, ventilating and air conditioning system (HVAC system) has been modelled in section 4.3. The model considers the steady-state operation of the HVAC system and neglects the transient characteristics during warm up and cool down. The HVAC consumption is generally higher during transient operation than during steady-state operation. Yet, the specific error from neglecting the transient consumption largely depends on the scenario. The error is statistically significant if (1) the delta between the ambient temperature and the cabin temperature is particularly large and (2) the transient operation has a comparatively large share of total travel time. Note, that HVAC consumption values are computed at supporting points for a reference cabin temperature of 22°C and are shifted and interpolated elsewhere, and thus, real-world measurements may slightly deviate.

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1 The HVAC model used in this section has been developed by M. Konz, V. Bader and the author and is property of Volkswagen AG. Part of the research has been supported by the E-Komfort project [Vol11] funded by the German Federal Ministry of Education and Research.
### Table 6.4: Sets of definitions of the parameters used to analyse the effects of climate comfort choice on travel performance.

<table>
<thead>
<tr>
<th>Choice dimension</th>
<th>Type</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>cabin temperature choice</td>
<td>variable</td>
<td>[17°C, 19°C, 22°C, 24°C, 26°C]</td>
</tr>
<tr>
<td>air recirculation choice</td>
<td>variable</td>
<td>{ON, OFF}</td>
</tr>
<tr>
<td>ambient temperature</td>
<td>variable</td>
<td>[-10°C, -5°C, 0°C, 8°C, 16°C, 24°C, 30°C]</td>
</tr>
<tr>
<td>sun irradiance</td>
<td>variable</td>
<td>[0 W m⁻², 500 W m⁻², 1000 W m⁻²]</td>
</tr>
<tr>
<td>departure time choice</td>
<td>invariant</td>
<td>8:00am</td>
</tr>
<tr>
<td>travel preference</td>
<td>invariant</td>
<td>&lt;1,750&gt;</td>
</tr>
<tr>
<td>choice of driving mode</td>
<td>invariant</td>
<td>level₁ (cp. chapter 3)</td>
</tr>
<tr>
<td>constant velocity choice</td>
<td>invariant</td>
<td>(v^{HT}) (cp. chapter 5)</td>
</tr>
<tr>
<td>acceleration choice</td>
<td>invariant</td>
<td>driver-generic and street-class generic</td>
</tr>
</tbody>
</table>

Effects of climate comfort choice on travel performance across ambient conditions and road topologies

Let \(x_{r,opt,i}\) be the optimal route choice of the \(i\)-th OD-pair for a given input vector from table 6.4, and let \(T^{\text{opt}}_{r}\) be the associated driving time and \(E^{\text{opt}}_{r}\) be the associated energy consumption. For the given input vector, let \(\bar{T}^{\text{opt}}_{r}\) be the average driving time over the optimal routes of the OD-pairs of the road topology \(r\). Analogously, let \(\bar{E}^{\text{opt}}_{r}\) be the average energy consumption. Moreover, let \(T^{\text{min opt}}_{r}\) be the shortest average driving time across the set of choice vectors \(X\). Then, the deviation of driving time for a given input vector is defined as the difference between \(\bar{T}^{\text{opt}}_{r}\) and \(\bar{T}^{\text{min opt}}_{r}\). Analogously, the deviation of energy consumption is defined as the difference between \(\bar{E}^{\text{opt}}_{r}\) and \(E (T^{\text{opt}}_{r})\).

Figures 6.14–6.17 show the effects of climate comfort choice on energy consumption and travel time and how these effects change across ambient conditions and road topologies. The ambient temperature is plotted on the x-axis. The cabin temperature choice is plotted on the y-axis. The relative deviations of travel time and energy consumption are plotted on the z-axis. Each figure contains two graphs: The first graph shows the travel performance at sun irradiance=0 W m⁻², and the second graph shows the travel performance at sun irradiance= 1000 W m⁻². The results are shown for the case where air recirculation choice=off.

It can generally be seen that the energy consumption rises with a growing delta between the cabin temperature and the ambient temperature. In extreme winter conditions (ambient temperature=-10°C), a change of the cabin temperature choice from 17°C to 26°C increases the energy consumption in average by 9.21%. In extreme summer conditions (ambient temperature=30°C), the same change of the cabin temperature choice reduces the energy consumption in average by 8.12%. Given a choice of cabin temperature of 26°C, a change in ambient temperature from -10°C to 30°C reduces the energy consumption in average by 26.99%. Given a choice of cabin temperature
of 17°C, the same change in ambient temperature reduces the energy consumption in average by 9.64%.

A comparison between energy consumption and travel time reveals that the travel time generally rises when the energy consumption drops, and vice versa. The overall HVAC consumption grows with travel time, and hence, faster routes reduce overall HVAC consumption. Conversely, the faster the route is, the higher the drive train consumption will be, as has been shown in section 6.4.1. A faster route becomes favourable when the savings in HVAC consumption exceed the increase in drive train consumption. Thus, the higher the HVAC power is, the more likely will be a change towards a faster route.

A comparison between the road topologies reveals that the effect of cabin temperature choice on energy consumption is largest in intra-urban environments (figure 6.15) and significantly smaller in both rural environments (not visualized here) and inter-urban environments (figure 6.17). The effect of cabin temperature choice on travel time is small in inter-urban environments (figure 6.16) and even smaller in intra-urban environments (figure 6.14).

A comparison between night-time $\approx 0 \text{ W m}^{-2}$ and sunny days $\approx 1000 \text{ W m}^{-2}$ allows for a quantification of the effects of sun irradiance. It can be seen that high values of sun irradiance reduce the energy consumption and simultaneously increase the travel time. Recirculating air operation [air recirculation choice=on] also reduces the energy consumption. At the same time, it increases the relative influence of the sun irradiance and reduces the relative influence of both the cabin temperature choice and the ambient temperature.

![Figure 6.14: Influence of climate comfort choice and ambient conditions on travel time in intra-urban road environments.](image)

Figure 6.14: Influence of climate comfort choice and ambient conditions on travel time in intra-urban road environments.
6.4 Results of Impact Assessment of Travel Choices on Travel Performance

Figure 6.15: Influence of climate comfort choice and ambient conditions on energy consumption in intra-urban road environments.

Figure 6.16: Influence of climate comfort choice and ambient conditions on travel time in inter-urban road environments.
6.4.5 Discussion

Existing routing approaches mostly optimize a single choice dimension using a single performance criterion. Most existing routing approaches minimize travel time. Some so-called green vehicle routing approaches minimize energy consumption. In general, literature lacks approaches that optimize multiple choice dimensions simultaneously using multiple performance criteria.

The author argues that travel performance (i.e. travel time, energy consumption, travel comfort) can significantly be improved if the routing approach (1) addresses the interdependencies between the choice dimensions, (2) incorporates a location-, time- and driver-dependent representation of the driving context, and (3) evaluates the choice sets with respect to multiple performance criteria instead of a single criterion.

This chapter has introduced a routing approach that (1) addresses the interdependencies between the choice dimensions \{velocity choice, acceleration choice, choice of driving mode, choice of comfort settings, vehicle route choice, departure time choice\}, (2) incorporates a representation of the driving context that respects driver related parameters (cp. section 4.2), vehicle related parameters (cp. section 4.3) and road environment related parameters (cp. chapter 5), (3) simultaneously optimizes the performance criteria \{driving time, energy consumption, adherence to comfort settings\}, and (4) evaluates the choice sets with respect to the driver’s relative valuation of the performance criteria.

Validation results have been shown for selected aspects of the approach presented. Section 6.4.1 has demonstrated that a multi-criteria optimization generates a set of routes which are Pareto-efficient with respect to travel time and energy consumption.
Moreover, it has quantified the effect of the travel preferences on the effective travel performance. Section 6.4.2 has examined the influence of departure time choice on travel performance and has identified time intervals when even small shifts in departure time provoke large shifts in travel performance. It has been found that shifts in departure time may provoke a change of the optimal route, even if all the remaining choices are kept constant. Section 6.4.3 has explored the effects of velocity choice and acceleration choice on travel performance. The effects of velocity choice have generally been larger than the effects of acceleration choice. A change of acceleration choice has altered the optimal route in up to 75% of the cases. A change of velocity choice has altered the optimal route in up to 100% of the cases. Section 6.4.4 has analysed the influence of climate comfort choice on travel performance, where the choice of cabin temperature has shown to influence the energy consumption by up to 12% and where the ambient temperature has shown to influence the energy consumption in extreme cases by up to 35%. It has been found that in the case of low HVAC power the optimal route tends to have a longer travel time and a lower drive train consumption; in the case of high HVAC power the optimal route tends to have a shorter travel time and a higher drive train consumption. The combined effects of the climate comfort choices and the ambient conditions on travel time have reached double-digit percentages.

In conclusion, this chapter has shown that a holistic, context-aware and personalized routing approach unlocks yet untapped potential. The findings support the author’s recommendation to holistically optimize the travel decisions.

As a final note, the approach presented in this chapter computes personal recommendations whose routes largely differ between the drivers with distinct personal behaviour and/or distinct travel preferences. It provides heterogeneous recommendations despite uniform road environment information. The approach therefore improves both the personal travel experience of each individual driver and the global traffic conditions, which even holds at high market shares.
7 Holistic and Personalized Scheduling of Electric Vehicles$^1, 2, 3, 4$

Chapter 3 has elaborated on the decision making problem of electric vehicle travel and has provided a holistic description of the EV travel choices and travel preferences. A discrete choice experiment has been conducted to estimate the travel preferences both at the level of the aggregate population and at the level of disaggregate customer segments. The estimation results have been shown in section 3.4.

Section 4.2 has analysed the similarities and differences in driving behaviour between various drivers. It has presented a context-aware driver model. The model has been calibrated on the basis of real-world driving data in order to quantify the driver-specific patterns of acceleration choice and velocity choice. Section 4.3 has introduced a grey-box EV consumption model, which combines the context-aware driver model with a physical vehicle model, in order to express the dependence of vehicle consumption on both the environment characteristics and the acceleration choices, velocity choices and comfort choices of the driver. Chapter 5 has presented a modular consumption prediction programme, which combines the grey-box EV consumption model with a graph theoretical environment model, in order to forecast the vehicle consumption, driving time and comfort adherence along a given route. In chapter 6, the modular consumption prediction programme has been broadened to include additional choice dimensions, namely departure time choice and the choice of route. Section 6.4 has examined the effects of route choice, departure time choice, acceleration choice, velocity choice and climate comfort choice on travel performance. The findings suggest that there is large potential for improving the travel performance if the travel choices and the performance criteria are treated as an integrated whole.

This chapter uses the calibrated component models and the prediction routines from the previous chapters in order to construct the hierarchical decision support system depicted in figure 2.3. The decision support system holistically optimizes the EV travel choices which have been discussed in section 3.3.1 and visualized in figure

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1 The software package that implements the electric vehicle scheduling routines and that is used in this chapter, has been developed in a joint development work between Volkswagen AG, namely N. Hoch and B. Werther, and Fraunhofer FOKUS in Berlin (Germany), namely K. Isakovic, H.-J. Goltz and A. Hoheisel, and is property of Volkswagen AG.

2 Note, that selected concepts presented are the basis for and shown in parts in selected patents and/or patent applications listed in Appendix A.1.

3 Routines use vehicle and environment data of the group research.

4 Note, that the implementation details of the software package are not part of this thesis.
3.1. It considers the travel choices \{vehicle route choice, pedestrian route choice, departure time choice, choice of charging strategy, parking choice, driving mode choice, velocity choice, acceleration choice, cabin temperature choice\} and expresses the effects of the choice combinations in terms of the meta-attributes \{travel time, travel cost, travel comfort\}. The logit estimates $\beta$ (cp. section 3.4) describe the driver’s trade-offs between the travel performance attributes.

The scheduling model is presented in section 7.1. The real-world benefit from the holistic and personalized choice optimization is demonstrated by means of representative scenarios. These scenarios are deduced from an extensive customer survey as described in section 7.2. Section 7.3 presents selected results.

7.1 Routing and Scheduling Model

The author has addressed the general EV scheduling problem in previous publications [HWB+11, HZWS12, MMH12a, MMH12b] and patent applications (cp. section A.1). The herein presented approach uses and extends the previously published framework.

7.1.1 Problem Description

Figure 7.1 shows the thematic and the temporal structure of the EV scheduling problem. The thematic structure has previously been discussed in section 3.3.1 and is not revisited here. The temporal structure has previously been published by the author in [HZWS12] where it has been defined as follows:

"All time variables are in the following format:

$\left[ t^Y_i \right]_{Z}, \quad i = 1, \ldots, n$

The index $i$ at the lower left indicates the appointment; valid values for $Y$ are $D$ (drive), $W$ (walk), $A$ (appointment), $P$ (park) and $C$ (charge); valid values for $Z$ are $S$ (start) and $E$ (end).

If several events of the same type are associated to a single appointment, they are expressed as $Y_j$ where $Y$ is as above and $j \in \mathbb{N}$. In particular this notation can be used for smart charging (including Vehicle2Grid), where several charging events are scheduled during the parking interval $[t^P_S, t^P_E]$:

$[[t^{C1}_S, t^{C1}_E], [t^{C2}_S, t^{C2}_E], \ldots, [t^{Cm}_S, t^{Cm}_E]]$ [HZWS12, p. 175]

Moreover, the following terminology has been introduced to describe the properties of car parks and charging stations:

1 The supervised thesis (also see Appendix A.3) of K. Zemmer [Zem12] has contributed to modelling.
"Car parks are defined as edge attributes $e^kP^f$, with $k \in \mathbb{N}$ being the capacity of the car park, $e$ the edge to which the car park is attached and $f$ a time dependent availability function (binary or distribution function). The same formalism applies to charging stations, which are represented by $e^{k'}C^{f'}$, $k' \in \mathbb{N}$. Parking is a necessary requirement for charging, hence $k' \leq k$ holds." [HZWS12, p. 175]

The notation previously presented to describe charging stations is broadened to include charging modes. Hereinafter, charging stations are defined as edge attributes $e^M C^{k'}$, with $M \in \{\text{Mode}_1, \text{Mode}_2, \text{Mode}_4\}$ being the charging mode. The charging modes are specified in table 7.1. The general classification of the charging modes is based on the international standard IEC-61851-1$^1$. The specific definition of the charging modes differs from the international standard in that $ct$ is defined as the duration required to charge the traction battery from SoC=5\% to SoC=95\% and $cc$ is defined as the unit energy cost.

Analogously, the notation previously presented to describe car parks (resp. parking lots) is broadened to include parking fees. Hereinafter, car parks are defined as edge attributes $F^eP^k$, with $F$ being the parking fee $[\frac{\text{e}}{\text{h}}]$.

Finally, the $i$-th activity (resp. appointment) of an activity-chain is defined as $e^iA^P$, with $i = 1, \ldots, n$ and $P$ being the activity purpose$^2$; valid values for $P$ are $H$ (home), $W$ (work) and $SP$ (secondary purpose). The index $e$ may either refer to an associated edge of the road graph, a geographical location or an area (resp. cell or zone) at which the activity takes place.

<table>
<thead>
<tr>
<th>Charging mode</th>
<th>$ct_{5-95}$</th>
<th>$cc$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mode$_1$</td>
<td>390 min</td>
<td>25 cent kWh</td>
</tr>
<tr>
<td>Mode$_2$</td>
<td>120 min</td>
<td>35 cent kWh</td>
</tr>
<tr>
<td>Mode$_4$</td>
<td>30 min</td>
<td>60 cent kWh</td>
</tr>
</tbody>
</table>

Table 7.1: Definition of charging modes by means of charge duration and unit energy cost. The value of $ct$ defines the charge duration from SoC=5\% to SoC=95\%. The value of $cc$ expresses the unit energy cost.

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$^1$ Update version available from International Electrotechnical Commision. Available at: http://www.iec.ch/. – Last accessed: 01.03.2015

$^2$ The activity purpose does not affect the solution set but the travel preferences of the traveller. Hence, it influences the utility of the elements of the solution set.
Figure 7.1: The EV scheduling problem has a thematic structure, which has previously been shown in figure 2.3 and figure 3.1, and a temporal structure, which is cited from the author’s publication [HZWS12] in a slightly modified form. Note, that intermediate charging stops are possible between consecutive activities and that these charging stops create additional trips.

7.1.2 Utility Function

The utility function is defined in accordance with the choice model previously presented in table 3.2:

$$U_{kj} = \beta_{k,1} X_{T\text{drive}_j} + \beta_{k,2} X_{T\text{walk}_j} + \beta_{k,3} X_{W\text{Tarr}_j} + \beta_{k,4} X_{W\text{Tch}_j} + \beta_{k,5} X_{C\text{drive}_j}$$

$$+ \beta_{k,6} X_{C\text{park}_j} + \beta_{k,7} X_{\text{num}_j} + \beta_{k,8} X_{\text{dyn}_j} + \beta_{k,9} X_{\text{temp}_j}$$

where $U_{kj}$ describes the utility of the $j$-th choice combination as perceived by the $k$-th traveller and where the taste vector $\overrightarrow{\beta}_k$ (cp. chapter 3) describes the relative importance of the travel performance attributes $X_j$. Note, that $\overrightarrow{\beta}_k$ is estimated by a logit model, and hence, the utility $U_{kj}$ is probabilistic. The travel recommendation of the decision support system must therefore be interpreted as the choice combination with the highest probability to have the highest utility value.

The travel performance attributes $X_j$ are cumulative values; they are summed up over the trips of the activity-chain $J_n = \{eA_1^P, eA_2^P, \ldots, eA_n^P\}$. They are defined as follows...
(the index $j$ is omitted for the sake of simplicity):

$$X_{\text{drive}} = \sum_{i=2}^{n} (t_E^D - t_S^D)$$

$$X_{\text{walk}} = t_W^2 + \sum_{i=2}^{n-1} \sum_{q=1}^{2} (\delta t^{Wq}) \text{, with } \delta t^{Wq} = t_E^W - t_S^W$$

$$X_{\text{park}} = \sum_{i=1}^{n} \left( F_i (t_E^P - t_S^P) \right) \text{, with } t \text{ defined in the interval } [00:00, 24:00]$$

$$X_{\text{num}} = \sum_{i=1}^{n} y_i \text{, with } y_i = 1 \text{ if the vehicle charges and } y_i = 0 \text{ otherwise}$$

In chapter 3, the taste coefficient $\beta_3$ has been defined to describe the relative influence of a late arrival on the travel utility. A high degree of consistency is assumed between an early/late departure and an early/late arrival. Hence, $\beta_3$ jointly represents the time categories mentioned. The taste coefficient $\beta_4$ has been defined to describe the relative influence of a charging induced waiting time period on the travel utility. The influence of the charging induced waiting time period on the travel utility is assumed to be negative, if the charging event provokes a late departure, and zero, if the charging strategy acts in favour of an early arrival. From these assumptions follows:

$$X_{\text{WTB}_i} = |t_E^{W1} - t_S^A|$$

$$X_{\text{WTA}_i} = i+1 t_S^D - t_E^W + |t_E^A - t_S^W|$$

$$X_{\text{WTarr}} = \sum_{i=2}^{n} (X_{\text{WTB}_i} \cdot z_i) + \sum_{i=1}^{n-1} (X_{\text{WTA}_i} \cdot (1 - y_i) \cdot z_i)$$

$$X_{\text{WTch}} = \sum_{i=1}^{n-1} (X_{\text{WTA}_i} \cdot y_i \cdot z_i)$$

where $y_i = 1$ if the vehicle charges at the $i$-th activity and $y_i = 0$ otherwise, and where $z_i = 0$ if the $i$-th activity has purpose $H$ (home) and $z_i = 1$ otherwise.

The driving cost is the sum of two costs: (1) the effective charging cost $X_{\text{CD}_i}$, accumulated over the set of activities $\{eA_1^P, \ldots, eA_n^P\}$, and (2) the consumption-adjusted cost $X_{\text{CD}}$, which reassesses the difference in SoC between the first activity and the last activity. If not otherwise specified, vehicles are assumed to charge overnight with Mode$_1$ (cost-efficient home charging). From this follows:

$$X_{\text{CD}} = cc (Mode_1) \cdot (\text{SoC } (1 t_S^A) - \text{SoC } (n t_E^A))$$

$$X_{\text{CD}_i} = cc (i Mode_l) \cdot (\text{SoC } (i t_S^A) - \text{SoC } (l t_E^A)) \text{, with } l = 1, 2, 4$$

$$X_{\text{Drive}} = X_{\text{CD}} + \sum_{i=1}^{n} X_{\text{CD}_i}$$
Note, that the definition of $X_{CD}$ allows for bidirectional charging (Vehicle2Grid).

The performance attribute $X_{\text{temp}}$ describes the difference between the driver’s preferred cabin temperature choice (as learned by a driver model) and the predicted cabin temperature of the $j$-th choice option, accumulated over the trips of the activity-chain. In the majority of cases, the driver’s preferred cabin temperature choice $\approx 22^\circ C$.

Finally, the performance attribute $X_{\text{dyn}}$ describes the adherence to the preferred (resp. natural) driving behaviour of a traveller accumulated over the trips of the activity-chain. It is non-trivial to develop a metric that captures the predicted difference between the traveller’s natural driving behaviour, as learned by a driver model, and his behavioural response towards incentives or restrictions, such as the driving mode levels discussed in section 3.3.1. The discussion of the metric is beyond the scope of this thesis. A metric outputs a scalar $b \in \mathbb{N}$, which is zero in the case of natural driving behaviour and grows with the effect of system intervention.

$$X_{\text{dyn}} = \sum_{i=2}^{n} b_i$$

### 7.1.3 Hard Constraints

Section 6.3 has introduced the constraints $\rightarrow h_z (\rightarrow z) \geq 0$. Additional hard constraints can be defined at the scheduling level. These include, amongst others, maximum charging frequency, exclusion of charging modes, maximum waiting time, maximum parking cost, maximum walking distance and minimum SoC.

From the perspective of the traveller, hard constraints ensure that the choice recommendations satisfy certain conditions. From a technical point of view, hard constraints may lead to a reduction of the size of the search space, assuming an adequate definition of the hard constraints. Hereinafter, the hard constraints are chosen in accordance with the author’s previous publication [HZWS12]:

"From a consumer perspective, it is important to respect appointment times and guarantee that the SoC of the vehicle never falls below a certain level. We thus require $t_E^{W1} \leq t_S^{A}$ and $t_E^{A} \leq t_S^{W2}$ for all appointments and $\text{SoC}(t) \geq \text{SoC}_{\text{min}}$ at all times $t$.

Parking spaces and charging stations must be feasible to be used. They are considered feasible if their availability function exceeds the availability threshold value and if the minimal route length from the appointment location $L_i$ to the parking space $P$ does not exceed the maximum walking distance
7.2 Generation of Representative Simulation Scenarios

This section proposes a set of test scenarios to assess the impact of holistic and personalized scheduling on travel performance. The test scenarios are described by means of the terminology used in [Cas09]. They are generated on the basis of survey data that comprises the travel diaries of 217 test persons, who were asked to provide
the following information (translated from German) for each single trip of a reference day (Friday):

- intended departure time [hh:mm]
- fully flexible departure time [true, false]
- actual departure time [hh:mm]
- intended arrival time [hh:mm]
- fully flexible arrival time [true, false]
- actual arrival time [hh:mm]
- trip distance [km]
- activity purpose [commute, business, shopping, escort, personal, leisure, other]
- travel time by mode
  - bike [min]
  - taxi [min]
  - motorcycle [min]
  - vehicle as driver [min]
  - vehicle as co-driver [min]
  - bus/tram/underground [min]
  - railway [min]
  - transit time [min]
  - traffic induced delay [min]
  - park search time [min]
  - walking time to the transportation medium [min]
  - walking time to the destination location [min]

The survey data is grouped by trip-chain size. The resulting arrival time distributions and travel distance distributions are shown in table 7.2.

As a general trend, the longer the trip-chain is, the earlier the mean arrival time at the reference activity will be. For example, the mean arrival time of the third trip is 18:31pm for the 3-trip-journey, 17:16pm for the 4-trip-journey, 16:48pm for the 5-trip-journey, 15:47pm for the 6-trip-journey and 15:36pm for the 7-trip-journey. The mean arrival time of the first trip is between 07:23pm and 7:46pm.

Generally, the journey distance grows with the number of trips. This trend holds true for all journeys except the 7-trip-journey. The trip distance gives an indication of the type of the subtour. For example, the mean travel distance of the first trip of the 5-trip-journey
is 28.06km. The mean travel distance of the second trip is 19.74km. Hence, it is most likely that the 5-trip-journey does not contain a primary tour between the home location and the work location.

Table 7.2 assigns activity patterns to the journeys. The activity patterns are in the format X-X-X, where each variable X represents an activity and indicates its purpose. Valid values for X are H (home), W (work) and P (secondary purpose). The activity patterns do not necessarily represent the mean activity patterns of the survey population; they are plausible assumptions in the light of the trip distances and the arrival times. Note, that the test persons have provided the travel information for the reference day of Friday and that a limited number of weekend trips with a travel distance of 100+ kilometres have been filtered out.

Given these findings, realistic test scenarios can be constructed. The scenario generation is accomplished in multiple steps: (1) activity locations are sampled from a road map, (2) an origin-destination matrix is constructed that reflects both the road topologies from chapter 6 and allows for a simulation of the trip distances from table 7.2, and (3) a start time and duration are assigned to the activities. The origin-destination matrix is shown in table 7.3. The assignment of activity start time, activity duration, activity purpose and activity location is shown in table 7.4. Finally, table 7.5 presents realistic sets of definitions for the input parameters of possible simulation scenarios.
<table>
<thead>
<tr>
<th>Trip Property</th>
<th>2 Trips</th>
<th>3 Trips</th>
<th>4 Trips</th>
<th>5 Trips</th>
<th>6 Trips</th>
<th>7 Trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>arrival time [hh.mm]</td>
<td>07.40</td>
<td>07.36</td>
<td>07.46</td>
<td>07.45</td>
<td>07.23</td>
<td>07.43</td>
</tr>
<tr>
<td>distance [km]</td>
<td>18.49</td>
<td>16.51</td>
<td>14.23</td>
<td>7.97</td>
<td>23.98</td>
<td>11.00</td>
</tr>
<tr>
<td>arrival time [hh.mm]</td>
<td>16.31</td>
<td>16.19</td>
<td>15.49</td>
<td>15.47</td>
<td>14.16</td>
<td>14.39</td>
</tr>
<tr>
<td>distance [km]</td>
<td>31.04</td>
<td>21.48</td>
<td>25.00</td>
<td>19.74</td>
<td>30.53</td>
<td>16.86</td>
</tr>
<tr>
<td>arrival time [hh.mm]</td>
<td>01.27</td>
<td>00.47</td>
<td>01.49</td>
<td>01.21</td>
<td>02.16</td>
<td>01.38</td>
</tr>
<tr>
<td>arrival time [hh.mm]</td>
<td>18.31</td>
<td>17.16</td>
<td>16.48</td>
<td>15.47</td>
<td>15.36</td>
<td></td>
</tr>
<tr>
<td>distance [km]</td>
<td>17.74</td>
<td>13.00</td>
<td>12.11</td>
<td>15.27</td>
<td>11.00</td>
<td></td>
</tr>
<tr>
<td>arrival time [hh:mm]</td>
<td>19.06</td>
<td>18.07</td>
<td>17.09</td>
<td>16.45</td>
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<tr>
<td>distance [km]</td>
<td>14.57</td>
<td>16.43</td>
<td>8.92</td>
<td>8.00</td>
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<td></td>
</tr>
<tr>
<td>arrival time [hh:mm]</td>
<td>19.23</td>
<td>18.02</td>
<td>17.30</td>
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<td></td>
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<tr>
<td>distance [km]</td>
<td>14.59</td>
<td>10.43</td>
<td>11.43</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>arrival time [hh:mm]</td>
<td>19.50</td>
<td>18.44</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance [km]</td>
<td>12.86</td>
<td>10.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>arrival time [hh:mm]</td>
<td>16.63</td>
<td>6.90</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance [km]</td>
<td>19.04</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>activity location$^1$</td>
<td>W</td>
<td>W-P</td>
<td>W-H-</td>
<td>W-H-</td>
<td>W-H-</td>
<td>W-P-</td>
</tr>
<tr>
<td>[H=Home]</td>
<td></td>
<td></td>
<td>P</td>
<td>P-P</td>
<td>P-H-</td>
<td>P-P-</td>
</tr>
<tr>
<td>[W=Work]</td>
<td></td>
<td></td>
<td></td>
<td>P</td>
<td></td>
<td>P-P</td>
</tr>
<tr>
<td>[P=Secondary Purpose]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7.2: Trip-chain properties of 217 test persons for the reference day of Friday. The standard deviation is computed under the subpopulation assumption. A number of weekend trips with a travel distance of 100+ kilometres have been filtered out.

$^1$ Each activity pattern is assumed to start and end at home.
### Table 7.3: Origin-destination matrix of the activity locations. OD-pairs describe intra-urban, rural2urban, inter-urban and rural trips. The trips are input to the simulation scenarios described in table 7.4. Distance is given in kilometres and represents a route choice as provided by up-to-date navigation systems.
Table 7.4: Assignment of activity start time, activity duration, activity purpose and activity location. A filled box depicts the minimum duration of an activity while a shaded box represents its variability. Activity locations are in the format $X_Y$ where $X \in \{L,M,N\}$ is the Area ID and $Y \in \mathbb{N}$ is the Cell ID as defined in table 7.3. Let the set $S$ contain all activity locations and let $X_j$ be the home location and $X_l$ be the work location of a trip-chain. Then, $S' = S \setminus \{X_j, X_l\}$ is the set of activity locations of secondary purpose. For any two consecutive activity locations $X_k \in S'$ and $X_{k+1} \in S'$ it generally holds: $X_k \cap X_{k+1} = \emptyset$. 

<table>
<thead>
<tr>
<th>Area ID by Activity Purpose</th>
<th>Activity Purpose</th>
<th>2 Trips</th>
<th>3 Trips</th>
<th>4 Trips</th>
<th>5 Trips</th>
<th>6 Trips</th>
<th>7 Trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td></td>
</tr>
<tr>
<td>$W$</td>
<td>$M_j, N_j$</td>
<td>$M_j, N_j$</td>
<td>$M_j, N_j$</td>
<td>$M_j, N_j$</td>
<td>$M_j$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$H/P_1$</td>
<td>$L_k, M_k$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_k$</td>
<td>$L_k$</td>
<td>$L_{k+1}$</td>
<td></td>
</tr>
<tr>
<td>$P_2$</td>
<td>$L_k, M_k$</td>
<td>$L_k$</td>
<td>$L_k$</td>
<td>$L_{k+1}$</td>
<td>$L_{k+2}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$H/P_3$</td>
<td>$L_k$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_{k+1}, M_k$</td>
<td>$L_{k+3}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P_4$</td>
<td>$L_k$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_{k+1}, M_k$</td>
<td>$L_{k+4}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P_5$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td>$L_j$</td>
<td></td>
</tr>
<tr>
<td>Parameter</td>
<td>Property</td>
<td>Set of definitions</td>
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<td></td>
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<td>-----------------------------------------------------</td>
<td>----------</td>
<td>-------------------------------------------------------------------------------------</td>
<td></td>
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</tr>
<tr>
<td>Trip-chain</td>
<td>variable</td>
<td>${J_2, \ldots, J_7}$</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Activity location</td>
<td>variable</td>
<td>${L_1, \ldots, L_7, M_8, \ldots, M_{11}, N_{12}, \ldots, N_{15}}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Activity duration variability</td>
<td>variable</td>
<td>$[0\text{min}, ..., 30\text{min}]$</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Customer travel preference</td>
<td>variable</td>
<td>${\beta_1, \ldots, \beta_9}$ (see section 3.4)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shortest walking route between activity location and feasible parking lot</td>
<td>variable</td>
<td>$[0\text{km}, 1.5\text{km}]$ with parking cost $F = [0\frac{\text{€}}{\text{h}}, 5\frac{\text{€}}{\text{h}}]$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shortest walking route between activity location and feasible charging station</td>
<td>variable</td>
<td>$[0\text{km}, 1.5\text{km}]$ with charging mode $M \in {\text{Mode}_1, \text{Mode}_2, \text{Mode}_4}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Route preference</td>
<td>variable</td>
<td>${&lt;1,0&gt;, \ldots, &lt;0,1&gt;}$ (see section 6.4.1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cabin temperature preference</td>
<td>variable</td>
<td>${+17^\circ\text{C}, +19^\circ\text{C}, +22^\circ\text{C}, +24^\circ\text{C}, +26^\circ\text{C}}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Driving dynamics preference</td>
<td>variable</td>
<td>${\text{driver}_1, \ldots, \text{driver}<em>n, \text{driver}</em>\mu}$ (see section 4.2.2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Driving dynamics preference (Constant velocity offset)</td>
<td>variable</td>
<td>${v^{\text{HT}}+0\frac{\text{km}}{\text{h}}, \ldots, v^{\text{HT}}+20\frac{\text{km}}{\text{h}}}$ (see chapter 5)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum capacity of the vehicle traction battery</td>
<td>variable</td>
<td>${24.2\text{kWh}, 28\text{kWh}, 31\text{kWh}, 34\text{kWh}, 41\text{kWh}, 60\text{kWh}, 85\text{kWh}}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vehicle battery SoC at 6am</td>
<td>variable</td>
<td>$[30%, 95%]$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum walking distance</td>
<td>variable</td>
<td>$[0.2\text{km}, 1.5\text{km}]$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Traffic information update rate</td>
<td>variable</td>
<td>$[5\text{min}, 30\text{min}]$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weather condition</td>
<td>variable</td>
<td>sun irradiation $= [0 \frac{\text{W}}{\text{m}^2}, 1000 \frac{\text{W}}{\text{m}^2}]$ ambient temperature $= [-15^\circ\text{C}, 35^\circ\text{C}]$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean walking speed</td>
<td>variable</td>
<td>$[2 \frac{\text{km}}{\text{h}}, 6 \frac{\text{km}}{\text{h}}]$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 7.5:** Realistic sets of definitions for the input parameters of possible scheduling scenarios.
7.3 Results of Impact Assessment of Holistic and Personalized Scheduling on Travel Performance

The scheduling model is used to compute personalized travel recommendations for the customer segments identified in chapter 3. The travel recommendations are compared between the customer segments in order to assess the impact of personalized scheduling on travel performance. The impact assessment of holistic and personalized scheduling comprises three sections: (1) Section 7.3.1 compares the best travel recommendation of a customer segment with its worst travel recommendation; (2) section 7.3.2 compares the best travel recommendation of the aggregate population (customer segment CS0) with the best travel recommendations of the disaggregate customer segments; (3) section 7.3.3 compares the travel utility of the best personalized travel recommendation with that of the best non-personalized travel recommendation.

The experimental setup is described in table 7.6. The customer segments and the respective travel preferences $β ∈ R^9$ are defined in accordance with section 3.4. The customer segments are in the format CSY; valid values for Y are 0 (aggregate population), 4-4 (customer segment 4-4), 3-4 (customer segment 3-4), 4-5 (customer segment 4-5), 2-2 (customer segment 2-2), 3-1 (customer segment 3-1) and EV (customer segment EV). The results presented are mean values which are averaged over several simulation runs. The $J_2$ trip-chain defines a 'lower bound' on the potential benefit of holistic and personalized scheduling. The potential benefit generally grows with the size of the activity chain.

7.3.1 Effect of Personalization on the Travel Performance Range

This section compares the best travel recommendation of a customer segment with its worst travel recommendation. It analyses the difference in both travel performance and travel utility between the recommendations and assesses how the difference changes across customer segments.

The mean difference in travel performance between the best and the worst travel recommendation of a customer segment is shown in figure 7.2. The travel performance criteria are plotted on the axes of the radar chart, where time is given in minutes, cost is given in euro and the comfort related attribute ‘driving dynamics’ is unit-less and follows from a metric as previously discussed in section 7.1.2.

The travel preferences determine how sensitive a customer segment reacts towards changes in value of the travel performance criteria, whereby the range of values is determined by the simulation scenario. The absolute difference between the best and the worst travel recommendation gives an indication of the combined effects of the travel preferences and the properties of the scenario. Note, that the absolute values generally grow with the size of the activity chain.

The mean relative difference in travel utility between the best and the worst travel recommendation of a customer segment is shown in figure 7.3. It is defined as the difference between the maximum utility value and the minimum utility value divided by
7.3 Results of Impact Assessment of Holistic and Personalized Scheduling on Travel Performance

Figure 7.2: Effect of personalization on the difference in travel performance between the best travel recommendation and the worst travel recommendation.

Figure 7.3: Effect of personalization on the relative difference in travel utility between the best travel recommendation and the worst travel recommendation.

the maximum utility value. The utility values are generally negative, and hence, the absolute value of the maximum utility is less than the absolute value of the minimum utility. Figure 7.3 shows the results for the customer segments CS0, CS4-4,..., CS_EV. It can be seen that the travel utility severely degrades when switching from the best travel recommendation (i.e. choice alternative with highest travel utility) to the worst travel recommendation. The mean relative difference in travel utility ranges from -607% to -344%.
7.3.2 Effect of Personalization on the Optimum Travel Performance

This section compares the best travel recommendations of the disaggregate customer segments with the best travel recommendation of the aggregate population (customer segment CS$_0$). Figure 7.4 shows the results for travel time, waiting time, travel cost and driving dynamics. The travel performance criteria are plotted on the axes of the radar chart, where time is given in minutes, cost is given in euro and the comfort related attribute ‘driving dynamics’ is unit-less.

Let $x_{in,\text{opt}}$ be the value of the $i$-th attribute of the best travel recommendation when given the utility function of the $n$-th customer segment. Let $x_{i\emptyset,\text{opt}}$ be the value of the $i$-th attribute of the best travel recommendation of the aggregate population (customer segment CS$_0$). Then, the difference in attribute value between the $n$-th customer segment and the aggregate population is defined as $\Delta x_{in,\text{opt}} = x_{in,\text{opt}} - x_{i\emptyset,\text{opt}}$.

Figure 7.4 shows $\Delta x_{in,\text{opt}}$ for $n = CS_0, CS_{4-4}, \ldots, CS_{EV}$ and the attributes ‘travel time’, ‘waiting time’, ‘travel cost’ and ‘driving dynamics’. The results indicate that the scheduling routine generates a sufficiently large set of distinct travel choice alternatives and that the differences in travel preference between the customer segments are sufficiently large to make use of the travel choice alternatives.

![Figure 7.4: Effects of personalization on the best travel recommendation across customer segments.](image)
7.3 Results of Impact Assessment of Holistic and Personalized Scheduling on Travel Performance

7.3.3 Effect of Non-Personalization on the Travel Utility

This section evaluates the loss of travel utility that occurs when a traveller receives the best travel recommendation of the aggregate population (customer segment $CS_0$) instead of the subjective travel optimum. It thereby quantifies the loss of travel utility from non-personalization.

Let $X_{\emptyset,\text{opt}}$ be the optimal choice vector of the aggregate population and let $U_{\emptyset,\text{opt}}$ be the respective travel utility. Let $X_{n,\text{opt}}$ be the optimal choice vector of the $n$-th customer segment and let $U_{n,\text{opt}}$ be the respective travel utility. Furthermore, let $U_{n,\emptyset,\text{opt}}$ be the travel utility for the case where $X_{\emptyset,\text{opt}}$ is evaluated by means of the travel preference $\beta_n$ of the $n$-th customer segment. Then, $\Delta U_{n,\text{opt}} = 1 - \frac{U_{n,\emptyset,\text{opt}}}{U_{n,\text{opt}}}$ describes the loss of travel utility of the $n$-th customer segment when receiving the travel recommendation $X_{\emptyset,\text{opt}}$.

Figure 7.5 shows $\Delta U_{n,\text{opt}}$ for $n = CS_{4-4}, \ldots, CS_{EV}$. It can be seen that the loss of travel utility from non-personalization ranges from $-21.3\%$ to $-0.7\%$. As would be expected, the larger the dissimilarities between the travel preferences of the customer segments are, the larger the loss of travel utility from non-personalization will be.

**Figure 7.5:** Effect of non-personalization on the travel utility across customer segments.

In conclusion, a joint optimization of the choice dimensions produces a large solution space which captures the additive effects of the individual choice dimensions. A personalized evaluation of the solution space significantly influences the properties of the optimum solution. The properties of the solution have a significant effect on the travel utility. Conversely, a non-personalized evaluation of the solution space leads to a significant loss of travel utility.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Property</th>
<th>Set of definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trip-chain</td>
<td>invariant</td>
<td>{J_2}</td>
</tr>
<tr>
<td>Activity location</td>
<td>variable</td>
<td>(eA^H_1 \leftarrow {L_1, \ldots, L_6})</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(eA^W_2 \leftarrow {M_8, \ldots, M_{11}})</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(eA^H_3 \leftarrow {L_1, \ldots, L_6})</td>
</tr>
<tr>
<td>Customer travel preference</td>
<td>variable</td>
<td>({\beta_1, \ldots, \beta_9}) (see section 3.4)</td>
</tr>
<tr>
<td>Shortest walking routes between</td>
<td>variable</td>
<td>({\approx 250m, \approx 500m, \approx 750m, \approx 1000m}) with parking cost (F = 0)</td>
</tr>
<tr>
<td>activity location and feasible parking lots</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shortest walking route between</td>
<td>variable</td>
<td>({\approx 500m}) with charging mode (M \in {\text{Mode}_1, \text{Mode}_2, \text{Mode}_3})</td>
</tr>
<tr>
<td>activity location and feasible charging station</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Route preference</td>
<td>variable</td>
<td>({&lt;1,0&gt;, &lt;1,4750&gt;, &lt;0,1&gt;}) (see section 6.4.1)</td>
</tr>
<tr>
<td>Cabin temperature preference</td>
<td>variable</td>
<td>({#17^\circ C, #19^\circ C, #22^\circ C})</td>
</tr>
<tr>
<td># fresh air</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Driving dynamics preference</td>
<td>variable</td>
<td>({\text{driver}_1^t, \text{driver}_4^t}) (see section 4.2.2)</td>
</tr>
<tr>
<td>(Acceleration behaviour)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Driving dynamics preference</td>
<td>variable</td>
<td>({v_{HT} + 20 \frac{km}{h}, v_{HT} + 10 \frac{km}{h}, v_{HT} + 0 \frac{km}{h}}) (see chapter 5)</td>
</tr>
<tr>
<td>(Constant velocity offset)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum capacity of the</td>
<td>invariant</td>
<td>({24.2\text{kWh}})</td>
</tr>
<tr>
<td>vehicle traction battery</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vehicle battery SoC at 6am</td>
<td>invariant</td>
<td>95%</td>
</tr>
<tr>
<td>Maximum walking distance</td>
<td>invariant</td>
<td>1.0km</td>
</tr>
<tr>
<td>Mean walking speed</td>
<td>invariant</td>
<td>(5 \frac{km}{h})</td>
</tr>
<tr>
<td>Traffic information update rate</td>
<td>invariant</td>
<td>15min</td>
</tr>
<tr>
<td>Weather condition</td>
<td>invariant</td>
<td>sun irradiation = 500 (\frac{W}{m^2})</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ambient temperature = 0 (^\circ C)</td>
</tr>
</tbody>
</table>

**Table 7.6:** Sets of definitions of the input parameters of the \(J_2\) scheduling scenario.
8 Conclusions and Future Work

In the previous chapters, this thesis has presented a context-aware, holistic and personalized approach for real-time decision support in electric vehicle travel. The findings give rise to future research topics and novel applications. Section 8.1 discusses theoretical research aspects. Section 8.2 discusses how the results of this thesis may impact on novel and existing applications.

8.1 Theory

This section revisits the following topics: (1) human behaviour modelling, (2) vehicle consumption modelling, and (3) routing and scheduling. It summarizes selected findings from the previous chapters and points at future research directions.

8.1.1 Human Behaviour Modelling

Chapter 3 has presented a discrete choice model and a stated-preference (SP) study to estimate the holistic travel preferences of electric vehicle travel. The sample population has been clustered into distinct customer segments by applying Ward’s method [War63] to the individual taste gradients of the test persons, thereby minimizing the heterogeneity of the travel preferences within the customer segments and maximizing the heterogeneity of the travel preferences between the customer segments. The coefficient estimates of a linear main effect model have been presented. The attribute set of the discrete choice model has combined widely accepted attributes (e.g. driving time, walking time, driving cost, parking cost), EV specific attributes (e.g. charging frequency, charging induced waiting time) and en-route comfort attributes (e.g. adherence to preferred driving mode, adherence to climate-comfort). Given the approach and the findings of chapter 3, the author suggests the following future research activities:

- Modelling: An open issue is the analysis of the interaction effects between the widely accepted travel attributes and the newly introduced comfort attributes. Another open issue is the analysis of the parameter elasticities of the EV specific attributes. It should be noted that these suggestions require a larger factorial and a much larger sample population.

1 Note, that selected concepts presented are the basis for and shown in parts in selected patents and/or patent applications listed in Appendix A.1.
• Customer segmentation: Customer segments are commonly derived from socio-economic characteristics. In this work, the sample is clustered on the basis of individual taste gradients. The approach is theoretically viable, and yet, it requires further empirical underpinning.

• Effects on travel demand: In general, vehicle travel is more comfortable than public transportation, whereas public transportation is usually more time and cost efficient than vehicle travel. The time and cost savings of public transportation are particularly pronounced in overly congested urban areas. This explains the modal-shift towards public transportation in these regions. Piloted driving, autonomous driving respectively, has the potential to increase the efficiency of road usage and thereby improve traffic flows and save travel time. The question is, will this revert the modal-shift in urban areas? The author argues, that the answer greatly depends on the comfort perception. A negative perception of the comfort of piloted driving will support the modal-shift towards public transportation in urban areas. A strongly positive perception will revert the urban modal-shift towards individual motorized travel. The herein presented DCE quantifies the trade-off between driving comfort and travel time. Future work will need to investigate the effects on travel demand, particularly on modal-shifts in urban areas.

8.1.2 Vehicle Consumption Modelling

Chapter 4 has introduced a black-box driver model that continuously learns the longitudinal guiding patterns of a driver with respect to the driving context and uses these patterns to predict the future guiding decisions of the driver. The model uses a polynomial function to describe the longitudinal guiding decisions of a driver. The model coefficients have been estimated on the basis of real-world driving data of multiple drivers in different cities. The estimates have been compared between the drivers and across the road topologies.

The driver model employs a context classification which comprises driver, vehicle and environment characteristics. Future research in the field should extend the context classification towards the emotional dimensions of the driver such as mood.

Chapter 4 has also introduced a white-box vehicle model and a grey-box EV consumption model. Chapter 5 has presented a modular consumption prediction programme in order to integrate the driver model and the white-box vehicle model with a graph theoretical environment representation in a runtime-efficient manner. The models have been calibrated and validated with real-world driving data. They have shown high prediction accuracy across the drivers and road topologies.

The models describe the dependence of vehicle consumption on vehicle component properties (e.g. traction battery, electric motor, HVAC system), environment characteristics and driver behaviour. Future research in the field should be twofold: (1) address open issues in component modelling such as the temperature effects in gear-box models and the cycle dependence of the battery state-of-health models, and (2) include real-
time filters to estimate the model coefficients that cannot be directly measured, such as
the rolling loss coefficient [see Man13].

8.1.3 Routing and Scheduling

Chapter 6 has introduced a multi-criteria routing approach which jointly optimizes
the choices \{route choice, departure time choice, velocity choice, acceleration choice,
climate comfort choice, driving mode choice\} with respect to multiple cost criteria. Sev-
eral analyses have been conducted to assess the effects of the choice dimensions on
the non-dominated solutions across the road topologies.

Chapter 7 has presented a holistic and personalized scheduling approach which
employs the models from the earlier chapters. The scheduling approach has intro-
duced additional choice trade-offs. The potential benefits of holistic and personalized
scheduling have been analysed. Future research should address the following topics:

- Algorithm performance: In the author’s previous publications [e.g. HZWS12,
  MMH12a] alternative approaches have been formulated to solve the problem at
  hand. Moreover, the author has implemented a dynamic programming approach,
a backtracking search and a heuristic search strategy, all of which are not part
of this thesis. While all of the latter approaches improve runtime performance,
they compromise the quality of the results. Dynamic programming requires a
simplification of the problem formulation. Heuristic search does not guarantee
global optimality of the solution. The author suggests that future work evolves in
two steps: (1) investigate new optimization strategies, for possible alternatives
refer to [PDG13, RN03], and (2) benchmark the alternative strategies, including
dynamic programming and heuristic search, with respect to runtime performance
and result quality in real-world scenarios.

- Mixed-competitive-cooperative scheduling\(^1\): The approach presented in the pre-
  vious chapters does not take into consideration the effects of local decisions on
aggregate travel demand. Future work should extend the proposed first-stage
decision support system towards a second-stage decision support system, which
takes into consideration both the forward effects of local decisions on global
demand and the feedback effects of global demand on local decisions. This
so-called dual problem of travel planning can be omitted in the following cases: (1)
in the case of oversupply, where aggregate demand is much smaller than network
supply, and hence, individual decisions are decoupled; (2) in the case of marginal
market share\(^2\), where the proportion of drivers with decision support systems is

\(^1\) Note, that selected ideas presented are shown in parts in: Patent Application DE102013218046A1,
Vorrichtung und Verfahren zur Mobilitätssteuerung, Patentee: Volkswagen Aktiengesellschaft, Inventor:
N. Hoch, Filing date: 10.09.2013.

\(^2\) Referring to the market share of first-stage DSSs with regard to the market of traditional navigation
systems and travel planning services.
small compared to the proportion of drivers without these systems. In this case, the decision support systems have a negligibly small forward effect on aggregate demand.

In most developed countries, the supply side is designed for peak hour demand. It is legitimate to assume oversupply during off-peak hours. However, during peak hours the dual problem of travel planning arises. The market share of the first-stage DSS is low at the time of market entry, and hence, it is legitimate to assume a competitive advantage for the drivers using the decision support systems. At higher market shares the competitive advantage ceases, and hence, solutions are required for the situation where the market share of the first-stage DSS proposed is high and travel demand exceeds infrastructure supply. The author suggests that future research investigates "bounded cooperative resource constrained routing and scheduling (BC-RCRS)", which shall be briefly outlined below:

The presentation departs from a discussion on the cause-effect relationships of competitive behaviour. It uses the notion of generalized cost of travel (CoT) in order to explain the consequences of competitive behaviour and illustrate the differences between competitive and cooperative behaviour. Let ICoT be the generalized cost of a travel decision of a driver. Let CuCoT be the sum of ICoT over all drivers. Then, the following two trends hold true: (1) competitive behaviour increases CuCoT but reduces the variance of ICoT, which means that resources are globally wasted but the individual cost is bounded, and (2) entirely cooperative behaviour minimizes CuCoT but increases the variance of ICoT, which means that resources are globally saved at an unboundedly high individual cost for some. Similar considerations can be found in literature, where system optimum is discussed in the view of user optimum [e.g. EANR95b, EANR95a].

Going on to the solution, the author argues that sustainable mobility requires cooperation with control mechanisms to bound the individual cost of travel. The approach is referred to as BC-RCRS and is briefly explained in the following. Let $u^j_i$ be the utility of the $j$-th travel alternative as perceived by the $i$-th driver. At time slice $t_k$, let $x_{m}(t_k)$ be the value of an external travel attribute (e.g. parking cost) and let $x_{n}(t_k)$ be the value of a travel attribute that is internal to the driver. Let $f_{m}^i$ and $f_{n}^i$ be preference functions of the $i$-th driver. Then, the utility of a travel alternative follows from:

$$u^i(x(t_k)) = \sum_{m=1}^{M} f_{m}^{i} x_{m}(t_k) + \sum_{n=1}^{N} f_{n}^{i} x_{n}(t_k)$$  \hspace{1cm} (8.1)$$

From the set of feasible travel alternatives $S^i$, a driver chooses the travel alternative with maximum utility $u_{\text{max}}^{i}(t_k)$. $S^i$ is ordered in descending order of utility and has cardinality $K$.

$$S^i = \{ u_{\text{max}}^{i}(t_k) \geq u_{2}^{i}(t_k) \geq u_{3}^{i}(t_k) \geq \ldots \geq u_{K}^{i}(t_k) \}$$  \hspace{1cm} (8.2)$$
Let the degree of cooperation of a driver be defined by \( L \), with \( L \leq K \) and \( L, K \in \mathbb{N} \). Let the cooperative set of travel alternatives be \( C^i \):

\[
C^i = \{ C^i \subset S^i | \{ u_{\text{max}}^i(t_k) \geq u_2^i(t_k) \geq \ldots \geq u_L^i(t_k) \} \}
\]  

(8.3)

For each pair of travel alternatives \( u_j^i(t_k), u_{\text{max}}^i(t_k) \in C^i \), a set of delta utilities exists. A delta utility \( \delta_m u_j^i(t_k) \) describes how much an attribute value \( x_m(t_k) \) must change, keeping the remaining attribute values constant, so that \( u_j^i(t_k) > u_{\text{max}}^i(t_k) \).

A driver is assumed to choose the utility maximizing travel alternative. A delta utility can therefore be understood as a piece of information that describes how the behaviour of a driver can be manipulated. This information can be exploited by operators (e.g., car park operator, traffic network operator) to influence the travel decisions of the driver. The degree of cooperation of the driver is bounded by the cooperative set, respectively the delta utilities of the elements of \( C^i \). A fully competitive driver is defined by \( L = 1 \). A fully cooperative driver is defined by \( L = K \). Each driver determines the value of \( L \) individually.

A driver is cooperative in the sense that he provides information about how a change of externalities influences his behaviour. A driver is competitive in the sense that he always chooses the utility maximizing travel alternative. It is up to the environment (e.g., car park operator) to use the delta utility information in order to manipulate the behaviour of the driver, which however is always bounded. If the environment uses the information, it is said to internalize the external cost of the driver. The BC-RCRS approach allows for an anonymised and decentralized coordination of the individual decisions and the aggregate demand in resource constrained environments, whereby each driver individually determines his contribution. As a result of this coordination, the CuCoT diminishes without the drawback of uncontrolled discrimination against some drivers.

The discussion provided on BC-RCRS leaves open the question of how the delta utility information can be exploited on the global level, in particular, how this information can be exploited in decentralized networks, where multiple vehicles and operators interact and where the stakeholder interests may conflict. The reader may refer to [HMM+15] where the author proposes a partly declarative and partly procedural approach to solve the global problem.

- **System Architecture**: This thesis discusses a first-stage decision support system. The previous paragraphs have proposed an extension towards a second-stage DSS. The BC-RCRS approach leaves open the question of how the knowledge processes and communication processes are distributed across the huge number of autonomous nodes in the transportation system.
Many of these aspects have been addressed by the ASCENS Project\(^1\), in particular, the e-mobility case study of the ASCENS project [HBA\(^{+}\)15]. The application of the ASCENS life cycle to the e-mobility case study has been shown in [BDNG\(^{+}\)13]. A detailed discussion on requirements engineering and architecture design can be found in [KBP\(^{+}\)13, AZH12, AHZ13, AHZ14, AHZ15]. These publications of the author present a sound discussion on open research topics in architecture design. The acquainted reader may refer to the aforementioned publications and the discussions on future research topics.

8.2 Application

This section discusses applications in three fields of study: (1) navigation systems, (2) driver information systems and (3) mobile online services. Section 8.2.1 discusses future developments of vehicle navigation systems, in tangible terms, the evolution from route choice support towards holistic and personalized decision support. Section 8.2.2 revisits EV range anxiety and shows how an adequate information management of future driver information systems may dispel this fear. Finally, section 8.2.3 revisits the BC-RCRS approach, which has been introduced in section 8.1.3. It is shown how future mobile online services may turn the BC-RCRS approach from vision to reality.

8.2.1 Personalized Navigation

Up-to-date navigation systems offer route choice support to the travellers. Advanced embodiments present three route alternatives, from which the traveller is asked to choose one. Route alternatives can be understood as choice profiles, which are described by a set of attributes. A non-trivial choice situation requires a minimum of two choice profiles, whereby the profiles must differ in at least two contrasting attribute values.

Current navigation systems have two drawbacks: (1) they consider very few and mostly non-contrasting attributes such as travel distance and travel time, and (2) provide the same travel recommendations to all travellers, independent of their personal travel preferences and vehicle characteristics. This causes "concentration" and "opportunity cost effects". Concentration effects describe a process where the decision support systems homogenize the initially heterogeneous travel decisions of the drivers; for a detailed discussion refer to [BADPI91, p. 254]. Opportunity cost arises when a non-personalized decision support system provides a recommendation to a traveller that is not utility maximizing with respect to the traveller’s personal travel preferences.

As to future applications, the author suggests an extension of the currently available navigation systems towards holistic and personalized DSSs where the choice options are given in the form of the profile set of figure 3.2. It is suggested that these systems

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monitor both the profile set that is displayed to the driver and his final travel decision in order to generate conclusive revealed preference (RP) data. This RP data differs from currently available RP data in that the choice alternatives are entirely known and efficiently designed, as is the case in SP studies. This setup allows for a comparison of SP data and RP data in real market situations, thereby providing new insights into consumer behaviour and giving rise to new choice models and applications thereof. Note, that even a relatively low market share of said systems generates a huge amount of RP data.

### 8.2.2 Range Assistance

Range anxiety is a major entry barrier for electric vehicles. The range anxiety of the customers originates from three causes: (1) the unfamiliarity with range restrictions due to their experience with internal combustion engine vehicles, (2) the lack of understanding of how their behaviour influences vehicle range, and (3) the fact that driver information systems do not adequately inform and educate the customer.

These shortcomings give rise to the objectives of future developments: (1) increase the accuracy of the range predictions in order to foster trust, (2) provide comprehensive information in order to educate the customer, and (3) provide active assistance in order to resolve contingency situations.

Range assistance focuses on the choices of route, driving behaviour and comfort settings. In the following, these choices are collectively referred to as configuration. The current choices of a driver at the reference time are referred to as current configuration. The range maximizing choices are termed maximum configuration. The range spectrum is defined as the range difference between the maximum configuration and the current configuration. The range potential is defined as the range difference between the current configuration and a preferred configuration.

Given these definitions, the aforementioned objectives can be expressed in technical terms. As a general requirement, range prediction must be configuration dependent. In particular, it needs to differentiate between current range, maximum range, range spectrum and range potential. Moreover, a control strategy is required that automatically changes the current configuration in order to avoid contingency situations. In the case where the maximum configuration does not resolve the contingency situation, the control strategy must restrict vehicle functions such as the electric motor power and eventually schedule charging stops along the route.

The author addresses the technical implementation in multiple patents. The acquainted reader is referred to the patent specifications, which are listed below. The computation of the time-energy optimal route is described in patent\(^1\). A method and device to precisely predict vehicle range on the basis of a range configuration can be

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found in patent\(^1\). A method and device to assist the driver in finding an appropriate configuration and resolve contingency situations can be found in patent\(^2\). Note, that only those patents are cited that are disclosed by the German Patent and Trademark Office before September 2014.

### 8.2.3 Balanced Mobility

This thesis has presented a holistic and personalized DSS. Section 8.1.3 has discussed an extension towards BC-RCRS. These approaches give rise to applications such as a mobile online service that improves both the personal travel performance and the global network performance. The author discusses the implementation in multiple patents. A first set of patents\(^3\)–\(^5\) describes a method and a device to compute an optimal journey which satisfies the personal constraints of the driver. Patent\(^6\) presents a method and a device for partially cooperative behaviour. Note, that only those patents are cited which are disclosed by the German Patent and Trademark Office before September 2014.

---

Bibliography

[AHLS10] Artmeier, Andreas ; Haselmayr, Julian ; Leucker, Martin ; Sachenbacher, Martin: The optimal routing problem in the context of battery-powered electric vehicles. In: CPAIOR Workshop on Constraint Reasoning and Optimization for Computational Sustainability (CROCS), 2010


[AZS+02] Axhausen, Kay W. ; Zimmermann, Andrea ; Schönfelder, Stefan ; Rindsfüser, Guido ; Haupt, Thomas: Observing the rhythms of daily life: A six-week travel diary. In: Transportation 29 (2002), Nr. 2, S. 95–124


[BAY+00] Barth, Matthew; An, Feng; Younglove, Theodore; Scora, George; Levine, Carrie; Ross, Marc; Wenzel, Thomas: Development of a comprehensive modal emissions model / National Cooperative Highway Research Program, Transportation Research Board of the National Academies. 2000 (NCHRP Project 25-11 Final Report). – Forschungsbericht


[Ins13] Institute for Mobility Research (Hrsg.): *'Mobility Y' - The Emerging Travel Patterns of Generation Y*. Munich : Institute for Mobility Research (ifmo), a Research Establishment of the BMW Group, 2013


New Jersey Avenue, SE Washington, DC 20590, March 2013 (FHWA-HOP-13-018). – Forschungsbericht


[LS06] Lange, Stephan; Schimanski, Michell: Energiemanagement in Fahrzeugen mit alternativen Antrieben, Technische Universität Carolo-Wilhelmina zu Braunschweig, Fakultät für Elektrotechnik und Informationstechnik, Institut für elektrische Messtechnik, Diss., December 2006

[LSB04] Louviere, Jordan J.; Street, Deborah J.; Burgess, Leonie: A 20+ Years’ Retrospective on Choice Experiments. In: Wind, Yoram (Hrsg.;


Bibliography


[Stab] Statistische Ämter des Bundes und der Länder:  
Bevölkerung nach Geschlecht für Kreise und kreisfreie Städte (Excel File).  

[Stac] Statistische Ämter des Bundes und der Länder:  
Haushalte und Familien (Excel File).  

[Stad] Statistisches Bundesamt:  
Berufsdaten der Bevölkerung (Excel File).  

[SV00] Schäfer, Andreas ; Victor, David G.:  
The future mobility of the world population.  

[SWTL03] Shah, V. P. ; Wunderlich, K. ; Toppen, A. ; Larkin, J.:  
Potential of advanced traveler information system to reduce travel disutility: Assessment in Washington, D.C., region.  
In: Transportation Research Record: Journal of the Transportation Research Board 1826 (2003), S. 7 – 15

[The] The World Bank Group:  
Motor vehicles (per 1.000 people) (web).  
Part of: World Development Indicators.  

[Tol04] Toliyat, Hamid A. (Hrsg.):  
Electrical and computer engineering.  
Bd. 120: Handbook of Electric Motors.  

[Tra07] Transportation Planning Capacity Building Program ; Federal Highway Administration ; Federal Transit Administration:  

[Unia] United Nations, Department of Economic and Social Affairs, Population Division:  
United Nations Press Release: World Population to reach 10 billion
by 2100 if Fertility in all Countries Converges to Replacement Level (PDF File). United Nations, Department of Economic and Social Affairs, Population Division. 03.05.2011. Available at: http://esa.un.org/unpd/wpp/Other-Information/Press_Release_WPP2010.pdf. – Last accessed: 01.03.2015


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A Appendix

A.1 List of Patents\(^1,2\)

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<td>Aktive Reichweitenbeeinflussung eines Fahrzeugs</td>
<td>03.12.2012</td>
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<td>DE 10 2012 011 605A1(^1)</td>
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<td>18.02.2012</td>
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<td>DE 10 2011 017 260A1(^1)</td>
<td>Verfahren zur Ermittlung einer optimalen Verzögerungsstrategie eines Elektrofahrzeugs, sowie entsprechende Vorrichtung und Fahrzeug</td>
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<td>EP 00 0002 669 632A2(^1)</td>
<td>Verfahren zum Berechnen einer Route und Navigationsgerät</td>
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<tr>
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<td>Vorrichtung und Verfahren zur Mobilitätssteuerung</td>
<td>10.09.2013</td>
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\(^1\) Patent and/or patent application as listed by the German trademark and patent office before September 2014. Source: [https://depatisnet.dpma.de](https://depatisnet.dpma.de)

\(^2\) Patent and/or patent application as listed by the German trademark and patent office after September 2014 and before August 2015. Source: [https://depatisnet.dpma.de](https://depatisnet.dpma.de)
A.2 List of Publications

This section lists publications and project reports of the author which are published or confirmed for publication before March 2015. Non-published material is not listed. Considered as non-published material are technical papers, internal reports, non-published reports of internal projects and/or funded projects, presentations, rejected submissions etc.

Chapters and Papers in Books


Journal Papers


Conference Papers


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### Funded-Projects and Research Reports


Volkswagen AG; Fraunhofer-Institut für Bauphysik; P+Z Engineering GmbH: E-Komfort. Förderprojekt im Auftrag vom Bundesministerium für Bildung und Forschung, 2011 [see Vo111]
A.3 Supervised Theses

This section lists the master’s theses and bachelor’s theses supervised by the author of this dissertation.

<table>
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<tr>
<td>Kevin Zemmer</td>
<td>Efficient Trip Planning for Electric Vehicles (unpublished master’s thesis) [see Zem12]</td>
<td>Swiss Federal Institute of Technology (ETH) Zurich, Zurich, Switzerland</td>
<td>2012</td>
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<tr>
<td>Sarah Habermann</td>
<td>Neumodellierung, Analyse und Bewertung einer plattformunabhängigen Einzellösung und darauf aufbauenden alternativen Implementationskonzepten zur Verbrauchsprognose von E-Fahrzeugen (unpublished bachelor’s thesis) [see Hab12]</td>
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