Demand Generation for Multi-Agent Transport Simulations based on an Econometric Travel Behavior Model and a Traffic-Count-based Calibration Algorithm

Masterarbeit im Fach

Multi-Agenten-Simulation von Verkehr

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Hiermit erkläre ich, dass ich die vorliegende Arbeit selbstständig sowie ohne unerlaubte fremde Hilfe und ausschließlich unter Verwendung der aufgeführten Quellen und Hilfsmittel angefertigt habe.

Berlin, 16.12.2013

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Abstract

The transport system is an essential prerequisite for the development of societies and economies. At the same time, it is a driver of severe problems like global warming. Therefore, innovative solutions – apart from the construction of new infrastructures – are sought to enable the provision of a efficient transport system while limiting negative effects of the transport system as much as possible. Transport models are the most important tool to assess transport policies and schemes and to forecast their outcomes. However, modeling is constraint by the availability of data – an issue that is likely to become even more relevant because of increased increased attention paid to topics like data privacy. Further, traditional models are often concerned with lacking representation of travelers' behavior. The goal of this study is to develop a transport model that suffices with a low amount of input data that are readily available. Also, few initial assumptions are made in order to minimize frequent sources of modeling flaws related to modeling assumptions. The model is based on an microscopic transport supply-demand simulation in which travelers gradually come to improved travel option. Initial suggestion for potential travel daily travel plans are generated by an econometric activity simulator. Calibration of the thus generated demand for transport is done by a novel calibration algorithm that interacts with the transport simulation. This way, an initial transport model used for adjustment of various model parameters and a more elaborate model based on a widely realistic population representation are created. The elaborate model is shown to possess a model fit that reaches the quality of more extensive travel-diary based transport demand models. The validity of the created transport (demand) model is proven on the basis of a travel survey.

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List of Abbreviations

ABDM	Activity-based demand modeling
Avg.	average
BVG	Berliner Verkehrsbetriebe (German: *Berlin public transport company)*
Cadyts	Calibration of dynamic traffic simulations
CEMDAP	Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns
cf.	confer
CO2	Carbon dioxide
°C	Degree Celsius
diff.	different
DTA	Dynamic traffic assignment
EC	European Commission
e.g.	for example
EU	European Union
Exec.	executed
FIFO	First-in/first-out, e.g. in *FIFO queue*
IPCC	Intergovernmental Panel on Climate Change
i.e.	id est (Latin: *this means)*
Innov.	innovative
LOR	Lebensweltlich orientierte Räume (German: *Live-reality-oriented regions)*
MATSim	Multi-agent transport simulation
Mod.	Module
MRE	Mean relative error
No.	Number
OD	Origin-destination
Pt	Public transport
Sel./Select.	Selection
SrV	System repräsentativer Verkehrsbefragungen (German: *System of representative transport surveys)*
Strat.	Strategy
VMT	Vehicle miles traveled

1. Introduction

According to the recently published report of the Intergovernmental Panel on Climate Change (IPCC) "warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia. The atmosphere and ocean have warmed, the amounts of snow and ice have diminished, sea level has risen, and the concentrations of greenhouse gases have increased" [IPCC, 2013, p.2]. The report further states that "it is extremely likely that human influence has been the dominant cause of the observed warming since the mid-20th century" [IPCC, 2013, p.15], with greenhouse gases being the major contributor. Most importantly, the report alerts that "continued emissions of greenhouse gases will cause further warming and changes in all components of the climate system. Limiting climate change will require substantial and sustained reductions of greenhouse gas emissions" [IPCC, 2013, p.17].

In 2004, about 13% of global greenhouse gas emissions were caused by activities within the transport systems [IPCC, 2007, p.105], making transport one of the major contributors to climate change. Alarmingly, the transport sector has (next to the energy supply sector) shown the largest growth from 1970 through 2004 with an increase by 120%[1] [IPCC, 2007, p.105].

In developed countries, the transport sector's share in greenhouse gas emissions is even higher. In the United States, for instance, transport accounts for about 28% of all greenhouse gas emissions[2] and also in Germany, with its more multimodal transport system, still about 17% of greenhouse gas emissions are attributable to transport. While Germany has been among the countries with the highest reduction rates concerning greenhouse gas emissions over the last two decades (ca. 25% reduction from 1990 through 2012 [Umweltbundesamt, 2013, p.3]), the reduction of emissions caused by transport (reduction of 5.5% from 1990 though 2012) has been significantly lower than those of all other sectors [Umweltbundesamt, 2013, p.4]. These observations point out both the importance of transport in terms of its impact on climate change as well as the specific difficulties associated with reducing greenhouse gas emissions caused by transport.

[1] During the same period, the increases in greenhouse gas emission attributable to other sectors [IPCC, 2007, p.105] were the following: Energy supply: 145%; industry 65%; land use, land-use change, and forestry: 40%; agriculture: 27%; and residential/commercial: 26%.

[2] Cf. `http://www.epa.gov/climatechange/ghgemissions/sources.html`, last accessed on 20 November 2013.

On the other hand, a reliable and efficient transport system is a pivotal prerequisite for our economy and society. "Since the beginning of civilization, the viability and economic success of communities have been, to a major extent, determined by the efficiency of the transportation infrastructure" [Bhat and Koppelman, 2003, p.39]. The transport system provides people and organizations with mobility, which is vital for markets and for the quality of life of citizens. Accordingly, the European Union, for instance, considers the establishment and maintenance of an efficient transport system one of its major long-term tasks as future prosperity "will depend on the ability of all of its regions to remain fully and competitively integrated in the world economy" [EC, 2011, p.4].

At the same time recognizing the urgent need to address global warming, the EU has called for "the need to drastically reduce world greenhouse gas emissions, with the goal of limiting climate change below 2°C. Overall, the EU needs to reduce emissions by 80–95% below 1990 levels by 2050. [...] A reduction of at least 60% of greenhouse gas emissions by 2050 with respect to 1990 is required from the transport sector"[EC, 2011, p.5].

The crucial question now is how to bring the provision of a capable transport system in line with earnest efforts towards greenhouse gas reduction. This question has to be addressed in times of more and more constraint national budgets, especially with regard to the global financial crisis. In developed countries like Germany, the need for increases in efficiency is further reinforced because of demographic changes and the related phenomenon of shrinking populations. But also from the perspective of other regions of the world, globalization has increased the need of national economies to become ever more efficient, while the demand for transport is steadily increasing because of the same development. This increase in demand is particularly pronounced with regard to freight transport whose volumes are increasing even in developed regions with declining populations because of rising volumes of international trade. At the same time, people – in developed countries as well as in developing countries – are becoming less willing to accept the negative impacts of traffic like noise, pollution, congestion, and accidents.

Accordingly, policy makers have started to acknowledge the fact that the increased demand for transportation cannot be handled by simply building more and more infrastructure. Instead, new, innovate solutions are sought to manage the increased demand for transport. Among them are, for instance, "demand-management policies such as VMT-reduction policies, employer parking restrictions and carpool mandates, vehicle user pricing, congestion pricing, flexible work schedules, carpooling and vehicle sharing; technological changes such as vehicle fuel efficiency, energy constraints and costs; transportation system actions such as capacity reductions, pedestrian-bike systems, transit improvements and transit-oriented development; transportation funding mechanisms such as tolling, and impact issues such as air quality, climate change, noise, induced travel, socioeconomic impacts, land use, urban form and equity issues" [Hartgen, 2013, p.10f].

To be able to come to good transport planning decisions, planners and engineers need to forecast the response of transport demand to changes in the transport system and changes in the attributes of the people using the transport system [Kitamura, 1988, p.10], [Bhat and Koppelman, 2003, p.39], [Moyo Oliveros, 2013, p.3]. Since transport systems are, however, very complex and constitute the outcome of the interaction of a high number of individual actors and innumerable interdependencies among them, predicting or estimating the effects of a proposed transport policy is a challenging task.

An approach to tackle this task is to create a model of the transport system which reacts to changes in its relevant characteristics like the real-world transport system. So, transport models are used to predict travel characteristics and the usage of transport services with regard to alternative socioeconomic scenarios or alternative transport policies and transport schemes [Bhat and Koppelman, 2003, p.39]. In order to be able to model the transport system, the major components of the transport system and its fundamental properties have to be understood.

Next, a brief description of the modeling of transport systems is given (cf. section 1.1). This is followed by a presentation of applied tools and the requirements imposed on them in section 1.2. In section 1.3, the basic idea, motivated by the aim to address current constraints in transport demand modeling, is outline. The chapter ends with a short outline of the remaining chapters of this study in section 1.4.

1.1. Modeling Transport Systems

Essentially, the transport system, as we can perceive it in our everyday lives, consists of two major components:

- Transport supply
- Transport demand

The interaction of transport supply and transport demand produces the traffic patterns that are observable in the transport systems.

1.1.1. Modeling Transport Supply

Transport supply consists of roads, sidewalks, bike lanes, train rides, bus rides, airplane flights etc., i.e. all the goods and services that enable movements of people and goods. Among these goods and services the notion of "supply", however, differs significantly in terms of its intuitiveness. An airplane ticket, for instance, is very intuitively understood as a service that supplies consumers with a form of transport.

One can easily check the quotes of different suppliers (i.e. airline companies) and observe the effects of Smith's *invisible hand* as quotes keep changing dependent on levels of supply and demand. A sidewalk, however, is also a form of transport supply. With transport being defined as the movement of people or goods from an origin to a destination, the sidewalk is the good that is needed to conduct this itinerary in case the desired mode of transport is walking by foot. As opposed to an airplane trip, which is a private good[3], the sidewalk is a public good[4].

In order to model the interaction of transport demand and transport supply and, in particular, how transport demand adapts itself to changes in transport supply induced by (proposed) transport policies and schemes, a model representation of the relevant elements of transport supply and its fundamental characteristics has to be found. In case the automobile transport system is to be modeled, the supply description consists of a representation of the roadway network. This representation is mostly based on a graph whose vertices represent intersections and whose edges represent roadway segments.

As transport supply can be assumed unaltered for the scope of assessment, the modeling of the overall transport systems is to a large extent concerned with the modeling of the demand for transport as dealt with in the subsequent section (cf. section 1.1.2).

1.1.2. Modeling Transport Demand

Transport demand arises from people's wishes to travel from an origin to a destination (passenger traffic) or to transport goods from an origin to a destination (freight traffic). Modeling the demand for (passenger) transport on a given portion of a transport system is related to answering the following questions:

1. How many people wish to travel?
2. From where to where do they wish to travel?
3. At what time do they wish to travel?
4. Which mode of transport do they wish to use?
5. Which route do they wish to follow?

[3] For a private good or service, the utilization is excludable and rivalrous, i.e. the supplier can control who can become a user and the utilization of the good by one user affects the utilization of the good by another user.

[4] For a public good or service, the utilization is non-excludable and non-rivalrous, i.e. anybody can use it and this does not affect anybody else in using it. As opposed to other public goods like air or (free) television, a sidewalk can, however, also be regarded a *common good* whose utilization is non-excludable, but rivalrous. Rivalry for a sidewalk can emerge when it becomes overcrowded so that it cannot accommodate additional users. This observation becomes somewhat more intuitive when a highway segment is considered instead of a sidewalk.

Leaving the third – though very important – question concerning time aside, the remaining questions constitute the basic concept of the first generation of widely-applied transport models, aptly referred to as *four-step models*.

The basic approach of these four-step models is to sequentially work through said four questions and, thus, generate the demand for transport on each route of the considered network [Bhat and Koppelman, 2003, p.39], [Raney and Nagel, 2006, p.305]. These models have been developed since the mid-20th century and revised versions of them are still applied today by practitioners all over the world. Thus, four-step models can be regarded as the state-of-the-practice approach to transport demand modeling. They are mostly of analytical type and consider transport as aggregate flows of travelers. While they are generally adequate for analyzing major transport investment proposals [Hartgen, 2013, p.7], their limitations have become more and more obvious as proposed transport system improvements change from construction-based schemes towards transport policies that aim to increase efficiency in the use of already existing infrastructure [McNally, 2007, p.36], [Hartgen, 2013, p.10]. This is due to several shortcomings of these model[5].

While remedies to overcome different shortcomings of four-step models have been proposed and implemented, researchers also developed fundamentally different modeling approaches, which consider decisions of travelers in a more behaviorally sound way. These approaches have been enabled through advances in computation and developed since the 1980s. Particular advantages of these models are that they often consider travelers on a disaggregate, individual basis[6]. Thus, specific attributes of travelers can be taken into account. Also, the interdependencies among the decisions regarding the above questions can be considered, which offers major advantages from a behavioral point of view. Finally, they do not analyze trips in isolation, but put the focus on the activities dispersed in space and time, that travelers pursue, which is why they are called *activity-based demand models*.

The last of the five aforementioned questions (i.e. *Which route do travelers wish to follow?*) is, however, even by most modern models still only answered on an aggregate level. This is due to the fact that most models terminate with the provision of origin-destination (OD) matrices [Flötteröd et al., 2011, p.482], which provide the numbers of travelers on different relations for each mode. In most cases, these OD matrices are, then, forwarded to a *route assignment* algorithm which basically does the same as the final step of the four-step model, i.e. answering the last of the above questions. So, the individual representation of travelers that offered advantages in the earlier modeling steps, is lost.

[5] These shortcomings as well as other properties of these models are described in a more detailed way in section 2.1.

[6] These models are discussed in more detail in section 2.2.

It would, however, be highly beneficial if the individual representation of travelers could be maintained in the route assignment step, too. Therefore, the transport demand modeling process, which answers the first four above questions on a disaggregate basis, will in this study be coupled with a modeling framework that is capable to answer the final question on a disaggregate level as well. This goal motivates the application of microsimulation, which is briefly presented in the following section (cf. section 1.2).

1.2. Tools

In order to answer the five central questions concerning transport demand posed in the previous section (cf. section 1.1.2) on a fully disaggregate level, microsimulation is applied in this study. Microsimulation is a mechanism for reproducing or forecasting the state of a dynamic, complex system by simulating the behavior of the individual actors in the system over both time and space [Miller et al., 2004, p.10], [Guo and Bhat, 2007, p.2].

A microsimulation modeling approach seems reasonable since "the behavior of the actors within the system being modeled is significantly non-linear in nature, and, hence, significant bias can exist if one attempts to model such a system using arbitrary aggregations of these actors" [Miller et al., 2004, p.16]. Via a microsimulation approach every traveler is considered individually with all their relevant attributes retained throughout the whole modeling process [Meister et al., 2010, p.2].

Specifically, two types of models are used in this study. First, an activity-based demand model (ABDM, cf. section 1.1.2) based on microsimulation is used to generate an initial, disaggregate demand representation. As pointed out in the previous section (cf. section 1.1.2), these demand models, however, typically end with the travel pattern of individuals. Thus, no informations concerning the individual's concrete travel activities on the network are given.

In order to obtain this information on a disaggregate (i.e. microscopic) level as well, a microscopic transport simulation is used, which simulates the interaction of the disaggregate transport demand with the supply of transport. In technical terms, the disaggregate travel patterns from the activity-based demand model are forwarded to the transport simulation framework.

Since the traveling individual is the unit of observation and analysis, these type of models are also called *agent-based models*. The term is rooted in the "computational paradigm where individual entities called *agents* have their own objectives and make autonomous decisions. They interact with other agents in an independent way and the effects of the interactions are evaluated globally"[Moyo Oliveros, 2013, p.5].

According to Miller et al. [2004, p.23], "agent-based microsimulation is ideally suited to activity-based travel modeling given the disaggregated, dynamic, complex nature of the phenomenon." Furthermore, "it is hypothesized that agent-based microsimulation, in fact, represents the best approach currently available to modeling large, complex, dynamic, open-ended socio-economic systems. [...] It is believed that microsimulation may prove to be the most computationally efficient, practical approach to modeling highly complex systems" [Miller et al., 2004, p.12]. As a result, microsimulations have been applied with increasing frequency since the end of the last century, in particular in the field of transport research [Miller et al., 2004, p.10].

1.3. Vision

State-of-the-*art* models allow for the analysis and assessment of basically any proposed transport policy or scheme as well as any socioeconomic scenario. The major problem of many current models is, however, that they are data-hungry and require a high amounts of resources [Flötteröd, 2010, p.1]. This is problematic in the following (and potentially additional) modeling contexts:

- In preliminary studies, first estimations, and many other contexts, a high input of resources is not feasible. Neither can the required amount of data be provided without incurring prohibitively high expenses.
- In many regions of the world, required data are not available. While this is particularly true for developing regions, many types of very specific data (e.g. time-use surveys) are not available in many highly-developed countries either.
- The collection, processing, and storage of many kinds of data needed for transport models is strictly protected or even forbidden by reason of information privacy. In particular, data with geographical coordinates which are highly relevant for transport planning are often regarded as risky in terms of data abuse.

Accordingly, one major goal of this study is to build a model that suffices with a very low amount of input data and still yields a good representation of real-world traffic patterns. Hence, the overarching premise of this study is not to use any data that are not readily accessible and, thus, inexpensive to obtain. So, this model does not utilize any form of data which is regarded as risky in terms of information privacy. As will be shown, the established approach is also viable in regions with low general levels of data available because only some labor market data and traffic counts are necessary. Chances are high that labor market data are available since these data are important for taxing. Traffic count data can – in case of need – even be obtained by simple manual counting. This is realistic in countries where costs per working hour are low, which is often the case in those regions where data availability is low.

While comparable modeling approaches to transport demand generation exist, the unique property of this study's approach is that transport demand modeling is done with a much lower amount of input data. The major goal of this study is to examine the quality of the demand for transport that is generated based on this modeling approach.

1.4. Outline of this Study

The remainder of this work is organized as follows: In the following two chapters the modeling approaches, which are applied for the transport model to be built, are discussed conceptually: While demand modeling is addressed in chapter 2, chapter 3 deals with transport simulation. Then, a detailed description of the applied methodology along with a discussion of the justification of this approach is presented in chapter 4. This chapter also includes a description of input data and data used for calibration and validation. Next, the setup, the properties, and the results of an initial model based on the approach developed in this study together with an analysis and assessment thereof is presented in chapter 5. Here, a particular focus is one examining the influence of various configurable parameters. Building on the knowledge gained from the initial model, a more elaborate model based on this study's methodology is built, analyzed, and validated in chapter 6. The work is finished with a discussion and conclusion in chapter 7.

2. Demand Modeling

In this chapter, approaches to transport demand modeling are presented. The discipline concerned with modeling transport demand, referred to as *transport demand modeling*, has developed since the 1950s [McNally, 2007, p.35]. First models were analytical in nature and split up the demand modeling process in four subsequent steps. Since the unit of analysis (around which these models are based) is single trips, these models are also referred to as *trip-based models*. They are described in the next section (cf. section 2.1), followed by a presentation of newer approaches to transport demand modeling in section 2.2. Finally, the demand generation framework applied in this study is presented in section 2.3.

2.1. Trip-Based Demand Modeling

Trip-based demand models based on analytical methods have been developed since the 1950s, starting with Mitchell's and Rapkin's landmark study, which called for a comprehensive modeling framework [McNally, 2007, p.35]. As their name suggests, the unit of analysis, which these models are based on, are uncorrelated trips. The model output is flows of traffic on the routes of the network. Thus, these models describe the demand for transport in aggregated form, neglecting the fact that these flows are made up by individual travelers that may react differently to changes in the transport system.

These models found their first comprehensive application in the Chicago Area Transportation Study that was established in 1955 to "provide the basis for a unified transportation development program for the [Chicago] area" [Chicago Area Transportation Study, 1959, p.2]. The study's objective is defined as "to maximize the ease of travel within the urban region"[Chicago Area Transportation Study, 1959, p.2]. Hence, the focus of applications of these demand models "was decidedly highway-oriented with new facilities being evaluated versus traffic engineering improvements"[McNally, 2007, p.36].

The fundamental approach of these trip-based models is to sequentially work through the following four subsequent steps in order to calculate the demand for transport on each route of the considered network [Bhat and Koppelman, 2003, p.39], [Raney and Nagel, 2006, p.305]:

- Trip Generation: The magnitude of total daily travel originating and terminating at given geographical locations is defined.
- Trip Distribution: Trip ends from trip generation are combined to trips. A typical procedure applied for this is the *gravity model*, which – just like its name-giving natural phenomenon – accounts for attraction and impedance between two entities (bodies in physics and activity locations in transportation) and, thereby, calculate the forces (physics) and traffic flows (transport), respectively, between them. The output is mostly given by so-called *origin-destination (OD) matrices*, which state the magnitude of traffic flows between any origin and destination of the considered scenario.
- Mode Choice: Modes of transport are chosen for parts of traffic flows yielding mode-specific OD matrices.
- Route Assignment: Mode-specific OD trip matrices are loaded on the (mode-specific) networks. Algorithms are used to arrange the flows on each network link so that the outcome constitutes a *user equilibrium* [Gawron, 1998, p.2] (also referred to as *Nash equilibrium*), where all paths utilized for a given OD pair have equal impedances. Thus, these equilibrium-based aggregate assignment algorithms yield results that adhere to Wardrop's first principle [Wardrop, 1952, p.345], which describes the state of a system where no individual can improve their situation by a unilateral change in behavior. Probabilistic elements in the algorithm may be used so that the procedure becomes *stochastic assignment* and the outcome becomes a *stochastic user equilibrium.*

By reason of their structure, these models became widely known as *four-step models.* With new federal legislation established in the United States the 1960s, requiring *continuous, comprehensive, and cooperative* urban transport planning, four-step models became more and more institutionalized and the standard approach to demand modeling [McNally, 2007, p.36]. Up to today, improvements to this modeling approach have been made by considering time dependency (to a limited extent) and by introducing a *feedback* of information concerning network status from the route assignment step in earlier model steps. Since various versions of these models are still applied by practitioners all over the world, they are considered state of the practice.

As exemplified by the objectives of the Chicago Area Transportation Study, trip-based models "were initially developed to evaluate alternative major transportation actions such as new roads, major widenings and major new fixed-guideway transit proposals" [Hartgen, 2013, p.10]. For these type of transport schemes, trip-based models could be proven suitable [Bhat and Koppelman, 2003, p.41]. With the emergence of more diverse policy options (as, for instance, summarized in chapter 1), the limitations and inadequacy of trip-based models have become more and more obvious [McNally, 2007, p.36], [Hartgen, 2013, p.10] because of the following model properties.

First, the time of day of trips is either not modeled in trip-based models or only modeled in a limited way. In case it is considered, it is mostly introduced by applying time-of-day factors to daily travel volumes [Bhat and Koppelman, 2003, p.39]. If time of day is not or not suffienctly well integrated, "it is difficult or impossible to model any kind of time-dependent effect, such as emissions (which depend on engine temperature, which in turn depends on how long the car has been running), or peak traffic spreading" [Raney and Nagel, 2006, p.305].

Second, "a fundamental conceptual problem with the trip-based approach is the use of trips as the unit of analysis [...] without consideration of dependence among trips" [Bhat and Koppelman, 2003, p.40]. Hence, no distinction is made between single-stop trips and multiple-stop trips (trip chaining). "Thus, the organization of trips and the resulting inter-relationship in the attributes of multiple trips is ignored in all steps of the trip-based method. This is difficult to justify from a behavioral standpoint" [Bhat and Koppelman, 2003, p.40], as, for instance, the destination of a trip of a *tour*[1] is dependent on the previous destinations of this tour. Moreover, the mode of transport chosen for a single trip of the tour is obviously highly dependent on the mode chosen for preceding trips of thats tour [Meister et al., 2010, p.3]. By considering trips in isolation from other trips, these essential dependencies cannot be taken into account by the trip-based approach [Kitamura, 1988, p.15].

Third, because trips are the unit of analysis, decisions are decoupled from persons and therefore from demographic attributes" [Raney and Nagel, 2006, p.305f], which, however, mostly constitute essential determinants for travel demand.

Finally, the sequential structure of most trip-based models is hard to interpret behaviorally, since it implicitly assumes that people take decisions in the same sequence as the model represents these decisions. Its inadequacy is easily exemplified by a person who first decides to go to a cinema by car and then chooses one of the cinemas accessible by car, instead of first choosing the destination and then the mode like the four-step model would assume.

These shortcomings led to the realization that the traditional trip-based approach towards travel demand modeling "needs to be replaced by a more behaviorally-oriented activity-based modeling approach" [Bhat and Koppelman, 2003, p.39].

[1] A tour is defined as a chain of trips without returning to the origin of the first trip in the meantime. The tour ends when the origin of the first trip is reached after multiple trips have been conducted.

2.2. Activity-Based Demand Modeling

As described in the previous section (cf. section 2.1), trip-based approaches to travel demand modeling are concerned with various shortcomings, which can be summarized as follows:

- Time of day of trips is either not modeled or only modeled in a limited way.
- Dependences among trips of a given traveler are not considered.
- Decisions are not related to persons and their demographic attributes.
- The sequential structure of models brings about behavioral inadequacies.

Especially, with more diverse transport policies (cf. chapter 1) that go beyond infrastructure improvement schemes, the shortcomings of trip-based models became more and more obstructive [McNally, 2007, p.36], [Hartgen, 2013, p.10]. Therefore, beginning in the 1970s, researchers started to develop new approaches towards the modeling of the demand for transport [Pas, 1985, p.460].

Firstly, in contrast to trip-based models, more attention was paid to the fundamental fact that the overwhelming majority of trips are not conducted for their own sake. Instead, the demand to conduct trips is *derived* from the desire to pursue activities dispersed in space, leading to the notion of transport as a *derived demand* [Pas, 1985, p.460], [Kitamura, 1988, p.15], [Bhat and Koppelman, 2003, p.40], [Charypar and Nagel, 2005, p.369]. Therefore, it was emphasized that one "must understand the mechanism of activity engagement, i.e. what activity we pursue, when and where, how long, with whom, in what sequence, and how the engagement patterns are interrelated over time" [Kitamura, 1988, p.20]. So, "the consideration of revealed travel patterns in the context of a structure of activities [...] with a framework emphasizing the importance of time and space constraints [became] common ground"[Kitamura, 1988, p.11] in these new approaches to travel demand modeling. Because the unit of analysis, thus, changed from single trips towards the activities, these models are referred to as *activity-based model*. Based on the knowledge of people's wishes to pursue certain activities distributed over space and time, it becomes immediately inferable what trips people seek to pursue in order to attain to these activities and their locations.

Secondly, activity-based models "pay more attention to the sociodemographic characteristics of individuals and households that affect the demand for activity participation [...] and that often constrain activity and travel choices" [Pas, 1985, p.460]. These models enable the consideration of the impact of sociodemographic changes such as increasing proportions of working women, single parents, and elderly drivers on travel demand [Kitamura, 1988, p.29]. In line with this, the notion of *lifecycle stages* was developed [Kitamura, 1988, p.14]. This concept describes effects of household interdependencies on individual activity choice represented by measures such as presence of working spouse, number of adults, and household structure [Guo and Bhat, 2001, p.4]. Hence, activity-based models overcome the isolation of trips from the demographic attributes of the traveling individual (cf. section 2.1).

Accordingly, many essential phenomena that have a significant influence on activity participation and, thus, travel decisions can be analyzed with activity-based models. These phenomena include, for instance, activity substitution [Bhat and Koppelman, 2003, p.40], multi-day behavior, and interpersonal linkages [Kitamura, 1988, p.28].

Most importantly, activity-based models have shown to be suitable to determine which households and individuals will be affected by a new policy and how they will adapt to the change [Kitamura, 1988, p.24]. Accordingly, the activity-based modeling paradigm has received additional impetus by legislations[2], which require travel demand models to provide information at a high level of resolution along the timeline and also to provide more specific attributes of traveling vehicles. A classic example in this respect is engine temperature as mentioned in section 2.1. Since activity-based demand modeling constitutes a more holistic approach with detailed representation of the temporal dimension, it is better suited to assess novel transport policy proposals [Bhat and Koppelman, 2003, p.41].

However, most activity-based demand models have in common that they only answer the first three questions of the traditional four-step model, i.e. *How many people wish to travel?*, *From where to where do they wish to travel?*, and *Which mode of transport do they wish to use?* (cf. section 2.1). Specifically, most activity-based models end with time-dependent, mode-specific OD matrices [Flötteröd et al., 2011, p.482]. As discussed in section 2.1, these OD matrices provide information concerning the number of travelers on different relations for each mode. In order to answer the fourth question, i.e. *Which route do travelers wish to follow?*, these OD matrices are then fed to separate route assignment packages, which are basically the same as the fourth step (route assignment) of the four-step process described in section 2.1. Via equilibrium-based aggregate assignment algorithms, the route assignment yields the required information concerning traffic on the network routes, which may be fed back to the activity-based demand model in form of time-dependent travel impedances [Flötteröd et al., 2011, p.482].

While it is advantageous to consider travelers individually to generate OD matrices (e.g. in terms of the aforementioned consideration of demographic attributes [Raney and Nagel, 2006, p.306]), the disaggregate information considered up to this point gets, of course, lost in providing OD matrices as they are – by definition – aggregate

[2] An example for such legislation is the 1990 United States Clean Air Act Amendments.

forms of representation.

Other activity-based models "generate a sequential list of activities and trips connecting these activities for every person in the study area" [Meister et al., 2010, p.3]. Thus, the spatial and temporal consistency of the daily activity-travel patterns of the individual is maintained. While maintaining disaggregate information of travelers, the approach does still not provide the required information concerning routing. While this fact could, at first consideration, be regarded as a disadvantage of activity-based models, it offers, on the other hand, the opportunity to represent the interaction of transport demand and transport supply (cf. section 1.1) on the network in a disaggregate way as well. Instead of the equilibrium-based aggregate assignment algorithms that are used to assign OD pairs to routes, disaggregate information may be used to find new routes for each traveler on an individual basis.

Now that the conceptual background of activity-based demand models has been discussed, it seems reasonable to briefly consider the different functional approaches, which these models employ. Two major approaches to activity-based demand modeling can be distinguished [Bhat et al., 2004, p.1], [Meister et al., 2010, p.3].

On the one hand, there are models which are based on *random utility theory*[3], which are referred to as *random utility models* or in this context also simply as *econometric models*. These models use "systems of equations to capture relationships among activity and travel attributes and to predict the probability of decision outcomes. The strength of this approach lies in allowing the examination of alternative hypotheses regarding the causal relationships among activity-travel patterns, land use, and sociodemographic characteristics of individuals" [Bhat et al., 2004, p.57]. Examples for such models are – among others – the Sacramento Activity-Based Travel Simulation Model (SACSIM) and the Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns (CEMDAP) [Meister et al., 2010, p.3].

On the other hand, there are models based on *rule-based approaches* (also referred to as *computational process models*), which employ psychological decision rules derived from surveys. They constitute implementations of sets of rules in the form of condition-action (if-then) pairs that specify how the solution to a given task is found [Bhat et al., 2004, p.57]. Examples include – among others – the Travel Activity

[3] Random utility theory is concerned with approaches that model *discrete choices*. Discrete means that the alternatives of the choice are mutually exclusive and collectively exhaustive. These models are based on the notion of *utility maximization*, which assumes that decision makers aim to increase their personal utility in taking choices. Operational models consist of parameterized utility functions in terms of observable independent variables and unknown parameters. The corresponding values can be estimated from a sample of observed choices. Since it is not possible to estimate a model that is perfect, the concept of *random utility* is adopted from psychology. So, the true utilities of the alternatives are regarded as random variables so that the following identity is true: The probability that a given alternative is chosen equals the probability that this alternative is the one which has the greatest utility among the available alternatives [Ben-Akiva and Lerman, 1985, p.2f].

Scheduler for Household Agents (TASHA) and ALBATROSS (A Learning-BAsed TRansportation Oriented Simulation System) [Meister et al., 2010, p.3].

In this study, the random-utility-based model CEMDAP is used, which is described in more detail in the following section (cf. section 2.3).

2.3. CEMDAP

The Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns (CEMDAP) is a software implementation of a system of econometric models that represent the decision-making behavior of individuals [Bhat et al., 2008, p.2]. CEMDAP has been developed at the University of Texas at Austin, USA, and brings together various activity-based modeling efforts [Guo and Bhat, 2001, p.5]. The following description of CEMDAP is based on Bhat et al. [2004].

Following the modeling paradigm to represent the relevant components of a complex system, i.e. the travelers in the transport system, individually (cf. section 1.2), CEMDAP is implemented as a microsimulation, a process through which the choices of individuals are simulated dynamically on the basis of underlying econometric models [Bhat et al., 2004, p.57]. The modeling system follows a holistic approach that recognizes the complex interactions in activity and travel behavior It is, therefore, in line with the notion of *derived demand* as pointed out in section 2.2. It explicitly recognizes that individuals make choices about the activities they pursue during the day and that travel is the result of the fact that some of these activities are locally dispersed . In particular, CEMDAP constitutes one of the first models to comprehensively simulate the activity-travel patterns of working as well as non-working individuals along the time line [Bhat et al., 2004, p.57], [Guo and Bhat, 2001, p.4].

CEMDAP requires input information concerning land use, activity system, transport level-of-service attributes as well as sociodemographic characteristic on household and person level (cf. figure 2.1 and section 2.3.2). As the latter are mostly only available on aggregate level, methods such as synthetic population generation can be used to obtain them on disaggregate level[4].

As output, CEMDAP provides complete daily *activity-travel patterns* for each individual in each household of a population (cf. figure 2.1 and section 2.3.4). Activity-travel patterns are defined as the sequence of activities and intermediate traveling that a person undertakes during the day [Bhat et al., 2004, p.58].

In CEMDAP, an activity-travel pattern is represented by a hierarchical structure that – enumerated in bottom-up direction – consists of the levels *stop*, *tour*, and *pattern*. A stop constitutes a single activity out of home, i.e. an activity which

[4] For details concerning synthetic population generation, cf. Guo and Bhat [2007].

can only be reached via traveling. It is characterized by its type, its duration, its location, and the travel time to this location. A chain of stops made from home, from work, or one of the two commutes from home to work or back is referred to as a tour. Tours are characterized by their modes, durations, number of stops within the tour, and the home-stay duration immediately before the tour. The sequence of all tours during one day make up a pattern.

The modeling of the activity-travel patterns of individuals consists in the determination of all attributes that characterize the three-level representation structure. As the number of attributes as well as the number of possible choice alternatives for each attribute are very large, the joint modeling of all these attributes is not viable. Therefore, the determination of all these attributes is broken down into a modeling system that consists of several sub-models, which are integrated into a modeling framework.

2.3.1. Framework

The modeling framework of CEMDAP consists of two major components: The *generation-allocation model system* and the *scheduling model system*. First, in the generation-allocation model system, decisions of individuals to participate in activities are represented. Then, based on these decisions, the scheduling system creates the complete activity-travel pattern of individuals [Bhat et al., 2004, p.58].

One of the most fundamental daily decisions for the determination of the properties of an activity-travel pattern is the decision whether or not the individual participates in out-of-home mandatory activities such as work or school. It is obvious that this decision imposes constraints on participation in other types of activities. Therefore, individuals are classified as workers or non-workers in CEMDAP according to their decision whether to pursue a work activity on a given day. While work start and end times serve as points of reference for the other decisions of workers, this point of reference does, obviously, not exist for non-working individuals.

Accordingly, the first components of the generation-allocation modeling system focus on the individual's decision to pursue mandatory activities such as work or school. This decision is based on the employment status of the individual. If a person is classified as a worker, the work-based duration and work start times are determined next [Bhat et al., 2004, p.59]. Then, the generation-allocation modeling system determines whether or not shopping activities are pursued. Subsequently, five sub-models determine the decisions to pursue activities for personal business, social recreation, to serve a passenger, eat out, and undertake other activities.

On the basis of the distinction of workers and non-workers, separate scheduling model systems are applied. The scheduling of workers is modeled by three sequentially applied sub-model systems: the pattern-level, the tour-level and the stop-level model systems [Bhat et al., 2004, p.60] . Each of these systems corresponds to one level in the daily activity-travel representation framework, i.e. patterns, tours, and stops.

First, based on demographics, land use, transportation system characteristics, and, most importantly, the results of the generation-allocation model system, the pattern-level sub-model determines the properties of the commutes, i.e. the trips from home to work and back. These attributes include travel mode, number of stops, and commute duration. The number of commute stops is, of course, only modeled for travelers for whom the generation-allocation model system has determined that they pursue activities other than work during the considered day. If the traveler has no other activities during the day, their activity-travel pattern is complete at this point. If not, the number of tours is modeled. On the basis of work times (modeled by the generation-allocation model system) and the commute durations (modeled on pattern level), the times of departure and arrival at home are determined. This yields the times available for undertaking tours before work, at work, or after work and is used as input for the model which determines the number of tours.

Second, the tour-level model system is applied which determines mode and number of stops first. Then, tour duration is modeled, followed by the duration of the stay at home or work, respectively, before the tour.

Third, the stop-level model system is used to determine stop characteristics. Using a discrete choice model, the activity type of each stop is determined. Then, regression models are applied to model activity duration and the travel time to stop. Last, a location choice model is applied to determine stop location.

Like the scheduling model system for workers, the scheduling model system for non-workers is also broken down into three sequential systems corresponding to patterns, tours, and stops. In contrast to workers, the schedule fixity, given by the need to be at work or school at a certain time, does not exist for non-workers. Thus, the total number of tours is determined in the pattern-level model system. By the tour-level modeling system, the attributes of each tour are sequentially determined from the first to the last tour based on the number of tours as it has been determined by the pattern-level modeling system. The available time left after the first tour is, thereby, used as an explanatory variable for the determination of the attributes of the second tour, which introduces linkages among the choices of the different tours. Last, the stop-level model system is used to model the characteristics of each stop in the tours [Bhat et al., 2004, p.61].

The whole modeling framework is based on input data (cf. section 2.3.2) and a model specification (cf. section 2.3.3) [Bhat et al., 2008, p.10]:

2.3.2. Model Input

As input data, CEMDAP needs transport system properties (i.e. levels of service for different times of day) and the land use patterns of the planning area as illustrated in figure 2.1. Also, CEMDAP requires disaggregate demographic characteristics of the population. As pointed out in section 2.3, these are, however, in most cases not available. Synthetic population generation, however, offers a method to generate a statisitcally-correct, disaggregate representation of the real population, often referred to as *synthetic population*. A synthetic population reflects the real population of the planning area in terms of major sociodemographic and socioeconomic properties like age structure, gender, employment situation etc. Thus, "the synthetic population is a random realization of the census, that is, a census taken from the synthetic population would return, within statistical limits, the original census" [Raney and Nagel, 2006, p.306].

Accordingly, synthetic population generation is applied as a pre-process to CEMDAP in order to provide CEMDAP with a disaggregate demographics needed as input data. Another model can be applied upstream to provide CEMDAP with input variables whose values result from medium-term choices like choices concerning residential location, employment, or car ownership [Bhat et al., 2004, p.62]. These choices are – as opposed to those choices that are modeled in CEMDAP – not taken on a daily, but on a longer-term basis. This medium-term choice simulator as well as the synthetic population generator are not part of CEMDAP itself.

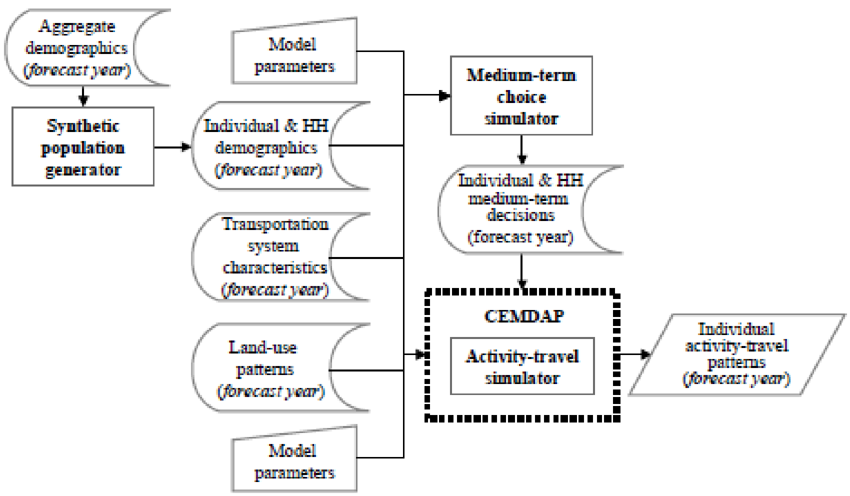


Figure 2.1.: CEMDAP

The required input data are forwarded to CEMDAP via text files for households, persons, level-of-service characteristics, zones, zone-to-zone relations, and vehicle types [Bhat et al., 2008, p.10]. The detailed preparation of the input data for this study is given in appendix B.

2.3.3. Model Specification

As explained in section 2.3.1, CEMDAP consists of several models that represent the various decisions a traveler takes during a day. These models fall into seven model categories: Linear regression, hazard duration, binary logit, multinomial logit, location choice, ordered probit, or work start/end time [Bhat et al., 2008, p.41]. All models used in CEMDAP, along with their variables and parameters, are specified in a so-called model specification file [Bhat et al., 2008, p.12]. In this study, a ready-made model specification file provided in the CEMDAP test package is used [Bhat et al., 2008, p.21]. More details concerning the model specification file are given in appendix B.

2.3.4. Model Output

As discussed in section 2.3, the output of CEMDAP consists in the complete daily activity-travel patterns of each individual of the synthetic population [Bhat et al., 2004, p.57], [Bhat et al., 2008, p.10]. In technical terms, this output is given by seven text files which correspond to a description of the modeled attributes of adults, children, workers, non-workers, students, tours, and stops. Some information are given redundantly in these files. Of particular interest for the analysis of this study is the stops files, which list all *activities* of each individual of the synthetic population including activity type, start time, duration and location of the stop as well as the location of the previous activity and the distance between the previous and the current stop [Bhat et al., 2008, p.14]. Thus, the full daily activity-travel pattern of any individual can be reconstructed from the information given in the stops file. Technical details are outlined in appendix B.6.

2.3.5. Extensions

Later CEMDAP was extended a simulator of activity-travel patterns into a *comprehensive Econometric Model of Urban System* called *CEMUS* (also referred to as *CEMDAP-II* or *second-generation CEMDAP*. Next to the integration of a synthetic population generator, which is always needed as a pre-process for CEMDAP, CEMUS also encompasses a module for longer term decision of individuals like car ownership or residential location called *CEMSELTS*, which stands for *Comprehensive Econometric Microsimulator for Urban Systems*. Details are given in Eluru et al. [2007].

3. Transport Simulation

Owing to the notion of the demand for transport as a *derived demand* that is *derived* from individuals' wishes to pursue activities dispersed in space and time (cf. section 2.2), the knowledge of individuals' activity patterns is the foundation for travel demand modeling.

As in any market, however, demand is dependent on supply. So, travel decisions of individuals are "interrelated with the availability and ease of transportation between potential activity locations" [Kitamura, 1988, p.20], i.e. the quality of transport supply. Hence, the interaction of supply and demand (cf. section 1.1) needs to be modeled to analyze how a given transport supply influences transport demand.

In traditional transport (demand) models (i.e. trip-based models, cf. section 2.1), this is done in the fourth and final modeling step (route assignment). As pointed out in section 2.1, route assignment uses algorithms to distribute aggregate flows of traffic on the network so that a *user equilibrium* is reached. As route assignment is already part of four-step models, no additional model is needed to cater for the representation of the interaction of supply and demand. On the other hand, these models are concerned with various shortcomings as discussed in section 2.1.

As discussed in detail in section 2.2, therefore, an activity-based demand model, which overcomes these shortcomings, is used in this study. Activity-based models, however, mostly end with travel patterns of individuals that do not contain routing information (cf. sections 1.1.2 and 2.2). These patterns are mostly aggregated into OD matrices so that route assignment algorithms (as used in trip-based models) can be applied. In case a disaggregate representation of travelers for the modeling of the interaction of supply and demand on the network is desired, however, the task becomes much more complicated.

Thus, a specific model is needed for this task. Here, two mechanism are relevant. First, it is crucial to analyze what happens when the demand for transport is realized on the physical network. This is simulated in a representation of the physical transport system (traffic simulation or physical simulation, cf. section 3.1). Second, it is important to examine how the travelers react to the result of the traffic simulation. Therefore, the choice processes (decision making) that travelers undertake based on what they experienced while traveling are simulated (mental simulation, cf. section 3.2). The model combining these two layers of simulation into an integrated simulation framework called MATSim, is then presented in section 3.3.

3.1. Physical Simulation (Traffic Simulation)

In this section, approaches towards the modeling of the physical reality, which traveling vehicles are surrounded with, are presented. These approaches are also referred to as *traffic simulation*, *traffic flow simulation*, *mobility simulation (mobsim)*, *network loading* or *execution*. The underlying models used for traffic simulation can be divided into macroscopic and microscopic models [Gawron, 1998, p.31].

3.1.1. Macroscopic Models

Macroscopic models do not discern individual vehicles, but describe traffic as a fluid or flow. Accordingly, they are also referred to as *flow-based models*. This traffic flow is considered on the basis of aggregate traffic characteristics like traffic density, traffic flow, and average speed[1] on a given part of the transport network. Accordingly, the focus of these models is on sections of the roadway network. These sections are described by aforementioned three (and potentially additional) variables. The relations of these variables are expressed by (differential) equations.

According to the notion of streams or flows, first such models were derived from fluid dynamics leading to the development of Lighthill's and Whitham's kinematic wave model in 1955. This model can, for instance, be applied to analyze bottlenecks and their effects on speed on a roadway section and to model how disturbances of the traffic flow propagate through a roadway section.

It was soon regarded as a shortcoming, however, that this model lacks a consideration of the fact that traffic is not always in equilibrium and that drivers do not behave perfectly rational. To take these phenomena into account, additional terms were added to the equations, e.g. to reflect driver's reaction times. For each such additional variable in the model, however, a corresponding variable has to be introduced for the description of each roadway section [Gawron, 1998, p.31]. Thus, using these equations for the description of traffic flow dynamics either becomes computationally expensive or fundamental aspects of traffic dynamics have to be omitted.

Furthermore, since neither individual drivers nor individual vehicles are taken into account in macroscopic models, it is unreasonable to consider individual travelers' attributes and characteristics in these models. The accounting for the individuality of travelers is, as pointed out in section 2.2, however, advantageous in many respects. In order to make improvements to travel options, for instance, it is mandatory to know which route a given driver took. This is why macroscopic traffic models do not qualify as component of the modeling framework of this study.

[1] The graphical representation of the relations of these three measures is called the *fundamental diagram of traffic flow*.

3.1.2. Microscopic Models

Microscopic models are based on the description of the movement of individual vehicles through the network. Thus, individual vehicles or their drivers constitute the unit of analysis in these models. Hence, they are also called *vehicle-based models* or *driver-based models*. Microscopic models also have the advantage that additional information like origin, destination, route, and departure time can be added to the data structures of the model easily [Gawron, 1998, p.32]. This property is important.

Microscopic models can be further divided into car-following models (cf. section 3.1.2) and mesoscopic models (cf. section 3.1.2) depending on the degree to which the interaction of individual vehicles is taken into account.

Car-Following Models

Car-following models have been applied since the 1950s. According to Ranjitkar et al. [2005, p.1582], nearly hundred models of this type have been developed so far. The first type of car-following models were stimulus response models, which are based on delayed differential equations. The delay is, thereby, associated with the reaction time of drivers. Like most other car-following models, the stimulus response model is, however, computationally costly [Gawron, 1998, p.33].

An approach to overcome this problem is time discretization. In each time step – in its magnitude mostly representing drivers' reaction time – vehicles are simultaneously moved forward in a system of coupled maps, which consider the interaction of adjacent vehicles. "While the idea behind the delayed differential equation models is to make the description of the vehicle dynamics as detailed as possible, the interesting question for the coupled-map models is how minimalistic a model can be while still maintaining the fundamental features of traffic flow" [Gawron, 1998, p.34]. The most minimalistic among such approaches are cellular automata models, most prominently the Nagel-Schreckenberg model [Nagel and Schreckenberg, 1992]. Despite their simplicity, these models reproduce fundamental properties of traffic flow. "Above a certain density, traffic jams occur spontaneously, the density-flow relation is qualitatively correct, the time interval between two cars passing a traffic light — the crucial parameter for the capacity of signalized intersections — is modeled correctly [...] This is especially surprising since one of the basic properties of cars, namely the finite deceleration, is not modeled at all" [Gawron, 1998, p.34].

Different types of car-following models are based on different underlying principles. They, however, share the common property that they model the longitudinal interaction between adjacent vehicles. While increasingly important for many applications like intelligent transportation systems or safety engineering [Ranjitkar et al., 2005, p.1582], this information is not mandatory for the application in this study.

Mesoscopic Models

As pointed out in the previous section (cf. section 3.1.2), important properties of driver-oriented models are the ability to track individual drivers and to be able to access their individual properties. The explicit consideration of car-following behavior, on the other hand, is not needed for the model used in this study. Instead, so-called *mesoscopic models* offer a suitable compromise. These models are driver-oriented, but do not model car-following behavior. Therefore, mesoscopic models are computationally significantly faster than car-following models, even the Nagel-Schreckenberg model [Gawron, 1998, p.33]. A well-known example of a mesoscopic model is Daganzo's cell transmission model "which can be viewed as a spatial discretization of an underlying fluid-dynamical model" [Gawron, 1998, p.36].

Still simpler, however, is a model in which each link is represented by a simple queue. Accordingly, the model is referred to as *queue model* or *queuing model*. In contrast to the cell transmission model, the links are not divided into smaller parts. Instead, each link is considered in its entirety. Travel times on links are calculated as the sum of the time needed to travel through the link and the time that may be spent waiting in queue. Despite its simplistic approach, this model still provides a good approximation of the travel times and is comparable with conceptually more complicated car-following models [Gawron, 1998, p.36].

Because of its computational performance, its vehicle-based modeling paradigm, and its sufficient representation of travel times, the simulation applied in this study is based on a queue model (cf. section 3.3.1).

3.2. Mental Simulation (Decision Making)

Since models which represent traffic or traffic flow are applied in various contexts besides traffic microsimulation, it was possible to start the discussion on traffic models in the previous section (cf. section 3.1) with a broader view on the topic and, then, gradually narrow down the focus to mesoscopic models as they are applied in the transport simulation framework employed in this study (cf. section 3.3).

For the modeling of decision-making processes – here referred to as mental simulation in order to illustrate them as some kind of counterpart to the physical simulation of the traffic on the network – a general discussion is not that readily viable.

As opposed to the physical simulation of traffic, mental simulations are novel to transport simulations and are exclusively applied in disaggregated models with a focus on the sound behavioral representation of the traveler. Accordingly, only a brief general overview of different approaches to evaluate and improve travel options seems reasonable at this point. For the approach's novelty and its relative uniqueness to the transport simulation framework applied in this study, the major part of the discussion will be done within the scope of the presentation of the transport modeling framework applied in this study in section 3.3.

By traveling on the network (i.e. by the traffic simulation), travelers gain experience, e.g. by having to wait in congestion. Thanks to the application of a fully disaggregated microsimulation approach, this experience is retained throughout the whole modeling process and attached to the respective individual. Accordingly, the travel experience can afterwards be used by travelers to evaluate their chosen travel options, develop new travel alternatives, try them out again in the traffic simulation (cf. section 3.1) and – over the course of time – come to improved travel decisions in terms of satisfying their individual transport demand. The steps of evaluation and development of alternative travel options is done within the mental part of the transport simulation. Arbitrary choice dimensions to which travelers can make improvements can be applied. These encompass for instance:

- Route choice
- Time choice
- Location choice
- Mode choice

In order to come to decisions among these choice dimensions, different approaches are viable. First, a discrete-choice approach (cf. footnote on page 14) based on a *nested multinomial logit model* may be applied. In nested multinomial logit models, the aforementioned decisions are split up into multiple hierarchical decision levels. To take a decision concerning a travel option, the performance of all options concerning a given choice dimension – handled on each hierarchical level – have to be calculated. Therefore, the decision tree has to be worked through from the leaves to the root. The performance of alternatives on each level is based on the notion of *utility*, a numerical value which is the higher the better the solutions is.

Once the performances of all alternatives on all hierarchical decision levels have been calculated, the decision tree is worked trough step by step from its root to the leaves taking one decision on each hierarchical layer at a time. The choices are thereby related to calculated utilities. The decision concerning a (composite) travel option is made up of the single decisions taken on each layer of the decision tree [Charypar and Nagel, 2005, p.372].

This approach, however, becomes computationally costly [Flötteröd et al., 2011, p.484] to infeasible the bigger the search space gets. Since the options concerning time choice and location choice, for instance, are numerous, the search space concerning transport simulations is huge. The approach is also conceptually questionable because certain measures that affect the integrity of a travel option are, in fact, an outcome of the model and, thus, not truly known in the process even though they are considered in it [Flötteröd et al., 2011, p.484].

An alternative approach, which is particularly well-suited for huge search spaces, is *genetic algorithms*. As the name suggests, "genetic algorithms are biologically inspired optimization methods that are relatively inefficient computationally, but extremely flexible" [Charypar and Nagel, 2005, p.370]. In contrast to discrete choice models, which enumerate all possible alternatives, genetic algorithms do not find a globally optimal solution, but one *good* solution [Charypar and Nagel, 2005, p.372].

In genetic algorithms, a scope of possible solutions is maintained during the search process. It is not important where initial solutions for starting the genetic algorithm come from as they are to be improved through the search process. In general, the search process of genetic algorithms encompasses mutation, crossover, and selection. In the case of transport simulations, the possible solutions are represented by daily activity-travel patterns.

Similar to the discrete-choice approach, also in this approach a performance evaluation based on the notion of utility is conducted. To do so, a *utility function* based on individual's participation in intended activities and their travel experience is used. Everytime a better daily activity-travel pattern is found, the worst maintained pattern is removed, keeping the number of possible solutions (i.e. daily activity-travel patterns) constant. This procedure is repeated until no further improvement can be observed. The best solution at the time of termination is considered the solution of the problem [Charypar and Nagel, 2005, p.374].

The approach of genetic algorithms is contrasted to the discrete-choice approach in that individuals do not take individual decision for each choice dimension, but choose from patterns which constitute a (momentarily) fixed set of decisions concerning these choice dimensions. Further approaches to model traveler's decisions are discussed in Charypar and Nagel [2005, p.373].

3.3. MATSim

The core component of the modeling approach applied in this study is MATSim, which stands for *multi-agent transport simulation*[2]. MATSim is a transport simulation, which – among other things – encompasses the physical simulation of the transport system and the mental simulation of the individuals who use the transport system. These two major simulation steps were conceptually described in the two previous sections (cf. sections 3.1 and 3.2).

The physical simulation used in MATsim is based on a mesoscopic traffic model according to the description in section 3.1. The evaluation of travel options (*plans* in

[2] Cf. `http://www.matsim.org/`, last accessed 25 November 2013.

MATSim terminology) is done with a utility function (cf. section 3.2). In MATSim, this step is referred to as *plan scoring* (cf. section 3.3.2. The selection of plans (daily activity-travel patterns) and potential creation of new, alternative plans, is done in a step called *plan selection* (cf. section 3.3.3). Plan scoring and plan selection together constitute the mental layer of the simulation as described conceptually in the previous section (cf. section 3.2).

Conforming with the microsimulation paradigm, the software objects representing travelers (*agents* in MATSim terminology) are retained during the whole simulation process. Each agent "makes independent decisions about its desired use of the transportation system during a typical day. An agent keeps a record of its decisions in a plan. A plan contains the agent's schedule of activities it wants to perform during the day, including times and locations, along with the travel modes[3] and routes it intends to utilize to travel between activities" [Raney and Nagel, 2006, p.305]. Just like the agents, their "personal attributes such as sociodemographic properties, the activity plan, and other internal variables can be accessed during the entire modeling process" [Meister et al., 2010, p.4].

In order to start the MATSim simulation process, input data concerning supply and demand are necessary. As a minimum, a network file as a description of transport supply and an initial plans file as a description of transport demand are needed. MATSim's so-called agent database reads in the initial plans file, creates the agent objects from it, and loads their plan(s) into their memory [Meister et al., 2010, p.5]. Once this is set up, the actual transport simulation, which models the interaction of transport supply and transport demand is started. As illustrated in figure 3.1, the simulation procedure can be divided into three steps: Traffic simulation constitutes the simulation of vehicles on the roadway network. Plan scoring and plan selection together represent the mental simulation that describes the decision-making process of the simulated agents.

[3] In MATSim, it is possible to simulate different modes of transport within one scenario. Currently, automobile traffic and public transport can be simulated on a physical network. Other modes are treated by *teleportation*, which means that their respective travel times are only dependent on mode speed, beeline distance and a configurable factor.

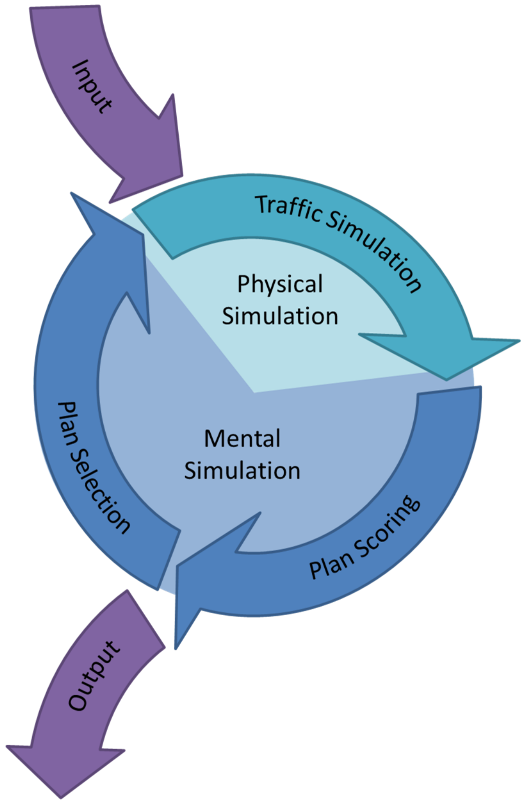


Figure 3.1.: MATSim

3.3.1. Traffic Simulation

In physical simulation of the transport system (traffic simulation) of MATSim, the selected plans of all agents (i.e. the activity-travel patterns of all traveling individuals) are simultaneously simulated. This traffic simulation is based with a queue model, which falls within the type of mesoscopic traffic models as described in section 3.1.2. A directed graph is used, whose nodes/vertices (mostly) represent intersections and whose links/edges represent roadway segments. Every roadway segment is modeled as a first-in-first-out (FIFO) queue and has the following properties:

- Free-flow speed
- Link length
- Flow capacity
- Number of lanes
- Allowed modes

In every time step of the simulation (usually one second), the state of each queue is updated. First, it is checked whether there is at least one agent in the FIFO queue.

If this is the case, the agent on top of the considered queue is put into the FIFO queue of the next link of its route and assigned with a time stamp. This is, however, only done if the following conditions are fulfilled:

- The agent has spent at least the free-flow travel time on the link. The free-flow travel time is calculated based on the free-flow speed and the link length. The time spent on the link is calculated based on current simulation time and the time stamp the agent received on entrance to the current link.
- The flow capacity has not been exceeded in this time step. This is calculated by checking whether the inverse of the flow capacity has passed since the last agent left the queue.
- The next link on the agent's route has free storage capacity. The storage capacity is calculated based on link length, number of lanes and a typical vehicle length.

In the next time step, the same procedure is repeated for all queues, i.e. all network links. This procedure ensures that the boundary conditions of the infrastructure, in which activities and traveling are performed, are accounted for. The flow capacity, for instance, may cause congestion on a link by defining the maximum number of agents that can leave a link within a given period of time. The storage capacity accounts for the maximum number of agents on a link and may cause upstream congestion spill-back as agents may have to wait on upstream links before being allowed to enter the downstream link. Besides constraints with regard to the network, activity plans impose constraints on agents as they are, for instance, not allowed to leave an activity before they have arrived at it.

The outcome of the traffic simulation is called *events*. Events are occurrences which are localized in time and space, e.g. departures, arrivals, starts or ends of activities, or enterings or leavings a link. Through this events-based approach, the microsimulation can handle and track every agent at all times. These events are handled by the subsequent components of MATSim as described in the following sections.

3.3.2. Plan Scoring

In the next step, each plan is evaluated quantitatively based on its own performance after it has been executed in the synthetic reality [Moyo Oliveros, 2013, p.34], i.e. the traffic simulation (cf. section 3.3.1). More precisely, The events generated by the traffic simulation are used by the agents to calculate scores for their plans. In doing so, only new scores for the most recently selected plan are calculated. The scores of the other, non-selected plans stay untouched. Scoring in MATSim is done based on an utility-based approach as explained in section 3.2. The according utility function [Charypar and Nagel, 2005, p.377] encompasses the agents' activity participation and their travel performance. The utility $V(i)$ of a plan i equals the sum of (positive) utilities of activity participation plus the sum of (negative) utilities of traveling (also referred to as *(travel) legs*) between activities as expressed in equation 3.1.

$$V(i) = \sum_{act \in m} V_{perf,m} + \sum_{trav \in n} V_{trav,n} \tag{3.1}$$

where:
$V_{perf,m}$ is the utility of activity m and
$V_{trav,n}$ is the utility of travel leg n.

For the representation of the utilities gained from performing activities, a logarithmic form is employed as expressed in equation 3.2.

$$V_{perf,m} = \beta_{perf} \cdot t^*_m \cdot \ln t_{perf,m} \tag{3.2}$$

where:
β_{perf} is the marginal utility of performing activities at its typical duration,
t^*_m is the typical duration of a given activity m, and
$t_{perf,m}$ is the actual duration of a given activity m.

For the representation of utilities incurred by traveling from one activity to the next (i.e. a (travel) leg), a linear form is used as expressed in equation 3.3.

$$V_{trav,n} = \beta_{trav} \cdot t_{trav,n} \tag{3.3}$$

where:
β_{trav} is the marginal utility of traveling and
$t_{trav,n}$ is the actual duration of a given travel leg n.

Additional components, e.g. penalties for schedule delays like arriving late or departing too early, can be added to the scoring function [Charypar and Nagel, 2005, p.377]. The first and the last activity are handled as one activity. Therefore, there are always the same number of travel legs activities as there are activities.

3.3.3. Plan Selection

In the third step of the MATSim iteration, the agent decides which plan to execute in the traffic simulation (cf. section 3.3.1) of the next MATSim iteration.

Before doing so, agents may generate new plans. The creation of new plans is done by applying modifications to copies of randomly selected existing plans of the agent. Modifications may be done with respect to various choice dimensions (e.g. routing or time choice). To do so, *(innovative) strategy modules*, which correspond to different choice dimensions, are used. In order to find new routes, for instance, a time-dependent Dijkstra algorithm is applied. It determines best routes based on link travel times which are obtained from the traffic simulation [Flötteröd et al., 2011, p.485].

The probability for a particular strategy module applied to a copy of a plan, is related to a configurable weight that each strategy module is equipped with. If a new plan is created by one innovative strategy module, this plan is marked as the agent's *selected plan*, which guarantees that this plan will be used in the next iteration.

Agents may, however, also decide not to create a new plan, but instead execute one of their already existing plans. Accordingly, one of the existing plans has to be chosen as the selected plan for the next iteration. This choice is performed with a multinomial logit model, where the selection probability of a given plan i is related to the plan's score $V(i)$, which is determined by equation 3.1:

$$P(i) = \frac{e^{\beta_{score} \, \cdot \, V(i)}}{\sum_j e^{\beta_{score} \, \cdot \, V(j)}} \tag{3.4}$$

where:
$P(i)$ is the selection probability of plan i out of all j plans in the agent's memory,
$V(j)$ is the score of plan j, and
β_{score} is the score parameter for plan selection. The higher the value of this parameter, the more the agent tends to choose a plan with a higher score.

This choice is referred to as *probabilistic selection*. The difference towards the aforementioned innovative strategy modules like route choice or time choice is, however, that probabilistic selection does not create new plans. Just like the innovative strategy modules, the probabilistic selection module also possesses a weight, which determines the probability that this module is chosen.

In most simulations all innovative strategy modules are switched off after a certain number of iterations. Afterwards only the probabilistic selection with a probability of being applied in a given iteration of 100% is active. Thus, a MATSim simulation run can be viewed as existing of two phases[Flötteröd et al., 2011, p.489]. The first phase, in which new plans are generated and tested, can be regarded as *choice set generation*. In the second phase, where only probabilistic selection according to equation 3.4 is active, the choice set are, thus, fixed and agents do only select from these fixed choice sets.

The maximum number of plans is limited for every agent by a configurable parameter. On the one hand, this is due to memory constraints. On the other hand, plans with a low score do not need to be considered any further. Accordingly, the plan with the worst performance is deleted at the beginning of the next iteration in case the maximum number of plans would be exceeded otherwise.

In most simulations, the weight for probabilistic selection is set equal or higher than the sum of the weights of all other strategy modules to allow for a sufficient amount of existing plans to be maintained by the agent.

If a plan has no score for any reason, e.g. in case it has just been created via an innovative strategy module, it is selected automatically. This is done to ensure that all existing plans are comparable to new activity plans generated by innovate strategy modules [Meister et al., 2010, p.6]. If multiple plans without a score exist, a random one of these it selected for execution.

Once a plan is marked as selected, either the next simulation iteration is started with its first step, the traffic simulation (cf. section 3.3.1), or the simulation is terminated in case the chosen number of iterations is reached. This number is mostly selected so that it can be assumed that no further significant plan improvements can be achieved though additional iterations. This system state is called an agent-based stochastic user equilibrium [Nagel and Flötteröd, 2009, p.2].

3.3.4. Model Input

As stated in section 3.3, MATSim requires as minimum input a network file (description of transport supply) and plans file (description of transport demand). For both, the `*.xml` format is used. A very simple example of a network consisting of two nodes and one link is given in the following. As pointed out in section 3.3.1, the links are further specified by length, capacity, free-flow spped, and number of lanes.

```
...
<network>
  <nodes>
    <node id="1" x="-20000" y="0"/>
    <node id="2" x="-15000" y="0"/>
    ...
  </nodes>
  <links capperiod="01:00:00">
    <link id="1" from="1" to="2" length="10000.00" capacity="36000" freespeed="
        27.78" permlanes="1" />
    ...
  </links>
</network>
```

An example of a plans file is given in the following. It states the (very simple) plan of one agent who has a home activity ("h"), followed by a short work activity ("w") and another home activity. The activity locations are given in terms of the nearest network link to the activity.

```
...
<population>
  <person id="1" employed="no">
    <plan selected="yes">
      <act type="h" link="1" end_time="06:00:00" />
```

```
            <leg mode="car">
            </leg>
            <act type="w" link="20" max_dur="00:30:00" />
            <leg mode="car">
            </leg>
            <act type="h" link="1" />
        </plan>
    </person>
    ...
</population>
```

Optionally, a counts file containing data from real-world traffic count station may be used for comparison between simulation and real-world measurements. In the following, a simple example of one count station on a network link labeled as number 14 with the first ten hourly values of a day is given.

```
<counts>
    <count loc_id="14" cs_id="handmade_01">
        <volume h="1" val="0" />
        <volume h="2" val="0" />
        <volume h="3" val="0" />
        <volume h="4" val="0" />
        <volume h="5" val="0" />
        <volume h="6" val="0" />
        <volume h="7" val="200" />
        <volume h="8" val="0" />
        <volume h="9" val="0" />
        <volume h="10" val="0" />
        ...
    </count>
    ...
</counts>
```

Other input files, for instance, regarding information on activity locations (facilities) may be used optionally depending on the simulation setup.

3.3.5. Conclusion

As pointed in section 1.1, approaches to simulate the transport system have to account for the interaction of transport supply and transport demand. Based on this, the demand can be optimized with respect to a momentarily fixed supply and thus a representation of the real-world travel patterns can be found. In MATSim this task is carried out on the basis of microsimulation, which constitutes a mechanism for reproducing or forecasting the state of a dynamic, complex system by simulating the behavior of the individual actors in the system over both time and space [Miller et al., 2004, p.10], [Guo and Bhat, 2007, p.2].

The optimization in MATSim, i.e. the optimal exploitation of given transport supply by transport demand, adheres to the concept of *evolutionary algorithms*, which describes the iterative generation, evaluation, and selection of agents' daily plans [Moyo Oliveros, 2013, p.27]. The repetition of the MATSim iteration effects that agents to improve their plans over many iterations, which is why this process is referred to as *learning* [Flötteröd et al., 2011, p.484]. This notion becomes even more insightful when considering the fact that an agent can hold a set of activity plans in its memory from which a choice can be taken. Thus, the agent does not forget "past" plans, but may use them again later and see how good they are as compared to other plans. In particular, a plan may perform differently in different iterations [Meister et al., 2010, p.4] as it is dependent on the behavior of other agents that steadily adapt their plans as well. This process may also be regarded as a *genetic algorithm* as plans compete with each other. Every time a new plan is added to the agent's memory, the worst-performing existing plan is deleted because of the maximum number of plans that may not be exceeded. "This is a variation of elitist selection in genetic algorithms, which guarantees that the individual with the highest fitness will survive the selection process to the next generation" [Meister et al., 2010, p.6].

As "each traveler in the simulation is individually resolved" [Charypar and Nagel, 2005, p.370], the approach is referred to as *agent-based simulation* or *multi-agent simulation*. As "not only routes are considerd for fitness evaluation, but also the realization of activities" [Moyo Oliveros, 2013, p.27], MATSim constitutes an *activity-based* approach. Besides other advantages, it can, thus, be easily coupled with activity-based demand models (ABDM), where each traveler is kept as an individual throughout the whole modeling process as well [Charypar and Nagel, 2005, p.369].

In fact, MATSim itself can be regarded as an activity-based demand module [Meister et al., 2010, p.4]. MATSim overcomes the separation of demand generation and route assignment that exists in traditional four-step models (cf. section 2.1) as well as approaches to couple activity-based demand models with network aggregation-based route assignment modules (cf. section 2.2). Instead, the interaction of supply and demand are simulated in an integrated way.

MATSim's genetic algorithm effects that transport demand adapts itself to transport supply over the course of iterations. It is, thus, possible to start the simulation procedure with little initial assumptions and have the evolutionary algorithm cater for the improvement of the initial demand representation. Depending on how elaborate the representation of transport demand is at startup of this process, it can, thus, be argued that MATSim itself becomes the (activity-based) demand generation module.

Specifically, Balmer [2007] shows how MATSim's iterative simulation process applied leads to an improvement of agent's plans with regard to various choice dimensions. To do so, a respective strategy module for each choice dimension to which agents are supposed to conduct optimization has to be included. If the modules work correctly, the properties of the corresponding choice dimensions (e.g. modes shares or travel times) will converge to realistic values. In this respect, it is fundamental to distinguish fixed from unfixed choice dimensions. "Based on what [choice] dimension of the demand will be optimized, and which [choice] dimension will stay fixed during optimization, the initial demand modeling process has to make sure to model the fixed part such that it reflects reality. For example, if the system does not allow agents to optimize their choice of mode of transport, the initial demand of the scenario needs to produce a realistic modal split on the basis of available survey data. But if the agents can choose the modes by themselves, the modal split process step can be left out. Therefore, the relaxed state of the optimization process should reflect reality by comparing its result with measurements" [Balmer, 2007, p.52f]. In other words, only those properties of the choice dimension to which no modification will be done in MATSim's iterative procedure, have to be initially correct.

By this approach, "elements of demand generation are thus elevated from a simple pre-process [of route assignment] to an integrated part of demand-supply equilibration, as mode choice, departure time choice or even the activity sequence may be susceptible to changes in traffic patterns" [Meister et al., 2010, p.4].

3.4. Cadyts

As discussed in section 1.2, microsimulations have become an important tool for the dynamic model representation of the interaction of transport demand and transport supply [Miller et al., 2004, p.10], [Flötteröd, 2009, p.2], [Flötteröd, 2010, p.1].

Advantages (as already mentioned in section 1.2) of microsimulations over traditional, aggregate, analytical models are that they offer a behaviorally much more sound representation of the transport system. Because "the behavior of the actors [...] within the system being modeled is significantly non-linear in nature, and, hence, significant bias can exist if one attempts to model such a system using arbitrary aggregations of these actors" [Miller et al., 2004, p.16]. In a microsimulation approach, every traveler is considered individually with all its relevant attributes retained throughout the whole modeling process [Meister et al., 2010, p.2].

Furthermore, the iterative simulation procedure of the microsimulation applied in this study has an intuitive interpretation as a learning process which travelers conduct in optimizing their daily schedules (cf. section 3.3.5. This is an advantage compared to "mathematically more involved" [Flötteröd, 2009, p.2] analytical approaches.

The drawbacks of microsimulations are, however, that they pose high needs on data supply and that "the intuition of learning alone is too weak to analyze the results of an iterated simulation" [Flötteröd, 2010, p.1]. In contrast to analytical models, microsimulations do not have an explicit mathematical specification of the respective sub-model, but rather a sequence of processing steps that build the model output. The absence of a mathematical description for the process of generating the output "has, until recently, rendered the calibration of the system a task based on intuition and, unfortunately, the arbitrariness this brings along"[Flötteröd et al., 2011, p.487].

The aim of the tool *Cadyts* (Calibration of dynamic traffic simulations), which is presented in this section, is to overcome these drawbacks. To do so, Cadyts uses a mathematically well-defined stochastic view on the simulation and calibrates it in a Bayesian setting [Flötteröd, 2010, p.1]. Cadyts is designed as a flexible, disaggregated demand calibration tool, which can interact with any stochastic, dynamic, and iterative transport simulation framework [Moyo Oliveros, 2013, p.51], [Flötteröd, 2010, p.2]. It allows to calibrate arbitrary choice dimensions of individual-level travel behavior from real-world measurements [Flötteröd, 2010, p.2], [Flötteröd et al., 2011, p.487], [Moyo Oliveros, 2013, p.51]. Given a set of macroscopic observations, Cadyts thus answers the question of "how the physical or behavioral microscopic rules of the agent-based simulation need to be modified in order to move the simulation closer to the observations" [Moyo Oliveros, 2013, p.4].

3.4.1. Interaction with Transport Simulation

First, in order to apply Cadyts to a concrete dynamic transport microsimulation, Cadyts needs to be initialized. Specifically, it also needs to be provided with the measurement data based on which the calibration is to be conducted [Flötteröd, 2010, p.2].

These measurements have to be registered by Cadyts. The type of measurements can – in principle – be of any kind. The most common, which will also be used in this study is vehicular traffic counts on an hourly basis. Based on such data, Cadyts has been employed for the estimation of vehicular travel demand in a number of simulators and scenarios (cf., for instance, Flötteröd et al. [2011]). It has, however, also been run for a microscopic public transport demand model, in which real-world counts were given as passenger counts at stop facilities on an hourly and daily basis [Moyo Oliveros, 2013, p.51].

Second, Cadyts must be able to affect the agents' plan choice [Flötteröd, 2010, p.3]. For the calibration of a simulations in which choice is based on utility-maximization models like MATSim, calibration works by calculating a so-called *linear plan effect.* The introduction of this effect into the transport simulation is flexible and can be done via different mathematically consistent ways. In case choices are modeled with a multinomial logit model, the calibration is achieved by adding the linear plan effect to the already calculated utility of this plan[4] [Moyo Oliveros, 2013, p.53].

The agents' plan selection based on this modification is, then, reported to Cadyts, which runs a regression model for every measurement location and every time bin. The real-world measurement constitutes the dependent variable, while the number of agents that intend to cross the measurement location is used as the explanatory variable. The slope of the resulting regression line provides sensitivity information to the calibration [Moyo Oliveros, 2013, p.53].

Third, Cadyts must be informed about the simulated network conditions in order to compare them to the measurement data [Flötteröd, 2010, p.3]. Therefore, Cadyts reads the output of the transport simulation into a container which stores time-bin-specific traffic volumes for any measurement location [Moyo Oliveros, 2013, p.53].

The way these three steps are implemented depends on the transport simulation that Cadyts is coupled with. From a computational perspective, two different approaches are possible. First, if the transport simulation is implemented in the same programming language as Cadyts, i.e. Java, Cadyts and the transport simulation may interact via direct function calls. Technical details are outlined in section 3 of Flötteröd [2010]. Second, if the transport simulation is implemented in a programming language other than Java, a file-base interaction can be used, which is presented in detail in section 4 of Flötteröd [2010].

3.4.2. Calibration via Plan Selection

The description of the calibration approach of Cadyts in this section is to some extent based on Flötteröd et al. [2011]. In section 3.3.3, it was explained how agents select one of their plans to be executed in each iteration of the simulation process in MATSim. If they do not create a new plan in a given iteration by applying an innovative strategy module, then one plan i of their existing plans is chosen according to a choice probability $P(i)$. Agents do not create a new plan when no innovative strategy modules is selected in the given iteration and always in later iterations of the simulation run when all innovative strategy modules are switched off (cf. section 3.3.3) – as it is the case for almost every configuration. This choice probability $P(i)$ is determined on the basis of the scores (cf. equation 3.1) of the plans through equation 3.4, which represents a multinomial logit model. Capturing the essence of this equation and taking care of the fact that multiple agents $n \in N$ will be considered from now on, equation 3.4 may be written as

$$P_n(i) \sim exp(V(i)) \tag{3.5}$$

[4] The details concerning the calculation a given in the following section (cf. Section 3.4.2.

Formula 3.5 is called the *a-priori choice probability* (of agent n to choose plan i), indicating that this is the choice probability of the plan *prior* to considering how the choice probability changes when, additionally, real-world observation data are taken into account by Cadyts.

For calibration, Cadyts combines the a-priori choice distribution $P_n(i)$ with the available traffic counts $\vec{y}$ into a *a-posteriori choice distribution* $P_n(i|\vec{y})$ in a Bayesian manner [Flötteröd et al., 2011, p.487]. "The approach uses the freedom that is left when individual decisions are modeled as random draws from a discrete choice model: Decisions that are congruent with the observations become preferred over those that are not" [Moyo Oliveros, 2013, p.51]. In its most simple and general representation[5],

$$P_n(i|\vec{y}) \sim exp\left(\frac{\partial L(\vec{y})}{\partial P_n(i)}\right) \cdot P_n(i) \tag{3.6}$$

where:
$P_n(i|y)$ is the a-posteriori choice probability of plan i of agent n,
$P_n(i)$ is the a-priori choice probability of plan i of agent n,
$\vec{y}$ is the vector of all measurement data, and
$L(\vec{y})$ is the log-likelihood function of observing the measurement data $\vec{y}$.

Substituting equation 3.5 into the posterior choice model (i.e. equation 3.6) yields[6] equation 3.7:

$$P_n(i|\vec{y}) \sim exp\left(V(i) + \frac{\partial L(\vec{y})}{\partial P_n(i)}\right) \tag{3.7}$$

As stated in equation 3.7, the application of the a-posteriori choice distribution requires nothing but adding a *plan-specific utility correction* (also referred to as *utility correction*, *utility offset*, or *linear plan effect*) to every considered plan. In adding this utility correction, "Cadyts does not make any assumption about the form of the choice distribution or about the choice dimensions it represents" [Flötteröd et al., 2011, p.487]. Cadyts does not change anything about the parameters of the choice model that generates the a-priori choice probabilities $P_n(i)$. Thus, this approach is independent of the specification of the choice model and therefore very felxible [Flötteröd et al., 2011, p.488].

If traffic counts are independently distributed,

$$L(\vec{y}) = \sum_{ak} L(y_a(k)) \tag{3.8}$$

[5] For more theoretical background, cf. [Flötteröd, 2009, p.4f].
[6] Here the identity $exp(x) \cdot exp(y) = exp(x + y)$ is utilized.

Using this identity, equation 3.7 becomes

$$P_n(i|\vec{y}) \sim exp\left(V(i) + \sum_{ak\in i} \frac{\partial L(y_a(k))}{\partial P_n(i)}\right) \tag{3.9}$$

where:
$y_a(k)$ is the real-world measurement of traffic count location a in time bin k.

Introducing a notation for the plan-specific utility corrections $\sum_{ak\in i} \Delta V_a(k)$, formula 3.9 may be rewritten as:

$$P_n(i|\vec{y}) \sim exp\left(V(i) + \sum_{ak\in i} \Delta V_a(k)\right) \tag{3.10}$$

The plan-specific utility corrections are composed of link- and time-additive correction terms $V_a(k)$, which are determined per measurement location and per time bin. They are determined independent of affected plans. The utility correction of a full plan of a given agents is calculated as the sum of all $V_a(k)$ that are covered by this plan [Flötteröd et al., 2011, p.488]. In case congestion can assumed to be light and the traffic counts are independently and normally distributed, the utility correction term becomes

$$\Delta V_a(k) = \frac{y_a(k) - q_a(k)}{\sigma_a^2(k)} \tag{3.11}$$

Therefore, the a-posteriori choice probability of plan i of agent n becomes

$$P_n(i|\vec{y}) \sim exp\left(V(i) + \sum_{ak\in i} \frac{y_a(k) - q_a(k)}{\sigma_a^2(k)}\right) \tag{3.12}$$

where: $P_n(i)$ is the a-priori choice probability of plan i of agent n,
$y_a(k)$ is the real-world traffic count at location a for time bin k,
$q_a(k)$ is the simulated traffic count at location a for time bin k,
$V_n(i)$ is the score of a plan i of agent n as calculated with equation 3.1, and
$\sigma_a^2(k)$ is the variance of the traffic count at location a for time bin k. It is calculated as $\sigma_a^2 = \max\left(varianceScale \cdot y_a(k),\ minStdDev^2\right)$. The variance scale is a configurable factor – here chosen as 1.0 – for measurements without explicit variance declaration, assuming to be proportional to the measured value $y_a(k)$ to maintain consistency with the assumption of Poisson distributed measurements [Moyo Oliveros, 2013, p.54].

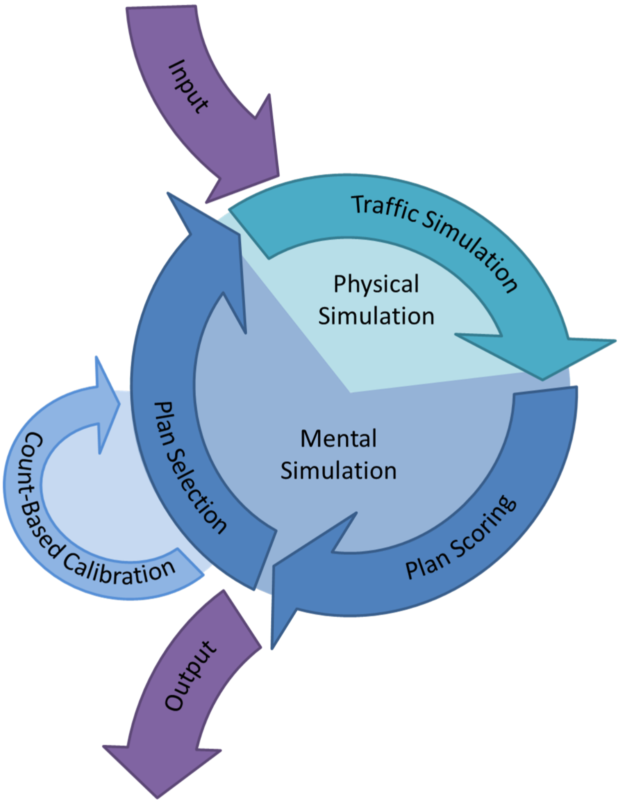


Figure 3.2.: MATSim with Cadyts Calibration via Plan Selection

To conclude, in this calibration approach Cadyts affects the transport simulation in the plan selection step (cf. section 3.3.3) in this calibration approach. To illustrate this graphically, the MATSim structural schema (cf. figure 3.1) can be modified as depicted in figure 3.2.

Cadyts effects that plan selection becomes – in addition to being dependent plan scores – a function of real-world measurements (e.g. real.world traffic counts). The more a plan contributes to reproducing the real-world measurements in the simulation, the more likely it will be selected by the agent. Therefore, Cadyts "adjusts the plan choice probabilities of all agents such that they result in simulated network conditions that are consistent with the traffic counts" [Flötteröd, 2009, p.3].

3.4.3. Calibration via Plan Scoring

A discussed in section 3.3, the mental simulation of MATSim consists of two steps: Plan Scoring and plan selection. In the previous section (cf. section 3.4.2), it was shown how the calibration based on Cadyts can be carried out by influencing the agents' plan selection by a utility correction (linear plan effect). More precisely, the linear plan effect calculated by Cadyts was used to modify the (a-priori) plan choice probability by including the utility correction alongside the considered plan's score in the logit model (cf. equation 3.12) used for plan selection.

Thus, Cadyts acted as a selector on the basis of its own internal plans evaluation [Moyo Oliveros, 2013, p.64]. This has the disadvantage that the utility correction is not a part of the plan score which the agent maintains (*learning mechanism*, cf. section 3.3.5). Instead, it is only temporarily calculated and only applied in the moment when the plan selection process is influenced by it. Since there is no data structure to carry the information along over more iterations, the utility correction is discarded after being applied in the plan selection.

An alternative to the integration of the Cadyts utility offset into the choice process is to embed the Cadyts utility correction into the MATSim scoring function (cf. equation 3.1. Thus, the Cadyts utility correction becomes an extra component of the compound MATSim scoring function next to activity scoring and travel leg scoring [Moyo Oliveros, 2013, p.64]. Formally, the MATSim utility function given in equation 3.1 is, thus, modified to:

$$V(i) = \sum_{act \in m} V_{perf,m} + \sum_{trav \in n} V_{trav,n} + w \cdot \sum_{ak \in i} \Delta V_a(k) \tag{3.13}$$

where:

w is the weight of Cadyts utility correction.

Illustrating this approach graphically, the MATSim structural schema (cf. figure 3.1) can be modified as depicted in figure 3.3.

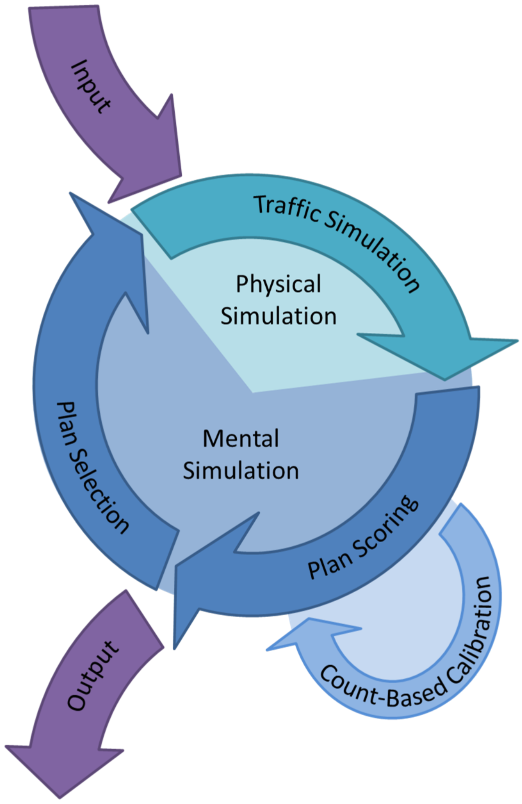


Figure 3.3.: MATSim with Cadyts Calibration via Plan Scoring

This procedure constitutes a novel approach of coupling MATSim with Cadyts and is first presented and applied by [Moyo Oliveros and Nagel, 2013, p.9] and comes along with advantages.

On the one hand, through the integration of the calibration utility correction with the other scoring components, the performance in terms of real-world measurement reproduction is also included as part of the plan evaluation. Thus, both performance in terms of traffic behavior (activity and travel leg scoring) and measurement reproduction (Cadyts utility offset) can be evaluated together with compound utility formulation [Moyo Oliveros, 2013, p.74].

On the other hand, the information from measurement reproduction has a higher longevity. By including the utility offset into the scoring function, good plans in terms of calibration can persist along iterations. Also, this information is available when deciding which plan to discard in case the maximum number of agent plans is exceeded. These properties are positive in terms of calibration effectiveness [Moyo Oliveros, 2013, p.74].

3.4.4. Demonstration

In order to briefly demonstrate the functioning of Cadyts, the so-called equil network, a simple network regularly utilized for demonstration purposes in MATSim, is used. It consists of one-way links, which can only be passed in clockwise direction, and is depicted in figure 3.4.

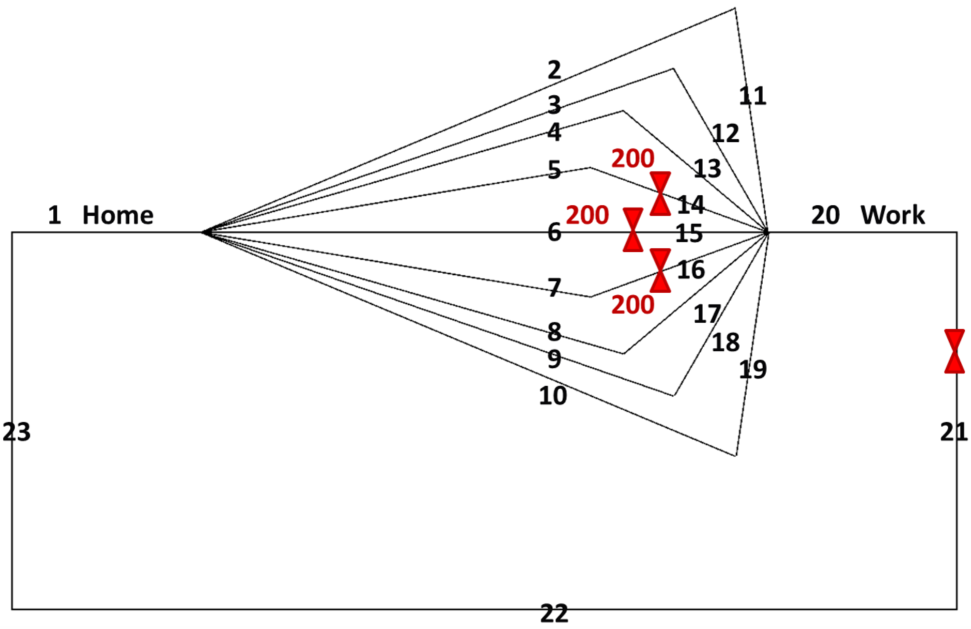


Figure 3.4.: Equil Network

1000 agents are simulated. For demonstration purposes they are all assigned with identical plans as given in the example in section 3.3.4. They start with a home activity on link 1 in the upper, left part of figure 3.4 and leave for a work activity on link 20 in the upper, right part of figure 3.4 at 6 a.m. As depicted, there are nine alternative routes for the trip from link 1 to link 20. Since these nine alternative routes all have the exact same length[7] and exact same capacity, it is expected that traffic will distribute equally among them. Accordingly, about 111(= 1000/9) vehicles can be expected on each of these nine links in the time bin from 6 a.m. through 7 a.m.

For demonstration purposes, four fictitious traffic count stations are used. According to them, 200 vehicles have (allegedly) been counted on links 14, 15, 16 in the time bin from 6 a.m. though 7 a.m. The fourth count station on link 21 does not need to be considered since it is the only route which agents can use on their way back home from work and, thus, trivial. If traffic is distributed equally on the nine alternative link on the way from the agents' home to their work, it is expected

[7] The links have the same length in the network properties, although figure 3.4 implies differently.

that the number of simulated vehicles which pass the three links with the count stations will be lower by $89 = 111 - 200$ than given fictitious count data. Figure 3.5 depicts the difference between simulated volumes and (fictitiously) counted volumes over the course of a MATSim simulation run with 200 iterations. The innovative strategy module by which agents change routes in their plans is switched off after 90 iterations. The module for the probabilistic selection among plans according to equation 3.4 is active over all iterations. It can be seen that differences between simulated and (fictitiously) counted volumes are in the expected magnitude.

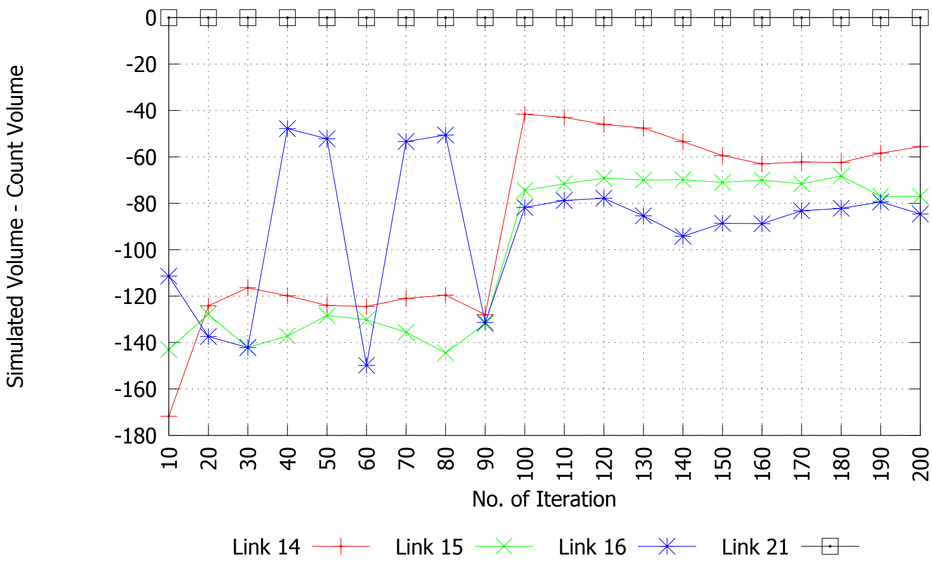


Figure 3.5.: Simulated and Counted Volumes without Calibration

Now, Cadyts is used. As explained in section 3.4.2, Cadyts combines the thus far used a-priori choice probability to select a given plan with the information concerning observed traffic volumes into an a-posteriori choice probability. If the algorithm works correctly, it can, thus, be expected that Cadyts modifies agents' plan selection in such a way that the differences between simulated and (fictitiously) counted volumes become smaller. Figure 3.6 illustrates that this is the case. The differences for the trivial case of link 21, where no alternative route exist, are expectedly always zero.

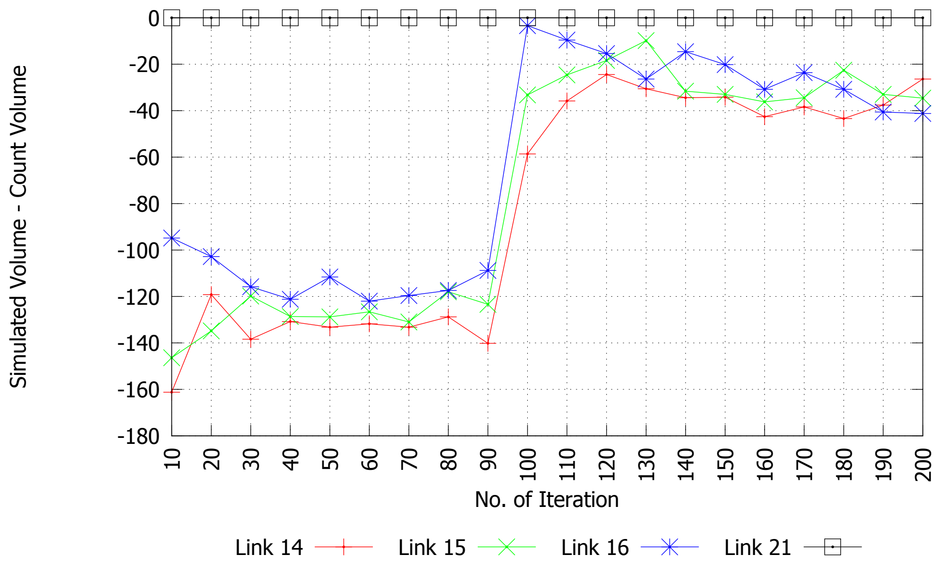


Figure 3.6.: Simulated and Counted Volumes with Calibration

It is obvious in figure 3.6 that the difference measures for links 14 though 16 do not converge to zero, but to a value of around -30. This is due to the fact that Cadyts does not influence agents behavior as much as to perfectly reproduce (fictitiously) given observations form measurements.

Such a calibration behavior would, however, neither be expected nor intended. Next to the Cadyts utility offset, the utility function also encompasses the scoring terms related to activity participation and traveling (cf. section 3.4.3). Since these two terms, which effected the behavior depicted in figure 3.5, are still active, they counteract the Cadyts utility offset to some extent. This counteraction of the two behavioral scoring components against the Cadyts scoring component seems logical, because (fictitiously) observed measurements are somewhat illogical form a behavioral point of view. They assume that significantly more travelers travel on routes 14 though 16 than on the six alternative routes even though these are fully equal in any relevant respect. Therefore, the observation that Cadyts can only influence agents' choices to a limited extent is perfectly in line with expectations.

3.4.5. Conclusion

In the previous section 3.4.4, it was shown how the Cadyts calibration algorithm takes effect. Specifically, it was observed that some agents are rerouted in such a way as to reproduce (fictitious) observations from reality. At the same time, it became clear that the effect of Cadyts is (as expected) limited in case it has to counteract the behavioral parts of the plan scoring (i.e. the scoring components for activity participation and travel legs).

Specifically in the demonstration in the last section, it was shown how Cadyts makes agents choose some routes with a higher probability than others even though all of these routes were identical in terms of all relevant attributes. But why should an agent prefer one route over another if they are identical in terms of all relevant attributes? An interpretation of this observation may be some kind of unobserved. For instance, links 14 through 16 may have wider lanes, a better synchronization of traffic lights, or just look nicer. All these potentially relevant properties are not considered in the behavioral model, but may still be important for travelers' choices and, thus, result in observed conditions. Therefore, Cadyts may be regarded as a tool to bridge the gap between modeled behavior neglecting unobserved attributes and (unexplained) observed behavior. Hence, the Cadyts *utility correction* (cf. sections 3.4.3 and 3.4.2), which is responsible for the calibration effect, can be considered an equivalent to an *alternative-specific constant* of a *discrete choice model* [Flötteröd et al., 2011, p.489]

Another intuitive interpretation of Cadyts according to Flötteröd et al. [2011, p.488] is that of a "controller that steers the agents towards a reasonable fulfillment of the measurements: For any sensor-equipped link, the according [correction term] is larger than one if the measured flow is higher than the simulated flow such that the choice probabilities of plans that cross this link are scaled up. Vice versa, if the measured flow is lower than the simulated flow, the according factor is smaller than one such that plans that cross this link are penalized."

4. Methodology

The scenario considered in this study consists of the two German federal states of Berlin and Brandenburg, of which the city-state Berlin constitutes the *planning area*[1], while the areas of Berlin and Brandenburg together make up the *evaluation area*[2]. Only automobile traffic is considered. In the following section 4.1, the modeling approach is described in detail, including a discussion of alternatives. In section 4.2 the modeling approach is justified (i) in terms of its internal soundness and (ii) with regard to current issues in travel demand modeling. Then, the creation of the model with a focus on input data is outlined in section 4.3. Finally, approaches and data for validation is addressed in section 4.4.

4.1. Modeling Approach

In order to model the demand for transport, the activity-based demand model CEMDAP (cf. section 2.3) is used. As already explained, CEMDAP produces as output the *complete daily activity-travel patterns* of individuals. Being an activity-based demand generation model, the answers to the first four of the five fundamental questions raised in section 1.1.2 are contained within the output of CEMDAP:

1. How many people wish to travel?
2. From where to where do they wish to travel?
3. At what time do they wish to travel?
4. Which mode of transport do they wish to use?
5. Which route do they wish to follow?

Since only automobile traffic is considered in this study, the fourth question is rendered obsolete. The activity-travel patterns generated by CEMDAP can, however, not be regarded as valid representations of the travel demand of the agents in the

[1] The planning area is the spatial region for which an action plan is to be developed. Often, it is the area which a certain planning administration is in charge for [Richter and Schreiber, 2011, p.50].

[2] The influence of planned policies regularly exceeds the planning area which is why the evaluation area encompasses the planning area plus its area of influence with regard to traffic [Richter and Schreiber, 2011, p.50].

scenario. This is due to the fact that the fifth aforementioned question (*Which route do travelers wish to follow?*) has not yet been answered. This is true for almost all activity-based demand models as already pointed out in sections 1.1.2 and 2.2.

Thus, the interaction with transport demand and transport supply (cf. section 1.1 and the introduction of chapter 3) has not been considered at the point of finalization of the activity-based demand model. For instance, only beeline distances between different activity locations have been taken into account in this study's application of by CEMDAP[3]. In contrast, no network events, e.g. congestion, have been taken into account. As pointed out earlier, the interaction of supply and demand is, however, essential to understand the emergence of observable travel patterns and, thus, to become able to analyze chances in the transport system.

Therefore, the central question for the next sections (cf. sections 4.1.1 through 4.1.3) is how the interaction of transport supply and transport demand can be modeled under the assumption that an initial demand representation has already been generated with CEMDAP.

4.1.1. Activity-based Demand Model and Aggregate Route Assignment

As already mentioned in section 2.2, a common approach to load transport demand – in case it has been generated with an activity-based model – on the network is to draw isolated trips out of the individual activity patterns generated by the activity-based demand model (e.g. CEMDAP) and aggregate these trips into OD matrices. These OD matrices are, then, fed into a separate route assignment module [Flötteröd et al., 2011, p.482], [Meister et al., 2010, p.3]. This module basically works like the fourth step (route assignment) of the four-step model (cf. section 2.1). As explained in section 2.1, the route assignment module distributes all trips on the network so that a predefined criterion called *user equilibrium* or *Nash equilibrium* is reached. If time-dependency is considered, OD matrices are generated for predefined *time slices* enabling, for instance, the consideration of different levels of traffic at different times of day. If time dependency is taken into account, the procedure is referred to as *dynamic traffic assignment (DTA)* [4].

The approach of coupling a activity-based demand model with (dynamic) traffic assignment possesses advantages over the classic four-step process. For instance, individual attributes can be considered at least up to the point of the application

[3] The detailed functionings are given in appendix B.

[4] In a strict sense, dynamic actually means *related to forces*. Thus, the physical discipline of *dynamics* encompasses *statics* (non-moving forces) and *kinetics* (moving forces). Over the course of time, dynamics became to some extent synonymous to kinetics so that, today, we think of forces as being either static *or* dynamic (instead of being either static *or* kinetic). Since static bodies do not move (within the scope of observation), they are somewhat time-independent. By contrast, bodies that move are dependent upon time in various respects. Therefore, the adjective *dynamic* is widely understood as *time-dependent* today even though *instationary* would be the etymologically more correct term.

of the route assignment algorithm [Raney and Nagel, 2006, p.306]. By aggregating the demand into OD matrices before it is loaded on the network, however, the individuality of the travelers is lost. Thus, their corresponding properties are a lost before the step of choosing routes. Hence, "problems immediately show up if one attempts to base a route choice model in a toll situation on demographic characteristics — the demographic characteristics, albeit present in the ABDM, are no longer available at the level of the assignment. Similarly, in all types of intelligent transport system (ITS) simulations, any modification of the individuals decisions beyond route choice becomes awkward or impossible to implement" [Flötteröd et al., 2011, p.482].

This is due to the fact that route choice is carried out in the assignment step, while choice dimensions like location choice and time choice are conducted in the activity-based demand model. Thus, a separation exists between route choice and the other choice dimensions resulting in the aforementioned issues. While said separation may be comprehensible in the light of the development history of transport models, this splitting of choice dimensions is questionable from a behavioral perspective. "It can be argued that route choice is also a behavioral aspect, and in consequence the decision to include route choice into the assignment model rather than into the demand model is arbitrary" [Flötteröd et al., 2011, p.482]. This is why it has to be followed that this approach does not fulfill the requirements poses above, namely to simulate the *interaction* of supply and demand on the network. While interactions imply a bidirectional information exchange, this approach takes both counterparts largely as given, which may only be overcome to a limited extent via so-called feedback loops as discussed in section 2.1.

4.1.2. Integrated Demand-Supply Equilibration

An alternative approach, which overcomes the behavioral inadequacy of the separate consideration of route assignment and demand generation in the above-described procedure (cf. section 4.1.1) is using a simulation framework that explicitly considers the *interaction* of supply and demand. An example is MATSim which alternates between a physical simulation of the agents on the network and an interrelated mental simulation of the decision-making processes of agents as described in section 3.3. In MATSim, route choice is treated like any other choice dimension. All choice dimensions are iteratively optimized in the mental layer of the simulation (cf. sections 3.2, 3.3.2, and 3.3.3).

In technical terms, it can, thus, be argued that "route assignment" in MATSim – when viewed in the light of traditional models – is divided into a *route choice module* and a *network loading module* [Flötteröd et al., 2011, p.482]. While the route choice module is one of many *strategy modules* (cf. section 3.3.3) that carry out plan modifications in the mental layer of the integrated simulation procedure, network loading is represented by the traffic simulation (cf. section 3.3.1). Since a microscopic (or, more precisely mesoscopic (cf. section 3.1.2) traffic flow simulation is applied, the integrity of individual travelers (*agents*) is maintained throughout the entire modeling process.

This procedure can also be viewed as extending the iterative procedure of a dynamic traffic assignment (DTA) module towards choice dimensions beyond route assignment [Meister et al., 2010, p.4]. While in a DTA a (time-dependent) user equilibrium is found via iteratively adapting route assignment, the MATSim procedure iteratively modifies various choice dimensions to find a good set of travel options (*plans*) for each agent. So, "elements of demand generation are elevated from a simple pre-process to an integrated part of demand-supply equilibration" [Meister et al., 2010, p.4]. "This implies that, at least in principle, all choice dimensions of the ABDM can react to the network conditions"[Flötteröd et al., 2011, p.483].

Advantages over the procedure described in the previous section (cf. section 4.1.1) are that all choice dimensions "can be related to the characteristics of the synthetic person. For example, toll avoidance can be based on income, or emission calculations can be based on the type of vehicle" [Flötteröd et al., 2011, p.482]. Further, analyses can be done on arbitrary levels of aggregation or without any aggregation at all, since the properties of every individual agent are accessible during the whole simulation process.

Since the adaption of demand is central in this procedure, it can be argued that this procedure itself constitutes an (activity-based) demand model. In fact, it is possible to start the simulation procedure with very few initial assumptions and, then, have the evolutionary algorithm cater for the improvement of the initial demand representation (cf. section 3.3.5). To enable this optimization, a corresponding strategy module for each choice dimension to which agents are supposed to make modifications has to be included. If these modules work correctly, the properties of the corresponding choice dimensions will converge to realistic values. Therefore, the properties of the choice dimension to which modifications will be made during the procedure do not need to be represented fully correct at the initialization of the simulation. Importantly, however, those choice dimension to which *no* modification will be done in MATSim's iterative procedure, have to be initially correct [Balmer, 2007, p.52f].

In this specific study, however, many choices with respect to several choice dimensions have already been taken in the activity-based demand model CEMDAP. The next section (cf. section 4.1.3), therefore, describes how the information generated by CEMDAP can be used fruitfully in the simulation procedure that has been described in this section.

4.1.3. Coupling CEMDAP and MATSim

As pointed out above (cf. section 4.1), the answers to four of five central questions concerning transport demand modeling are contained within the output of CEMDAP. Unanswered, however, remains the question *Which route do travelers wish to follow?*. Thus, the goal of this study is to couple CEMDAP with MATSim, which addresses the selection of routes. At the same time, it is intended to use CEMDAP's output most effectively.

As CEMDAP's output is fully disaggregated to the individual-traveller level it is a perfect match with the requirements of the input population data for MATSim. Nothing more than some data structural rearragement is necessary to use the daily activity-travel pattern that CEMDAP provides as input for MATSim[5]. Hence, the application of CEMDAP in this study can be regarded as an *upstream* process for MATSim. It creates an initial demand representation so that MATSim only needs to be applied to simulate the interaction of supply and demand on the network, but only to a limited extent as a demand generation tool itself – as discussed in previous section 4.1.1.

This has the advantage that fewer iterations are necessary since a demand representation is already existing at the startup of the simulation. Moreover, fewer innovative strategy module need to be applied during the simulation since decisions concerning several choice dimensions have already been made in the activity-based demand model. This speeds up the simulation.

Besides conducting the assignment of individual agents with trips, the coupling of CEMDAP and MATSim has another purpose. Like any model, CEMDAP needs to be estimated[6] for the scenario of application. This step is, however, left out in this study, which is due to practical as well as conceptual reasons.

From a practical perspective, the estimation effort would have been very high[7] because of the sheer quantity of coefficients to be estimated and the challenging data requirements related to it. While this may, however, not be an important reason in its own right, saving the estimation effort is, however, perfectly in line with the following conceptional reason.

From a conceptional perspective, one goal of this study is to build a model that suffices with a very low amount of input data and still yields a good representation of real-world traffic patterns (cf. section 1.3). Therefore, instead of focusing on acquiring input data to estimate the coefficients of the applied modeling framework, the output is generated with readily available model parameters from a somewhat comparable setting.

As, by this means, the step of model estimation is omitted, the CEMDAP output

[5] Technical details are given in A.
[6] In more precise terms, the coefficients of model variables have to be estimated.
[7] The reasons for this are outlined in section refsec-justification.

may, obviously, not be regarded as representative activity-travel patterns of the real-world traveling population of the planning area. It can, however, still be utilized as an initial approximation towards real-world activity-travel patterns or, in other words, an initial guess of a potential demand representation.

The crucial question now is how to come from this initial demand suggestion to a representation of transport demand representation that can be considered valid in that it reflects the transport-relevant strata of behavior of the real-world population. As illustrated in the upper part of figure 4.1, the approach applied in this study is to run CEMDAP multiple times. Since CEMDAP involves probabilistic components in its sub-models, a to some degree different output is created each time CEMDAP is run. Thus, multiple suggestions for potential demand representations are created.

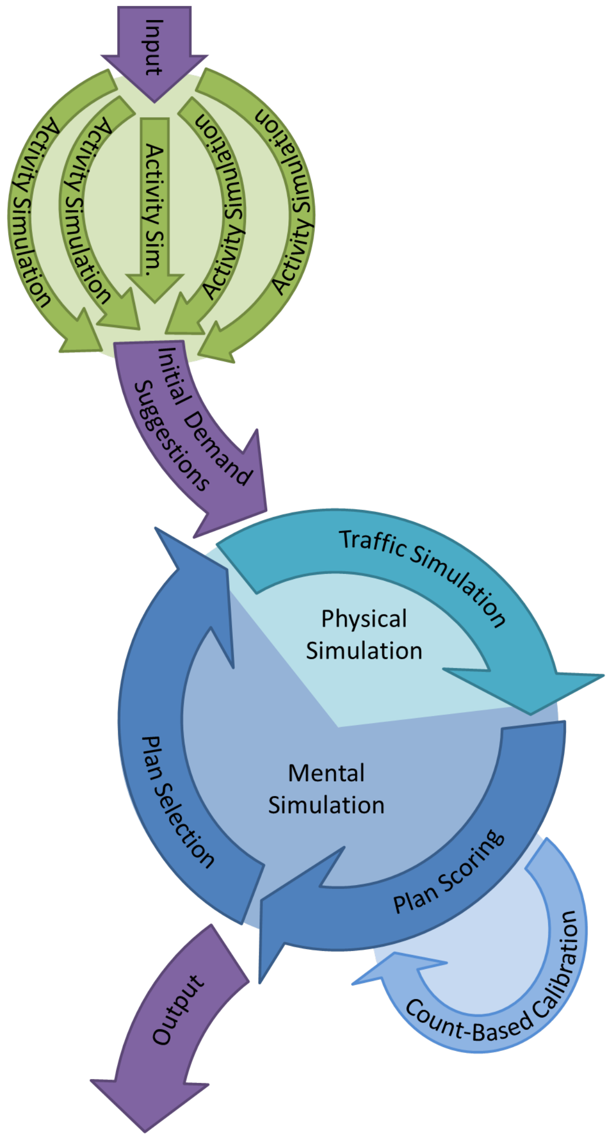


Figure 4.1.: Methodology

These potential representations of demand for transport are then fed into MATSim (cf. section 3.3). From this point, MATSim's iterative simulation procedure (illustrated in the central, circular part of figure 4.1) is carried out as described in detail in section 3.3 as well as in the previous section (cf. section 4.1.2). First, the realized demand for transport, i.e. traffic, is simulated in a representation of the physical transport system (physical simulation). Second, the choice processes that travelers undertake based on what they experienced while traveling are simulated (mental simulation). Via this mental simulation of the individual travelers' decision making, the demand optimizes itself in respect to supply utilization. So, those initial suggestions of a demand representation proposed by the preceding application of CEMDAP that do not turn out to be suitable are gradually sorted out.

As explained in section 3.3.5, the consideration of choice dimensions is central to this process. Only the model properties related to choice dimensions towards which *no* modification can be made during the simulation have to be represented correctly at the start of the simulation. Choice dimension whose properties are subject to modification, however, do not need to be initially correct. While in the approach described in section 4.1.1 only (an equivalent to) route choice was left after the demand generation, properties in respect to basically all choice dimensions were modifiable in the transport simulation in the approach described in section 4.1.2.

Which are the fixed and which are the unfixed choice dimension for the approach described here? First of all, since in this study only automobile traffic is considered, the choice of a mode of transport is fixed. Accordingly, the number of motorists should be initially correct.

Second, location choice and time choice are also regarded as fixed from the perspective of the transport simulation. This means that individuals cannot *create* new travel options in terms of timing or location choice during the transport simulation. The special feature of the approach here is, however, that they are still able to *adjust* their timing or to *switch* locations among the alternatives they are provided with by the initial demand suggestions generated by the activity simulation (cf. section 4.1.

This approach constitutes a compromise between fixed and unfixed choice dimensions. On the one hand, no innovative strategy modules (cf. section 3.3.3) for these choice dimension are needed. Thus, the effort of ensuring the correct functionings of these modules can be saved. At the same time, the output of CEMDAP can, as intended, be used as effectively as possible, since the decisions concerning these choice dimension are already dealt with in CEMDAP. In more technical terms, this approach enables the choice between discrete options as they are provided via the CEMDAP output. If location choice and time choice were included as innovative strategy modules in MATSim, agents would be able to optimize along a continuous scale of these dimensions. Since the scope of options concerning locations is limited anyway, this simplified procedure seems viable.

As pointed out above, it is central that properties in respect of a given choice dimensions are either represented correctly at initialization or that it is ensured that strategy module makes said properties converge in the right direction. In this approach, these properties can not be said to be initially correct as the CEMDAP output may only be regarded as an suggestion for potential demand representation (because of the omitted estimation of the model coefficients). Neither is there a module whose convergence is ensured.

In order to ensure that those initial demand suggestions prevail during the iterative MATSim simulation, Cadyts (cf. section 3.4) is used. Cadyts ties in with the scoring process in the mental layer of the MATSim transport simulation and makes those options prevail that are both reasonable from a behavioral perspective (as determined by the activity and leg scoring components) and, at the same time reproduce expected travel patterns (as determined by real-world traffic-count data).

In doing so, Cadyts does not pay attention in terms of which choice dimensions plans are different from each other. Cadyts is simply provided with the agents' executed plan by the simulation, adds a positive or negative offset to the plan's score dependent how well it helps reproducing observations, and thereby influences the chance of the plan to be selected again. Thus, it is obvious that the influence Cadyts can have is directly dependent on the variety of plans each agent has. This is why, CEMDAP is run multiple times and each of the thus generated multiple outputs is considered one potential solution.

Finally, route choice is enabled as a choice dimension with a corresponding strategy module in the transport simulation. This means that travelers are able to create and try out new routes during the transport simulation.

The portfolio of all choice dimensions an agent possesses is the sum of the choice dimensions that are enabled through innovative MATSim strategy modules (here only route choice) and the choice dimensions by which initial plans are different (different locations, actitvities, and timing as determined by CEMDAP).

After the iterative procedure is terminated, the travel demand generated and calibrated by it can be analyzed in order to validate it based on various real-world traffic data. In case a sufficiently accurate representation of the demand for transport can be found with this approach, the generated travel demand can be used to answer planning and policy questions as raised, for instance, in chapter 1.

This approach, in a way, turns the usual procedure in transport modeling upside down. While many models use aggregated measures like model split data for calibration and use traffic count data for validation [Meister et al., 2010, p.1], this approach utilizes traffic count data for calibration. Validation is, then, carried out on the basis of on traffic system characteristics (cf. section ?????????). The major goal of this study is to examine the quality of the demand for transport that is generated based on this modeling approach.

4.2. Justification of Research Approach

As pointed out in section 1.3, a major problem in modeling and, in particular, in the modeling of transport systems, is the availability of data. Especially CEMDAP, the modeling framework for activity-travel patterns applied in this study, requires a broad scope of data in order to estimate the coefficients of the model variables. In particular, time-use surveys concerning all activities pursued by individuals over the course of a day are needed [Bhat and Koppelman, 2003, p.41]. While travel surveys are already very extensive, the amount of information elicited from respondents in time-use surveys is even more extensive since additional informations on in-home activities are collected [Guo and Bhat, 2001, p.3f]. While experience suggests that the respondent burden or response rates are not significantly different between time-use and travel surveys, a major disadvantage of time-use surveys is that they are simply less common than travel surveys so that time-use information is much less readily available.

Owing to this fact and in line with the goal of this study is to build a model that suffices with a very low amount of input data and still yields a good representation of real-world traffic patterns (cf. section 1.3), the basic idea of this study is to forgo the model estimation step. Instead, a readily estimated model [8] for the Dallas/Fort Worth metropolitan area in Texas, USA is used. Using this model specification, the effort of collecting extensive amounts of data and calibrating all the model coefficients for Berlin, the planning area of this study, could be saved.

Obviously, one could bring forward the argument that the model is, thus, simply not valid. This objection would doubtlessly be true if the activity generator (i.e. CEMDAP) was used by itself or, in other words, if the output of the (not context-specifically estimated) activity simulation model was considered the final result. As already pointed out in section 4.1.3, however, the output of the activity simulator does not constitute the final solution. Instead, it is only regarded a set of potential solutions and further processed by the transport simulation (i.e. MATSim). Via the MATSim's mental simulation, agents are enabled to optimize their travel behavior and, thereby, to gradually arrive at improvement personal activity-travel patterns.

Thus, it becomes clear how a model that has not been estimated for the specific region, which it is to be applied to, can still be used in a meaningful way: The choice dimension related to the properties for which differences are expected between estimation and application regions, just have to stay unfixed in the transport simulation. If, then, a mechanism is applied which ensures that travel demand is modified so that its properties converge towards real-world observations, it becomes comprehensible to what extent the output of the (non-estimated) activity simulation

[8] Cf. `http://www.ce.utexas.edu/prof/bhat/CEMDAP_Files/CEMDAP_for_trial.zip`, last accessed 27 November 2013.

constitutes an important set of data to work with. It constitutes a very well-usable initial suggestions of a potential demand representation. As mentioned above (cf. section 4.1), the mechanism that ensures that these initial suggestions are modified in the intended way consists in a traffic-count-based calibration algorithm in this study. It ensures that next to behavioral soundness of selected plans also its representativeness with regard to real-world observations is preserved.

An analogous approach is employed by Moyo Oliveros [2013, p.74] who generates routing information of public transport riders. First, he generates random routes. Concerning this step, he argues that "random routes generation might seem inadequate from the classical assignment models perspective [and that] it would be impractical if it were implemented as a stand-alone module for route choice model" [Moyo Oliveros, 2013, p.74]. Since this is, just like the approach of this study, however, not the case, the appraisal becomes a different one: In case "the search of candidate solutions [i.e. routes] is combined with a selection mechanism (like Cadyts correction inside the scoring function) where new alternatives for each agents are evaluated and the worst are discarded, this coupling constitutes a composite co-evolutionary algorithm that directs the choice distribution to a count match convergence" [Moyo Oliveros, 2013, p.74]. These randomly generated routes behave to some extent analogous to the travel plans generated by the (not scenario-specifically estimated) CEMDAP model employed in this study. They have in common that they may not be regarded as correct solutions, but constitute useful potential solutions from which Cadyts, then, selects the most suitable one.

At this point, it seems worthwhile to have a look at the properties among which traffic patterns between Dallas/Fort Worth (the region for which the CEMDAP model applied in this study was estimated) and Berlin may actually be different. The most fundamental difference will arguably consist in different modal shares. One can easily image that travel patterns in a city whose inhabitants almost exclusively travel by car will be fundamentally different than travel patterns of a city with a multimodal transport system like Berlin. Since only vehicular traffic is considered in this study, the observation that mode shares differ between Dallas/Fort Worth and Berlin is rendered irrelevant.

The next most influential properties responsible for differences in travel patterns, are arguably shares of activity participation, activity locations, timing, and – probably to a lesser extent – route choice. Therefore, it needs to be taken into account that the activities, their locations, and the according scheduling (timing), which the (not estimated) activity simulation model create, may not correctly represent the activity schedules of traveling individuals of the planning area. In consequence, the choice dimensions of activity participation, location choice, and timing must not be fixed in the transport simulation.

To address this requirement, the activity simulation is run multiple times to generate initial demand suggestions that are different with regard to activities, locations, and timing. As already explained, this variety of possibilities is then forwarded to the iterative procedure of the transport simulation. In interaction with the traffic-count-based calibration algorithms, those initial demand suggestions that represent real-world travel patterns well are selected. The demand representation created this way needs to fulfill two basic conditions. First, it needs to fit the data it was calibrated with well. Second, it needs to be close to real-world observations and certain measures thereof, which were not already used for calibration. If these two conditions are fulfilled, the model can be validated.

Now that, the internal soundness of the applied approach has been clarified, it seems valuable to contemplate the proposed modeling approach in the context of general challenges related to transport (demand) models. According to Hartgen [2013, p.1], the four major weaknesses of transport demand models which lead to inaccurate models are:

- Non-behavioral context
- Inaccuracy of inputs and key assumptions
- Excessive complexity
- Policy insensitivity

The proposed models properties can be assessed in terms of these four issues as follows:

- The model used in this study entails behaviorally sound mechanism. Individual travelers are retained during the whole modeling process (in CEMDAP as well as in MATSim). Their decisions are modeled in a behaviorally consistent way.
- Since this model using little amounts of input data (as explained in section 1.3), the threat flaws may be induced by inputs is widely reduced. Also, no strong assumption which might be sources of errors (and potentially impede the whole subsequent modeling process) are made. Instead an optimization procedure based on the intentions of individual agents is used as a foundation for transport modeling.
- In this study, the activity generation module (CEMDAP) possesses a high complexity. On the other hand, this component is widely treated as a black box and could – if desired – be substituted by another, potentially simpler model that creates activity patterns. The utilization of this model's output in this study is, by contrast, easily comprehensible. Potential demand representations are drawn from CEMDAP and then a genetic-algorithm-based procedure is used to find a good solution.

- Policy sensitivity has not yet been shown and is left for follow-up studies.

4.3. Creation and Calibration of Model (Input Data)

In this section, the input data used to build the transport model are outlined. As described in section 1.1, the emerging traffic patterns that we observe in reality can be understood as the outcome of the interaction of transport supply and transport demand. Accordingly, these two fundamental components have to be represented in the transport model. The following sections describe the input data from which the representations of transport supply and transport demand are generated.

4.3.1. Transport Supply

Since only car traffic is to be simulated, the transport supply in this model only consists of a roadway network. It was created based on data from `OpenStreetMap`[9] and subsequently simplified [Zilske et al., 2011] in order to reduce the number of links and nodes. After simplification, the network consists of 11,345 nodes and 24,335 single-direction car-only links, of which 18,326 (or 75%) have a free speed of 50km/h, which equals the general speed limit within urbanized areas in Germany. 4,015 links have a free speed of 30km/h corresponding to the widely-used reduced speed limit for neighborhood streets in Germany. Since the network mainly consists of bigger roads, while many smaller roads are excluded for reasons of simplification, it is in line with expectations that the share of reduced-speed streets is lower than in reality. Most of the remaining links (e.g. urban and rural autobahns and extra-urban roads) possess a higher free speed. 15,938 (or 65%) of the links consist of one lane, while 7,327 (or 30%) posseses two directional lanes. 12,096 (or 50%) of the links have a capacity of between 1,000 and 2,000 vehicles/h, while 4,236 (or 17%) possess a capacity of less than 1,000 vehicles/h.

4.3.2. Transport Demand

Transport demand in this model is build on commuter data provided by the German Federal Employment Agency Bundesagentur für Arbeit [2010]. These data yield the home municipalities and workplace municipalities of that part of the working population that is subject to social insurance contributions, i.e. working persons who are not self-employed and whose income exceeds a certain minimum threshold[10].

[9] Cf. `http://www.openstreetmap.org`, last accessed 3 November 2013

[10] For the precise definition of *persons subject to social insurance contributions* (in German: *sozialversicherungspflichtige Beschäftigte*), cf. `https://www.destatis.de/DE/Publikationen/STATmagazin/Arbeitsmarkt/2008_01/WW_Sozialversicherungspflichtige.html`, last accessed on 4 November 2013.

In Berlin, the share of the working population that is subject to social insurance contributions equals about 66%[11] of all working persons (in German: *Erwerbstätige*).

For Brandenburg, the spatial resolution of these data is quite high as most of Brandenburg's municipalities are rather small. They accommodate between 549 inhabitants (Kleßen-Görne) and 159,695 inhabitants (City of Potsdam), with the overwhelming majority of 404 of out 419 Brandenburg municipalities having less than 25,000 inhabitants (Amt für Statsitk Berlin-Brandenburg [2012c]).

Berlin, however, is a so-called city-state, a special case in German administrative structure where a single city (= a single municipality) constitutes a federal state of its own. In other words, the state of Berlin consists of only one municipality, the City of Berlin. The largest German city, Berlin accommodates 3,375,222 inhabitans[12] and hosts 1,105,037 persons subject to social insurance contributions Bundesagentur für Arbeit [2010]. Because all of them are – owing to the definition of a city-state – part of one single municipality, the home and workplace locations are not specified any more detailed than on city-state level. Therefore, the spatial resolution of home and workplace locations in Berlin is not sufficient for the requirements of this study.

To remedy this issue, so-called live-reality-oriented regions (*LORs*, in German: *lebensweltlich orientierte Räume*) are used. The LOR zoning system has been developed since 2004 to create a uniform foundation for various types of spatial planning and space-related analyses for Berlin [Bömermann et al., 2006, p.366]. Amongst other criteria, LORs are spatially defined in a way that one LOR's population does not fall below or exceed certain minima or maxima, respectively [Bömermann et al., 2006, p.368]. They are defined at three levels of spatial resolution in consideration of the various administrative and planning tasks which they are intended for. The medium-level resolution divides Berlin into 138 (formerly 134) zones, which are called *district regions* (in German: *Bezirksregionen*), indicating that they are subregions of the 12 Berlin districts. These 138 district regions have an average population of about 25,000 inhabitants [Bömermann et al., 2006, p.369]. Together with the 419 Brandenburg municipalities, the evaluation area of this model, thus, consists of 557 zones altogether.

4.3.3. Counts for Calibration

As explained in section 3.4, the calibration algorithm applied in this study (i.e. Cadyts) is based on traffic counts. In this study 8,304 hourly count values for 346 count station are used. The count values are collected by the *Traffic Manage-*

[11] Own calculations based on Bundesagentur für Arbeit [2010] and Amt für Statsitk Berlin-Brandenburg [2012a].

[12] As of 31 December 2012, cf. `https://www.statistik-berlin-brandenburg.de/Publikationen/OTab/2013/OT_A01-10-00_124_201212_BE.pdf`, last accessed on 4 November 2013

ment Center (in German: *Verkehrsmanagementzentrale*) of Berlin and matched to the roadway network used for this study (cf. section 4.3.1).

4.4. Validation of Model

The first goal of any model is to represent reality in terms of the characteristics relevant in terms of the purpose of the model sufficiently well. Thus, the first objective is to create a model that exhibits a model fit as good as possible. A good model fit by itself, however, is no sufficient condition for the validity of the model [Ziemke, 2012]. Instead, the validity of the model has to be analyzed independently of the model generation based on data that have not been used to create the model.

As explained in section 3.4 Cadyts adds an offset to the agent's score depending on how well the traveler's scored plan (i.e. the most recently executed daily plan) reproduces aggregate attributes of observed travel behavior. If the magnitude to which this offest takes effect is set too high, Cadyts may produce overfitting.

In fact, if the weight of the Cadyts scoring component (cf. section 3.4.3) is overly high, Cadyts will interfere with travelers' plan selection as much as travelers will always choose a plan that nicely reproduces given traffic counts no matter how much sense choosing these plans makes from a behavioral point of view. Such an an overfitting may be detected by observing attributes of the simulation that are independent of the calibration algorithm. In the following two sections (cf. section 4.4.1 through 4.4.2) these data are briefly outlined.

4.4.1. Travel Survey

The major source of data for validation in this study is the travel survey *Mobilität in Städten - SrV 2008*[13] [Ahrens, 2009b], mostly referred to by its long-standing name *SrV*. In table 4.1, some reference values calculated based on the survey are summarized. These will be used to assess the quality of the results of the models created in the subsequent chapters (cf. chapters 5 and 6). These values are based on SrV's 2008 weekday travel survey for Berlin [Ahrens, 2009b], [Ahrens, 2010b], [Ahrens, 2010a], which encompasses 107,065 trips altogether. The detailed calculations of the values given in table 4.1 are outlined in appendix D.

[13] *SrV* stands for *System of Representative Travel Surveys* (in German: *System repräsentativer Verkehrsbefragungen*). The title has been changed some years ago to emphasize the increased comparability of these surveys with Germany's nationwide survey *MiD - Mobilität in Deutschland*.

Paramter	**Reference**
Normalized Log-Likelihood	-10*
Car Trips	3.2m
Car Trips/Person	3.4
Avg. Detour Ratio	1.58**
Avg. Trip Distance	9.5
Avg. Trip Duration	22.3

* cf. [Flötteröd, 2009, p.10]
** cf. section 4.4.2

Table 4.1.: Reference Values

4.4.2. Detour Factor

The shortest connection of two points (e.g. the origin and the destination of a trip) is a straight line. The according distance is called *beeline distance* or *crow-fly distance*. It is obvious that in real life the traveled distance from the origin to the destination of a trip is in almost every case greater than beeline distance. This distance may be referred to as the *routed distance*. The ratio of this routed distance to the beeline distance is an indicator of the detour a traveler has to undertake when getting from the trip's origin to its destination.

An unusually high ratio of the routed distance to the beeline distance may be an indicator of overfitting, i.e. that the calibration too strongly pushes travelers to do what is expected in terms of traffic counts and thereby to override the travel patterns that would be reasonable from a behavioral point of view. Specifically, it can be suspected that Cadyts might make agents choose overly long routes that seem unreasonable from a behavioral point of view, which, however, helps reproduce traffic counts.

To determine whether or not said ratio is unusually high, first a usual value of the ratio has to be determined. On the one hand, literature values for this ratio appear to be very rare. On the other hand, it is highly questionable how well such values would be transferable from one geographic region to another, since the ratio of routed distances to beeline distances will arguable be highly dependent on the specific attributes of the respective city. For instance, it may be relevant whether or not the city has a regular (e.g. a rectangular) street pattern or an irregular one. Likewise the continuity of the cityscape will arguably be relevant. This is related to the question whether the city is interrupted by rivers, lakes or other attributes of the physical landscape that need to circumnavigated by travelers.

Thus, an alternative approach is used to find a benchmark value to assess detour factor. A random ten-percent draw of the population of agents used for the runs in chapter 5 is taken. Then, their travel plans are routed on the network using MATSim built-in Dijkstra-algorithm implementation. By only using a ten-percent sample it can be considered ensured that agents can follow the shortest routes possible, since no congestion effects are to be expected (these would, however, not be relevant anyway, since only one iteration is carried out so that agents can not react to possible congestion effects from previous iterations). This procedure is conducted ten times and the average of the detour factors (which are somewhat different in each run because of the random selection of a ten-percent sample) is determined. The result is 1.57.

The exact same is also done for the population used in chapter 6. Here, the detour factor comes out with a value of 1.59. Expectedly, both values are quite similar. Accordingly, the value of 1.58, the average of the two detour factors, will be used as a reference value for subsequent analyses.

4.4.3. Benchmarks

In this section different approaches for the establishment of benchmarks that may be used to assess the quality of the generated transport models are presented. Also, some instruments and methods for analysis are introduced.

Population with Home-Work-Home Plans

In order to establish a point of comparison for the analysis of the effects of CEMDAP in interaction with MATSim and Cadyts, a very simple population of agents is created based on the commuter data provided by the Federal Employment Agency (cf. 4.3.2). For each 100 persons in the commuter file, one agent with home and workplace locations according to the commuter file is created, i.e. a 1% sample is used.

For areas in Brandenburg, the spatial mapping of agents is trivial as commuter data is provided with respect to municipalities, which is – as pointed out in section 4.3.2 – exactly the spatial resolution that the zoning of this CEMDAP model is also based on.

In Berlin, however, district regions (cf. chapter 4.3.2) are utilized. To map agents to these district regions, a random draw over district regions is conducted. Since every district region has a similar population, the likelihood for a given agent to live in one given district region is approximately equal for all district regions. Therefore, a random draw constitutes a valid approximation to real residential patterns. For workplace locations, however, the procedure of a random draw introduces a bias, because the number of workplaces varies significantly over the different district regions. This issue is discussed in chapter 7.

The agents start their trips to work at a randomly chosen point of time within a two-hour interval around 7:30 and their trip back home at a randomly chosen point in time within a two-hour interval around 16:00.

While it is obvious that such a model will not be able to reflect real traffic patterns, it is worthwhile to analyze how well morning and afternoon peak traffic can be represented when only raw commuter relations without any additional modeling effort are considered.

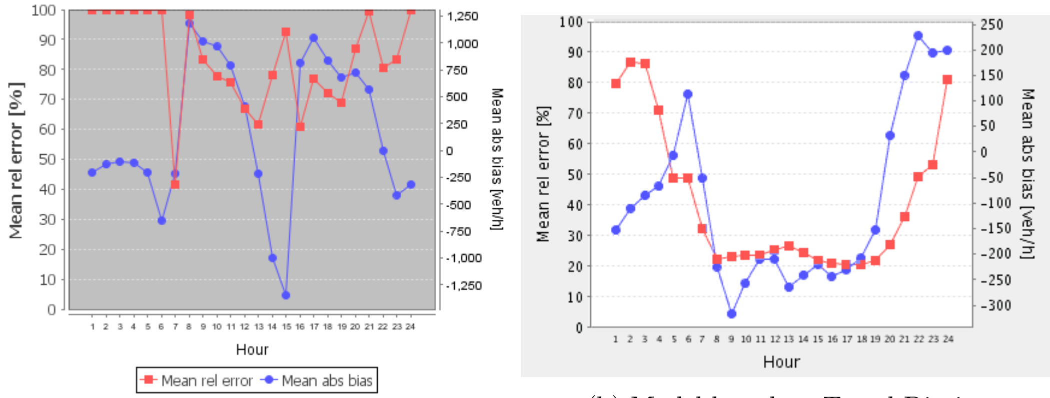
Table 4.2 contrast basic travel characteristics of the commuting population with the survey data described in section 4.4.1. It can be seen that in the simulation significantly fewer agents travel on the network than expected based on the survey. Also, travel characteristics like trip duration show unrealistic values.

Paramter	**Run 142**	**Reference**
Car Trips	2.53m	3.2m**
Car Trips/Person	2.0	3.4**
Avg. Detour Ratio	1.86	1.58***
Avg. Trip Distance	18.0	9.5**
Avg. Trip Duration	159.9	22.3**
Avg. Score of Exec. Plans	66	–

* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 4.2.: Settings and Results of Benchmark Models

The left part of figure 4.2 depicts an error graph of the simulated traffic volumes against given traffic counts for Berlin (cf. section 4.3.3). Specifically, the blue line depicts the absolute bias between simulated and observed traffic counts, averaged over all traffic count stations – for each hour of the day. The red line shows the mean relative error (MRE), which relates the absolute bias to the magnitude of the respective traffic flow. These graphs are, therefore, a measure to assess how well simulated traffic condition reproduce real-world traffic conditions. It can be seen that the simple model exclusively based on commuter relations without any further considerations produces very bad results. Traffic at peak hours is overly high. At the same time, the simulation puts much less cars on the network during other times of the day compared to expectations based on real-world counts. The goal of this study is to use the information given by commuter data more efficiently and, thus, come to significantly better results. Before that, however, a second benchmark in form of a demand representation based on travel diaries is presented in the following section (cf. section 4.4.3).



(a) Model based on Home-Work-Home Plans

(b) Model based on Travel Diaries

Figure 4.2.: Error Graphs of Benchmark Models

Demand based on Travel Diaries

This model entails 68,572 tripmakers of Berlin and was created by Andreas Neumann of the Transport Systems Planning and Transport Telematics Group at TU Berlin [14] for an internal study. It is based on 1998 household survey data conducted by Berlin's public transport operation company (*BVG-Haushaltsbefragung*). The right part of figure 4.2 depicts the respective error graphs. Expectedly, this demand representation reproduces real-world traffic significantly better. During daytime mean relative errors show values of around 20%. Reaching such values is a goal to be reach with the models to be developed in the subsequent chapters (cf. sections 5 and 6).

[14] Cf. `http://www.vsp.tu-berlin.de/`, last accessed on 15 December 2013.

5. Initial Model

In order to enhance the representativeness of the transport model, the Comprehensive Econometric Model for Daily Activity-Travel Patterns (CEMDAP, cf. section 2.3) is used for initial demand generation. Thus, in this chapter, a basic transport model whose initial demand is generated with CEMDAP is described.

The level of detail for the representation of transport demand is dependent on the intended use of the model. The model developed in this chapter is intended to analyze what improvements in terms of representativeness can be achieved by utilizing CEMDAP as a tool of initial demand generation, while keeping the scope of employed input data as simple as possible. Accordingly, this model is branded *initial*. While general descriptions of the transport supply and transport demand have been given in sections 4.3.2 and 4.3.1, the detailed model setup for the model developed in this chapter is outlined in section 5.1. Then, results of runs with different parameter configurations are discussed in section 5.2. Finally, the quality of the results is appraised in section 5.3.

5.1. Setup

As pointed out in section 2.3, CEMDAP produces the complete daily activity-travel patterns of each individual. Since MATSim is based on the simulated agents' daily activity plans (cf. section 3.3), it is intuitive that CEMDAP's output can be utilized to create these MATSim plans (cf. section 3.3.4). Therefore, the CEMDAP output only needs to be converted into a MATSim plan file[1].

In order to be able to run CEMDAP, its input data needs to be prepared. These input data encompass files with information on households, persons, zones, network level-of-service characteristics, and vehicles (cf. section 2.3.2). As the goal of this initial modeling approach based on CEMDAP is to assess the basic functioning of CEMDAP in interaction with MATSim and Cadyts and to analyze the influence to different model parameters, the premise is to only use as much input data as necessary.

The point of departure is again the commuter file provided by the Federal Employment Agency (cf. section 4.3.2). Again, for each 100 person in the commuter file, one agent with home and workplace locations according to the commuter file

[1] A technical description of this conversion is given in appendix A.

is created, yielding a 1% sample. While for areas in Brandenburg the spatial mapping of agents is trivial as commuter data is provided with respect to municipalities, in Berlin, again, a random district region (cf. section 4.3.2) is chosen. As already pointed out in section 4.4.3, a random draw constitutes a valid approximation to real residential patterns since the likelihood for a given agent to live in a given district region is approximately equal for all district regions.

According to the premise of simplicity (cf. section 1.3), the population only consists of one-person households of employed persons whose age is chosen randomly between 18 and 99 years. Each person possesses a car, is licensed, and has the same gender. These characteristics are stored in the household and person files[2] as part of the CEMDAP input.

To run CEMDAP, a slightly revised version (cf. appendix B.5) of the model specification from the trail package (cf. section 4.2 is used. After the finalization of the CEMDAP run, its output is converted[3] into a MATSim plan file (cf. sec 3.3.4), which stores the daily plans of each agent.

As explained in detail in section 4.1.3, the CEMDAP output may not be regarded the final solution for agents' travel patterns because of the missing context-specific estimation of the model coefficients. Instead, CEMDAP is run multiple times and each model output of one of these runs is considered one suggestion for a potential demand representation (cf. section 4.2).

To ensure that those plans prevail which possess a high representativeness, Cadyts (cf. section 3.4) is used. As explained in section 3.4.3, Cadyts ties in with the mental layer of the transport simulation, where plans' performance is scored by a utility function. Through the composite design of this utility function (cf. section3.3.2), which consists a activity scoring component, a travel leg scoring component, and a Cadyts component, plans are scored both in terms of their behavioral soundness and their representativeness in terms of real-world observations (here given as traffic counts). If not stated otherwise, all following runs are carried out over 150 iterations. The innovative strategy module (i.e. the `ReRoute` module to generate new routes) is active during the first 90 of these 150 iterations.

5.1.1. Validation of Plan Properties

After the initial plans for MATSim have been created based on CEMDAP, it seems reasonable to inspect these plans and analyze whether they possess the properties that they were intended to. Accordingly, the home and workplace locations of a randomly chosen agent are analyzed in the following.

[2] A precise description of the definition of each model variable along with respective descriptions of variables of the other files is provided in appendix B.

[3] Using the class `CemdapStops2MatsimPlansConverter`, which is contained in appendix E.

As pointed out in section 4.3.2, home locations are created based on commuter data. Depending on the magnitude of a commuter stream starting in a given municipality, the corresponding number of agents is chosen to have their home location in the corresponding Brandenburg municipality or a randomly chosen district region of Berlin in case their home municipality is the city-state Berlin. The concrete geographic location is then chosen randomly within the given zone. Thus, if the assignment works correctly, the potential home locations of different plans of a given agent should all fall into the same zone[4].

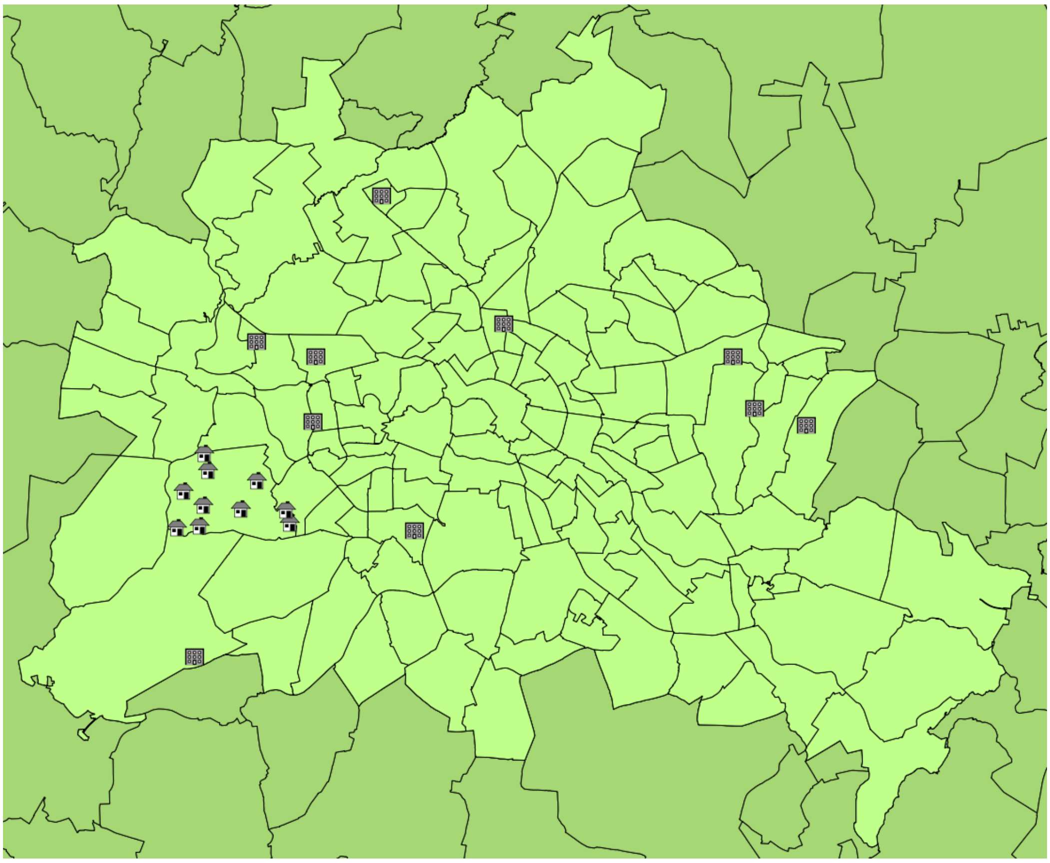


Figure 5.1.: Home and Workplace Locations of a Randomly Chosen Agent

The choice of workplace locations works analogous to the choice of home locations with one difference. For each plan of a given agent, a new random draw for the district region, which the workplace location will be located in, is performed. This means that people working in Berlin (for whom, as opposed to people in Brandenburg, the choice of a district region is actually conducted), have a variety of potential workplace locations in their initial plans. Thus, the workplace location choice is in contrast to the assignment of home locations not a fixed choice that stays constant

[4] Notably, it would equally well be possible to assign a unique home location that is fixed over the different plans to every agent. Since home locations are, however, chosen randomly within the correct zone, there is no justification to only use one particular randomly chosen location.

over the whole subsequent simulation-calibration process, but left as a modifiable dimension that may be influenced by the simulation-calibration process (cf. section 4.1.3). In line with the fact that properties in terms of choice dimensions that are modifiable during the simulation-calibration process do not need to be initially correct (cf. sections 3.3.5, 4.1.2, and Balmer [2007, p.52f]), it is, thus, acceptable, that initial workplace location do not reflect reality perfectly well.

In order to illustrate that the workplace assignment procedure works correctly, it is worthwhile to show that the potential initial workplace locations of a given agent fall either into the very same Brandenburg municipality or into different district regions. Figure 5.1 depicts the initial, potential home and workplace locations of one randomly chosen agent.

5.1.2. Anaylyis of Plan Diversity

For the selection of those plans' of agents which help reproducing observed behavior (as given by traffic counts), the Cadyts calibration algorithms is used. In order to be able to *select* these plans, Cadyts has to be offered an actual *selection*. This selection can only fulfill its purpose when its elements differ from each other sufficiently. The first major difference consists in the diversity of initial potential workplace locations for people working in Berlin as described in the previous section (cf. section 5.1.1).

In this section, two additional measures are defined to quantify initial plans' diversity. First, it is analyzed how many agents possess plans within their initial choice set whose number of activities is different. Then, for all those agents whose plans have the same number of activities, it is analyzed if there is variation in activity times between different plans. More precisely, it is examined whether or not the activities in different initial plans have the same end times over all plans.

In the input plans file with three initial plans (plus one stay-home plan), a 2.0x population expansion, and demand elasticity (as dealt with in subsequent sections), the following diversity is found. Altogether there are 18,775 agents. 2,456 of these agents have variations in the number of activities which they pursue during their day in their initial choice set, constituting 13.1% of all agents. The other 16,319 agents have a constant number of activities in their plans. Among these 16,319 agents, there are 10,757 (or 65.9%) who have some variations in terms of activity end times over their plans. For the remaining 5,562 agents the activity pattern is the same over all their three initial plans in terms of number of activities and activity timing. These plans may only be different in terms of activity locations.

5.2. Results

Now, the transport supply described in section 4.3.1 and the transport demand described in sections 4.3.2 and 5.1 are fed into MATSim and run. As described in section 3.4.3, MATSim is applied in interaction with Cadyts, which influences the scores of agents' plan dependent on how well these plans match expectations with regard to traffic counts. As pointed out before, the goal of this initial model is to find the combination of parameters that creates the best model and to analyze the various influences that parameter variations have on results. To find the best values for the parameters, more than 100 runs have been carried out. In the following, an illustrative choice of these runs, their respective setups, and their results is presented. Over the presented choice of runs the following parameters have been varied:

1. Population expansion
2. Demand elasticity
3. Number of plans
4. Number of initial plans
5. Flow capacity
6. Weight of the innovate strategy module
7. Cadyts scoring weight

It is worthwhile to mention at this point that none of these parameters is independent of the other parameters. In fact, many of them are – loosely or more strongly – correlated. Therefore, the analysis of the effects of one parameter – while holding the others constant – may only yield results of limited generality. Finding the best model fit by varying the different parameters is, therefore, a circular rather than a linear process. The following sections aim to present the outcome of this circular, iterative procedure in a concise, but still complete, linear way.

5.2.1. Population Expansion

As explained in section 4.3.2, the population used for this study is based on commuter data provided by the Bundesagentur für Arbeit [2010]. Even though CEMDAP is applied subsequently to produce *complete* daily activity-travel patterns (i.e. leisure-time, shopping and other forms of traffic that go beyond mere home-work-home travel patterns, cf. section 2.3), it is not fully clear whether the *amount* of agents in the simulation reflects the amount of real-world travelers sufficiently well.

In particular, only working people are considered in the very simple population representation on which the runs in this section are based. Thus, travelers whose travel activities are, not at all, based on commuting are systematically omitted.

A simple remedy consists in expanding the population by a certain factor, deliberately putting too many agents into the network, and at the same time assigning a stay-home plan[5] to every agent. On the one hand, this population expansion – if the expansion factor is chosen sufficiently high – assures that the number of traveling agents is not falsely low. On the other hand, this approach enables the Cadyts algorithm to make agents choose their stay-home plan in case there are too many agents on the network as compared to given traffic counts.

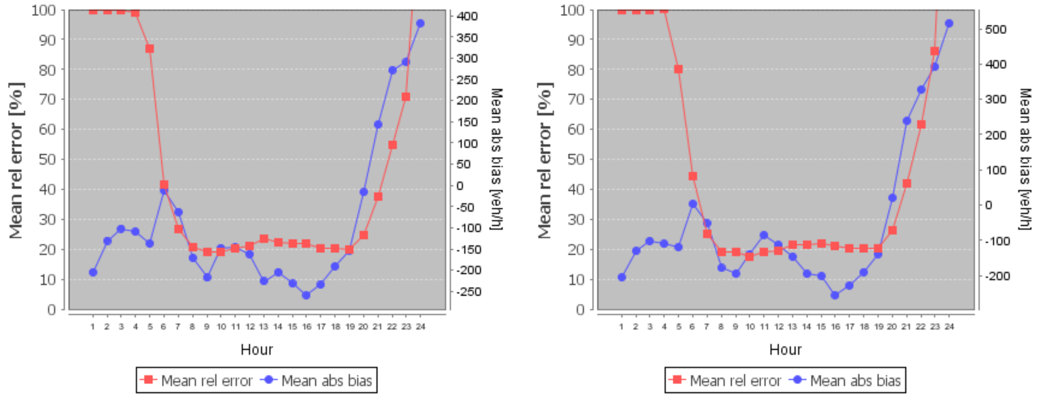
Paramter	**Run 112**	**Run 118**	**Reference**
Population Expansion	**2x**	**3x**	
Demand Elasticity	Yes	Yes	
Number of Plans	5	5	
Number of Initial Plans	4	4	
Flow Capacity Factor	0.01	0.01	
Innov. Strategy/Selection	1:1	1:1	
Cadyts Scoring Weight	10	10	
Calibration Time	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-63	-71	-10*
Home-Staying Agents	*7,858*	*15,429*	–
Traveling Agents	*10,914*	*12,829*	–
Car Trips	3.76m	4.27m	3.2m**
Car Trips/Person	3.9	3.8	3.4**
Avg. Detour Ratio	1.97	2.01	1.58***
Avg. Trip Distance	10.9	10.5	9.5**
Avg. Trip Duration	81.6	87.9	22.3**
Avg. Score of Exec. Plans	75	53	–

* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 5.1.: Settings and Results of Runs with different Population Expansion (1)

Thus, the population expansion coupled with the amplification of the agent's choice set by a stay-home plan can be understood as handing over an additional choice dimension to the Cadyts calibration algorithm. Table 5.1 gives an overview of the parameters of two simulation runs with different levels of population expansion and the corresponding results. Figure 5.2 depicts the error graphs of the two runs.

[5] A *stay-home plan* is a MATSim plan that consists only of one (whole-day-long) activity at the agent's home location and that does not contain any travel legs. Hence, an agent choosing their stay-home activity means to the MATSim traffic simulation basically the same as an agent that does not exist. The mechanisms of these stay-home plans are further discussed in section 5.2.2.



(a) Run 112 (2.0x-Exp. Population) (b) Run 118 (3.0x-Exp. Population)

Figure 5.2.: Error Graphs of Runs with different Population Expansion (1)

Both in the table as well as in the figure, it can be observed that both configurations yield very similar results[6]. Most interestingly, the greatest difference between the two runs consists in the number of agents who choose to stay at home (in table 5.1 labeled as *Home-Staying Agents*). This number is about twice as high in the run based on a 3.0x-expanded population (`Run 118`) than for the run with a 2.0x-expanded population (`Run 112`). The comparatively *invariant* measure here is the number of agents who conduct one or more trips on the network, labeled as *Traveling Agents* in table 5.1. This number is comparatively similar in both runs.

In accordance with given traffic-count data, Cadyts can only "allow" a certain number of agents to choose a plan which contains traveling. Thus, in the case of the more strongly expanded population, a higher amount of agents has to be sorted out (i.e. chosen to stay at home) so that the number of those agents who travel on the network can converge to the same number as it does in case the less strongly expanded population is used. This observation can be regarded as a indication that Cadyts correctly works in terms of extracting a realistic demand representation out of a overly expanded potential initial demand. In particular, Cadyts seems to achieve this to some extent independent of the magnitude of the over-expansion.

At this point, it is, however, not guaranteed that a bias is not introduced by only selecting certain types of plans and, thereby, possibly skewing certain distributions of population characteristics. Accordingly, it seems reasonable to find the lowest magnitude of population expansion that is still large enough.

Since the 2.0x-expanded population seems to be large enough so far, the next step is to assess how it compares to a 1.0x-expanded (i.e. a non-expanded) population. As pointed out above, the non-expanded population must, however, be expected to be too small from a theoretical point of view. In table 5.2, the settings and results of

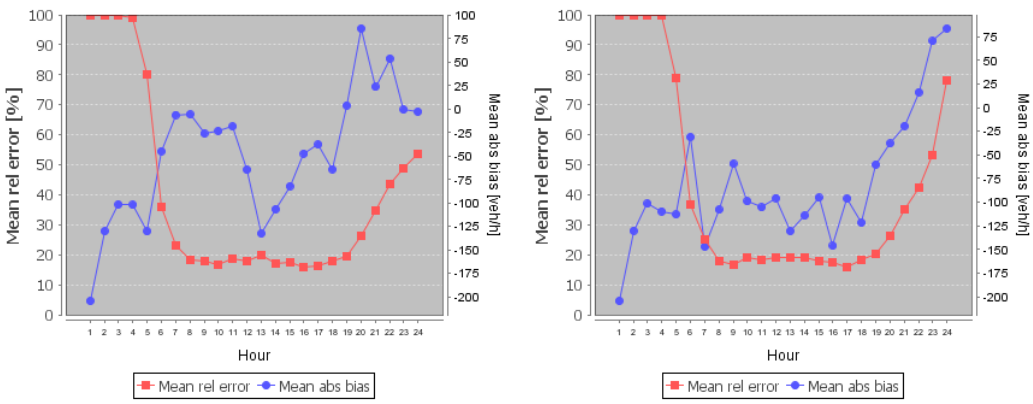
[6] It has to mentioned, however, that the results are not very good at this point, especially with regard to average trip durations. Improvements will be made gradually over the subsequent sections of this chapter.

two corresponding runs are given. Figure 5.3 shows the error graphs of these runs. It should be mentioned that a direct comparison is only reasonable among the runs contained in either table (i.e. table 5.1 or 5.2), but not between runs of different tables, as the configurations of the runs contained in different tables are different with respect to other parameters as well.

Paramter	**Run 127c**	**Run 127a**	**Reference**
Population Expansion	**1x**	**2x**	
Demand Elasticity	Yes	Yes	
Number of Plans	5	5	
Number of Initial Plans	4	4	
Flow Capacity Factor	0.015	0.015	
Innov. Strategy/Selection	1:1	1:1	
Cadyts Scoring Weight	30	30	
Calibration Time	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-31	-36	-10*
Home-Staying Agents	*1,688*	*7,732*	–
Traveling Agents	*7,622*	*11,043*	–
Car Trips	2.92m	3.89m	3.2m**
Car Trips/Person	4.2	4.0	3.4**
Avg. Detour Ratio	1.77	1.88	1.58***
Avg. Trip Distance	12.1	11.0	9.5**
Avg. Trip Duration	40.3	41.2	22.3**
Avg. Score of Exec. Plans	163	125	–

* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 5.2.: Settings and Results of Runs with different Population Expansion (2)



(a) Run 127c (1.0x-Exp. Population) (b) Run 127a (2.0x-Exp. Population)

Figure 5.3.: Error Graphs of Runs with different Population Expansion (2)

First of all, it attracts attention that these configurations perform significantly better than the above ones. While the discussion of other parameters does not appears meaningful at this point because most parameters have not yet been analyzed sufficiently, the differences in the number of car trips (as shown in table 5.2 are interesting. The run based on a 1.0x-expanded population contains only a significantly smaller number of agents who actually travel on the network. Even though this number is closer to the respective reference, it has to be regarded as a worse result than the overly high number of traveling agents in the run based on the 2.0x-expanded population. The reason is that the overly high number of agents will likely be reduced via the adjustments of other parameters in the subsequent sections. A amount of car trips that is too low at this point, however, can not be made converge in the intended direction since the agents which would produce these trips do simply not exist in the scenario. Therefore, the use of a somewhat expanded (e.g. a 2.0x expansion) population seems the right option at this point. This is in line with a-priori theoretical speculations that the 1.0x-expanded population may be too small because of the lack of representation of non-working travelers.

5.2.2. Demand Elasticity

As pointed out in the previous section (cf. section 5.2.1), the expansion of the population coupled with assigning a stay-home plan adds another choice dimension to the Cadyts algorithm.

Paramter	**Run 114**	**Run 115**	**Reference**
Population Expansion	2x	2x	
Demand Elasticity	**Yes**	**No**	
Number of Plans	10	10	
Number of Initial Plans	8	7	
Flow Capacity Factor	0.01	0.01	
Innov. Strategy/Selection	1:1	1:1	
Cadyts Scoring Weight	10	10	
Calibration Time	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-53	-118	-10*
Home-Staying Agents	*5,730*	*0*	–
Traveling Agents	*13,045*	*18,775*	–
Car Trips	4.59m	7.23m	3.2m**
Car Trips/Person	4.0	4.3	3.4**
Avg. Detour Ratio	2.00	2.07	1.58***
Avg. Trip Distance	10.6	11.8	9.5**
Avg. Trip Duration	95.3	225.3	22.3**
Avg. Score of Exec. Plans	163	125	–

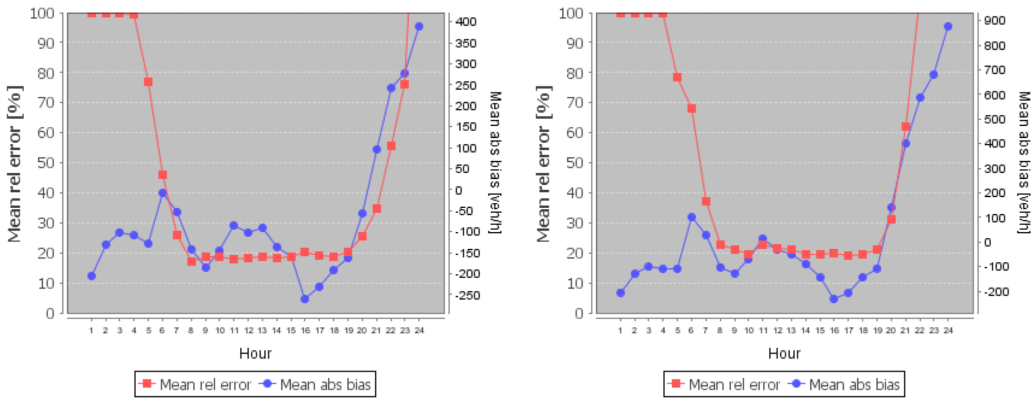
* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 5.3.: Settings and Results of Runs with/without Demand Elasticity

This choice dimension enables Cadyts to a certain extent to select the number of agents in the traffic simulation by making those agents who cause too much traffic in relation to given traffic counts stay at home and, thus, to be unconsidered in the traffic simulation.

While the application of an expanded population without demand elasticity appears inconsistent from a theoretical point of view, it still appears to be worthwhile to analyze the effect of not allowing Cadyts to determine the number of traveling agents by switching off demand elasticity. Table 5.3 depicts the settings and results of two respective runs. Figure 5.4 shows the corresponding error graphs.

While the general performance of both runs is not yet good, they still yield quite clear insights into the effects of the application of demand elasticity. It is obvious that in the case with no demand elasticity, there are simply too many agents on the network. Trip durations are unacceptably high. Also in terms of other measures, the configuration *without* demand elasticity performs discernibly worse than its counterpart *with* demand elasticity.



(a) Run 114 (With Demand Elast.) (b) Run 115 (Without Demand Elast.)

Figure 5.4.: Error Graphs of Runs with/without Demand Elasticity

The underlying behavior of the application of demand elasticity is that agents who have received bad scores for being stuck in congested conditions, gradually tend towards choosing their stay-home plan. If they do not find a better-scoring other plan over the course of the iterations, they keep executing their stay-home plan and, thereby, become inactive in terms of travel.

Thus, the expected result of this experiment is that demand elasticity should be applied. This seems logical in respect to theoretical considerations concerning fixed and unfixed choice dimensions (cf. sections 3.3.5, 4.1.3, and 4.2). Since the number of agents used in the runs of this initial model is not ensured to be initially correct, a module that enables adjustment with respect to this choice dimension needs to be employed. The application of *demand elasticity* described in this section constitutes this module.

5.2.3. Number of Plans

Since multiple initial plans are assigned to each agent before the beginning of the simulation-calibration process (cf. section 4.1.3), the number of plans during the simulation has to be at least as high as the number of initial plans so that no initial plan can unintentionally get lost without being evaluated. As agents create new plans via innovative strategy modules (by copying existing plans and applying modifications to them, cf. section 3.3.3), the amount of plans increases over iterations as long as innovative strategy modules are in use. Thus, it may be reasonable to set the number of plans somewhat higher than the number of *initial* plans so that reasonable plans, that are worth to be considered again, do not get discarded too early. In the following, two runs that only differ with respect to the number of plans are carried out. In table 5.4, the corresponding settings and results are outlined.

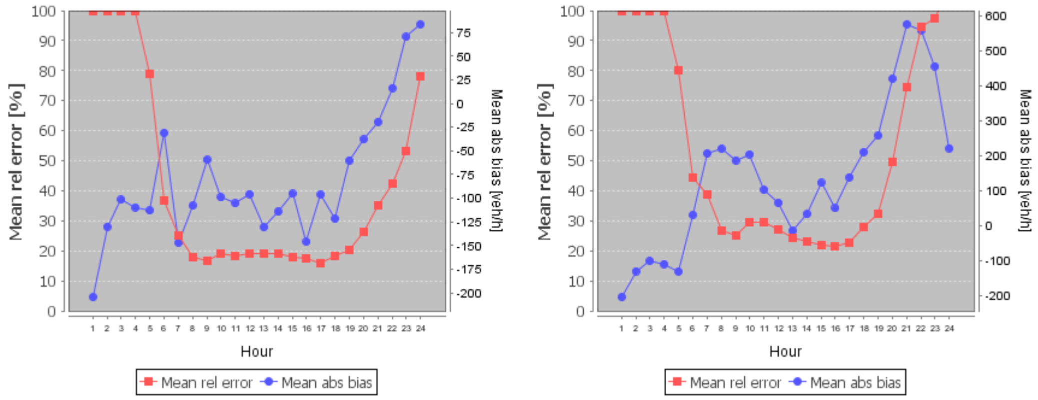
Paramter	Run 127a	Run 127b	Reference
Population Expansion	2x	2x	
Demand Elasticity	Yes	Yes	
Number of Plans	**10**	**5**	
Number of Initial Plans	4	4	
Flow Capacity Factor	0.015	0.015	
Innov. Strategy/Selection	1:1	1:1	
Cadyts Scoring Weight	30	30	
Calibration Time	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-36	-109	-10*
Car Trips	3.89	4.20	3.2m**
Car Trips/Person	4.0	4.0	3.4**
Avg. Detour Ratio	1.88	1.87	1.58***
Avg. Trip Distance	11.0	11.6	9.5**
Avg. Trip Duration	41.2	48.1	22.3**
Avg. Score of Exec. Plans	125	40	–

* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 5.4.: Settings and Results of Runs with different Number of Plans

As shown in table 5.4, the run with ten plans performs significantly better than the run with five plans. On the one hand, normalized log-likelihood as well as average scores of executed plans are much better. On the other hand, travel characteristics like number of car trips and average trip durations are much closer to expected values. In figure 5.5, it can also be seen that mean relative errors of the run with ten plans are discernibly lower. While both runs show simulated traffic volumes that are too high in the evening hours, this excess is significantly higher in the run with only five plans.

In conclusion, it seems worthwhile to raise the number of plans. Here, a good value appears to be a value about twice as high as the number of *initial* plans, which is discussed in the following section (cf. section 5.2.4).



(a) Run 127a (10 Plans) (b) Run 127b (5 Plans)

Figure 5.5.: Error Graphs of Runs with different Numbers of Plans

5.2.4. Number of Initial Plans

The number of initial plans is a measure of the variety of the choice which an agent possesses initially, i.e. at the beginning of the simulation-calibration process. As pointed out in section 4.2, properties of choice dimensions that are modifiable over the course of the iterations, do not need to be configured perfectly at initial conditions. Choice dimensions that are fixed over the whole process, however, need to be correct in terms of the properties of the real population which are related to these choice dimensions.

The analogous is true for diversity in plans. As discussed in section 5.1.2, there has to be a *selection of diverse alternatives* offered to the calibration. Only if this is accounted for, the calibration can influence the choice of that element of the selection which fits best in terms of behavior as well as in terms of real-world observations. Properties in terms of choice dimensions whose diversity is increased over the course of the iterations, do not have to possess diversity at initial conditions. For instance, if agents create new routes for their trips over and over again during the iterations, they do not need to be provided with a diverse selection of routes initially.

Regarding those properties for which *no* diversity is created during simulation, however, it has to be ensured that diversity is high enough right from the start. If the calibration can only select from indifferent or only minorly different options, the selection process becomes meaningless.

In this section, the influence of the magnitude of the initial choice set is examined. Table 5.5 gives an overview of the settings and results of four simulation runs used for the according analysis. Figure 5.6 depicts the corresponding error graphs.

Observing the simulation results and the error graphs of `Run 126a` (eight initial plans) and 127a (four initial plans), it seems like the number of initial plans does not have a big influence. To understand this observation, one has to question how much raising the number of initial plans actually increases diversity that agents posses among their plans. If a higher number of initial plans does not increase diversity that much, raising the number of initial plans will be influential.

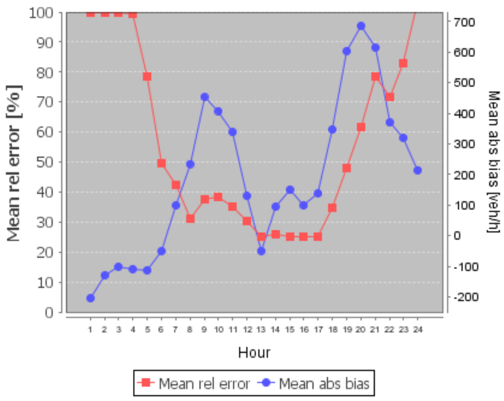
As pointed out in section 4.1.3, initial plans in this study (provided by the CEMDAP output) can be different in terms of number and type of activities, timing, and workplace location for people working in Berlin. As shown in section 5.1.2, the diversity concerning the choice dimensions *activity participation* and *activity timing* is not found to be very big. Therefore, it must be speculated that the diversity increase by going from four to eight initial plans is not very influential. Concerning the third choice dimension (i.e. *workplace locations*), however, diversity should increase linearly with any additional plan because of the random selection of district region for workplace location of people working in Berlin (cf. section 4.3.2). Here, however, additional locations may be not very influential as a small selection of spatially well-dispersed potential workplace locations may already be good enough to find a realistic workplace location.

Paramter	**Run 126**	**Run 127**	**Run 126a**	**Run 127a**	**Reference**
Population Expansion	2x	2x	2x	2x	
Demand Elasticity	Yes	Yes	Yes	Yes	
Number of Plans	10	10	10	10	
Number of Init. Plans	**8**	**4**	**8**	**4**	
Flow Capacity Factor	**0.02**	**0.02**	**0.015**	**0.015**	
Innov. Strategy/Selection	1:1	1:1	1:1	1:1	
Cadyts Scoring Weight	30	30	30	30	
Calibration Time	0 – 24h	0 – 24h	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-130	-86	-40	-36	-10*
Car Trips	5.06m	3.98m	4.69m	3.89m	3.2m**
Car Trips/Person	4.2	4.2	4.0	4.0	3.4**
Avg. Detour Ratio	1.83	1.78	1.92	1.88	1.58***
Avg. Trip Distance	10.9	11.1	10.7	11.0	9.5**
Avg. Trip Duration	31.7	26.5	46.2	41.2	22.3**
Avg. Score of Exec. Plans	72	105	110	125	–

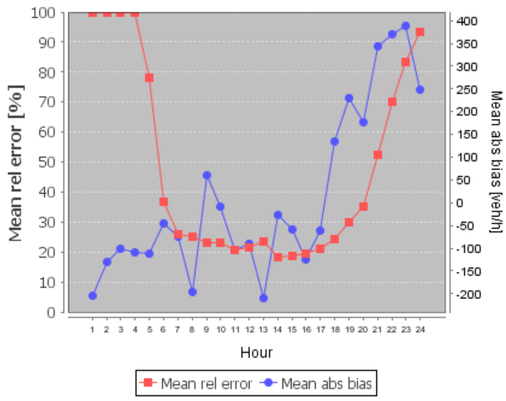
* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 5.5.: Settings and Results of Runs with different Number of Initial Plans

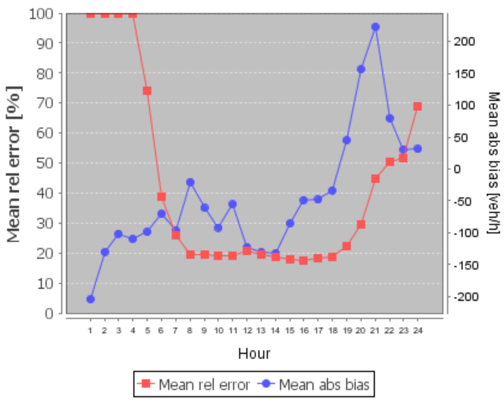
Now, two other runs (`Run 126` and `Run 127`, cf. table 5.5), which again only differ in terms of number of initial plans are observed. Here, the differences in performance are greater than between the two runs analyzed before. In fact, the run with the smaller number of initial plans (i.e. `Run 127` with four initial plans) performs better than its counterpart with eight initial plans in terms of reproduction of real-world observations (as measured by the log-likelihood), the score of executed plans, as well as all comparative aggregate transport system measures. It is suspected that this is rather due to a not fully converged simulation after 150 iteration than to any potential disadvantages that come along with using more initial plans. Also, the run with eight plans has the property that the numbers of plans and the numbers of *initial* plans are very close to each other (cf. section 5.2.3). This may result in slower convergence as more mediocre or yet unconsidered plans will be executed instead of being able to further improve well-performing plans more rapidly. Accordingly, the number of initial plans will be readdressed in respective section of the more precise model to be developed (cf. section 6.2.4).



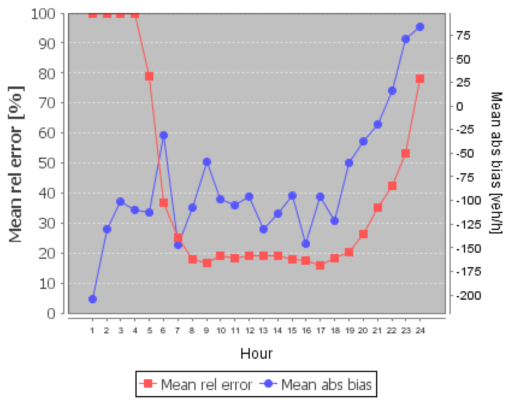
(a) Run 126 (8 Initial Plans)



(b) Run 127 (4 Initial Plans)



(c) Run 126a (8 Initial Plans)



(d) Run 127a (4 Initial Plans)

Figure 5.6.: Error Graphs of Runs with different Number of Initial Plans

Summing up, the preliminary result appears to be that the number of initial plans does not have a major influence after a certain threshold of plans is exceeded. Four initial plans (where one plan is a stay-home plan enabling demand elasticity, cf. section 5.2.2) seems to be enough. Secondly, the *ratio* between the number of plans during the simulation (cf. section 5.2.3) and the number of *initial* plans seems to be more relevant than the number of initial plans itself.

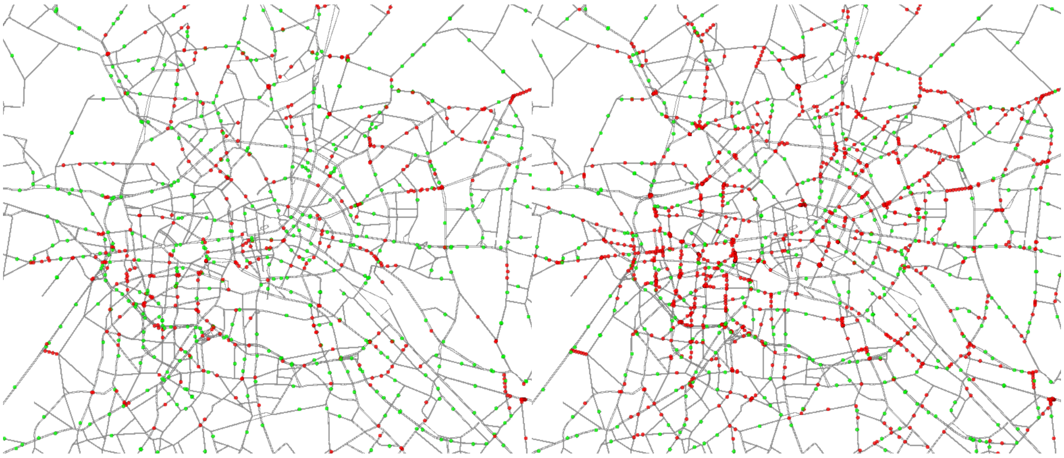
5.2.5. Flow Capacity

In table 5.5, two configurations are based on a flow capacity factor of 0.015, while the other two possess a flow capacity of 0.02. A flow capacity factor of 0.01 would constitute the same scaling as used for the scaling of the population (a 1%-sample is used). Experience has shown, however, that a scaling of flow capacity proportional to the scaling of population leads to distortion effects. Thus, the flow capacity may not be scaled to the same degree as the population.

To analyze effects of flow capacity, runs 126 and 127 as well as `Run 126a` and 127a in table 5.5 and figure 5.6 are compared. Both comparisons yield the same observations. The runs with the lower flow capacity factor (i.e `Run 126a` and `Run 127a`) show a better model fit (as measured by the normalized log-likelihood), but worse values in terms of detour factors and trip duration. In terms of trip distances and number of trips, the pairwise compared run perform similarly.

First, these observations exemplify why it is essential to observe different values for evaluation. Second, the fact that the flow capacity factor is of fundamental importance is confirmed. Last but not least, the results show one important observation quite clearly: The two runs based on a flow capacity of 0.015 show a very good model fit. At the same time most other parameters show acceptable values. If not for the deficient reproduction of travel times, these configurations could be regarded as good results. Only the overly high trip duration indicate that the otherwise good results are delusive.

The arguable reason may be due to the interplay of the behavioral scoring components and the Cadyts scoring component in the MATSim utility function described in section 3.4.3. As discussed in section 3.4.4, the Cadyts scoring component can to a certain extent counteract the behavioral components. The property is intended as the Cadyts utility correction (cf. section 3.4.2) can be interpreted as some kind of *alternative-specific constant* (as in a discrete choice model, cf. section 3.4.5), which captures unobserved attributes that cannot be described by the behavioral components of the utility function. This model property, however, entails the risk that Cadyts may counteract the behavioral model in an unreasonable way like arguable in `Run 126a` and `Run 127a`. Here, it seems that the calibration entices agents somewhat to much to choose somewhat congested routes. Since the fact that agents choose these routes is arguably in line with expectations in terms of traffic counts, agents receive a positive utility correction by choosing these routes. If this utility correction is big enough as to compensate the disbenefit that agents experience by spending more time than necessary in congestion, the observed conditions may result. Figure 5.7 depicts the traffic patterns of two runs with different flow capacity factor at 18:00. It can be seen that the configuration with the lower flow capacity factor leads to overly high levels of congestion.



(a) Run127 (FC = 0.02) @ 18:00 (b) Run127a (FC = 0.015) @ 18:00

Figure 5.7.: Traffic Patterns of Runs with different Flow Capacity Factors

While insightful from a theoretical point of view, the interpretation from a practical perspective is rather simple. First, a flow capacity factor of 0.015 is most probably too low. Second, the importance of observing a portfolio of traffic system properties to ensure that results with significant shortcomings are not spuriously evaluated as good results was exemplified.

5.2.6. Cadyts Scoring Weight

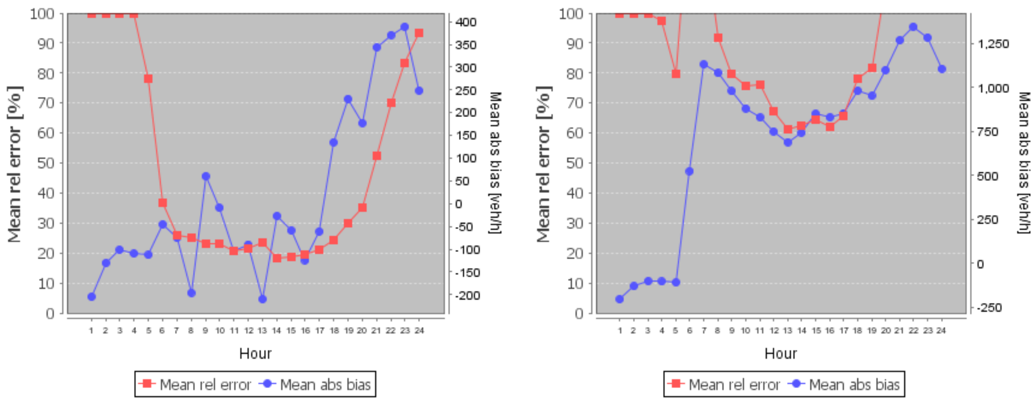
As pointed out in section 3.3.2, the plan scoring constitutes the first of two steps of the mental simulation in MATSim. It is the part of the mental simulation, in which agents evaluate their activity participation and travel experience of the preceding traffic simulation. This is also the component where Cadyts ties in to calibrate the behavior of the traveling agents. As explained in section 3.4.3, both performance in terms of travel behavior (activity and travel leg scoring) and measurement reproduction (Cadyts utility offset) are evaluated together with a compound utility function [Moyo Oliveros, 2013, p.74] given in equation 3.13. This formula contains the configurable weight w, which determines the strength of the calibration effect relative to the other (i.e. the behavioral) scoring components.

While a in-depth analysis of the influence of the Cadyts scoring weight w is left for chapter 6, the aim here is to exemplify the general effect of this value. If this value is set to zero, the Cadyts calibration functionality is switched off. Table 5.6 presents the settings and results of two runs of which one uses a Cadyts scoring weight of 30 – a value which showed reasonable results over the course of different runs – while the other run uses a Cadyts scoring weight of 0. Figure 5.8 shows the respective error graphs.

Paramter	Run 127	Run 129	Reference
Population Expansion	2x	2x	
Demand Elasticity	Yes	Yes	
Number of Plans	10	10	
Number of Initial Plans	4	4	
Flow Capacity Factor	0.02	0.02	
Innov. Strategy/Selection	1:1	1:1	
Cadyts Scoring Weight	**30**	**0**	
Calibration Time	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-86	-592	-10[*]
Car Trips	3.98m	6.19m	3.2m[**]
Car Trips/Person	4.2	4.2	3.4[**]
Avg. Detour Ratio	1.78	1.78	1.58[***]
Avg. Trip Distance	11.1	12.0	9.5[**]
Avg. Trip Duration	26.5	60.4	22.3[**]
Avg. Score of Exec. Plans	105	140	–

[*] cf. [Flötteröd, 2009, p.10]
[**] cf. scetion 4.4.1
[***] cf. section 4.4.2

Table 5.6.: Settings and Results of Runs with different Cadyts Scoring Weights



(a) Run 127 (w = 30)

(b) Run 129 (w = 0)

Figure 5.8.: Error Graphs of Runs with different Cadyts Scoring Weights

Very obviously, the configuration without calibration performs much worse than any other configuration shown thus far. The model fit is bad and significantly to many agents are on the network. It has to be mentioned, however, that not every run without calibration has to perform that poorly. As discussed in section 5.2.1, a population expansion with a factor of 2.0 is applied here. It has been pointed out that this property, along which the possibility to sort out agents by using *demand elasticity* (cf. section 5.2.2), is specifically designed to be applied in connection with Cadyts. In fact, this combination constitutes an additional choice dimension, namely the choice of the number of agents who travel on the network. This choice dimension, however, becomes defunct if one central element (the Cadyts calibration algorithm) is suspended. In fact, the generation of good demand representations in MATSim are well possible without the application of Cadyts. In order to attain them, however, the model setup has to be done differently. In conclusion, the analysis in this section has rather been a reaffirmation of the model properties described in the previous section, in particular that of *population expansion* (cf. section 5.2.1) and *demand elasticity* (cf. section 5.2.2). A detailed examination of the actual value of the Cadyts scoring weight w will be done in section 6.2.5 of the subsequent chapter.

5.2.7. Weight of Strategy Module

After the effects of the the first part of the mental simulation (i.e. plan scoring) have been analyzed in the previous section (cf. section 5.2.6), the aim of this section is to analyze the parameters of the second part of the mental simulation (i.e. plan selection). As outlined above (cf. section 4.1.3), the only internal MATSim strategy module used in this study is the `ReRoute` module which generates new routes based on Dijkstra's algorithm. The interesting parameter concerning the strategy module is the *strategy module weight*, which determines the probability of a strategy module to be applied (cf. section 3.3.3). Since the `ReRoute` module is the only innovative strategy module, its weight can be expressed in relative terms to the weight of the probabilistic selection (cf. section 3.3.3).

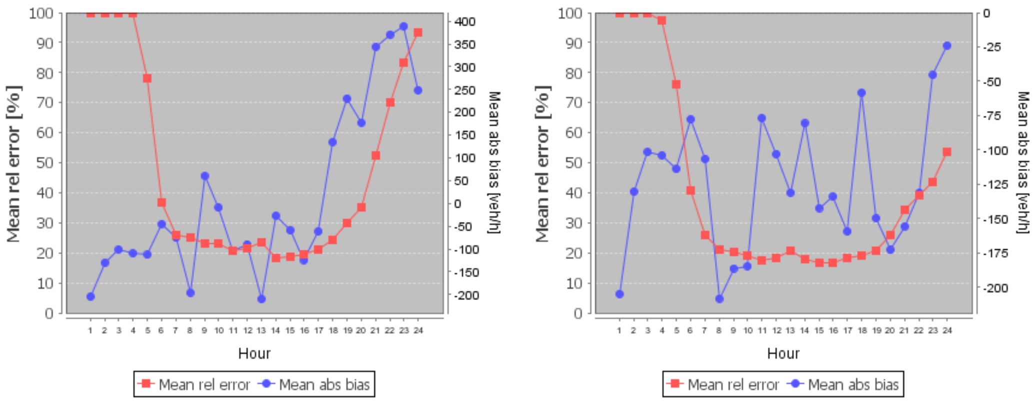
Paramter	**Run 127**	**Run 127e**	**Reference**
Population Expansion	2x	2x	
Demand Elasticity	Yes	Yes	
Number of Plans	10	10	
Number of Initial Plans	4	4	
Flow Capacity Factor	0.02	0.02	
Innov. Strategy/Selection	**1:1**	**1:2**	
Cadyts Scoring Weight	30	30	
Calibration Time	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-86	-31	-10*
Car Trips	3.98m	3.72m	3.2m**
Car Trips/Person	4.2	4.3	3.4**
Avg. Detour Ratio	1.78	1.76	1.58***
Avg. Trip Distance	11.1	10.9	9.5**
Avg. Trip Duration	26.5	24.9	22.3**
Avg. Score of Exec. Plans	105	140	–

* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 5.7.: Settings and Results of Runs different Weights of the Strategy Module

In table 5.7, two runs with different ratio of the weight of the `ReRoute` module and the probabilistic selection module are outlined. In figure 5.9 the respective error graphs are depicted.

It can be observed that the run in which the probabilistic selection is applied more often relative to the application of the innovative strategy module (i.e. the `ReRoute` module) performs better. Its model fit is better and also comparative measures like trip duration are closer to reference values. The interpretation to this observation is that in the configuration with a strategy-selection ratio of 1:1 new plans are generated too frequently so that they displace existing plans, which would have been worth to be considered again, too quickly.



(a) Run 127 (Strat./Sel. = 1:1) (b) Run 127e (Strat./Sel. = 1:2)

Figure 5.9.: Error Graphs of Runs with different Weights of the Strategy Module

5.2.8. Summary

Summarizing the analyses of the previous sections (cf. sections 5.2.1 through 5.2.7), the following *preliminary* results can be outlined:

- *Population expansion* should definitely be used as the correctness of the magnitude of the initial population is not certified.
- Thus, the opportunity to modify this value has to be granted to the simulation-calibration process by also switch on *demand elasticity*
- Choose the *number of plans* should be chosen about twice as high as the number of *initial* plans.
- A value of four seems to be sufficient for the *number of initial plans* as diversity handed over to the simulation-calibration process does not seem to increase with additional initial plans beyond a value of four.
- For the *flow capacity* a value of 0.02 was found to be reasonable.

- The analysis of the *Cadyts scoring weight* showed the importance of the application of Cadyts to come to reasonable results with this the configuration discussed so far. A more detailed examination of the Cadyts scoring weight is left for the subsequent chapter (cf. chapter 6)
- The *weight for innovative strategy module* should be selected somewhat lower than the weight for the probabilistic plan selection module. A value half as high was shown to yield good results.

5.3. Validation

In the previous section (cf. section 5.2) different parameter configurations for a transport model based on a very population representation – whose setup was described in section 5.1 – have been tested. In section 5.2.8, the arguably best parameter combination found has been outlined. Finding the values of these parameters, reference values have been used. To assess the model fit, normalized log-likelihood values were compared to respective values from a study by Flötteröd [2009]. To assess characteristics of the generated travel patterns, average values concerning travel times etc. were calculated from a travel survey conducted in 2008 in the study area (cf. section 4.4.1 and for a detailed calculation of reference values appendix D). Further detour factors (cf. section 4.4.2) as a specific indicator for overfitting were observed.

The goal of this section is to carry out some further validation by analyzing in more detail how travel characteristics in the simulation compare to real-world travel characteristics as contained in the travel survey. Most of these values were not contained in the published report of the SrV travel survey (cf. 4.4.1), but calculated on the basis of the original data files of it[7]. The calculations are done via the Java program `SrVTripAnalyzer`, which is contained in appendix E. Some of the thus calculated distributions had corresponding tables in Ahrens [2010b] and Ahrens [2010a]. Where possible, the distributions based on own calculation were assured by comparisons with data from the survey reports. One such assurance it exemplarily outlined in appendix D

`Run 127e`, whose properties are outlined in table 5.7, possesses the parameter combinations found to be best in section 5.2.8. Thus, this run will be used for the following validation.

As shown in table 5.7, the number of all daily car trips (3.72m in `Run 127e`) diverges from travel survey data (3.20m) by 16%, which appears acceptable, but improvable. On the other hand, this parameter is the one with the highest num-

[7] The author wishes to thank the Berlin Senate Department for Urban Development and the Environment (*Senatverwaltung für Stadtentwicklung und Umwelt*) for granting access to the SrV scientific use file.

ber of calculation steps necessary. Therefore, its force of expression should not be overrated.

Easier to determine and, thus, more insightful is the distribution of trips by time of day. Figure 5.10 depicts a comparison of departure times for all trips by time of day for the simulation (i.e. `Run 127e`) and the survey.

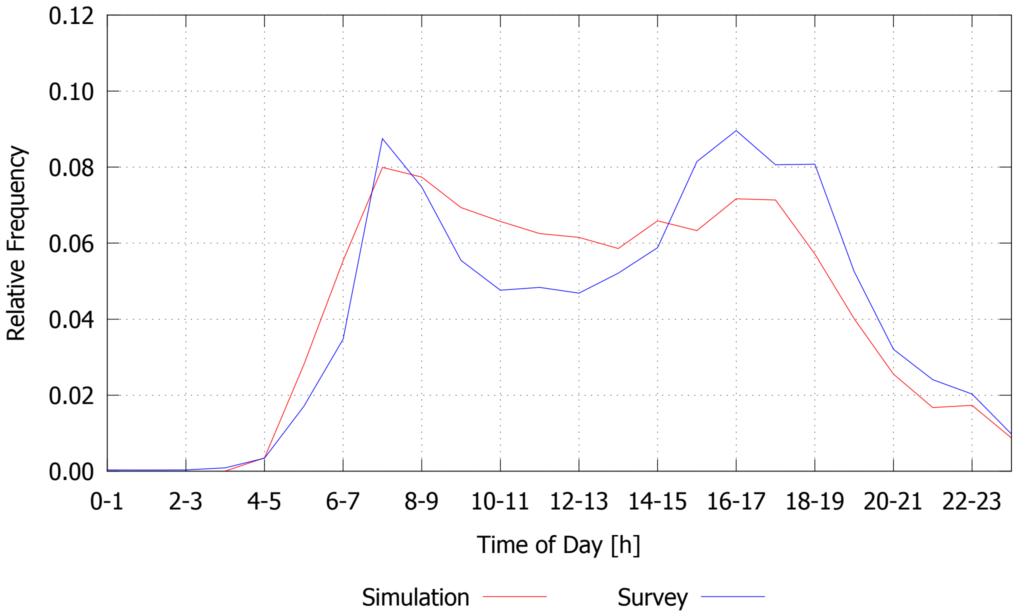


Figure 5.10.: Departure Times in Simulation and Survey

While in the simulation there is somewhat more traffic during daytime and a bit less traffic in the evening, the general pattern of trips by time of day is represented quite well.

Next, trip distances are analyzed. *Beeline distances* are used (cf. section 4.4.2) as they are more suitable for comparison. While a *routed distance* is given in the survey dataset [Ahrens, 2009a, p.48f.], it is not fully clear how it has been calculated and may, thus, be a source of flaw to the intended comparison. Figure 5.11 shows how the relative frequencies of trip distances (measures as beeline distances) compare between simulation results and survey data.

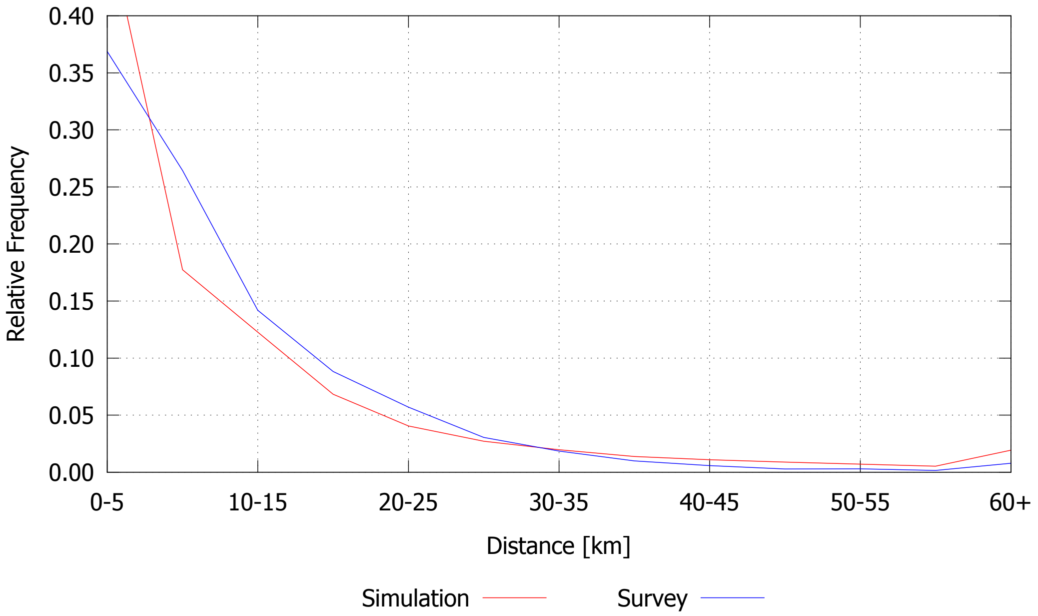


Figure 5.11.: Trip Distances (Beeline Distances) in Simulation and Survey

While the two distributions look alike at first observation, it can be seen that the survey contains somewhat more trips with short distances around five through ten kilometers. This is left for improvement to the model to be built in the subsequent chapter (cf. chapter 6).

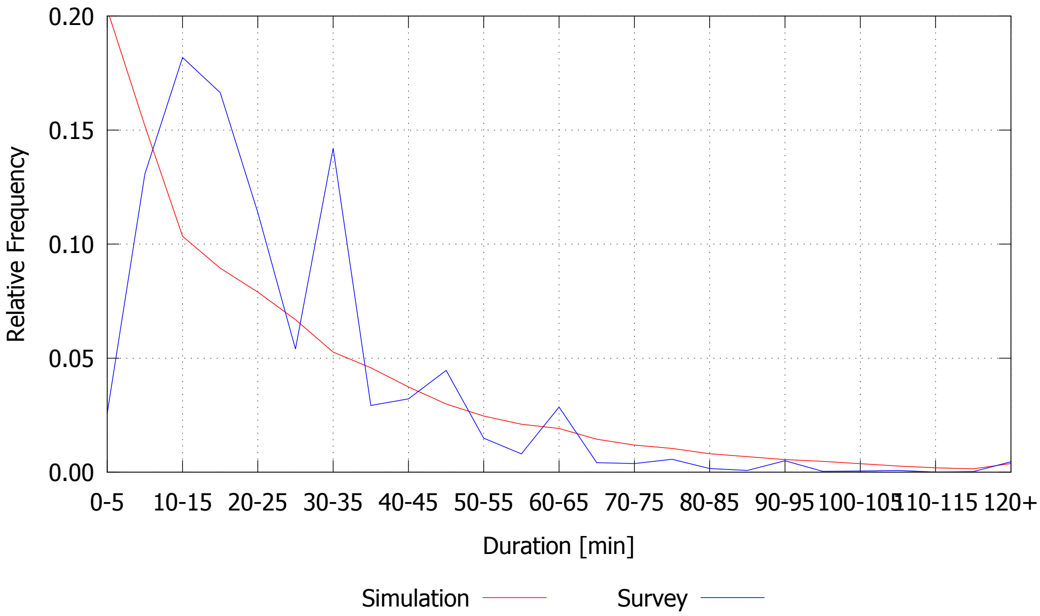


Figure 5.12.: Trip Durations in Simulation and Survey

Figure 5.12 shows how the relative frequencies of trip durations compare between simulation results and survey data. First of all, the peaks contained in the survey data are striking. They are due to the fact that durations are collected in *Mobilität in Städten - SrV* exclusively via survey participant's statements. It is obvious that travelers will likely round up value to numbers ending with 0 or 5 instead of stating a more precise since their effort in capturing the trip duration is comprehensibly limited. Said peaks are the result. A possible smoothing of the graphs is forgone in order to not distort the characteristics of the survey data.

If one evens out the peaks mentally, one can notice that the survey possesses a somewhat higher number of shorter trips. In the simulation, there is, on the other hand, a higher amount of trips with durations of over 50 minutes. By building an improved model in the subsequent chapter (cf. chapter 6), this effect is sought sought to be balanced.

Figure 5.13 shows how the relative frequencies of average trip speeds (calculated based on beeline distances) compare between simulation results and survey data. Obviously, the speed is a measure derived from trip durations and trip distances, whose data have, thus, in a strict sense already been presented. Still, it is worthwhile to considered average speeds separately. Indeed, figure 5.13 shows that speeds in the simulation match speeds from the survey strikingly well. This is comprehensible as both trip durations and trip distances in the simulation tended to be slightly overrepresented for higher values.

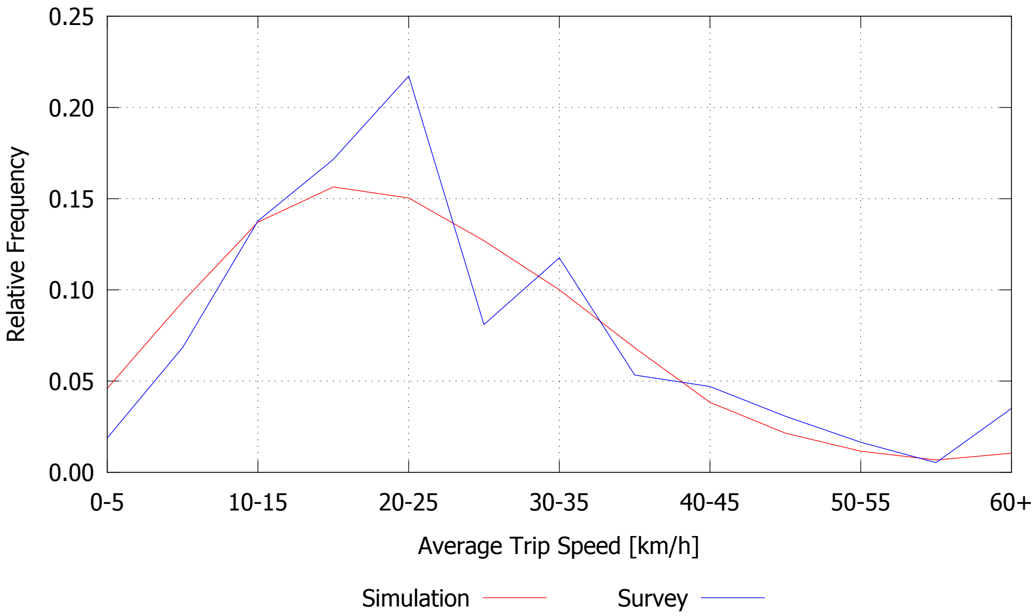


Figure 5.13.: Average Trip Speeds (Beeline Speeds) in Simulation and Survey

Last, the distribution of activity types at trip ends (i.e. the actual reasons why trips are actually conducted according to the notion of *derived demand*, cf. section 2.2) are analyzed. Figure 5.14 depicts how the according distributions from the simulation and the survey. Appendix D contains information on the preparation of activity shares.

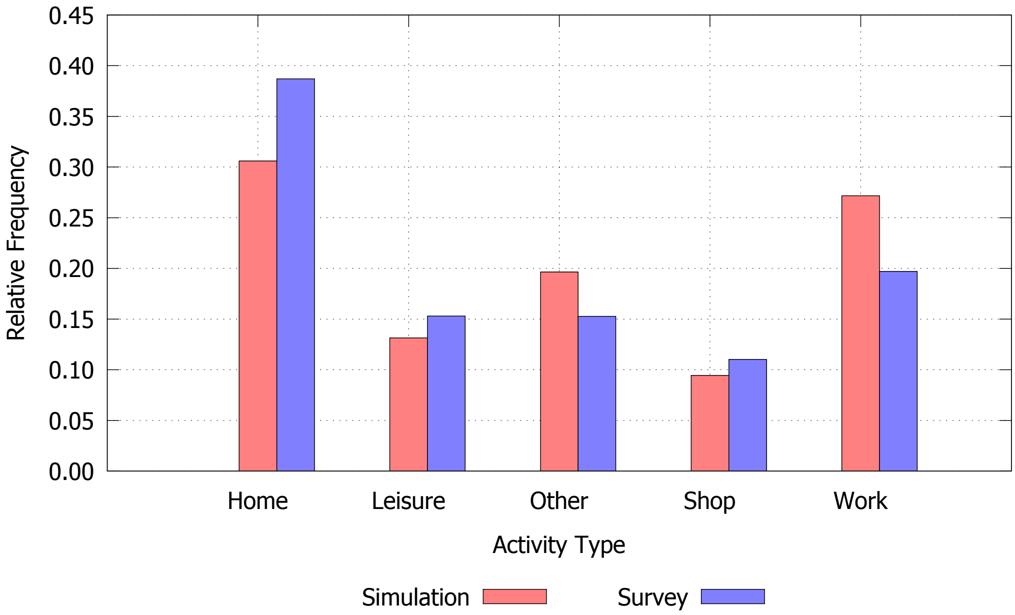


Figure 5.14.: Activity Types in Simulation and Survey

On the one hand, it is shown that the activity purposes from the simulation in general sense reflect the distribution given in the survey. On the other hand, differences concerning the shares of home and work activities are significant. Specifically, work activities are carried out relatively too often in the simulation. This is not surprising in the light of the fact that in this simple population representation – for reasons of simplicity – all people are assumed to be workers (cf. section 5.1). Furthermore, there is no mechanism in the simulation-calibration process that specifically pays attention to activities. Trips with a "wrong" activity purpose at their destination may only be sorted out via the scoring function that will deduct score in case the conducted activity does not fit well into the time window open for it between two trips. Since the translation of these effects into the scoring is, however, very indirect, it has to be followed that no real mechanism to adjust activities exists in this initial model. In a strict sense, this constitutes a violation of the paradigm concerning the treatmeant of choice dimensions whose properties can not be assured to be initially correct (cf. sections 3.3.5, 4.1.3, and 4.2). It is expected that the representation of activity purposes will improve in the model to be developed in the subsequent chapter (cf. chapter 6) as effort will be made to ensure that its population represents the real world population realistically, also in terms of employment status which arguable influences the share of work activities.

6. Elaborate Model

Like in the previous chapter (cf. chapter 5), again, the Comprehensive Econometric Model for Daily Activity-Travel Patterns (CEMDAP, cf. section 2.3) is used for initial demand generation. While in the previous chapter, the focus was on building a simple model with as few input data as possible and to be as efficient as possible, the goal of this chapter is to build a more *elaborate* model and to increase the model fit and the validity of this model. Thus, more effort is made to create a suitable input database. However, the fundamental premise of this study to only use input data that is readily available (cf. section 1.3) still holds. The general descriptions of the transport supply and transport demand have been given in sections 4.3.2 and 4.3.1. The detailed model setup for the model developed in this chapter is outlined in section 6.1. Next, results of different runs are presented in section 6.2. Finally, the validity of the model is shown in section 6.3.

6.1. Setup

The general model setups of the model developed in this chapter is analogous to the one presented in the previous chapter (cf. chapter 5). In contrast to the population used for the *initial model*, however, the population created in this chapter can be regarded as a *synthetic population*[1] in the more strict sense of the denotation. This means that the claim of this population is to reflect the real population of Berlin and vicinity in terms of major sociodemographic and socioeconomic properties like age structure, gender, employment situation etc. sufficiently well. In the previous chapter, by contrast, the focus was rather on getting the correct amount of travelers on the network as uncomplicatedly as justifiable, without paying much attention to the representation of further characteristics of the population. "As it is obvious that the representativeness of the synthetic population is critical for the simulations accuracy [...], a population approximating as accurately as possible the correlation structure of the true population" [Barthelemy and Cornelis, 2012, p.1] is

[1] A synthetic population is generated by disaggregating census data into individual people. So, a synthetic populations constitutes a random realization of the census, i.e. a census taken from the synthetic population would, within statistical limits, return the original census. A synthetic population typically encompasses households with their spatial location and some other attributes and individuals, who populate the households and possess additional attributes [Raney and Nagel, 2006, p.306].

fundamentally important to come to good results [Guo and Bhat, 2007, p.2].

Thus, the aim is to produce a population, which is in terms of important properties statistically close to the true one. To do so, again (cf. sections 4.4.3 and 5.1) the commuter file provided by the Federal Employment Agency (cf. section 4.3.2) is used as a starting point. As for the *initial model* (cf. chapter 5), for each 100 person in the commuter file, one agent with home and workplace locations according to the commuter file is created – so, again, a 1% sample is used.

Since only car traffic is to be represeted, the commuter relations taken from the Federal Employment Agency Bundesagentur für Arbeit [2010] are scaled by factors of 0.37 and 0.55 for Berlin and Brandenburg, respectively, based on information from Senatsverwaltung für Stadtentwicklung [2009, p.32]. As computed in section 4.3.2, only working people, or, more specifically, *persons subject to social insurance contributions* are contained in the commuter file. The share of the working population that is subject to social insurance contributions equals about 66%[2] in Berlin. Accordingly, commuter relations contained in the commuter file by the Federal Emplyment Agency are scaled up by a factor of 1.52 (i.e. the inverse of the share of 66%) to account for all working people.

Based on Amt für Statsitk Berlin-Brandenburg [2012b] and [Amt für Statsitk Berlin-Brandenburg, 2013, p.6], the relation between the population older than 18 years and working people was calculated as 1.9. Accordingly, the agents to be created are scaled up by this factor. Based on the same consideration it is determined wheter agents are employed or not. Age is assigned to agents based on the distribution given in [Amt für Statsitk Berlin-Brandenburg, 2013, p.6]. One or the other gender is assigned to agents with a probability of each 50%. People over 65 years are assumed to be retired. Among the 561,343 people aged 18 through 29 years, 266,671 are classified as not working under the assumption that shares of workers and non-workers do not differ significantly over different ages. As there are about 150,000 students[3] in Berlin, people aged 18 through 29 years who are not regularly working are with a probability of 56% (= 150/266) treated as students.

Based on this input, CEMDAP is run with the model specification from the trail package (cf. appendix B.5) as it was already done for the *initial model* in chapter 5. After the finalization of the CEMDAP run, its output is converted[4] into a MATSim plan file (cf. sec 3.3.4, which stores the daily plans of each agent. As the the CEMDAP output may not be regarded the final solution for agents' travel patterns because of the missing context-specific estimation of the model coefficients (cf. section 4.1.3), CEMDAP is, again, run multiple times. Each model output of

[2] Own calculations based on Bundesagentur für Arbeit [2010] and Amt für Statsitk Berlin-Brandenburg [2012a].

[3] Cf. `https://www.statistik-berlin-brandenburg.de/pms/2011/11-11-28.pdf`, last accessed 16 December 2013

[4] Using the class `CemdapStops2MatsimPlansConverter`, which is contained in appendix E.

one of these runs is considered one suggestion for a potential demand representation (cf. section 4.2). Cadyts (cf. section 3.4) is used to ensure that plans are scored both in terms of their behavioral soundness and their representativeness in terms of real-world observations (here given as traffic counts). If not stated otherwise, all following runs are carried out over 150 iterations. The innovative strategy module (i.e. the `ReRoute` module to generate new routes) is active during the first 90 of these 150 iterations.

6.2. Results

The transport supply described in section 4.3.1 and the transport demand described in sections 4.3.2 and 6.1 are fed into MATSim and run. Just as for the *initial model* (cf. chapter 5), MATSim is applied in interaction with Cadyts (cf. section 3.4.3), which influences the scores of agents' plan dependent on how well these plans match expectations with regard to traffic counts. As explained above the goal of the model developed in this chapter is to find a demand representation with a model fit and a validity as good as possible while still adhering to the premise of this study to use only easily available data inputs (cf. section 1.3).

Based on the insight gained with the initial model (cf. chapter 5), the following model parameters are varied over the subsequent sections to find the intended transport demand representation:

1. Population expansion
2. Flow capacity
3. Demand elasticity
4. Number of plans and Number of initial plans
5. Weight of the strategy module
6. Cadyts scoring weight
7. Time span for calibration

6.2.1. Population Expansion

In the section on *population expansion* of the previous chapter (cf. section 5.2.1), it was argued that the population should be expanded. This was due to the fact that assurance was given that the number of agents to be put on the network was initially correct. In line with the discussion on fixed and unfixed choice dimensions (cf. sections 3.3.5, 4.1.3, and 4.2), it was pointed out that modifications to the number of agents have to be enabled to come to a valid representation with regard to number of agents.

This more *elaborate model* is – as pointed out in section 6.1 – based on a much more precise population representation. Specifically, working status of agents is considered so that the argument that non-working people are systematically underrepresented does not hold anymore. In fact, attention was paid to create a population whose magnitude is initially correct and whose distribution with regard to employment status reflects reality sufficiently well.

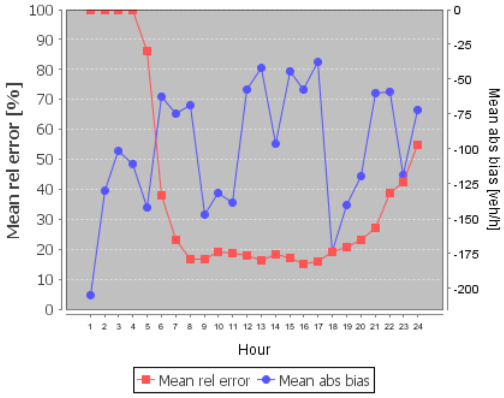
Thus, a population expansion for this chapter's more *elaborate model* seems unnecessary from a theoretical point of view. To check this assumption, four runs whose settings and results are outlined in table 6.1 are used. The according error graphs are depicted in figure 6.1.

Paramter	Run 132	Run 140	Run 136	Run 141	Reference
Population Expansion	**1x**	**1.5x**	**1x**	**1.5x**	
Demand Elasticity	Yes	Yes	Yes	Yes	
Number of Plans	10	10	10	10	
Number of Initial Plans	4	4	4	4	
Flow Capacity Factor	**0.02**	**0.02**	**0.015**	**0.015**	
Innov. Strategy/Selection	1:1	1:1	1:1	1:1	
Cadyts Scoring Weight	30	30	30	30	
Calibration Time	0 – 24h	0 – 24h	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-28	-79	-38	-37	-10*
Home-Staying Agents	*2,523*	*5,132*	*1,817*	*4,736*	–
Traveling Agents	*9,659*	*13,026*	*10,365*	*13,422*	–
Car Trips	3.20	4.18	3.34	4.08	3.2m**
Car Trips/Person	4.0	3.9	3.9	3.8	3.4**
Avg. Detour Ratio	1.70	1.78	1.80	1.88	1.58***
Avg. Trip Distance	11.0	10.9	11.6	11.0	9.5**
Avg. Trip Duration	23.4	25.2	38.5	39.4	22.3**
Avg. Score of Exec. Plans	201	126	158	132	–

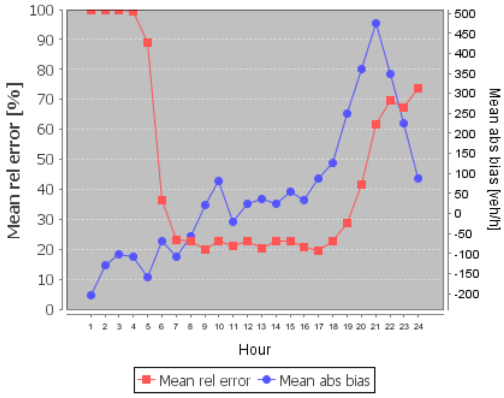
* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 6.1.: Settings and Results of Runs with different population Expansion

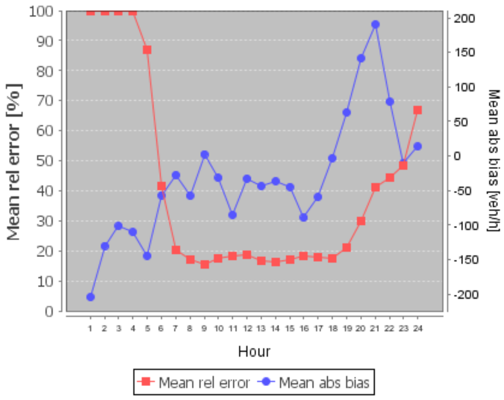
It is shown in table 6.1 that the runs with the expanded population put too many agents on the network (number of car trips) who take longer detours. In terms of other characteristics the runs based on an unexpanded population perform equally or better. Thus, the hypothesis that population expansion is unnecessary (or rather impedimentary) in connection with a synthetic population – whose magnitude and basic characteristic are ensured to be represented well – can be confirmed.



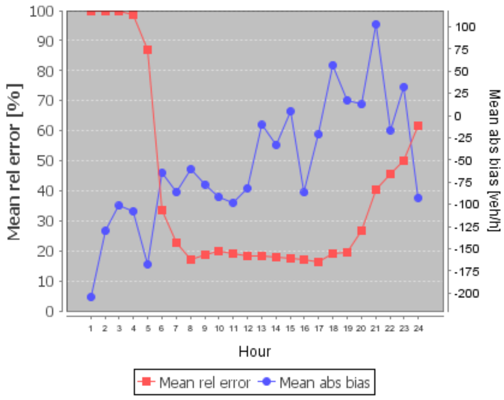
(a) Run 132 (1.0x-Exp. Population)



(b) Run 140 (1.5x-Exp. Population)



(c) Run 136 (1.0x-Exp. Population)

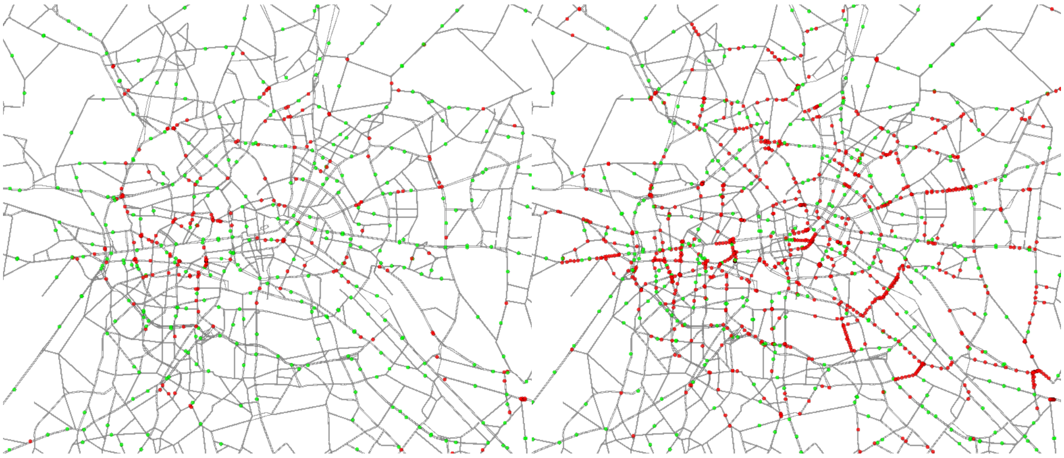


(d) Run 141 (1.5x-Exp. Population)

Figure 6.1.: Error Graphs of Runs with different Population Expansion

6.2.2. Flow Capacity

The configurations shown in table 6.1 and figure 6.1 also differ in terms of flow capacity factors. This enables a reconsideration and potential reaffirmation of the insights drawn in section 5.2.5 of the previous chapter with respect to the *initial model*. Comparing the two configurations based on an unexpanded population (i.e. `Run 132` and `Run 136`), the configuration based on flow capacity factor of 0.02 shows more realistic results. While most other measures perform similar, trip durations are too high in the configuration with the smaller flow capacity factor (i.e. with a value of 0.015). This is perfectly in line with the reasoning from section 5.2.5 where it was explained why a configuration like `Run 136` must be treated cautiously since only trip duration tells that the configuration is not ideal while most other values delusively suggest a good result. Figure 6.2 depicts the traffic patterns of two runs with different flow capacity factor at 18:00. It can be seen that the configuration with the lower flow capacity factor leads to overly high levels of congestion.



(a) Run132 (FC = 0.02) @ 18:00 (b) Run136 (FC = 0.015) @ 18:00

Figure 6.2.: Traffic Patterns of Runs with different Flow Capacity Factors

6.2.3. Demand Elasticity

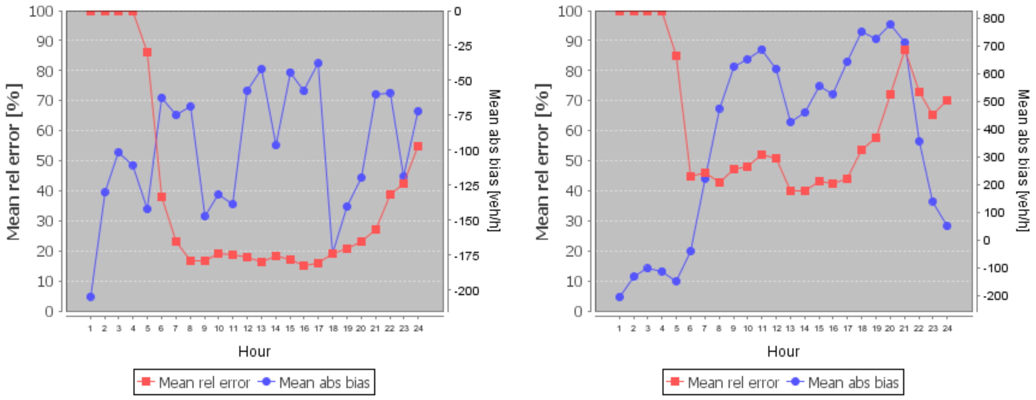
It was shown in section 6.2.1 that a population expansion is not recommendable in this model setup that is based on a realistic population representation.

Paramter	Run 132	Run 131	Reference
Population Expansion	1x	1x	
Demand Elasticity	**Yes**	**No**	
Number of Plans	10	10	
Number of Initial Plans	4	3	
Flow Capacity Factor	0.02	0.02	
Innov. Strategy/Selection	1:1	1:1	
Cadyts Scoring Weight	30	30	
Calibration Time	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-28	-208	-10*
Home-Staying Agents	*2,523*	*0*	–
Traveling Agents	*9,659*	*12,182*	–
Car Trips	3.20m	4.13m	3.2m**
Car Trips/Person	4.0	4.0	3.4**
Avg. Detour Ratio	1.70	1.73	1.58***
Avg. Trip Distance	11.0	12.5	9.5**
Avg. Trip Duration	23.4	33.3	22.3**
Avg. Score of Exec. Plans	200	61	–

* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 6.2.: Settings and Results of Runs with/without Demand Elasticity

As pointed out before, specifically in section 5.2.6, the function of *demand elasticity* ties in with *population expansion* and the Cadyts calibration functionality to enable the modification of the number of agents during the simulation-calibration process. Since this number should be initially correct the freedom for adjustment (cf. section 5.2.2) during the simulation-calibration process does not seem necessary. Table 6.2 outlines the settings and results of two configurations suitable to test this hypothesis and figure 6.3 depicts the respective error graphs.



(a) Run 132 (With Demand Elast.) (b) Run 131 (No Demand Elast.)

Figure 6.3.: Error Graphs of Runs with/without Demand Elasticity

Somewhat unexpectedly, the configuration with demand elasticity shows discernibly better results than the one without demand elasticity. As can be seen in table 6.2 the functionality to modify the number of agents makes about one fifth of all initially existing agents of the population stay at home, i.e. become inactive in terms of traveling. The number of car trips, which perfectly matches expectations based on survey data, reaffirms that the process of sorting out some agents was reasonable. Accordingly, demand elasticity will be switched on this model as well to allow the simulation-calibration process some for freedom fro adjustments.

6.2.4. Number of Plans and Number of Initial Plans

In sections 5.2.3 and 5.2.4, the number of plans and number of initial plans were analyzed. First, it was found that the number of plans should be higher (probably at least by a factor of 2) than the number of initial plans to allow enough "freedom" for all plans to be copied and evaluated sufficiently well before potentially being discarded because of agent's memory restriction related to their maximum number of plans.

Second, it was questioned in section 5.2.3 how much diversity increase is actually achieved by a higher number of initial plans (which is the actual aim of doing so) in case the process of generating new plans does only involve a limited amount of probabilism (cf. section 5.1.2).

Third, it seemed that the number of iterations may not have been high enough as to allow for the simulation process, especially for those runs with a higher number of plans, to fully converge.

To address the last issue, the number of iterations is increased from 150 iterations (the standard value used if not stated otherwise) to 250 iterations for the four runs considered in this section. Their settings and results are given in table 6.3. The error graphs of the runs are shown in figure 6.4.

Paramter	**Run 134a**	**Run 137**	**Run 139**	**Run 138**	**Reference**
Population Expansion	1x	1x	1x	1x	
Demand Elasticity	Yes	Yes	Yes	Yes	
Number of Plans	**10**	**20**	**10**	**20**	
Number of Initial Plans	**8**	**8**	**4**	**4**	
Flow Capacity Factor	0.02	0.02	0.02	0.02	
Innov. Strategy/Selection	1:1	1:1	1:1	1:1	
Cadyts Scoring Weight	30	30	30	30	
Calibration Time	0 – 24h	0 – 24h	0 – 24h	0 – 24h	
Number of Iterations	*250*	*250*	*250*	*250*	
Normalized Log-Likelihood	-141	-23	-20	-20	-10*
Car Trips	3.94	3.55	3.23	3.25	3.2m**
Car Trips/Person	4.0	4.0	4.0	4.0	3.4**
Avg. Detour Ratio	1.71	1.70	1.70	1.70	1.58***
Avg. Trip Distance	11.9	11.0	11.0	11.0	9.5**
Avg. Trip Duration	26.9	24.3	23.5	24.0	22.3**
Avg. Score of Exec. Plans	116	215	208	205	–

* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 6.3.: Settings and Results of Runs with diff. No. of Plans and *Initial* Plans

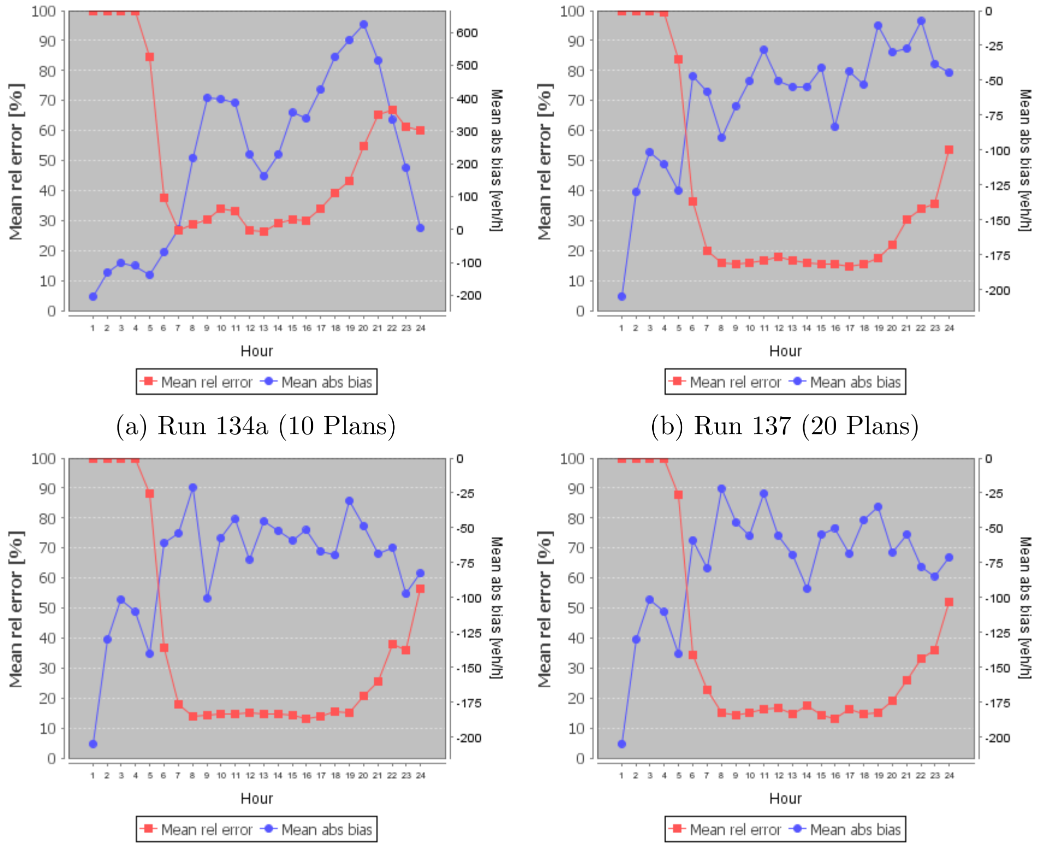
As shown in table 6.3, `Run 134a` possesses the already-mentioned property that the number of plans and the number of *initial* plans are quite similar. As speculated, this property seems to be somewhat hindering the finding of a good solution when compared to `Run 137`, which is identical except that agents are allowed to hold 20 instead of ten plans during the simulation process. The error graphs of the two runs depicted in figure 6.4 reaffirm the superiority of the configuration of the run with the higher number of plans very clearly.

Therefore, the hypothesis from section 5.2.4 that the *ratio* between the number of plans during the simulation and the number of *initial* plans is more relevant than the number of initial plans itself can be seen as confirmed.

The other two configurations (i.e. `Run 139` and `Run 138`) contained in table 6.3 mirror the two runs discussed thus far, with the only difference that agents are equipped with only four initial plans instead of eight.

First, these two runs perform strikingly similar. It can, thus, be followed that an increase of the ratio between the number of plans during the simulation and the number of *initial* plans does not have a significant effect beyond a certain value. As speculated before, a ratio of two seems to be sufficient.

Secondly, these two runs also perform very similar as `Run 137`, which also has a sufficiently high plan-to-initial-plans ratio, but a higher number of initial plans. This observation as a confirmation to the assumption that an increase in the number of initial plans does – beyond a certain value – not lead to a utilizable increase in diversity.



(a) Run 134a (10 Plans)

(b) Run 137 (20 Plans)

(c) Run 139 (10 Plans)

(d) Run 138 (20 Plans)

Figure 6.4.: Error Graphs of Runs with different Numbers of Plans and *Initial* Plans

To sum up, a ratio between the number of plans during the simulation and the number of *initial* plans should at least reach a value of two. Four initial plans (where one plan is the stay-home option to enable demand elasticity) seems sufficient.

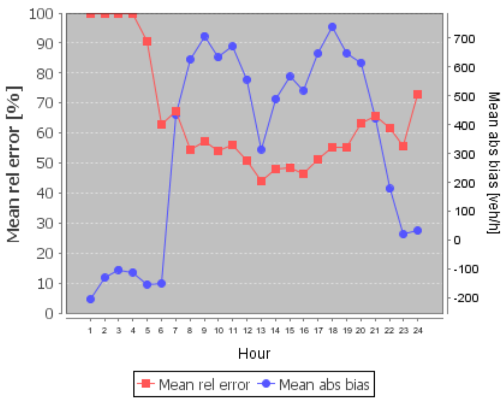
6.2.5. Cadyts Scoring Weight

In the respective section on the Cadyts scoring weight in the chapter of the *initial model* (cf. section 5.2.6), only the general meaning of the Cadyts scoring weight was discussed. Here, a detailed analysis of the concrete value w is conducted, for which the four configurations outlined in table 6.4 are used. The respective error graphs are depicted in figure 6.5.

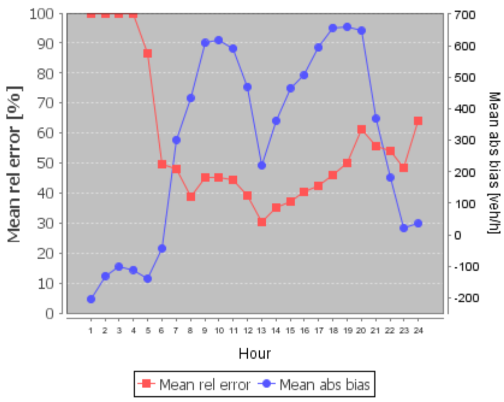
Paramter	Run 130	Run 132e	Run 132	Run 132a	Reference
Population Expansion	1x	1x	1x	1x	
Demand Elasticity	Yes	Yes	Yes	Yes	
Number of Plans	10	10	10	10	
Number of Initial Plans	4	4	4	4	
Flow Capacity Factor	0.02	0.02	0.02	0.02	
Innov. Strategy/Selection	1:1	1:1	1:1	1:1	
Cadyts Scoring Weight	**0**	**10**	**30**	**50**	
Calibration Time	0 – 24h	0 – 24h	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-222	-168	-28	-22	-10*
Car Trips	4.12m	4.05m	3.20m	2.99m	3.2m**
Car Trips/Person	4.0	4.0	4.0	3.8	3.4**
Avg. Detour Ratio	1.76	1.77	1.78	1.77	1.58***
Avg. Trip Distance	12.3	12.1	11.0	11.3	9.5**
Avg. Trip Duration	30.7	29.5	23.4	23.7	22.3**
Avg. Score of Exec. Plans	172	141	200	248	–

* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

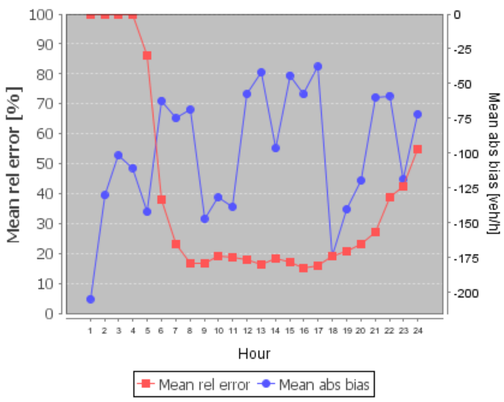
Table 6.4.: Settings and Results of Runs with different Cadyts Scoring Weights



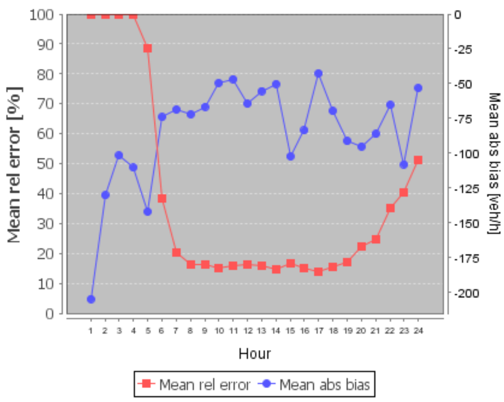
(a) Run 130 (w = 0.0)



(b) Run 132e (w = 10.0)



(c) Run 132 (w = 30.0)



(d) Run 132a (w = 50.0)

Figure 6.5.: Error Graphs of Runs with different Cadyts Scoring Weights

First of all, the results show that the choice of the Cadyts scoring weight w is, in fact, influential. Not only the fact that Cadyts calibration is applied (i.e. that w is chosen greater than zero), but also the strength of this application make a difference. For instance, it is shown quite clearly in figure 6.5 that the effects of a Cadyts scoring weight of 10.0 are much different from those effected by a scoring weight of 30.0. In fact, mean relative errors of the configuration with $w = 10.0$ are very similar to those without obtained without calibration (i.e. `Run 130` with $w = 0.0$). The configuration with $w = 30.0$, by contrast, yields heavily improved result in terms of all relevant measures. Increasing w further does not lead to additional improvement. While the normalized log-likelihood (i.e. the model fit) is improved somewhat further, measures of travel characteristics show slight debasements. In particular, the number of car trips falls below the number of expected trips in terms of survey results. Thus, the deduction suggest itself that a Cadyts scoring weight greater than 30 may promote overfitting (cf. section 5.3).

6.2.6. Weight of Strategy Module

In the respective section on the weight of the strategy module the chapter of the *initial model* (cf. section 5.2.7, it was found quite clearly that runs in which the probabilistic selection is applied more often relative to the application of the innovative strategy module (i.e. the `ReRoute` module) perform better.

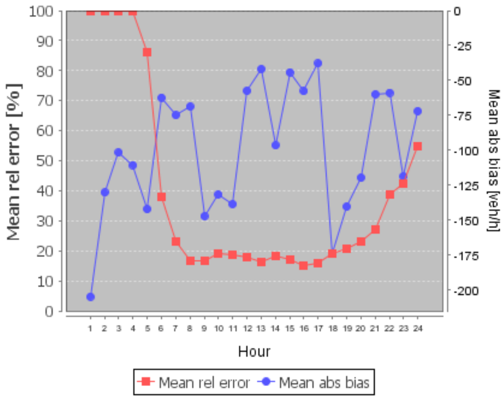
Paramter	**Run 132**	**Run 132d**	**Run 136**	**Run 136b**	**Reference**
Population Expansion	1x	1x	1x	1x	
Demand Elasticity	Yes	Yes	Yes	Yes	
Number of Plans	10	10	10	10	
Number of Initial Plans	4	4	4	4	
Flow Capacity Factor	**0.02**	**0.02**	**0.015**	**0.015**	
Innov. Strategy/Select.	**1:1**	**1:2**	**1:1**	**1:2**	
Cadyts Scoring Weight	30	30	30	30	
Calibration Time	0 – 24h	0 – 24h	0 – 24h	0 – 24h	
Normalized Log-Likelihood	-28	-23	-38	-23	-10*
Car Trips	3.20	3.13	3.34	3.18	3.2m**
Car Trips/Person	4.0	4.0	3.9	3.9	3.4**
Avg. Detour Ratio	1.70	1.69	1.80	1.76	1.58***
Avg. Trip Distance	11.0	11.0	11.6	11.3	9.5**
Avg. Trip Duration	23.4	22.5	38.5	36.0	22.3**
Avg. Score of Exec. Plans	201	213	158	206	–

* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

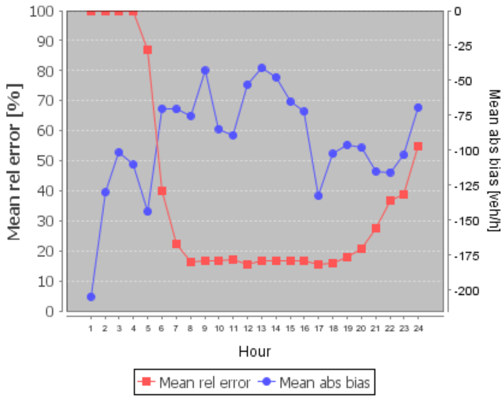
Table 6.5.: Settings and Results of Runs with different Weights of the Strat. Mod.

The aim of this section is to reaffirm this observation also on the basis of the more elaborate population representation used in this section.

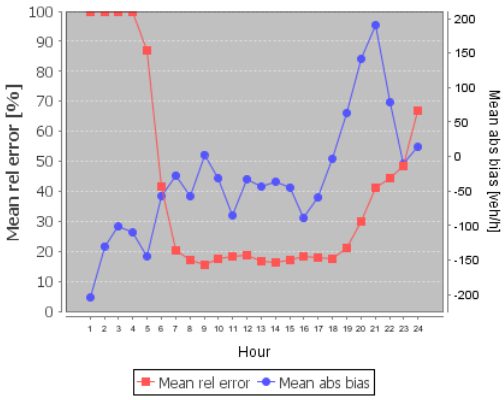
In table 6.5, four runs with different ratio of the weight of the `ReRoute` module and the probabilistic selection module are outlined. In figure 6.6 the respective error graphs are depicted.



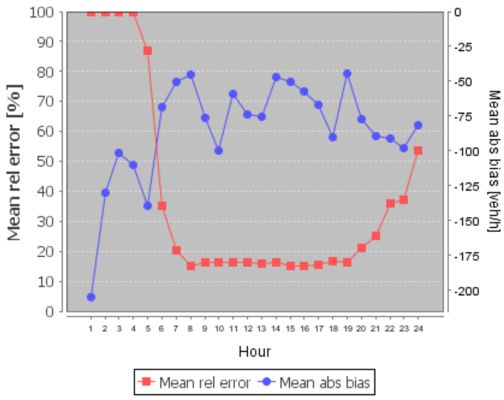
(a) Run 132 (Strat./Sel. = 1:1)



(b) Run 132d (Strat./Sel. = 1:2)



(c) Run 136 (Strat./Sel. = 1:1)



(d) Run 136b (Strat./Sel. = 1:2)

Figure 6.6.: Error Graphs of Runs with diff. Weights of the Strategy Module

Comparing the results of the runs in table 6.5, it can be seen that – as before (cf. section 5.2.7) – the configuration where the weight of the strategy module is lower than the weight of the probabilistic selection perform better than there counterparts where both said weights are eqaul. In contrast to observation made with the *initial model* (cf. section 5.2.7), however, improvements made by increasing the weight of probabilistic selection are not as big. This is likely due to be fact that configurations in terms of other parameters have already been improved further. While the observation that higher weights for probabilistic selection leads to a better convergence still holds, its effect is simply not as big anymore. As a side note, the observations concerning flow capacity factor made in sections 5.2.5 and 6.2.2 can be reaffirmed by observing the, again, too high travel times of the two runs based on a flow capacity facotr of 0.015 shown in the right part of table 6.5.

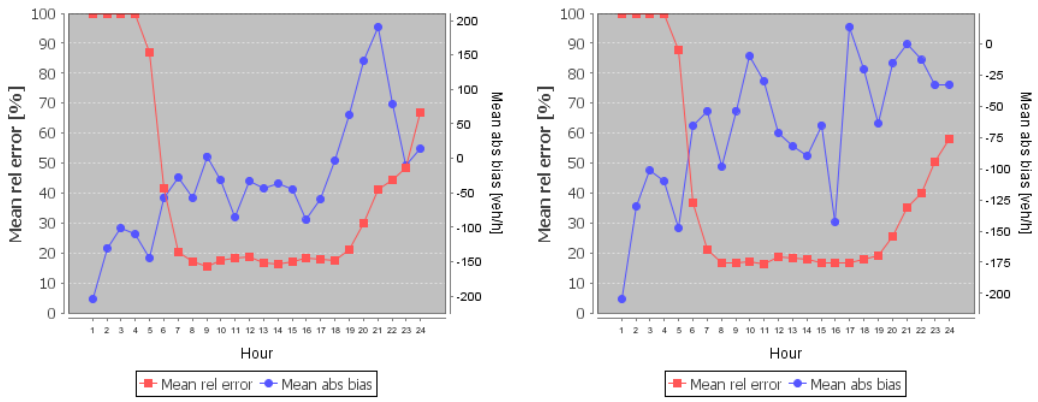
6.2.7. Time Span for Calibration

The time span which is used for the Cadyts calibration can be selected. The default is 00:00:00 through 24:00:00. In order not to spoil results, it may be reasonable to exclude very early hours of the day from the calibration, because CEMDAP plans do not contain any traffic before 3 a.m.[5]. Since traffic count data starts at midnight, there would be a systematic deviation if very early hours are used. Accordingly, two runs whose configurations are given in table 6.6 are compared. The according error graphs are depicted in figure 6.7.

Paramter	**Run 136**	**Run 136a**	**Reference**
Population Expansion	1x	1x	
Demand Elasticity	Yes	Yes	
Number of Plans	10	10	
Number of Initial Plans	4	4	
Flow Capacity Factor	0.015	0.015	
Innov. Strategy/Selection	1:1	1:1	
Cadyts Scoring Weight	30	30	
Calibration Time	**0 – 24h**	**4 – 24h**	
Normalized Log-Likelihood	-38	-27	-10*
Car Trips	3.34	3.32	3.2m**
Car Trips/Person	3.9	3.9	3.4**
Avg. Detour Ratio	1.80	1.80	1.58***
Avg. Trip Distance	11.6	11.5	9.5**
Avg. Trip Duration	38.5	37.6	22.3**
Avg. Score of Exec. Plans	158	169	–

* cf. [Flötteröd, 2009, p.10]
** cf. scetion 4.4.1
*** cf. section 4.4.2

Table 6.6.: Settings and Results of Runs with different Time Spans for Calibr.



(a) Run 136 (Calibr. Time = 0 – 24h) (b) Run 136a (Calibr. Time = 4 – 24h)

Figure 6.7.: Error Graphs of Runs with different Time Spans for Calibration

[5] A CEMDAP day starts by default at 3a.m. [Bhat et al., 2004, p.58].

The run with time span for Cadyts calibration from 04:00:00 through 24:00:00 (`Run 136a`) shows an improvements in model fit (as measured in terms of normalized log-likelihood) over a run whose Cadyts calibration time spans from from 00:00:00 through 24:00:00. Looking at the other parameters, however, it becomes clear that no much has changed in terms of agents' travel behavior. Basically, the log-likelihood values seems to only have improvement because early morning our, which seem to have spoilt the value to some extent, are not considered anymore. As no relevant changed in terms of travel behavior could be detected, the choice of the time span for calibration seems to be of very minor importance.

6.2.8. Summary

Summarizing the analyses of the previous sections (cf. sections 6.2.1 through 6.2.6), the following insights for the creation of a transport model as close to reality as possible can be outlined:

- As opposed to the *initial model* – where the inital amount of agents was not guaranteed to be correct (cf. section 5.2.1) – a *population expansion* is not necessary in this model, where efforts are taken to ensure that the initial population is correct in terms of its basic distributions as well as the amount of its members.

- Still, the opportunity to modify this value to some extent was found to be beneficial which is why the option of *demand elasticity* should, again, be switched on.

- In line with preliminary results (cf. section 5.2.8), it is recommended to choose the *number of plans* about twice as high as the number of *initial* plans.

- Again, a value of four seems to be sufficient for the *number of initial plans*.

- For the *flow capacity*, again, a value of 0.02 was found to be reasonable.

- The *Cadyts scoring weight* should be chosen to a value of about $w = 30.0$. Lower values were detected to be not influential enough as to cause the desired calibration effect. Values higher than $w = 30.0$ showed some slight indications of overfitting (cf. section 5.3).

- It has to be confirmed that the *weight for innovative strategy module* should be selected somewhat lower than the weight for the probabilistic plan selection module. If the simulation configuration is, however, well-balanced up to this point, the choice of this value seems to be of minor importance.

- The choice of *time span for calibration* seems to only influence results cosmetically as long as it is guaranteed that those hours of the day in that significant amounts of traffic exist, are included in this time span.

6.3. Validation

Analogous to the procedure of the validation of the *initial model* (cf. section 5.3, the best model in terms of the parameter combination tested in the previous sections of this chapter and outlined in section 6.2.8 is validated now. To do so, travel characteristics of the simulation are compared to real-world travel characteristics as contained in the travel survey (cf. 4.4.1). As mentioned before, the comparative values from the survey were prepared via the Java program `SrVTripAnalyzer`, which is contained in appendix E based on the originl survey data Ahrens [2010c].

`Run 132d` possesses the properties outlined in section 6.2.8. Its configuration is given table 6.5. It can be seen in the table that the number of all daily car trips (3.13m in `Run 132d`) hardly diverges from travel survey data (3.20m). this constitutes an improvement over the *initial model*.

The distribution of trips by time of day is depicted in figure 6.8.

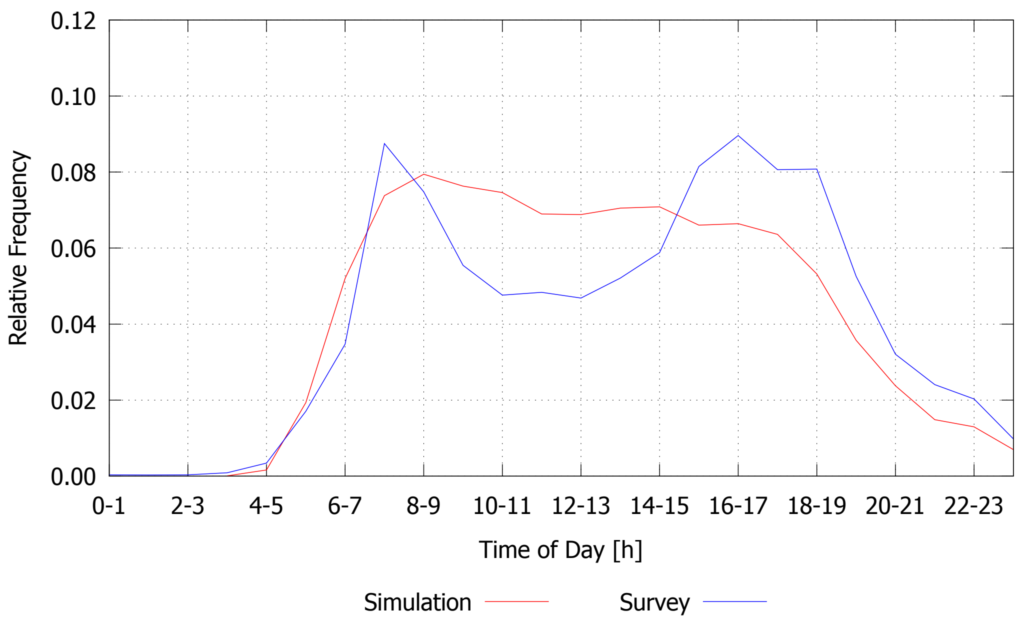


Figure 6.8.: Departure Times in Simulation and Survey

As in section 5.3, there is somewhat more traffic during daytime and a bit less traffic in the evening.

Next, trip distances are analyzed on the basis on *beeline distances* (cf. section 4.4.2). Figure 6.9 shows how the relative frequencies of trip distances compare between simulation results and survey data.

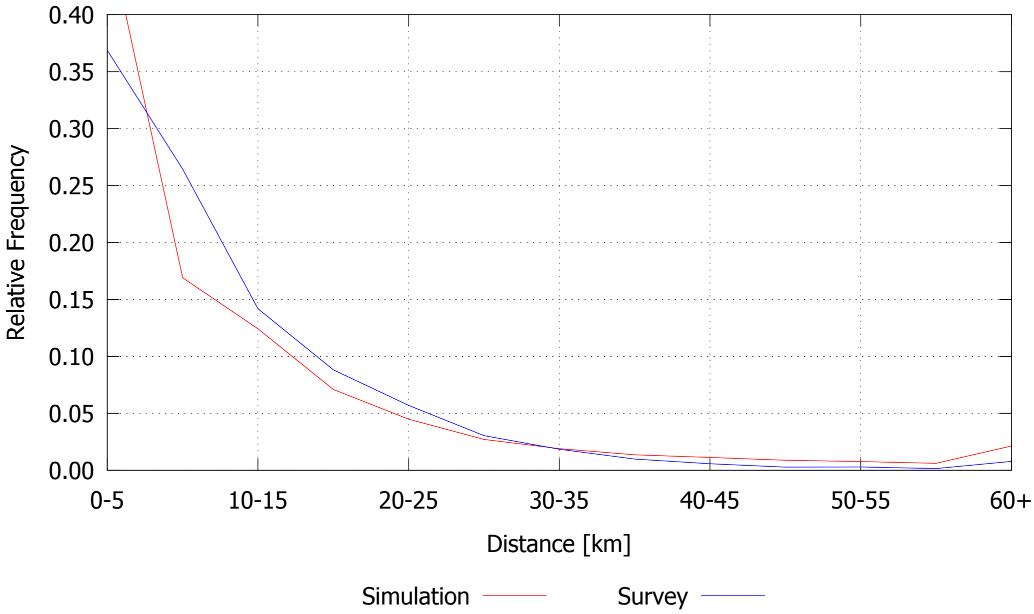


Figure 6.9.: Trip Distances (Beeline Distances) in Simulation and Survey

The figure is very similar to figure 5.11 for the *initial model*. It can be seen that the survey contains somewhat more trips with short distances around five through ten kilometers.

Figure 6.10 shows how the relative frequencies of trip durations compare between simulation results and survey data.

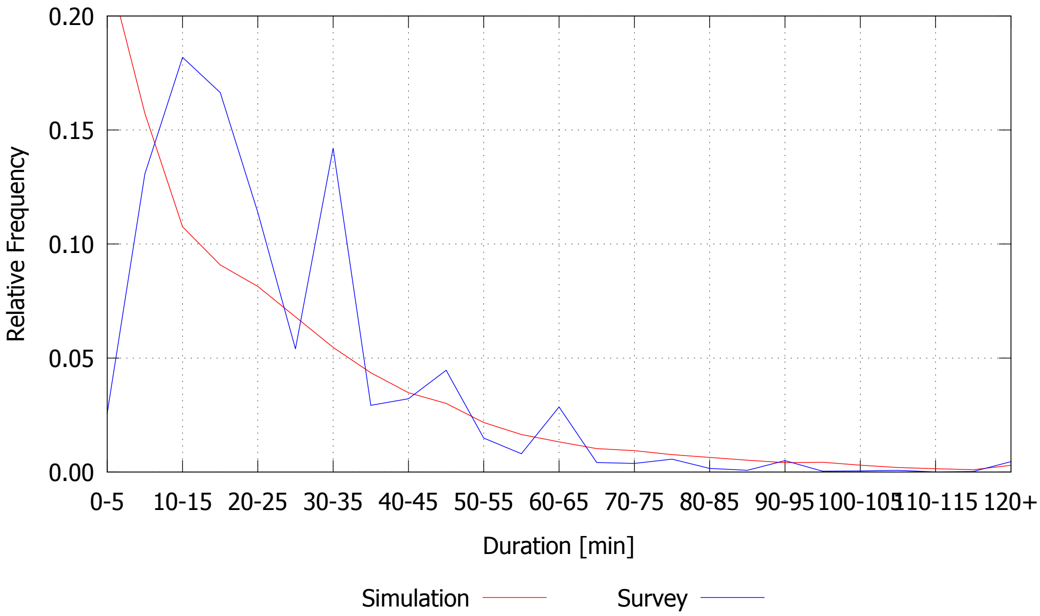


Figure 6.10.: Trip Durations in Simulation and Survey

Again, differences to the comparion drawn before between the *initial model* (cf. section 5.3) are very small. Again, if one evens out the peaks contained in the graph for the survey data mentally, one can notice that the survey possesses a somewhat higher number of shorter trips. The little excess of trips with durations of over 50 minutes appear, however, slightly reduced when comapred to results for the *initial model*.

Figure 5.13 shows how the relative frequencies of average trip speeds (calculated based on beeline distances) compare between simulation results and survey data.

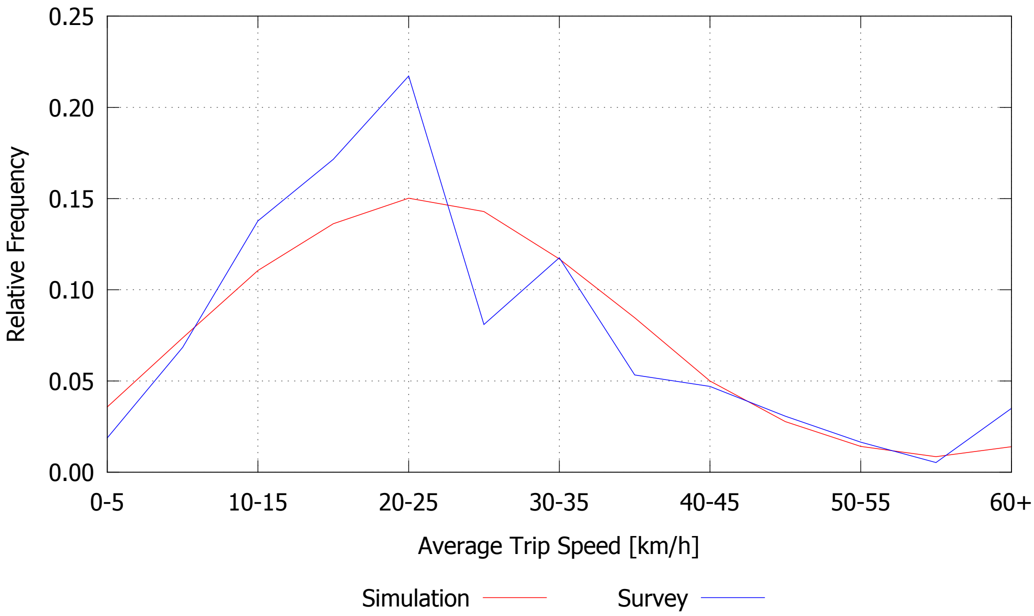


Figure 6.11.: Average Trip Speeds (Beeline Speeds) in Simulation and Survey

It is shown in figure that speeds in the simulation match speeds from the survey well.

Finally, the distribution of activity types at trip ends is analyzed. Figure 6.12 depicts how the according distributions from the simulation and the survey. Appendix D contains information on the preparation of activity shares.

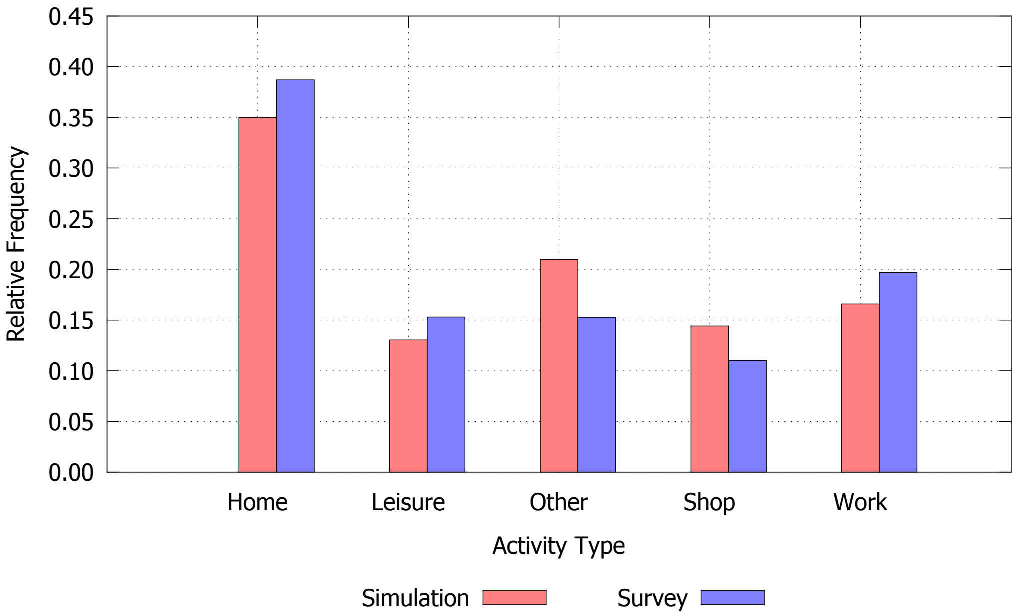


Figure 6.12.: Activity Types in Simulation and Survey

Compared to the activity distribution of the *initial model* (cf. section 5.14, a discernible improvement can be seen. While work activities were carried out relatively too often in the simulation of the *initial model*, here the share of work activities as given in the survey is met much better. This was expected because to the fact in the simple population representation of the *initial model* all people were assumed to be workers (cf. section 5.1), whereas in this model employment status is explicitly considered (cf. section 6.1).

In fact, the simulation produces, in contrast to observations made for the *initial model*, somewhat too few work activities. Overall, the distribution of the survey is met quite well.

As pointed out in section 5.3, there is no specific mechanism in the simulation-calibration process that caters for the right representation of activity types. Therefore, the the distribtion of activites at trip end needs to be initially correct (cf. discussion of fixed and modifiable choice dimension in sections 3.3.5, 4.1.3, and 4.2). As mentioned above, this fact has been taken into account in setting up the population representation for the model developed in this chapter.

In fact, the simulation produces, in contrast to observations made for the *initial model*, somewhat too few work activities. Overall, the distribution of the survey is met quite well.

7. Conclusion, Discussion, and Outlook

Transport systems of the modern world are situated in a dilemma. On the one hand, they are fundamentally important for the development of societies and economies and, thus, an important prerequisite for welfare. On the other hand, they constitute an important cause of most urgent problems of our times like global warming because they are a big contributor to the emission of greenhouse gases (cf. chapter 1). At the same time, transport systems are also responsible for other negative effects impairing the well-being of people and the preservation of the environment.

It has been acknowledged that novel solution are needed to come to balanced solutions that enable the provision of an efficient transport system while limiting and reducing adverse effects. The assessment of proposed solutions is, however, a challenging task. Numerous actors are involved and interdependencies among induced effects are hard to overlook. Therefore, suitable tools are needed in order to gain insights concerning the effects of changes in the transport system. Transport models have been shown to be able to serve this need (cf. section 1.1). Their establishment and maintenance is, however, mostly expensive as well as the obtaining of the required input data. Due to data privacy issues the collection of suitable input data may become even more strenuous in the future. Furthermore, many models, in particular traditional ones based on aggregate considerations of traffic flows, are not suitable to assess novel transport policies that go beyond the construction of infrastructure.

This is why, a simple transport model has been developed in this study. The overarching premise was to only use input data that are readily available and easy to obtain (cf. section 1.3). Thus, only data on commuter relations and some socio-demographic population characteristics for the metropolitan area of Berlin, the study area of the model, were used.

A microscopic modeling approach (MATSim, cf. section 3.3) based on a genetic algorithm is used to find a transport demand representation. In this approach, each traveler is retained individually with all their relevant properties during the whole simulation process. Travel behavior is explicitly considered as each traveler, referred to as an *agent*, assesses their own behavior based on a utility function.

Since the amount of input data is limited, it becomes more challenging to find an initial demand representation upon which modifications can be made by the iterative simulation procedure of MATSim. Therefore, an econometric activity simulator

(CEMDAP, cf. section 2.3) is used to create initial suggestions of travel demand representations. Notably, the CEMDAP output may, at first, not be considered a valid representation of travel demand. This is due to the fact that no estimation of the CEMDAP model parameters is carried out for the region of application. Instead, a model configuration for another geographic region is applied. This limitation is compensated by regarding the CEMDAP output as initial suggestions of demand instead of final solution as it would be possible if a correctly estimated model configuration was used.

Multiple CEMDAP output (called sets of *activity-travel patterns*) are created and fed into the MATSim transport system simulation. In connection with a calibration algorithm (Cadyts, cf. section 3.4), it is ensured that those initial demand suggestion prevail that constitute good solutions to the problem of finding a valid transport demand representation. The difference towards other applications of MATSim is, thus, that less effort is put into finding a suitable initial demand. This is balanced by ensuring that realistic traveling population develops over the course of the iteration via the application of the Cadyts algorithm.

In the previous two chapters (cf. cahpters 5) and 6), two transport demand models were created, analyzed, and validated. The first model, branded as *initial* (cf. chapter 5) was intended to analyze effects of applying variation to several model parameter. The second model, branded as *elaborate* (cf. chapter 6) was intended to make use of the insights gained from the *initial model* and, based on them, build a model, which, on the one hand, possesses a good model fit and, on the other hand, can be validated in terms of traffic characteristics. These characteristics are mainly drawn from the Berlin 2008 SrV travel survey (cf. section 4.4.1).

The *initial model* is based on a very simple representation of the real-world population. The guiding idea (cf. section 5.1 in creating this population representation has been to get started as quickly as possible in order to obtain first, preliminary results that can be used for analyses of various characteristics of the model. After several variations of model parameters had been tested, a model with a good model fit was found. In fact, the preferred configuration of parameters which was used for model validation in section 5.3 is largely compatible with the preferred configuration of parameters of the *elaborate model*.

The *elaborate model* is, by contrast, based on a population that reflects the real-world population in its basic characteristics (e.g. age distribution or employment status of its members etc.). The transport model built on the basis of this population shows slight improvements over the *initial model*. While differences in terms of travel characteristics like trip durations and trip distances are not majorly different, the *elaborate model* performs significantly better in terms of representation of activity participation. This was expected since activity participation is, obviously, highly dependent on sociodemographic characteristics. As mentioned above, such characteristics are only modeled with sufficient accuracy in the *elaborate model*.

It can be considered a strength of the simulation-calibration process that it manages to select a valid demand representation out of a rough initial population representation in the *initial model*. To achieve this, a quite complex interaction of the different applied functionalities is needed. For instance, it is not initially clear whether the size of the population (i.e. the number of agents) is correct. An expansion of the population beyond its actual (assumed) size, connected with the freedom to make agents become inactive (i.e. to "stay at home", referred to as *demand elasticity*) and the Cadyts calibration algorithm, which controls this effect, provides the functionality to determine the number of agents during the simulation-calibration process. This example illustrates how a significant amount of information that is usually necessary at the initialization of a transport model can be forgone (cf. section 4.1).

Still, a more realistic reproduction of activity participation as it is achieved by the *elaborate model* may be essential if the transport model created by the discussed procedure is used for policy analysis. An examination of this assumption is left for subsequent studies.

In terms of further refining the created model, some additional modifications seem feasible. Residential patterns for people living in Berlin, for instance, have been modeled on the basis of district regions, which subdivide Berlin into geographic area that are homogeneous in terms of the number of people who live it (cf. section 4.3.2). Accordingly, a random choice of one district region to become the home location for a given agent is used to reproduce real-world residential patterns of Berlin. For workplace locations, however, the approach is not feasible as they are distributed differently. In this study, random geographical entities are chosen as potential workplace locations and it is left to the simulation-calibration procedure to sort those out that lead to realistic travel pattern. It seems worthwhile, however, to assess the effects of using data that contain information on the spatial workplace distribution of Berlin and to select workplace locations on the basis of this data. A potential source may be so-called *enterprise registry data* (in German: *Unternehmensregisterdaten*) as for instance described by Bömermann and Heymann [2011].

Notably, a quite novel treatment of choice dimension has been introduced through the application of CEMDAP and Cadyts in this study. Usually, choice dimensions (e.g. departure time choice, mode choice, route choice etc.) can be considered either fixed or unfixed from the point of view of the simulation (cf. sections 3.3.5, 4.1.3, and 4.2). The properties in terms of unfixed choice dimension can be modified during the simulation process and need, thus, not be perfectly represented at simulation initialization in case a mechanism (referred to as *(innovative) strategy module*, cf. section 3.3.3) is used in the simulation process to guide the development of the considered properties in the desired direction. If no module for a given choice dimension is applied in the simulation process, however, it needs to be assured that the respective property is correct at initialization as it will stay unchanged during the simulation process. In this study, only the `ReRoute` module – responsible for finding new routes – is applied. Thus, route choice is, in the stricter sense of the concept, the only unfixed choice dimension in this model.

Even though no explicit module for time choice or location choice is applied in the simulation process, these choice dimension are still modifiable to a limited extent. This is due to the fact that multiple initial plan suggestion are provided to the simulation process by CEMDAP (cf. section 4.1.3). Since these outputs contain diversity (cf. section 5.1.2) in terms of activity timing and activity locations, a choice among this diversity is possible during the simulation process. The major difference towards the application of explicit strategy modules for these choice dimension is that in this study only modifications to the discrete options provided by CEMDAP are possible while an explicit module would theoretically enable an infinite amount of options to select from.

An arguable disadvantage of the approach applied in this study may be, though, that no feedback from MATSim to CEMDAP is given. So, location choice and time choice (according options being provided via CEMDAP initially) are not dependent on network conditions. This may be improved by the introduction of some feedback loop from MATsim to CEMDAP in potential follow-up studies.

Finally, it has to be concluded that the model created in this study can be validated very well. First, the model fit of the preferred parameter combination (cf. `Run 132d` given in table 6.5 and figure 6.6) fulfills the general quality criteria in modeling. MRE error for volumes of traffic are (as shown in figure 6.6) discernibly below 20% during daytime hours. The performance in terms of model fit is, thus, better as that of the benchmark model shown in section 4.4.3, even though the modeling effort is arguably lower.

The validation based on the preferred parameter combination carried out in section 6.3 can also be seen as successful concerning all considered properties, which encompass the total amount of car trips, the distributions of departure times, trip duration, trip distance, and average trips speeds as well the the distribution of activity participation at trip ends.

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A. Documentation of Workflow

In this appendix, the workflow from receiving input data via running CEMDAP and MATSim in interaction with Cadyts until drawing conclusions on analyzed output data is documented. As opposed to the chapters above, the focus here is on the technical side.

- Preparation of input data for CEMDAP
  - Use the files `B2009Ga.xls` (outward commuters) and `B2009Ge.xls` (inward commuter) as provided by the Federal Employment Agency (cf. section 4.3
  - Open the files in Microsoft Excel, switch off thousand seperation, and save them as tab-separated text files
  - Run the Java program `DemandGeneratorOnePerson`, which among others generates an instance of the Java object `CommuterFileReader`. The `CommuterFileReader` takes care that only lines with commuter data (i.e. no headers, footers etc.) are read. Also, it checks whether commuter relations fall within the planning area by comparing municipality keys of the trips' origins and destinations with keys gained form a shapefile that contains all municipalities to be considered (all Brandenburg municipalities and the city-state Berlin, which constitutes a municipality as well). The output are one `households.dat` and a specified number of `person[number].dat` files.
  - For each persons file, load the `households.dat` and one of the different `persons[number].dat` files along with `.dat` files concerning zones, zone-to-zone relations, level of service data, and vehicle data into a `PostGreSQL` database as instructed in the CEMDAP user manual [Bhat et al., 2008, p.60], i.e. create a new database (set encoding to `SQL_ASCII` and run two query files given in [Bhat et al., 2008, p.61] to create tables and indices.
  - On the command line, navigate to the `PostGreSQL` bin folder and open the database with `psql -d [database name] -U [user name]` and load all input files (e.g. `copy households from ../households.dat`).

- Run CEMDAP
  - Open CEMDAP (using CEMDAP5Threads)
  - Load the database [Bhat et al., 2008, p.15] via `Input` in the `Data` menu. Choose `New...` in the register card `Machine Data Source` and select `SystemDataSource`. Select `PostGreSQL (ANSI)` as driver and specify the database by its name. Name and save the configuration.
  - Select an output folder, load a suitable model specification file, and start the simulation run.
  - Do this as many times as there are different person files to be considered. Each of these runs constitutes one initial potential solution for a daily activity-travel pattern for every agent (cf. section 4.1.3)
- Convert CEMDAP output into MATSim input
  - Use the multiple `stop files` of the output of CEMDAP as described in appendix B.6.
  - Run `CemdapStops2MatsimPlansConverter` to create a MATSim `XML` plan file that contains the activity-travel patterns drawn from all assigned CEMDAP `stop files`.
- Run MATSim in connection with Cadyts
  - Start Eclipse where MATSim needs to be set-up according to instruction form the MATSim website[1].
  - Set the above-created MATSim `XML` plan as input in the MATSim setup outlined in appendix C (which is also part of appendix E).
  - Run the `CadytsControllerBerlin`.
- Analyze MATSim output
  - Several analysis programs implemented in Java can be used to create the analyses presented in chapters 5 and 6. These analyses are largely based on events[2] and are contained within appendix E.

[1] Cf. `http://www.matsim.org/docs/tutorials/8lessons`, last accessed 16 December 2013.
[2] Cf. `http://www.matsim.org/docs/tutorials/8lessons/output/events`, last accessed 16 December 2013.

B. CEMDAP Setup

In this section, the technical setup for the CEMDAP scenario including the definition of all used variables (cf. [Bhat et al., 2008, p.10f] and [Bhat et al., 2008, p.55f]) and the adaption of a ready-made and provided model specification file (cf. [Bhat et al., 2008, p.21]) are presented.

B.1. Households File

The file `households.dat` encompasses 32 variables altogether (cf. [Bhat et al., 2008, p.57]), of which six are "required" and 26 are "optional". The required variables and the corresponding values used in this study are given in table B.1. Information concerning the optional variables was not easily available, which is why the optional variables were unconsidered in this study and set to zero [1].

Paramter	Description	Initial Model	Elaborate Model
HHID	Household ID	ascending from 1	ascending from 1
NADULT	Number of adults	1	1
NVEH	Total number of hh. veh.	1	1
HOMETSZ	Home TSZ location	randomly selected*	randomly selected*
NCHILD	Number of children	0	0
HHSTRUCT	household structure	1	1
	26 remaining variables	0	0

* constant over multiple plans of a given agent

Table B.1.: Variables in Households Input File

B.2. Persons File

The file `persons.dat` encompasses 59 variables altogether. The considered variables and the corresponding values used in this study are given in table B.2. All other variables are set to zero along with corresponding adjustments in the model specification (cf. section B.5).

[1] It needs to be mentioned that using a zero here, i.e. for the *value* of a variable, does not have a particular meaning. In fact, it simply constitutes a randomly chosen placeholder value that is necessary because any column expected to exist according to the modeling system needs to be filled with a value. By corresponding adjustments in the model specification file (i.e. setting the respective *coefficient* to zero, cf. section B.5), the model is told which variables effectively stay unconsidered.

Paramter	Description	Initial Model	Elaborate Model
HHID	Household ID	cf. B.1	cf. B.1
PerID	Person ID	HHID + 01	= HHID + 01
Aemp	Adult is employed	1	0 or 1***
Stu	Adult or child is a student	0	0 or 1***
License	Person is licensed to drive	1	1
WorkTSZ	Work TSZ	randomly selected*	randomly selected*
SchTSZ	School TSZ	-99	randomly selected*
Female	Person is female	1	0 or 1****
Age	Age	randomly selected**	?***
Parent	Parent	1	0
	42 remaining variables	0	0

* also variant over multiple plans of a given agent
** out of a range from 18 through 99
*** according to own calulations described in section 6.1
**** each with a probability of 50%

Table B.2.: Variables in Persons Input File

B.3. Zones File and Zone-to-Zone File

The file `zones.dat` encompasses 45 variables altogether. It is assigned according to municipality IDs in Brandenburg and LOR IDs in Berlin (cf. section 4.3.2). All other variables are set to zero along with according adjustments in the model specification (cf. section B.5). The file `zone2zone.dat` carries four variables. The according values used in this study are given in table B.3.

Paramter	Description	Initial Model	Elaborate Model
Origin_zone	TSZ zone ID - origin	municip. or LOR ID*	municip. or LOR ID*
Dest_zone	TSZ zone ID - destination	municip. or LOR ID*	municip. or LOR ID*
Adjacent	Orig. and dest. are adjacent	0	0
Distance	Distance between zones	Centroid beeline dist.	Centroid beeline dist.

* In Brandenburg, zoning is based on municipalities. Here, the according municipality IDs are used. In Berlin, zoning is based on medium-level LORs. Here, the according LOR IDs are used (cf. section 4.3.2).

Table B.3.: Variables in Zone-to-Zone Input File

B.4. Level of Service File

The CEMDAP database contains four level of service tables corresponding to two peak periods (a.m. and p.m.) and two offpeak periods (a.m. and p.m.) labeled `losoffpkam.dat`, `losoffpkpm.dat`, `lospeakam.dat`, and `lospeakpm.dat`. The file `losdir.dat` tells CEMDAP which of the four level of service files to use for which period. In this study only one level of service file is used for all four time periods for reasons of simplicity. The layout for each of these four files is the same and comprises 14 variables. The variables and their according values used in this study are given in table B.4.

Paramter	**Description**	**Initial Model**	**Elaborate Model**
Origin	TSZ zone ID - origin	B.3	cf. B.3
Destination	TSZ zone ID - destination	cf. B.3	cf. B.3
samezone	Orig. and dest. are in same zone	1 if yes, 0 if no	1 if yes, 0 if no
Adjacent	Orig. and dest. are adjacent	0	0
Distance	Distance between zones	B.3	cf. B.3
autoIVTT	Auto in-vehicle travel time	1.2 $\times$ Distance	1.65 $\times$ Distance
autoOVTT	Auto out-of-vehicle travel time	3.1	3.27
Travail	Public transp. is available	0	0
TrIVTT	Pub. transp. in-vehicle tr. time	0	0
TrOVTT	Pub. transp. out-of-vehicle tr. time	0	0
TrCost	Public transp. cost	0	0
COST	Auto cost	Distance / 15.0	Distance / 13.8
SRIVTT	Shared ride travel time	= autoIVTT	= autoIVTT
SRCOST	Shared ride cost	= COST	= COST

Table B.4.: Variables in LOS Input File

B.5. Model Specification File

For this study a ready-made and provided model specification is used (cf. section 4.2). Since not all variables are expected to be given by this model specification, some adjustments to the model specification file had to be made. First, the `constants.h` file of the CEMDAP source code, where all exogeneous and endogeneous model variables are defined, had to be inspected to reconcile internal variable IDs with ID descriptions according to [Bhat et al., 2008]. Some differences were found, mainly due to the addition of further descriptive variables, so that the meaning of variables not defined in the manual had to be reassured. Then, the coefficients of those variables that were not to be considered by the several models included within CEMDAP had to be set to zero in the model specification file.

A test showed that two CEMDAP runs based on the ready-made and provided model specification file and the adjusted model specification file as described above yielded the exact same results. This is in line with the observation that the coefficients of almost all unconsidered variables were very small and, therefore, their impact on the simulation outcome negligible. Consequently, the original model specification file could have been used instead of the adjusted model specification file without the danger of adulterating the results.

B.6. Model Output

As explained in section 2.3.4, the full daily activity-travel pattern of any individual can be reconstructed from the information given in the stops file. The variables contained in each line of the stop file along with their column numbers are presented in table B.5 [Bhat et al., 2008, p.14]. Note that the terms *stop* and *activity* can be used interchangeably here.

Column No.	Description
1	Household ID
2	Person ID
3	Tour ID
4	Stop ID
5	Activity type
6	Start time of travel to the stop
7	Travel time to stop
8	Stop duration
9	Stop location (zone) ID
10	Origin zone ID
11	Trip distance
12	Activity type at the previous stop

Table B.5.: Variables in Stops Output File

C. MATSim Setup

In this section, the Java class `CadytsControllerBerlin` is outlined. As all configurations are set directly in this controller class no additional `config` file as frequently used otherwise[1] is necessary.

```
public class CadytsControllerBerlin {
	private final static Logger log = Logger.getLogger(CadytsControllerBerlin.class);

	public static void main(String[] args) {
		final Config config = ConfigUtils.createConfig();

		// global
		config.global().setCoordinateSystem("GK4");

		// network
		String inputNetworkFile = "D:/Workspace/container/demand/input/iv_counts
			/network.xml";
		config.network().setInputFile(inputNetworkFile);

		// plans
		String inputPlansFile = "D:/Workspace/container/demand/input/
			cemdap2matsim/24/plans.xml.gz";
		config.plans().setInputFile(inputPlansFile);

		// simulation
		config.addQSimConfigGroup(new QSimConfigGroup());
		config.getQSimConfigGroup().setFlowCapFactor(0.02);
		config.getQSimConfigGroup().setStorageCapFactor(0.02);
		config.getQSimConfigGroup().setRemoveStuckVehicles(false);



		// counts
		String countsFileName = "D:/Workspace/container/demand/input/iv_counts/
			vmz_di-do.xml";
		config.counts().setCountsFileName(countsFileName);
		config.counts().setCountsScaleFactor(100);
		config.counts().setOutputFormat("all");

		// vsp experimental
```

[1] Cf. http://www.matsim.org/docs/tutorials/8lessons/getting-started, last accessed 16 December 2013.

```
config.vspExperimental().addParam("vspDefaultsCheckingLevel", "abort");

// controller
String runId = "run_id";
String outputDirectory = "D:/Workspace/container/demand/output/" + runId
    + "/";
config.controler().setRunId(runId);
config.controler().setOutputDirectory(outputDirectory);
config.controler().setFirstIteration(0);
config.controler().setLastIteration(150);
Set<EventsFileFormat> eventsFileFormats = Collections.unmodifiableSet(
    EnumSet.of(EventsFileFormat.xml));
config.controler().setEventsFileFormats(eventsFileFormats);
config.controler().setMobsim("qsim");
config.controler().setWritePlansInterval(50);
config.controler().setWriteEventsInterval(50);
Set<String> snapshotFormat = new HashSet<String>();
//snapshotFormat.add("otfvis");
config.controler().setSnapshotFormat(snapshotFormat);

// strategy
// StrategySettings strategySettings1 = new StrategySettings(new IdImpl(2));
// strategySettings1.setModuleName("ChangeExpBeta");
// strategySettings1.setProbability(1.0);
// config.strategy().addStrategySettings(strategySettings1);

StrategySettings strategySettings2 = new StrategySettings(new IdImpl(1));
strategySettings2.setModuleName("ReRoute");
strategySettings2.setProbability(0.5);
strategySettings2.setDisableAfter(90);
config.strategy().addStrategySettings(strategySettings2);

StrategySettings strategySetinngs3 = new StrategySettings(new IdImpl(2));
strategySetinngs3.setModuleName("cadytsCar") ;
strategySetinngs3.setProbability(1.0) ;
config.strategy().addStrategySettings(strategySetinngs3);

config.strategy().setMaxAgentPlanMemorySize(10);

// planCalcScore
ActivityParams homeActivity = new ActivityParams("home");
homeActivity.setTypicalDuration(12*60*60);
config.planCalcScore().addActivityParams(homeActivity);

ActivityParams workActivity = new ActivityParams("work");
workActivity.setTypicalDuration(9*60*60);
config.planCalcScore().addActivityParams(workActivity);

ActivityParams leisureActivity = new ActivityParams("leis");
```

```
		leisureActivity.setTypicalDuration(2*60*60);
		config.planCalcScore().addActivityParams(leisureActivity);

		ActivityParams shopActivity = new ActivityParams("shop");
		shopActivity.setTypicalDuration(1*60*60);
		config.planCalcScore().addActivityParams(shopActivity);

		ActivityParams otherActivity = new ActivityParams("other");
		otherActivity.setTypicalDuration(0.5*60*60);
		config.planCalcScore().addActivityParams(otherActivity);

		// ActivityParams educActivity = new ActivityParams("educ");
		// educActivity.setTypicalDuration(9*60*60);
		// config.planCalcScore().addActivityParams(educActivity);

		// start controller
		final Controler controler = new Controler(config);

		// cadytsContext (and cadytsCarConfigGroup)
		final CadytsContext cContext = new CadytsContext(controler.getConfig());
		// CadytsContext generates new CadytsCarConfigGroup with name "cadytsCar"
		controler.addControlerListener(cContext);

		controler.getConfig().getModule("cadytsCar").addParam("startTime", "
			00:00:00");
		controler.getConfig().getModule("cadytsCar").addParam("endTime", "24:00:00"
			);


		// plan strategy
		controler.addPlanStrategyFactory("cadytsCar", new PlanStrategyFactory() {
			@Override
			public PlanStrategy createPlanStrategy(Scenario scenario,
				EventsManager eventsManager) {
				return new PlanStrategyImpl(new
					CadytsExtendedExpBetaPlanChanger(
						scenario.getConfig().planCalcScore().
							getBrainExpBeta(), cContext));
			}
		});

		// scoring function
		final CharyparNagelScoringParameters params = new
			CharyparNagelScoringParameters(config.planCalcScore());
		controler.setScoringFunctionFactory(new ScoringFunctionFactory() {
			@Override
			public ScoringFunction createNewScoringFunction(Plan plan) {

```

```
                ScoringFunctionAccumulator scoringFunctionAccumulator =
                    new ScoringFunctionAccumulator();
                scoringFunctionAccumulator.addScoringFunction(new
                    CharyparNagelLegScoring(params, controler.getScenario().
                    getNetwork()));
                scoringFunctionAccumulator.addScoringFunction(new
                    CharyparNagelActivityScoring(params)) ;
                scoringFunctionAccumulator.addScoringFunction(new
                    CharyparNagelAgentStuckScoring(params));

                final CadytsCarScoring scoringFunction = new
                    CadytsCarScoring(plan, config, cContext);
                final double cadytsScoringWeight = 10.0;
                scoringFunction.setWeightOfCadytsCorrection(
                    cadytsScoringWeight) ;
                scoringFunctionAccumulator.addScoringFunction(
                    scoringFunction );

                return scoringFunctionAccumulator;
            }
        });
        controler.run();
    }
}
```

D. Reference Values from Survey

In this section, the calculation of reference values (e.g. as stated in table 4.1) used for the analysis and validation of the transport models developed and outlined in chapters 5 and 6 is described.

- The number of car trips is calculated as follows: According to own estimations based on [Amt für Statsitk Berlin-Brandenburg, 2013, p.12f.], approximately 1,042,395 (as of 30 June 2013) Berliners live within the *S-Bahn ring*, the circular line of Berlin's commuter rail that is often used to distinguish inner-city neighborhoods from the rest of the city. The analysis of the SrV travel survey also uses this spatial separation, which is why it is also relevant for this study. These people conduct on average 3.0 trips per day [Ahrens, 2010b, p.3], of which 22% [Senatsverwaltung für Stadtentwicklung, 2010, p.3] are made by car. Berlin's overall population (as of 30 June 2013) is 3,489,422. Thus, 2,447,027 people live outside of the S-Bahn ring. On average, they make 2.7 trips per day [Ahrens, 2010a, p.3], of which 38% [Senatsverwaltung für Stadtentwicklung, 2010, p.3] are made by car. Accordingly, 3,198,630 car trips are made by Berliners on an average weekday.

- The average number of trips per person is calculated as follows: Leaving the share of car trips among all trips aside, one can calculate the number of all trips made by Berliners on a typical workday (9,734,158 trips) analogous to the calculation of the number of car trips above. The share of all trips within the S-Bahn ring is calculated to be 32%. Using this share and the information that *mobile* people who live within the S-Bahn ring make 3.6 trips per day [Ahrens, 2010b, p.3] and those living outside the S-Bahn ring make 3.3 trips per day [Ahrens, 2010a, p.3], the average number of all trips per Berliner is calculated as 3.4.

- In a similar way, a share of car trips made inside the S-Bahn ring among all Berlin car trips is calculated as 22%. Using this share, the average trip distances of 8.5km per trip [Ahrens, 2010b, p.43] for trips by car within the S-Bahn ring and 9.8km per trip [Ahrens, 2010a, p.43] for trips by car outside the S-Bahn ring, are combined into a average Berlin value of 9.5km per car trip (only considering trips with a distance of less than 100km, cf. [Ahrens, 2010b, p.43] and [Ahrens, 2010a, p.43]).

- Analogously, the average trip duration for car trips in Berlin is calculated as 22.3min.

The validation sections 5.3 and 6.3 in the two model chapters draw on data that is not available in the published SrV survey reports. The necessary distribution of, for instance, trip distances or departure times were, thus, calculated from the original survey data Ahrens [2010c]. These calculations are carried out by the Java program `SrVTripAnalyzer` contained in appendix E. In the following an example of one such calculation is given to illustrate how it was assured that the `SrVTripAnalyzer` carries out the correct calculations.

In the validations sections (i.e. sections 5.3 and 6.3), the distribution of activities at trip ends for trips made by car are used to validate the output of the simulation. The used values for the creation of figures 5.14 and 6.12 are stated in the second column of table D.1. No corresponding data is given in the published reports. However, distribution of activities at trip ends for all trips (independent of mode of transport) are given in Ahrens [2010b, p.24] and Ahrens [2010a, p.24]. To assure the correctness of the calculation of the distribution of activities at trip ends for trips made by car, the same procedure is used to calculate the distribution of activities at trip ends for all trips, which can be compared with data given in the published survey reports.

Activity	Car Trips (Own)	All Trips (Own)	All Trips (Report)
Home	38.7%	41.1%	41.1%
Leis	15.3%	15.3%	15.4%
Other	15.3%	16.8%	16.5%
Shop	11.0%	11.9%	11.8%
Work	19.7%	15.0%	14.9%

Table D.1.: Distribution of Activities at Trips Ends

One can see in table D.1 that there are – as intended – only minor deviations between the values of the third and fourth columns. To come to comparative values given in the rightmost column of table D.1 some rearragement of the data given in the tables of the survey reports [Ahrens, 2010b, p.24] and [Ahrens, 2010a, p.24] was necessary. First, activities had to be redefined as they were categorized differently. The respective conversion is outlined in table D.2.

German Categories (Report)	Categories (Report)	Categories (This Study)
Arbeit	Work	Work
Kindereinrichtung	Kindergarten or similar	Other
Schule/Ausbildung	School/Education	Other
Dienstl./Geschäftl.	Business	Work
Einkauf	Shopping	Shopping
Private Erledigung	Private Errands	Other
Freizeit	Leisure	Leisure
Wohnung	Home	Home
Sonstiges	Other	Other

Table D.2.: Conversion of Activity Types

Next, the values given separately for trips inside and outside of Berlin's S-Bahn ring had to be combined via the calculated shares of trips in- and outside the S-Bahn ring explained above. The results of this calculation of comparative values are, as already explained, given in the rightmost column of table D.1. Analogous calculations for assurance of correct use of reference data for other distributions were done where possible.

E. Java Programs / Classes

On the CD-ROM attached below, all Java programs / classes that were used to create the data on which is study is based are contained. All MATSim runs contained in this study have been run with MATSim revision r23738 as of 20 July 2013.

F. Deutsche Zusammenfassung

Funktionierende Verkehrssysteme sind eine fundamentale Voraussetzung für die Entwicklung von Gesellschaften und Wirtschaftssystemen. Gleichzeitig tragen die Verkehrssysteme zu großen globalen Problemen der heutigen Zeit bei, wie z.B. dem Klimawandel bei. Es sind daher innovative Lösungen (i.d.R. die über die bloße bauliche Erweiterung der Infrastruktur hinausgehen) nötig, um dafür zu sorgen, dass für den Verkehrs von Menschen und Waren langfristig effiziente Verkehrssysteme zur Verfügung stehen und die gleichzeitig nachhaltig dazu beitragen negative Auswirkungen von Verkehrsvorgängen zu reduzieren. Verkehrsmodelle stellen das wichtigste Werkzeug dar, um Verkehrsmaßnahmen und –projekte zu bewerten und ihre Auswirkungen zu prognostizieren. Die Erstellung derartiger Modelle ist jedoch eine herausfordernde Aufgabe. Insbesondere die Verfügbarkeit brauchbarer Eingangsdaten stellt häufig eine Hürde dar. Probleme im Zusammenhang mit der Verfügbarkeit von Eingangsdaten werden zukünftig eher größer werden, da dem Thema Datenschutz wohl auch langfristig eine hohe Aufmerksamkeit zukommen wird. Weiterhin sind viele heute in der Praxis angewendete Verkehrsmodell mit Schwächen behaftet, die häufig in Zusammenhang mit der Modellierung des Verhaltens der Verkehrsteilnehmer stehen. Das Ziel dieser Arbeit ist daher, ein Verkehrsmodell zu entwickeln, welches ausschließlich Eingangsdaten benötigt, die leicht verfügbar und zugänglich sind und in dem das Verhalten der Verkehrsteilnehmer realitätsnah abgebildet wird. Hierbei soll der Umfang an Modellierungsannahmen so weit wie möglich reduziert werden, da derartige Annahmen häufige Fehlerquellen darstellen. Das erstelle Modell basiert auf einer mikroskopischen Verkehrssimulation, bei der die Verkehrsteilnehmer sowie all ihre relevanten Charakteristika während des gesamten Simulationsprozesses auf individueller Ebene zur Verfügung stehen. Durch einen iterativen Prozess der als generischer Algorithmus aufgefasst werden kann, verbessern die Verkehrsteilnehmer nach und nach ihr Verkehrsverhalten, sodass sie langfristig zu für sie befriedigenden Lösungen kommen. Initiale Vorschläge für mögliche Tagespläne werden hierbei mit Hilfe eines ökonometrischen Aktivitätenerzeugungsmodells erstellt. Die Kalibrierung der so erzeugten Verkehrsnachfrage geschieht zusammen mit der Verkehrssimulation durch die Einbindung eines Kalibrierungsalgorithmus, der in die Nutzenfunktion, die für die Entscheidungen der Verkehrsteilnehmer verantwortlich ist, eingreift. Auf Basis dieses Ansatzes werden in dieser Arbeit zwei Verkehrsmodelle erstellt. Zunächst wird initiales Modell erstellt, welches der Untersuchung der Auswirkung verschiedener Modellparameter dient. Auf Basis der dabei gewonnen Erkenntnisse wird ein zweites, verfeinertes Modell auf Basis einer realistischen Abbildung der Bevölkerung des Untersuchungsraums erstellt. Es wird gezeigt, dass dieses Modell eine hohe Modellgüte besitzt, die vergleichbar ist mit jener von aufwändigeren, auf Reisetagebüchern basierenden Verkehrsmodellen. Die Validität der auf Basis dieses Modells erzeugten Verkehrsnachfrage wird mit Hilfe einer Verkehrserhebung bewiesen.