Calibration of Public Transit Routing for Multi-Agent Simulation

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Zusammenfassung

Der öffentliche Personennahverkehr (ÖPNV) ist heute ein weltweit verbreitetes Verkehrsmittel. Aufgrund seiner einfachen und meist erschwinglichen Nutzung haben seine Akzeptanz und Bedeutung sowohl im städtischen als auch im ländlichen Raum zugenommen. Außerdem wurde der ÖPNV unter anderem zur Lösung von Umwelt-, Wirtschaftlichkeits- und Urbanisierungsproblemen vorgeschlagen. Die effektive Nutzung der Vorteile des ÖPNV setzt allerdings eine systematische Planung voraus.

Das Verkehrsingenieurwesen hat Richtlinien und Techniken hervorgebracht, welche den Verkehrsbetrieben beim Entwurf, der Planung, der Verwaltung und der Bewertung von ÖPNV-Systeme helfen. Hierbei kommt eine besonders wichtige Rolle der Verkehrsumlegung zu, was durch eine Vielzahl von Studien, welche den Fluss von Passagieren durch die Verkehrsnetze untersuchen, deutlich wird. Allerdings beschäftigen sich die meisten dieser Untersuchungen mit aggregierten Modelle, welche nicht berücksichtigen, dass sich Entscheidungen bezüglich der Nutzung von Verkehrssystemiten auf der Ebene des Individuums abspielen. Insofern können diese Modelle keinen Beitrag zu einem besseren Verständnis und einer feingliedrigeren Analyse des Verhaltens von Fahrgästen leisten. Dies ist jedoch von großer Bedeutung zur Umsetzung spezifischer, zur Effizienzsteigerung und zur Adaption der Nachfrageentwicklung geeigneter Maßnahmen.

Genau hierzu trägt diese Dissertation bei. Zuerst wird die Anwendung bestehender Optimierungsansätze auf Herausforderungen des Verkehrsingenieurwesens und der Routenauswahl bewertet. Im Anschluss werden Ansätze zur Kalibrierung der Fahrgastrouten im Kontext einer agentenbasierten Mikrosimulation untersucht. Die besondere Herausforderung bei der Kalibrierung liegt darin, bei einer gegebenen synthetischen Population mit festen Quelle-Ziel-Beziehungen die Verkehrsverhaltensregeln so zu modifizieren, dass die Simulation den realen, anhand der wirklichen Auslastungsvolumina der Haltestellen gegebenen Fahrgastentscheidungen möglichst nahekommt. Die verwendete Methodik umfasst die folgenden Aspekte:

- Zur Mikrosimulation des Verkehrs wird das Open-Source-Framework MATSim verwendet. Durch seine Fähigkeit umfangreiche ÖPNV-Szenarien zu simulieren sowie seinen modularen Aufbau ist es besonders geeignet zur Untersuchung von Kalibrierungsmodellen. Der hierbei verwendete vorläufige Optimierungsprozess beruht auf mehreren Anpassungen der Verkehrsknotenpunkte, um diese den tatsächlichen Eigenschaften des berücksichtigten Szenarios anzunähern. Außerdem wird ein manueller Kalibrierungstest auf Basis eines iterativen Prozesses von parametrischen Modifikationen der Reisepräferenzen umgesetzt, um eine sehr große Anzahl von kombinatorischen Routenalternativen zu erzeugen und um herauszufinden, welche der Optionen eine gute Annäherung an das tatsächliche Fahrgastaufkommen auf der gegebenen Buslinie darstellen. Auf Basis

dieses umfangreichen Sets an Wahlmöglichkeiten wird ferner die grundsätzliche Vielfalt von Routen getestet, indem für jeden Agenten nur die drei Routenalternativen ausgewählt und simuliert werden, welche die kürzesten Fußwegdistanzen, die schnellsten ÖV-Verbindungen sowie einen ausgeglichenen Kompromiss aus den beiden erstgenannten Alternativen enthalten.

- Die automatische Kalibrierung wird umgesetzt durch den gemeinsamen Einsatz von MATSim und Cadyts, einem auf einem Bayes-Ansatz basierenden Tool zur Nachfrageschätzung in disaggregierten Modellen, welches ursprünglich zur Kalibrierung von PKW-Fahrrouten entwickelt und eingesetzt wurde. Sein Ansatz nutzt die Freiheitsgrade, die verbleiben, nachdem die Entscheidungen der Individuen als Zufallsziehungen in einem Discrete-Choice-Modell abgebildet worden sind. Im Rahmen seiner Integration in die Verkehrsmikrosimulation beeinflusst Cadyts den Entscheidungsprozess, indem jeder Alternative durch Nutzenkorrektur eine Bewertung gegeben wird, welche dem individuellen Beitrag zur Abbildung der realen Verkehrsaufkommen an den Haltestellen entspricht.

- In einer anschließenden Studie werden die Kalibrierungsergebnisse eingesetzt. Hierbei besteht die Herausforderung darin, Erkenntnisse aus Schätzungen zu erhalten und diese zur Nachfragevorhersage einzusetzen. Das Vorgehen analysiert kalibrierte Auswahlmöglichkeiten und nutzt die Methode der kleinsten Quadrate um individuelle Parameter zu bestimmen, welche das Auswahlverhalten erklären.

Das ÖPNV-System von Berlin wird als Szenario für alle Kalibrierungstests verwendet. Zwei reale Subszenarien werden spezifiziert: zum einen ein kleiner Teil des Bezirks Neukölln, welcher von einer Buslinie mit 17 Haltestellen abgedeckt wird und deren Fahrgastaufkommen in Form von stündlichen Werten verfügbar ist. Die berücksichtigte Nachfrage umfasst 36.119 Nutzer, welche ihre alltäglichen Aktivitäten im Umfeld der Bushaltestellen ausführen. Das zweite Szenario umfasst das gesamte Berliner Verkehrsnetz mit 329 Nahverkehrslinien und berücksichtigt dabei 231.369 Nutzer. Für dieses größere Szenario wird das tägliche Fahrgastaufkommen von 2.723 Haltestellen betrachtet. Für beide Fälle wird die Fahrtennachfrage auf Basis von Umfrageinformationen generiert, welche die üblichen Aktivitäten von Personen an verschiedenen Stellen der Stadt innerhalb eines ganzen Tages beschreiben, jedoch ohne dabei die Verkehrsverbindungen zwischen diesen Aktivitäten zu definieren. Die Simulations- und Kalibrierungsläufe werden bezüglich der Übereinstimmung von simulierten Fahrgastzahlen mit real beobachteten Fahrgastaufkommen bewertet.

Die manuellen Kalibrierungsversuche zeigen hierbei erwartungsgemäße Ergebnisse wie z.B. die Tatsache, dass Fahrgäste lange Fußwege und häufiges Umsteigen vermeiden. Die gefundenen Koeffizientenwerte der Reiseparameter stimmen außerdem mit weiteren methodischen Studien überein, welche in verschiedenen Städten weltweit durchgeführt worden sind.

Die mit automatischer Kalibrierung durchgeführten Experimente zeigen, dass der Kalibrierungsansatz zudem mit einem Verkehrsverhaltensmodell verknüpft werden kann, um die Annäherung des Standardroutenwahlmechanismus an geeignete Routenoptionen umzusetzen. Die zugrundeliegende Interpretation hierbei ist, dass jene Routen die besten sind, welche dazu beitragen, dass die Simulation möglichst genau mit (in der Realität) beobachteten Zähldaten übereinstimmt. Dies wird unabhängig davon, ob Cadyts bei der Auswahl oder bei der Bewertung der Wahlmöglichkeiten eingesetzt wird, erreicht. Sowohl die Implementierung der Simulations- als auch der Kalibrierungstools erweist sich als angemessen und geeignet, um große, reale Szenarien zu schätzen. Außerdem ist der Ansatz in der Lage, die intertemporalen Aspekte, die durch die vorhandenen Messdaten impliziert werden, zu berücksichtigen.

Das durch die Kalibrierungsergebnisse neu gewonnene Wissen wird so untersucht, dass es zur Vorhersage in künftigen Studien zu Routenwahlentscheidungen auf mikroskopischer Ebene eingesetzt werden kann.

Abstract

Public transport is a widely used transport mode around the world. Its acceptance and importance have increased in both urban and rural areas due to its use simplicity and affordability for most users. Likewise, public transport has been proposed as a solution for environmental, economic, and urbanization issues, among others. However, in order to operate effectively, transit operations require methodical planning and design.

Transport engineering has provided guidelines and techniques that help transit agencies in tasks of modeling, planning, administration, and evaluation of public transport systems. Among them, one of the most relevant topics is transit assignment. Its importance is asserted by a large number of studies that focus on passenger flows through transit networks. Nonetheless, most investigations on the matter address aggregated models, sweeping aside the problem of travel decisions on an individual level. Unfortunately, this does not contribute to a more favorable understanding and fine-grained analysis of passengers' behavior. The knowledge of passengers' needs and preferences is an invaluable factor to implement appropriate measures related to service improvement and demand development adaptations.

This dissertation addresses the aforementioned problem. First, existing optimization approaches applied to engineering problems and route choice are reviewed. Then, passenger route calibration approaches are investigated in an agent-based microsimulation environment. The calibration challenge implies that, given a synthetic population with fixed OD pairs sets, the travel behavioral rules should be modified in order to bring the simulation closer to passengers' travel decisions, reflected on their observed occupancy volumes at stations. The methodology includes these aspects:

- For transit microsimulation, the open source framework MATSim is employed. Its capacity to simulate large scale public transport scenarios and its modular architecture make it appropriate for calibration research. The first route optimization attempts included a number of adaptations to the transit router to make it well-suited to actual properties of the considered scenario. A manual calibration test is also realized on the basis of an iterative process of parametric modifications of travel priorities to generate a combinatorial explosion of route alternatives. Then, one can find among those alternatives the routes that reflect better simulation approximations to real passenger flow on a bus line. Based on that large enriched choice set, basic route diversity is tested too, by picking out and simulating for each agent only 3 route alternatives that involve shortest walks, fastest transit trips, and a balance between those two priorities.
- The automatic calibration is implemented with the coupling of MATSim and Cadyts, a Bayesian setting-based tool for the demand estimation of disaggregated models that was

originally employed for auto drivers' route calibration. Its approach uses the freedom that is left when individual decisions are modeled as random draws from a discrete choice model. In its integration with the transit microsimulation, Cadyts influences the choice process giving to each alternative a grade in form of utility correction, in accordance to the individual contribution of that alternative to the reproduction of volumes at stations.

- A study is carried out to take advantage of calibration results. The objective is to create knowledge from estimation runs in order to make it useful for demand prediction. The procedure analyzes calibrated choices and uses a least square solution to extract individual parameters which explain the choices behaviorally.

The transport system of Berlin is considered as scenario for all calibration tests. Specifically, two real sub-scenarios are defined: First, a small area of the Neukölln district covered by a bus line that travels along 17 stops, in which hourly passengers' occupancy volumes are available. The demand encompasses 36,119 public transport users who carry out daily activities near the bus stops. The second scenario contemplates the complete Berlin transit network with 329 transit lines and considers 231,369 persons. For this larger scenario, passenger occupancy volumes for 2723 stations are described on daily basis. In both cases, the travel demand is generated from survey information which is structured to describe a normal complete day of activities of persons in different locations in the city, but without the description of transit trips between them. Simulation and calibration runs are evaluated according to the compliance between simulated and observed passenger counts.

Manual calibration attempts show not only expected results like the fact that passengers avoid long walks and many transfers. The travel parameters coefficients values that were found are also in concordance with other methodical studies carried out in diverse cities around the world.

The experiments realized with automatic calibration prove that the calibration approach can be coupled also to a transit behavioral model to assume the task of leaning the standard route choice mechanism toward appropriate options. The interpretation here is that an option is appropriate, if it helps to bring the simulation to a state most consistent with the observed measurements. This is achieved, no matter if Cadyts performs during the selection or the performance evaluation process. The implementation of both simulation and calibration tools proves to be reasonable and suitable for its use in estimations of large scale real world scenarios. In addition, the approach is also able to deal with the inter-temporal aspects implied by available measurements. Acquisition of knowledge from calibration results is studied in the sense of making it usable for forecasts in further route decisions studies at microscopic level.

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Abbreviations

BVG	***B**erliner **V**erkehrs-A**G*** (The Berlin public transport company)
Cadyts	**Ca**libration of **dy**namic **t**raffic **s**imulations
MATSim	**M**ulti-**A**gent **T**ransport **Sim**ulation
minStddev	**M**inimal **S**tandard **D**eviation
MRE	**M**ean **R**elative **E**rror
MUTDT	**M**arginal **U**tility of **T**ravel **D**istance **T**ransit
MUTTT	**M**arginal **U**tility of **T**ravel **T**ime **T**ransit
MUTTW	**M**arginal **U**tility of **T**ravel **T**ime **W**alk
MUTWT	**M**arginal **U**tility of **T**ransit **W**aiting **T**ime
OD	**O**rigin-**D**estination
S-Bahn	***S**tadtschnell**bahn*** (german suburban metro railway system)
SVD	**S**ingular **V**alue **D**ecomposition
ULS	**U**tility of **L**ine **S**witch

Chapter 1

Introduction

1.1 Motivation

Public transport grants mobility supply to a large percentage of travelers. Actually, in most industrialized countries public transport plays there a major role among transportation modes [Lit11, Bai07, Eur11] in spite of the high car ownership rate. On the other hand, public transport is the only accessible mean of transportation for residents of most developing countries who want to reach essential services that are not located within walking or cycling distances [Wri02].

Indeed, availability of public transport promotes economic, educational, and recreational activities which result in higher life quality level for the users. The advantages are also for institutions, organizations, and firms located near transit[1] infrastructure locations, which see themselves benefiting in many practical aspects as a result of the flow of passengers. Public transport importance is also adduced with its positive influence on communities with efficient transport systems. Because of its advantages, public transport is present in many topics of prevailing policies:

- Congestion reduction: Whereas the use of private autos is associated to congestion in central, business or commercial areas, public transport has proved to be useful to diminish vehicular bottlenecks. The congestion reduction brings reduction of delays and also economic benefits. A monetary evaluation [ACS10] summarized studies about the congestion reduction effect for scenarios in Australasia, Europe, and North America. The economic

[1] *Transit* is used in this dissertation as synonym for public transport

relief impact due to public transport is valued at an average of 45.0 cents (AUD$, 2008) per marginal vehicle kilometer.

- Ecological deliberation: Public transport is proposed as an alternative in urban environmental issues. Most of contemporary transportation still depends on consumption of fossil sources. Most public transport vehicles are included in this, but the fact that their percentage contribution to total emissions is low [Ken03] and that some of them are electrical vehicles, make them look as a further step on sustainable mobility.

- Energy efficiency: The excessive motorization related to private auto usage leads to huge consumption of fossil energy. The promotion of public transport usage is always a central topic in discussions about energy efficiency. Energy per seat kilometer required for public transport operations represents only a small percentage in comparison to the energy used in private cars in urban scenes. A study [Pot03] set that percentage in a third or less.

- Urban planning: The accentuating tendency of urban and compact settlement patterns demands massive mobility for residents. Public transport is in many of those cases the most convenient and affordable transportation mode. Moreover, public transport optimizes urban areas because it reduces significantly the space required for the movement of large number of persons in comparison with private autos. Public transport systems reduce also the parking requirements that are inherent to ownership of private autos. A study reports the reduction by 20% for household and 12% to 60% for commercial parking [BFG+02].

- Economical impact: Availability of public vehicles is an indispensable option for low-income households [Cri08]. It increases the possibility of access to employment locations, education facilities, shopping centers, and social and leisure activities. The proximity to the transit infrastructure also impacts on property values, sometimes with value increments up to 20% [SGL12]. In terms of economic health, the reduction of private autos congestion due to public transport availability is significant. The American Public Transport Association (APTA) calculates in a report [DNG12] the savings in US$16.8 billions in the United States, for the fiscal year 2010.

- Travel safety: The same APTA 2012 report proves with statistics that the use of public transport is safer than traveling by private motor vehicle. From 2003 to 2008, bus travels resulted in 0.05 deaths per 100 million passenger miles, compared to 1.42 deaths for motor vehicles.

- Public health: Passengers usually have to walk to, and from stops, which implicitly involves physical activity. A research conducted by Besser and Dannenberg [BD05] reveals that persons who usually travel by public transport, spend in average 19 minutes pro day walking, and 29% of them achieve the recommended 30 minutes of physical activity.

1.2 Problem Description

In spite of public transport advantages, some common problems related to deficient operation are palpable in many transport systems. Poor planning or inadequate implementation may lead to unreliable service and severe inconveniences for passengers. Some of these situations like bus bunching or overcrowded vehicles at peak demand hours can be observed in urban settlements equally in developing and developed countries. These problems are not trivial, since their consequences are translated not only into discomfort and delays but also into monetary losses that might affect potentially to millions of users every day.

Planning, design and maintenance of large public transport systems are challenging tasks. Examples of critical operations that transport agencies have to face commonly include demand forecasting, evaluation of effectiveness of transit policies, and the impact study of disruptive incidents. Engineering methods and scientific principles can help to reach the objective of optimization of transport operations.

Transport modeling has proved to be an effective tool to understand public transport systems and to propose pertinent solutions and improvements. Specifically, travel demand models are useful to forecast how the demand adapts itself to changes that can be observed on the transport system or on the passengers' travel behavior patterns. A determinant factor for the successful demand modeling is the knowledge of passengers' travel preferences. Transit assignment is the study of passengers' route choice from origin and destination locations through a transit network. Much investigation has been done on the topic of passengers' routing. Most recent studies board the problem with approaches like: Agent-based modeling which considers autonomous entities, microscopic simulation which considers entities individually, behavioral modeling of route choice on an individual level, individual routing calibration validated with real data, and calculation of transit routes with the consideration of passengers' taste variations.

An important challenge for the agent-based approach for the recent past has been computational: Finding an implementation that is both close to the agent-based concepts and fast enough for real world scenarios. Another challenge has been calibration. More technically: Given a set of macroscopic observations, how should the physical or behavioral microscopic rules of the agent-based simulation be modified in order to move the simulation closer to the observations?

This topic belongs to a class of problems which are quite common in agent-based simulations. Agent-based simulations were usually built around the notion of “emergence”, that is, they are expected to be particularly useful where certain macroscopic properties, in our case congestion, vehicle overloading, and resulting delay patterns, cannot be derived in analytical ways from the microscopic input data (including the behavioral rules), and in consequence one needs to run the simulation in order to obtain them. However, because the connection from input data to emergent properties is by simulation, the mathematical connection is not as well established as in normal numerical modeling.

The case presented here takes up the situation where the simulated scenario includes passenger volumes for certain or all transit lines, demand for population from trip diaries, but no route data at all from the survey. The task is to generate passenger paths and possibly modify the passenger demand such that the simulation matches the volumes. Those challenges raise the next research questions:

- Is it possible to optimize behavioral route decisions and make them more realistic?
- Which methodology should be used to correct microscopic route choices to bring their results to an observed state?
- Is it possible to make transit demand forecasts based on calibrations results?

This dissertation explores also the problem of realistic generation of transit routes in an agent-based microscopic environment. The insertion of a calibration tool in the evolutionary process of routes selection is presented in order to move the simulation to available passenger observations in two scenarios of different magnitude. In the end, a demand prediction exercise from calibration-based knowledge extraction is proposed.

1.3 Conceptual Framework

1.3.1 Transport Modeling

Transport modeling involves the mathematical and physical representation of transport systems. This work considers the following modeling approaches from transport engineering and computer science for the study of transit routing:

- Transport simulation: Simulation models are common tools in transportation modeling. They involve the use of computational paradigms that can bring automatic calculations and predict demand before a new measure is undertaken in the real world. Simulation analysis saves resources and grants consistent data about the new measurement impact. For example, the repercussions of a new subway line creation can be simulated after its planning, and analyzed before its construction. The objective of a simulation is to create a representation of the transport system as real as possible. See [LR01].

- Activities-based model: For this approach, each modeled person (whose data come usually from a survey of activities) includes an activity diary to be accomplished. The demand is a component of the activity planning decisions and it is generated from the definition of activities that agents carry out in a given scenario with spatial and temporal dimensions. The analysis unit is the chain of activities and trips normally on a day basis. See [BK03].

- Microsimulation: In contrast to macrosimulation where average amounts of persons are considered, microsimulation represents every single entity (like travelers or vehicles) individually with all his relevant attributes. The simulation considers interactions among the entities in the system that might have an impact on the demand prediction. The microsimulation attempts to achieve a detailed representation, so that the entities or their interactions may be positioned with exact spatial and temporal dimensions at every step of the simulation. Some implementations even involve an event-based approach, in which the temporal dimension is structured in a discrete sequence of small time steps in which events take place and can be easily tracked and analyzed. See [Dru98].

- Agent-based model: This is a computational paradigm where individual entities called agents have their own objectives and make autonomous decisions. They interact with others agents in an independent way and the effects of the interactions are evaluated globally.

They follow configurable decisions and behavioral rules, but they can individually learn, adapt, and evolve if the simulation incorporates evolutionary algorithms. See [RG12].

- Co-evolutionary algorithms: Evolutionary algorithms are inspired on natural biological evolution processes like reproduction, mutation, and selection. Solutions are evaluated with a fitness function in an iterative process. In the special approach of co-evolution, the interaction among agents has special attention. In order to reach their objectives, agents can compete or cooperate with other members of the simulated population. Co-evolution models give particular attention to the fitness evaluation since it is mostly based on the interaction with others. See [Bul01].

- Transit assignment: An essential element in transit simulation models is the search of transit routes for passengers. Usually two models are considered: First, frequency-based assignment in which transit lines are labeled with average headway frequencies. Thus, transfers and waiting time are not calculated with precise values. They are appropriate for the simulation of transit systems with incomplete schedule information or the planning of future systems. On the other hand, schedule-based assignment considers detailed departure and arrival times at stations for each transit line, which produces not only accurate time calculations but also route alternatives depending on the passenger departure time. This approach is suitable for scheduling planning studies, for the study of scenarios with long headway frequencies like inter-city systems, or for microscopic models with high level of details. See [SF89].

  The schedule-based type of transit assignment has become rather mainstream. Reasons for this include on the one hand that certain aspects of the complexity of public transit, e.g. multi-stage trips, reliability, different vehicle sizes, are difficult to capture in more traditional flow-based models; and on the other hand that growing computational capabilities make it now possible to run schedule-based transit assignments for large scenarios. The step from schedule-based transit assignment to agent-based transit assignment is not very large. As a tendency, the agent-based approach attaches more information to the individual traveler, for example the full daily plan rather than treating each trip separately.

In order to integrate those paradigms in the transit routing calibration study, this investigation adopted the MATSim (Multi-Agent Transport Simulation) [BRN05, RN06] simulator. MATSim is an open source, agent-based framework that implements a co-evolutionary algorithm for mobility microsimulation of large scenarios. The simulation can be also carried out for public transport systems. The aforementioned paradigms are implemented in MATSim:

- The agent-based approach is implemented with individual definition of agents with own attributes. They are the persons of a synthetic population. Every vehicle is also described with its particular characteristics.
- An activity-based approach includes the generation of agents' plans which contain a chain of normal daily activities that agents intend to accomplish and the trips generated between them.
- In the mobility microsimulation, each particular agent is handled at a very detailed level and the execution of their plans can be tracked in a very precise way.
- A co-evolutionary algorithm involves re-planning strategies that mutate, evaluate, and select agents' plans in an iterative process. Congestion is identified as the main interaction consequence with other agents.
- The transit assignment requires the transit schedule description that provides exact information about transit lines and their departures times. The transit router makes a trade-off of travel priorities to calculate paths through the transit network.

1.3.2 Calibration

Calibration is a regular topic in transportation models. Many methods are proposed to adjust individual parameters in order to bring the transportation system to more realistic states. Most of them refer to applications that are suitable only for aggregated models dealing with passengers' flows.

For this routing calibration study, Cadyts (**C**alibration of **d**ynamic **t**raffic **s**imulations) [Flö13, Flö08, FBN11] was adopted. It is a very flexible disaggregated demand calibration tool that interacts with any stochastic, dynamic and iterative transport simulator. The estimation approach calibrates the behavior in a Bayesian setting from real data of counts. Cadyts does not perform directly in evaluation or selection mechanisms. It is just integrated to propose to the simulator a plan evaluation correction that may help to select plans that reduce the gap between the real and simulated measurements.

1.4 Dissertation Structure

The structure if this dissertation is as follows: In Chapter 2 a theoretical review and literature survey about route search from the optimization perspective is presented. Chapter 3 introduces MATSim transit simulation, focusing on modules and settings that are relevant for the development of transit routing calibration methods in following chapters. Chapter 4 outlines Cadyts calibration model and its integration into the transit microsimulation selection module. Chapter 5 describes another type of Cadyts-MATSim coupling, in which Cadyts core formulation acts like a component in the agent's plan performance evaluation. An existing route diversity generation method is also integrated. Chapter 6 describes a study to make public transportation demand forecasts on the basis of calibration outputs. Chapter 7 resumes and discusses the results of the research and enumerates possible future works.

Chapter 2

Bibliography Revision on Routing Optimization

The Optimal Path Search Problem is a noteworthy topic in many engineering practices and it has been widely addressed in many theoretical models and practical applications. When multiple objectives are involved, the path search is commonly addressed as the calculation of an optimization solution.

This chapter presents a literature review on Multi-Objective Optimization with a subsequent focus on the special studies that handle the Multi-Objective Path Search problem. The chapter starts with a basic optimization theory introduction and references to illustrative general optimization works. Then, the Multi-Objective Path Search problem is reviewed presenting also its theoretical background and the relevant studies realized under its perspective. The last section reviews particularly the Multi-Objective Transit Routing problem.

2.1 Introduction

A balanced solution is usually searched in experimental models and engineering problems, in which multiple conflicting objectives are present. The Multi-Objective Optimization aims to find the best available solutions considering that all objectives should be simultaneously and proportionately improved.

Although the Multi-Objective Optimization is a concept originally developed in Economy studies, it is now an important and very valuable research field that is present also in a large number of scientific and engineering disciplines like Operations Research, Computer science, and Decision Management. Practically, there is not an engineering area in which Multi-Objective Optimization is not employed.

Some examples of usual optimization problems are presented in discrete mathematics. For instance, the shortest path search problem in weighted graphs consists in finding routes with minimal cost between origin and destination nodes. This definition requires no further efforts in specific situations with one cost criterion. However, very frequently and in many different type of scenarios, the concept of cost includes a number of criteria that might come in conflict with each other. Under the context of Multi-Objective Optimization, this investigation topic becomes the Multi-Objective Path Search, which due to its importance is included in the list of classical optimization problems in Operations Research.

This chapter reviews current existing engineering solutions based on Multi-Objective Optimization approaches. Always under the optimization perspective, the chapter goes from most general concepts to most specific transportation topics.

The chapter is structured in this form: The survey is justified in Section 2.2 by emphasizing the increasing relevance of optimization methods in many and diverse contemporary engineering branches. Next, the study examines the utilization of Multi-Objective Optimization in contemporary real-world applications. Section 2.3 presents introductory formal descriptions of general optimization theory and Multi-Objective Optimization. Previous surveys that reviewed exhaustively the Multi-Objective Optimization literature are also enumerated there. More recent studies related specifically to the Multi-Objective Path Search problem are also reviewed. Section 2.3.4 presents the normalization related to Multi-Objective Path Search in public transport networks and also reviews recent articles focused on it. Section 2.4 explores the implementation of route generation and Multi-Objective Path Search optimization on the basis of public transport microsimulation. The last Section 2.5 summarizes the review.

2.2 Multi-Objective Optimization and Multi-Objective Path Search

In the last decades optimization models have achieved importance in scientific research, computational theory and technological applications. The optimization theoretical framework was originally developed in Economy studies by Francis Y. Edgeworth and Vilfredo Pareto in the late 19th century and in the early 20th century. More strictly, some authors state that primary optimization methods were already initiated some centuries ago. In a historical review, Singiresu [Rao09] tracks the first optimization models to Newton, Lagrange, and Cauchy. Hinnenthal [Hin08] attributes the first optimization technique to Carl Friedrich Gauss. Coello Coello[1] et al. [CLV07] hint that the optimization concept as part of economic equilibrium dates back to the 18th century. They also quote more studies to date the origins of Multi-Objective optimization mathematical foundations between 1895 and 1906, the formation of optimization as a proper mathematical discipline in 1951, and its consolidation in the 1960's. Rasmussen [Ras86] remarks the renewed interest on Multi-Objective Optimization after World War II, and its increasing attention since the 1970's. The translation of Pareto's work into English in 1971 [Par71] aroused the interest on Multi-Objective Optimization methods in applied mathematics and engineering, according to de Weck [de 04].

The optimization theoretical approaches have been the base for the application of engineering techniques to real-world problems. Singiresu [Rao09] states that optimization is practically applicable to all engineering areas. In this sense, Zhou et al. [ZQL$^+$11] presented a structured summary of multi-objective evolutionary algorithms-based applications classified in 48 engineering subjects. The reviews of several other authors assert also the widespread utilization of optimization methods for specific solutions in a long number of research areas: resource scheduler evaluation, chemical hyper-structures generation, task planning, digital multiplierless filter design, resource scheduling, gas turbine engine controlling, pre-planning of shipping container layouts, electromagnetic systems design, laminated ceramic composites design, plane trusses optimization, gas supply network design [Coe99], submarine stern design [VL00], environmental impact assessment processes, data allocation in distributed databases, electronic circuit board design, concurrent engineering solving, submarine design optimization, electric energy distribution, air quality management, nonlinear system identification, automated synthesis, and

[1] Two surnames are the standard in Latin America and Dr. Coello Coello has by coincidence the same surnames.

robot configurations [Lam00], design-space exploration, embedded multiprocessor systems application mapping, systems-on-chip architecture exploration, electronic system design applications [GBTO05], investment portfolio optimization, train timetable information, airline crew scheduling, radiotherapy treatment design [Ehr09], fleet planning, production line improvement [Hin08], inventory control, selection of a site for an industry, optimal design for: aircraft and aerospace structures, civil engineering structures, material handling equipment, electrical machinery, and chemical processing equipment [Rao09].

In the same regard, optimal path search methods have also gained wide acceptance not only in theoretical operation research investigation, but also in many different types of engineering implementations. Well-known applications of optimal path search are: online journey planers, GPS based-navigation, game path-finding, and circuit design. The literature enumerates another specific contributions: urban traffic planning, emergency evacuations way finding, collective facilities location, wastewater treatment processes [CRCC99], route planning in traffic networks, the Quality of Service (QoS) routing problem, data scheduling, linear curve approximation applied to cartography, computer graphics, and imaging processing [Zie01], maritime routing [HH04, Hin08], routing in IP networks [Ehr09], genetic algorithms for robot, personal, and car navigation systems, tourist sight-seeing itinerary [KH08], networked embedded systems optimization [GLW$^+$08], routing in multimedia networks, satellite scheduling, and domain independent planning [MMP09].

2.3 Basic Optimization Theory

In this section, basic optimization theory is introduced. The presentation is extended also from general to particular optimization topics.

2.3.1 Single-Objective Optimization

Optimization models aim at finding best results for problems whose possible solutions can be explored on the basis of a quantitative analysis. A general formulation starts with the introduction of the objective function $f(X)$. It stands for the optimal value search, which (depending on the problem) could be the minimum or maximum. Decisions variables are identified and represented within the *design vector* ***X***. It represents any instance out of the whole range of feasible solutions among which optimal values will be searched.

Typically, a single-objective optimization problem is formulated like:

$$\text{Find } X = \{x_1, x_2, ...x_n\} \text{ which minimizes } f(X)$$

subject to constrains expressed as inequalities or equalities:

$$\begin{aligned} g_j(X) &\leq 0 \quad j = 1, 2, ..., m \\ h_r(X) &= 0 \quad r = 1, 2, ..., p \end{aligned} \tag{2.1}$$

The feasible set defined by g and h is typically multi-valued. The optimization routine selects the value of minimal f value within that set.

2.3.2 Multi-Objective Optimization

2.3.2.1 Theory Introduction

For problems whose characteristics include a set of competing criteria, usually it is not possible to find a solution that satisfies completely each criterion. The increasing value of a single objective might mean a decrement for other criterion value. Multi-objective optimization looks for balanced solutions or trade-off among several objectives.

$$min(max)f = [f_1(X), f_2(X), \ldots, f_k(X)] \tag{2.2}$$

A k number of objective functions $f_1(X), f_2(X), ..., f_k(X)$ is defined, where X represents a decision variable vector $X = (x_1, x_2, ...x_n)$. A solution is searched that minimizes (or maximizes) the components of the vector of objective functions

$$(min)F(X) = (f_1(X), f_2(X), ..., f_k(X))$$

subject to constrains

$$g_j(X) \leq 0 \quad j = 1, 2, ..., m$$
$$h_r(X) = 0 \quad r = 1, 2, ..., p$$

As it is unlikely to find a solution that satisfies every objective component with its best value, Pareto efficient solutions are proposed as a balanced answer to Multi-Objective Optimization needs. A solution X is called Pareto optimal if there is not other solution Y that decreases some objective function, without incrementing any other objective function simultaneously. That is, the Pareto optimal solution X should perform better in at least one of the objective functions without worsening the performance of the other objectives. Formally, the Pareto dominance $X \prec Y$ of decision variable vector $X = (x_1, x_2, ...x_n)$ over vector $Y = (y_1, y_2, ...y_n)$ is described like:

$$\begin{aligned} \forall i \in [1, 2, ..., n] : \; x_i \leq y_i \\ and \; \exists i \in [1, 2, ..., n] : x_i < y_i \end{aligned} \tag{2.3}$$

Usually there is not a single optimal solution, but a Pareto optimal or Pareto efficient set of solutions. They are also called non-dominated set of solutions because their respective decision variable vectors are not dominated by any other member of the solution set. The set of objective functions of non-dominated vectors form a surface in objective function space called the Pareto frontier or Pareto curve. They constitute the domain of reasonable or optimal solutions.

2.3.2.2 Literature Survey

A number of exhaustive surveys on Multi-Objective Optimization have collected most of the representative works on the matter. Ulungu and Teghem [UT94] presented a descriptive and comparative survey of Multi-Objective Optimization works up to 1994. First, 5 previous reviews on diverse optimization categories were mentioned. Then, multi-objective combinatorial optimization theory was presented. Next, papers were categorized, reviewed and compared according to their topic problem complexity. P-class problems comprehend: assignment and allocation, the multi-objective transportation problem, the multi-objective network flow or transshipment problem. NP-Hard problems are: the multi-objective location problem, the multi-objective traveling salesman problem, the multi-objective set-covering problem, the multi-objective knapsack problem. The authors regretted the scarcity of Multi-Objective Combinatorial Optimization literature by the time of that publication.

In a review by Coello Coello [Coe99], 6 evolutionary Multi-Objective Optimization techniques were analyzed according to their applications, strengths, and weaknesses. A proposal of metrics for the effectiveness of the techniques is also presented. His conclusion predicted the notable evolution that Multi-Objective Optimization has reached nowadays. Moreover, Coello Coello maintained up to 2010 a repository [Coe13] with 4,861 references on Evolutionary Multi-Objective Optimization that is still available on line up to the date of this dissertation submission.

A frequent reference in optimization works is the bibliography compilation by Ehrgott and Gandibleux [EG00]. The literature was classified there according to four categories: combinatorial structure, objective functions types and number, problem type, and solution method applied. Solutions methods are distinguished according to the moment in which the decision maker interacts during the resolution process: a priori, a posteriori or interactive mode. Solution methods are separated as exact and approximated. Exact methods include: weighted sum scalarization, compromise solutions method, goal programming, ranking methods like the k-best solution, dynamic programming, branch and bound, and the two phases method. Approximation methods include heuristics and metaheuristics like constraint logic programming, evolutionary methods, neural networks, non-monotonic search strategies, greedy randomized adaptive search, ant colony systems, variable neighborhood search and scatter search, but the survey gives a special overview of simulated annealing, tabu search, and genetic algorithms (the so-called population-based methods). Regarding the specific studies, 53 papers were listed for resolution of shortest path problems, 28 for the assignment problem, 33 for transportation and transshipment problems, 26 for network flow problems, 13 for the spanning tree problem, 5 for matroids and matroid intersections, 17 for the traveling salesperson problem, 26 for Knapsack problems, 24 for multi-objective scheduling problems, 22 for location problems, 3 for the set covering problem and 27 for other multi-objective problems.

Van Veldhuizen and Lamont [VL00] follow the same interaction classification based on the decision process. The interaction classification is based on the influence of decision maker preferences on final results. A priori methods (decide $\rightarrow$ search) combine objectives into a cost function. Progressive methods (search $\leftrightarrow$ decide) connect updated decisions and optimization steps. A posteriori methods (search $\rightarrow$ decide) present optimal candidate solutions to the decision maker. The classification used in the evaluation by Marler and Arora [MA04] replaces the progressive interaction classification with the "no articulation of user preferences". That is, the decision maker cannot define precisely his or her preferences. Thus, these methods do not requiere the articulation of preferences. Methods a posteriori are better ranked because of their capacity to present preference information. Among those methods, genetic multi-objective algorithms are remarked for their effectiveness potential.

Altogether, the profuse interest on optimization methods can be corroborated for example, by the enumeration of uncountable works in other exhaustive surveys [Van99, Lam00, GD04, Coe06, Coe13, ZQL+11] on the topic of Multi-Objective Evolutionary Algorithms, which according to Guliashki et al. [GTK09], represents nowadays one of the three fastest growing topics in computational intelligence.

2.3.3 Multi-Objective Path Search Problem

2.3.3.1 Theory Introduction

The purpose of route search algorithms is to find a path containing the minimal accumulated link cost from the origin to destination points. For the simple shortest path search problem formulation, the network is usually represented as a directed graph $G = (N, L)$ where N symbolizes the set of nodes and L the set of directed links. A link l is associated with a pair of nodes $l = (o, d)$ where o stands for its initial node and d for its final node, $\forall o, d \in N$. In a static approach, each link l has also an associated weight function $w(l)$ representing the cost for traversing it. A path P from an origin node o' to the destination node d' is described as a set of q consecutive links between them: $P(o', d') = (l_1, l_2, \ldots, l_q) : \forall(l_1, l_2, \ldots, l_q) \in L$. The total cost of $P(o', d')$ is the sum of the individual weights w related to each link in P. Then, the weight sum with minimal value $min \sum_i w(l_i) : l_i \in P$ corresponds to the shortest path.

The Multi-Objective Path Search Problem is based on the simple shortest path search but it considers not only one weight label, but a weight vector for each link. Due to the presence of many criteria that might come into conflict with each other, not only one optimal path is searched, but a set of paths with acceptable trade-offs among the routing criteria. Instead of a simple weight value, multiple objective-based cost calculation is represented formally with a set O of n objectives in function of a path link $O(l) = (O_1(l), O_2(l), \ldots, O_n(l)), l \in P(o', d')$ The cost C for each objective with index j is $O_{j,P(o',d')}$ is $C(O_{j,}) = \sum_i^q w(l_i)_{O_j} : l_i \in P(o', d')$. where w is the associated weight of a path link to an objective function. Then, the Multi-Objective Path Search tries to find the value $min\ C(O_{P(o',d')})$.

The Multi-Objective Path Search Problem is a common topic in operation researches and optimization applications in spite of its computational complexity. The literature [HFZT08, GPS10, Zie01, PJ07, RE09] says that known algorithms for the Multi-Objective Path Search Problem cannot resolve the optimal solutions set in polynomial time. That is, it is a NP complete problem. In fact, it is intractable because the size of the Pareto frontier grows exponentially with the number of nodes of the network. In this sense, Multi-Objective Optimization algorithms do not intend to build a complete optimal set, but an approximation of it, that represent the whole range of choices [DY09]. Some recent works like Müller-Hannemann and Weihe [MHW06] research on adapted procedures to get polynomial size solutions.

2.3.3.2 Literature Survey

Optimal Path search has been widely handled as a Multi-Objective Optimization problem. Among multi-objective combinatorial optimization problems, it seems to be the most studied topic, according to Chinchuluun and Pardalos [CP07]. Martins [Vie13] presented a compilation of 39 abstracts published until 1996. More recent works on the problem can also be found in newer reviews [DSSW09, PCC06, Tar07].

Skriver [Skr00] presented a survey about algorithms dealing with the Bi-criterion Shortest Path Problem. Algorithms are categorized there in Path/Tree and Labeling. Path/Tree algorithms are sub-classified in Two Phases and K- Shortest Path. Labeling algorithms are sub-classified in Label Setting and Label Correcting. According to the final examination of reviewed works, it turns out that labeling algorithms and the Label Correcting approach have better computational performance.

Concerning recent individual works, Barbier-Saint-Hilaire et al. [BSHFHS00] developed TRIBUT, a bi-criterion assignment approach coupled with Visum [Fri98]. First, a conventional path choice general objective function is introduced for the minimization of the generalized cost that considers toll cost and value of time converted into cost. The innovation consists in the fact that time is not longer presented as a constant value for all links, but as a random variable with (log-normal) distribution. The efficient frontier for each path search is the set of efficient routes that limits the range of relevant cost-time combinations and only these routes are stored for the assignment procedure. Equilibrium for an OD pair is reached when no more efficient paths can be found, the flow-dependent travel time is identical for the efficient paths on the same cost level, and the shares of demand of different cost correspond to the value of time distribution.

Hsu and Hsieh [HH04] presented a bi-objective model for maritime freight routing to minimize shipping and inventory costs in a scenario where the choice consisted in sending the shipment through a hub or directly to its destination.

Hochmair [Hoc07] implemented a highly interactive route planner prototype. In it, users select their routes by stating their preferences among a set of optimal routes on a street map. The Pareto optimal route set pre-computation is achieved through the use of line graphs and genetic algorithms. A large number of criteria for bicycle riders and car drivers are considered. Those criteria are classified in two groups: 14 higher-level and 4 lower-level criteria. To correct the route diversity, the prototype uses a Principal Component Analysis which finds unrelated factors from lower-level criteria.

Pangilinan and Janssens [PJ07] made use of the PISA platform [BLTZ03] to carry out tests to prove that evolutionary algorithms are a plausible option for the Multi-Objective Path Search problem. The results show that the performance of evolutionary algorithms is polynomial in function of the network size. But evolutionary algorithms make the problem tractable even with large and dense networks.

Kanoh and Hara [KH08] presented a hybrid multi-objective genetic algorithm implementation for car navigation system. The model considers 3 optimization objectives: route length, dynamic travel time, and ease of driving. The characteristics of easy of driving routes are: reduced number of signals, typed as arterial road, wide, less traffic jam and reduced number of turns. These properties are expressed as constraints on the multi-objective formulation. The genetic algorithm starting population consists of initial routes calculated with the Dijkstra's algorithm [Dij59] with time and length as cost components. Arterial roads are modeled as virus whose purpose is to insert infection as special genetic operation that provokes further route mutations to encourage the usage of arterial roads. The main innovation is the inclusion of available measured traffic data for path search. The results of the tests on the central Tokyo scenario show that the incorporation of available historical traffic data on road map increases the effectiveness of routes calculation.

Raith and Ehrgott [RE09] evaluated the strategies to face bi-criteria shortest path problems such as label correcting methods, label setting methods, and ranking techniques like the k-shortest path method. Label correcting means that a node may have several labels, each for one path. With label selection each label is handled separately. With node selection all labels are extended through all outgoing links. K-shortest methods are reported to have a high cost, but instead of them, a Near Shortest Path method is introduced, setting a deviation to get a maximal path length. A Two Phase method computes the supported points (only the solutions situated on the curved boundary of all feasible solutions) apart from the non-supported ones when searching the path and it is reported to be the most suitable for road networks.

Delling and Wagner [DW09] presented speed-up techniques for multi-criteria routing. The techniques are in fact an improvement of the SHARC algorithm [BD08], which is based on graph pre-processing. SHARC creates graph partitions and pre-calculates paths to them with a generalized Dijkstra method. Then, links are flagged if they lead to a certain partition. After that, an iterative process contracts the graph selecting only relevant nodes. Finally, the arc-flags refinement introduces several reasonable constraints to prune unattractive paths both during pre-processing and queries. The Multi-Objective Path Search approach include the following: A multi-criteria version of Dijkstra algorithm operates on the prepared graph. In order to be able to reduce the Pareto set and so also to deal with real big scenarios, travel time is set as main dominance criterion. Other paths are considered in the optimal set, only if they do not represent a big bad impact on the time optimization. The effect of speed-up techniques on the performance is reported on a West Europe network scenario test: Pre-processing is reported to last 5 hours, and a route query is resolved in 8 ms.

Tian et al. [TLL09] deal with the problem of finding non-dominating paths. In order to solve the performance decay of non-dominated paths computation in large networks and large distances, they propose a solution by filtering out sub-paths that do not contribute to the eventual non-dominated path finding. The proposal consists in a so-called Skypath algorithm with two components: First, a partial dominance test, which discards intermediate paths that are found to be dominated and are useless for the complete non-dominated path calculation, and second, a full path dominance definition which discards a candidate non-dominated path containing a dominated intermediate path, in favor of a non-dominated path containing the corresponding dominating intermediate path. The algorithm makes both tests on partial candidate paths that are expanded in an iterative process, until a non-dominated path from origin to destination is found.

Mandow and Pérez de la Cruz [MPdlC10] presented NOMOA*, a Multi-Objective Path Search implementation based on the A* algorithm [HNR68]. NOMOA* is an adaptation of the MOA* [Ste91] algorithm, but it considers paths instead of nodes for selection and expansion operations. The presentation of arguments shows that a less number of operations is needed. Concretely, NOMOA* avoids unnecessary simultaneous extensions of paths that reach a selected node.

2.3.4 Multi-Objective Transit Routing

2.3.4.1 Theory Introduction

The Multi-Objective Transit Routing problem consists in finding optimal paths for passengers traveling along a public transport network. Passengers' preferences and the characteristics of the specific public transport system must be considered. Thus, typically the optimal transit route search deals with the problem of giving the passenger a solution that represents a trade-off between different objective functions. Common considered objective functions to minimize in optimal transit routing studies are travel time, number of transfers and walk time [WH04, BHL05]. Some authors add fare cost [SYHS10, MS05]. Although in graph theory the term "length" is used as synonym of cost, the travel distance seems to draw less attention in transit routing investigations. Thus, the fact of giving the passenger a set of optimal solutions could be described also as a Multi-Objective Optimization problem.

Picking up the definitions of section 2.3.3.1:
$P(o', d')$: is a transit route going from origin node o' to destination node d'.
$P(o', d') = (l_1, l_2, ...l_q)$: the transit route is a vector of a q number of consecutive directed links that lead from o' to d'.
O: is the vector of n number of objective functions.
w: is the associated weight of a path link to an objective function.
$O_{j,P(o',d')}$ is $C(O_{j,}) = \sum_i^q w(l_i)_{O_j} : l_i \in P(o', d')$: the value of each objective function in relation to the route is given by the sum of each associated objective value (with index j) over the transit route links.

Then, the route path $P(o', d')$ is dominant in relation to another route $Q(o', d')$ that has the same origin and destination nodes, if the objective vector $O(P(o', d'))$ dominates $O(Q(o', d'))$ like:

$$\begin{aligned} &\forall j \in [1, 2, ..., n] \ : \ O_j(P(o', d')) \leq O_j(Q(o', d')) \quad \text{and} \\ &\exists j \in [1, 2, ..., n] \ : \ O_j(P(o', d')) < O_j(Q(o', d')) \end{aligned}$$

The transit route $P(o', d')$ is Pareto optimal if there is not any other transit route $Q(o', d')$ that dominates $P(o', d')$. Thus, a Pareto optimal set of transit paths is described as all dominant paths from the set of all possible routes between two stations of the transit network. The choice of an optimal path requires the search of the non-dominants paths set. The multi-criteria transit routing problem consists in finding the set of all efficient objective vectors, and to find for each of these vectors a Pareto optimal path from a route query from a origin node o' to destination node d' [TC92].

On the network modeling counterpart, two main approaches are proposed in literature [Sch05b, MHSWZ07, DMS08, DPW12]: Time-expanded networks represent time events like arrivals, and departures with nodes. In contrast, each node of a time-dependent network represent a transit stop, and a link between two nodes represent a trip of a public vehicle between the stations that both nodes represent. Pyrga et al. [PSWZ04] evaluated the performance of both approaches defining two objectives for Multi-Criteria Path Search: earliest arrival and minimum number of transfers. They concluded that the time-expanded approach is appropriate for complex scenarios but the time-dependent has generally a better performance.

2.3.4.2 Literature Review

The Multi-Objective Transit Routing problem is a current trend topic on transport research. Although most contemporaneous studies are focused as journey planner implementations for passengers, other approaches with increasing interest are the transit network equilibrium [TGBI13] and transit network design [GH08, FM04]. As this dissertation is focused on the demand calibration, this section reviews optimization works from the passengers' route perspective. In contrast, network design optimization constitutes the public transport supply that is outside of the scope of this work.

Many previous studies on Multi-Objective Transit Routing were already enumerated in the review made by Liou et al. [LBF10]. They classify the works in static transit assignment, within-day dynamic transit assignment, and emerging approaches. Similarly, Fu et al. [FLH12] made a structured review and analysis of works with the focus set on the network congestion problem.

A preliminary work was published by Foo et al. [MYW99]. They presented RADS, a multi-modal passenger journey planner for the Singapore public transport system. The travel parameters to minimize were total distance, traveling time, and total fare. However, as a transit journey planner, it had the objective to help passengers to plan their transit routes according to their preferred criteria. Therefore, it is not intentionally designed in terms of a formal Multi-Objective Optimization model.

Li and Su [LS03] described a simple bi-criteria route choice algorithm whose objectives are transfer number and travel distance minimization. For optimal route search, the sets of routes with incremental number of transfers are calculated and then the travel distances between them are compared. Unfortunately, performance results were not reported.

Müller-Hannemann and Weihe [MHW06] carried out a study on bi-criteria shortest path search on a scenario with real schedule information of the german train system. The objective was to determine if the Pareto optimal set size could be set to a polynomial size or not. The approach identifies key characteristics on the scenario that lead to a smaller number of optimal solutions which practically makes the problem tractable, instead of getting an exponentially growing solution size in the worst case. The method set restrictions to paths according to an edge model classification and discards node labels that are dominated by labels at the destination node.

Müller-Hannemann and Schnee [MS07] presented a model with 3 main optimization objectives: travel time, fare, and transfer number minimization. For it, the concept of Relaxed Pareto Dominance is introduced to find potentially attractive routes without discarding “near optimal” solutions. It consists in the use of a relaxation function that takes into account other travel aspects not considered originally in the main optimization objectives. Routes that are attractive from these other travel aspects, are set incomparable. In that way, these attractive routes are not suppressed by the normal route dominance comparison. The reported performance surpasses the journey planner of the german rail firm Deutsche Bahn, which collaborated for the scenario of the german public railroad network.

Aifandopoulou et al. [AZC07] describe a multi-objective integer linear programming model to create a web information gateway to calculate optimal transit paths according to users’ preferences. The multi-objective includes the personal travel preferences expressed as optimization constraints: desired departure time, waiting time preference, maximum allowed transfers, transfer possibility in time and space, and route selection. Optimization objective functions are also expressed as constraints: fare price preference and total route duration. For optimal set definition, first routes surpassing time constraints are calculated. Then, they are ranked according to the other criteria. The computational evaluation reports that CPU time is linear in function of links number.

Hochmair [Hoc08a] presented his first analysis of objective parameter reduction in a multimodal routing model. It is the next step after his previous analyses [Hoc07] that showed that bicycle route diversity is achieved also by a reduced number of route criteria. The change of mode is modeled with turn costs in the line graph. The complexity of a multimodal route is a linear combination of turns and route transfers. Very similarly, he presented his model [Hoc08b] oriented to the routing criteria simplification with an extra scenario. For routing calculation, benefit criteria (like parks) and cost criteria (like travel time) are considered. First, a Dijkstra-based algorithm is used to initialize the original population through cost criteria minimization. The next step is the optimization of a benefit criterion with a genetic algorithm which uses crossover and mutation operators. The mutation takes two parent chromosomes parts as basis, but one of them is recalculated and replaced. Moreover, a form of original chromosomes is always kept, and duplicated solutions are discarded. For Pareto frontier diversity analysis, the Principal Components Analysis is applied again to reduce the dimension of routing criteria. Using data of Bremen and Vienna scenarios, 15 original path criteria are reduced to 4 components: simple, fast, scenic and shopping.

Disser et al. [DMS08] presented a Dijkstra generalization algorithm for a time dependent graph. Nodes have multidimensional labels which makes possible to expand them multiple times during the path search. Each label represents an optimization objective and includes a reference to its predecessor on the path. New labels are compared to the complete list of previously revised labels for node and a list of non-dominated list of labels is updated, and dominated labels are removed. In addition to time and transfer number, “reliability of transfers” is considered, which is a criterion related to a buffer waiting time for delayed transfer vehicles. The performance is improved with the use of speed-up methods. Testing on a base-line implementation, the speed-up factor is 20 with respect to original label creation process and 138 with respect to original label insertion process.

In a similar way, Delling et al. [DPWZ09] presented a routing algorithm in flight networks. It uses a generalization of the Dikjstra algorithm, in which each node is labeled with 3 cost components: travel time, transfer numbers and monetary cots as optimization criteria. For node expansion, a dominance rule is applied: A node dominates another one if its cost label comprise at least one better individual cost value, and none worse value with respect to the rest of components. In the flight network model, a node stands for an airport, which reduces the network complexity in comparison with road networks. Because of that, all routes between airports are conveniently pre-calculated and stored in tables for queries which retrieve routes in microseconds.

Fan et al. [FME09] presented a routing passenger and transit network design model whose objective is to balance passengers’ and operator requirements. The evolutionary multi-objective optimization framework finds routes with minimal travel time in transit network, creates small moves in feasible routes for neighborhoods with a special routine and generates feasible route set by the trade-off evaluation of two conflicting objectives: travel time as passenger cost and travel length as transit system operator cost. Other work [Fan09] presented a metaheuristic framework with hill-climbing and simulated annealing algorithms. Based on Mandl work [Man80], transfer penalty was added in addition to travel time minimization. The optimization method is expressed as a weighted sum of those two criteria, excluding waiting time.

Ambrosino and Sciomachen [AS09b] presented a routing algorithm whose objective is to force the calculation of routes through multimodal commuting nodes. The method is focused on multimodal transfer cost calculation. The evaluation of links considers several attributes: connectivity, accessibility, and expected time. Pareto optimal path evaluation considers travel time and monetary cost.

Abbaspour and Samadzadegan [AS09a] presented a genetic algorithm application for single-objective path search for 3 modes. The objective function considers the minimization of waiting time and in vehicle travel time. Coding chromosomes show the elemental route with mode and node. For route mutation, a combination of single point and two point crossover is used depending on the coincidence of nodes in the chromosome. Chromosome costs are calculated with fitness (objective) function. After it, chromosomes are sorted according to cost and thus, the best ones are kept for selecting iterations. The implementation on the Teheran public transport system showed a multimodal path tendency (use of walk, bus, subway modes) after the iterations.

In his doctoral thesis [Sch09], Schnee proposed the concept of *advanced Pareto optimality* to retrieve more route options and discard unattractive routes. The concept considers relaxation functions to make more pairs of paths mutually incomparable. It includes also dominance concept tightening in order to remove undesired elements from the Pareto optimal set. The considered multi-criteria to optimize are departure and arrival times, travel time, comfort and ticket cost. Moreover, special transit systems situations are analyzed as criteria for choice: reduced fares, transfer reliability and direct routes for night trains. An in-depth analysis of speed-up techniques is also presented. The performance test scenario consists of 5,000 queries for the train schedule of Germany in 2003. The described multi-criteria journey planner developed with the model is reported to solve 95% of the queries in 1.5 seconds.

Another genetic algorithm solution is presented by Yu et al. [YL10]. There, routes are represented by chromosomes with several sub-chromosomes where integer representation is used as gene codification. For a single mode evolution, crossover and mutation operations are used. For multimodal environment, negative integers represent the mode and positive integers the coded routes. Then, the self-defined operators hyper-crossover and hyper-mutation are applied for evolution inside sub-chromosomes. The multi-criteria optimization is realized with a multidimensional vector representing criteria such as travel time, route length or transfer time that are evaluated by the fitness function with a ranking method. However, for computational performance comparison, the algorithm is marked as much time demanding.

Bast et al. [BCE+10] introduce the concept of transfer patterns. Their model implies the pre-calculation of specific intermediate nodes as *transfer patterns* and fast direct-connections. The network is reduced to only nodes of relevant transfer hubs and links between them. The multi-criteria cost component considers only travel time and transfer penalty in links. Thus, the concept of Pareto dominance is applied in relation to the sum of those two cost components. The model is tested on scenarios of Switzerland, the larger New York area, and a part of North America. After pre-computing, 50 route search queries are reported to be solved in 50 ms.

Kasturia and Verma [KV10] presented a multimodal journey planner for the city of Thane in India. The multi-objective generalized cost calculation aims to minimize in-vehicle time, transfer time, waiting time, walking time, and travel fare. Some criteria like number of transfers and waiting time are configurable for user preference, and therefore, they are set as objective constraints. A special feature is the definition of multimodal viable path, which allows only one multimodal transfer and one maximal metro sub-path.

Jariyasunant et al. [JMS11] developed an algorithm to pre-calculate K-shortest path based on transit operators information to be used as passenger journey planner. The k-shortest path routing is based on the Transit Node Routing algorithm [BFM+07] that pre-calculates distances between nodes selected according to their relevance. Pre-calculation of feasible paths is realized from origin of every bus route to the terminus of every bus route, taking travel and wait time as cost calculation basis. In order to deal with the performance difficulties inherent to pre-calculate, store, and retrieve routes, special routines had to be implemented. For example, explicit transfer number is constrained to four, and excessive time requiring queries are deliberately dismissed.

Delling et al. [DPW12] introduced a router called Raptor. It computes Pareto-optimal routes between two stops minimizing two criteria: arrival time and transfers. Instead of applying the widespread Dijkstra algorithm, Raptor makes direct searches on the schedule data. The mechanism consists in the pre-calculation of possible routes in rounds, one per transfer, and then per found lines. Arrival times are computed by traversing every transit line at most once per round. Speed techniques comprehend pruning rules and parallelization. An extension called McRAPTOR can handle extra criteria (like fare zone), since it stores labels for stops and rounds.

The test scenario is the complete public transport system of London. A standard query between two stops is reported to be solved in 8ms.

Recently, Antsfeld and Walsh [AT12] adapted the TRANSIT algorithm [BFSS07] reducing the number of nodes in the time-expanded network. The normalization approach is used in order to deal with the Multi-Objective Optimization. A linear utility function reduces the multi-criteria to a single-criterion optimization. The pre-calculation procedure operates in two layers: station graph and events graph. The public transport system of Sidney is tested as scenario. After implementing a number of speed up methods, the performance report tested 1,000 location to location queries that last in average 20 ms.

2.4 Multi-Objective Transit Routing in a Microsimulation Environment

The Multi-Objective Transit Routing problem attempts to find solutions that represent a trade-off among passengers' travel preferences. The last sections reviewed previous surveys and recent works on the route search problem from the Pareto optimal perspective. However, the Multi-Objective Transit Routing problem becomes even more demanding and acquires more complexity when it is implemented in a microsimulation environment. In the simulation of a real public transport system, route queries could be counted in millions. Moreover, in an agent-based simulation, each agent has to interact with many other agents that also try to reach simultaneously their destinations. Consequently, the transit assignment model must be able to deal with the fact that agents have to integrate adaptability and reaction to congestion into their route decisions.

2.4.1 Route Generation

The MATSim transit microsimulation [Rie10] adopts the time-dependent approach to model its transit network. The transit schedule element contains the information of the simulated transport system supply. The transit schedule constitutes also the basis to create the transit network layer for routing. Network nodes are created from stops. The schedule provides also the necessary temporal information like departure and arrival time at stations. Links between stops are generated to include the vector of criteria to optimize. Those criteria are: walk time, waiting time, travel distance, in-vehicle travel time, and transfer cost.

As the transit routing algorithm adopts a utility-based approach, the routing cost values are internally expressed as configurable utility coefficients that are applied to all agents. In this regard, the Opportunity Cost of Time might be also included as route cost component. Next chapter will introduce the transit routing process with more detail in Section 3.2.1.

2.4.2 Optimization

Optimal paths are not calculated in MATSim by a special mechanism oriented to the creation of an optimal route set. The optimization is pursued by methods that are in compliance with standard evolutionary algorithm procedures [CN05]: iterative regeneration, evaluation and selection of routes. The simulation follows also an activity-based approach. It means that not only routes are considered for fitness evaluation but also the realization of activities. An utility function is used inside the evaluation process, namely a sum of weighted travel routes and activity realization scores. Agents maximize their utility and learn through an iterative evolutionary process.

Previous works have already been made on the MATSim framework from the optimization perspective. Motorist routing optimization [ESBM06] and behavioral model parameters calibration according to volumes at counting locations [FCN11a] are some examples. The study of optimization implementations for microsimulation is a trend research topic. This dissertation is part of those efforts, as it collaborates on the optimization of public transport routing process.

2.5 Conclusions

A review of previous surveys and recent works on optimization and Multi-Objective Path Search was presented. The literature proves that optimization approaches have gained acceptance in scientific researches that deal with all kind of routing problems. Elemental label-based routing algorithms like Dijkstra's algorithm are still the base for most advanced and sophisticated routing models and speed up techniques. Special attention is to give to evolutionary algorithms that have been increasing in popularity in all types of engineering implementations.

Recent works on transit routing optimization were also presented. Most of them present common optimization objectives in route search: minimization of travel time, transfer counts, and fare cost. That relative uniformity is accompanied with other methodological tendencies. The application of algorithms inspired on natural evolution and the use of high computing power for pre-calculation seem to be a trend for the present and near future research on the area.

Chapter 3

Agent-Based Transit Microsimulation in Outline

3.1 Introduction

The implementation of a microscopic approach for the simulation of passengers' travel behavior represents a valuable tool for route choice analysis[1]. In this way, transit assignments models recognize more constituent elements than route choice approaches for private cars. When people make use of the public transport infrastructure to fulfill their daily activities in different locations, the individual route choice considers the adaptation to actual timetables with the minimization of some travel properties like time, distance, number of vehicle changes. Thus, a realistic microsimulation must recognize passengers' travel preferences. In order to model them, they are to be parametrized, measured, and validated with real transit usage data.

MATSim [MAT13] is an agent-based transport simulation framework that is able to handle scenarios with millions of agents. Its microsimulation approach represents the public transport elements in great detail, which makes it appropriate for the experiments realized on this routing calibration study.

[1]Most sections of this chapters are excerpts from previously published or presented works [MN12, MN13], and they were adapted here for this dissertation format.

3.2 Background

This section describes the MATSim framework with special focus on the transit simulation aspects that are relevant for the later routing calibration investigation.

3.2.1 Transit Simulation

The key processes of MATSim for the transit simulation [RN09, Rie10] are briefly described in the following.

3.2.1.1 Initialization.

The simulator loads information from the considered scenario. Any missing data can be also generated by synthetic procedures.

- Data Loading. Required **input data** are: transportation demand, description of street network, transport system timetable, definition of transit vehicles and passengers volumes at stops.
  - Plans. MATSim assumes that a synthetic *population* of travelers is given in order to represent the travel demand. The population consists of a list of persons to be simulated. Each *person* discloses a daily activity-based structure called plan. A *plan* describes the usual routine of activities (like being home, at work, education, shopping or leisure) described with their start and end times, and geographic locations.

    The demand per se is deduced from the normal travel itinerary between activity locations. For it, plans also enumerate the sequences of trip that are necessary to accomplish the planned activities. Each trip is represented by a *leg* whose description includes travel time, route, and transport mode.

  - Transit Schedule. It denotes the public transport system supply necessary for the simulation. Its data structure contains stop facilities-related information which includes geographical location and the timetable with detailed arrival and departure times. A *transit line* is understood here as an organized public transport supply normally labeled with an alphanumeric or color identifier that covers a defined area with a set of transit routes. A *transit route* denotes a distinctive fixed trip between an initial stop and a final stop. As a rule, two transit routes of the same transit line travel the same path but in opposite directions, but also more transit routes with slightly different paths may be included in a transit line. A *stop facility* or just *"stop"* is a defined location where transit vehicles make a time-planned pause to pick up or drop off passengers.

- Multimodal network. It is modeled as a directed graph. For the transit simulation, the network considers at least two layers:

  Physical network: In it, nodes represent possible turn moves and links represent streets. They are used primarily for the mobility simulation of vehicles.

  Transit network: It is more a logical layer used mainly for routing passengers. Nodes represent the transit stops. The directed *transit links* between nodes store a data vector about the trip between both stops, mainly for routing purposes. Both nodes and links are created on the basis of the transit schedule data. *Transfer links* are added to allow transfers between stops that are next to each other.

  Both layers are merged to create a multimodal network that is used for the complete transit and traffic flow simulation.

- Passenger Counts. Boarding, occupancy, and alighting counts can be used optionally for comparative analysis of observed and simulated passenger volumes at stops. In the case of transit calibration tests, it is necessary at least one of these type of counts as actual estimation reference. For convenience, only occupancy counts have been taken into account as adequacy parameter in this work.

• Passenger route search. Synthetic methods can help to complete any lacking information. This includes generating suitable connections through the transit network for each trip that is part of the passenger's plan. If the transit system has a detailed transit schedule available, passengers must adjust their trips to the fixed arrivals and departures of public vehicles, according to the timetable of each stop.

The **transit user route calculation** is described in Section 4.3 of [RN09] and (very similarly) in Section 7.4 of [Rie10]. The transit router uses a Dijkstra's algorithm adaptation, which allows multiple starting and ending nodes. The routing process looks for least compound cost paths with a trade-off between walk time, waiting time, in-vehicle travel time, travel distance, and vehicle change count. Following an economical approach with utility-based appraisal, the transit router considers these trip elements as a vector of personalized transit travel parameters. The behavioral parameters determine the travel preferences of passengers assigning a numeric value (in utility units) to each property.

In the transit simulation, common values for the behavioral parameters are:

- Marginal Utility of Travel Time Walk (MUTTW) = -6.0 / 3600, representing -6 utilities/h.
- Marginal Utility of Transit Waiting Time (MUTWT) = -6.0 / 3600 representing -6 utilities/h. See the remark below.
- Marginal Utility of Travel Time Transit (MUTTT) = -6.0 / 3600, representing -6 utilities /h.
- Marginal Utility of Travel Distance Transit (MUTDT) = -0.0, representing 0 utilities/km.

  It is the product of Marginal Utility of Money default value 1.0 and Monetary Distance Cost Rate default value 0.0. The reason for this choice is that on the one hand MATSim currently does not have a transit router that deals with zone structures, and on the other hand the rather large flat rate inner zone of the Berlin public transit system seems better approximated by assuming a completely flat rate in the router than by a distance based fare.
- Utility of Line Switch (ULS) = -1.0, representing one minute penalty per vehicle change.

The values presented for MUTTW, MUTWT, and MUTTT do not take into account here the Opportunity Cost of Time. The Utilities are taken as dimensionless quantities; $-6/3600s$, say, means "minus six utils per hour".

Formally, the parameterized calculation for the cost C of transit path p is:

$$C(p) = \beta_w t_{wa} + \beta_v t_{va} + \sum_{i=1}^{n} [\beta_t t_{li} + \beta_d d_{li}] + \sum_{j=1}^{m} [\beta_w t_{wj} + \beta_v t_{vj} + \beta_s] + \beta_w t_{wb} \quad (3.1)$$

Where:

β_w = Marginal Utility of Travel TimeWalk (MUTTW)

t_{wa} = initial walk time from origin point to first station

β_v = Marginal Utility of Transit Waiting Time (MUTTWT)

t_{va} = initial waiting time at first station

n = number of transit links in the transit route

β_t = Marginal Utility of Travel Time Transit (MUTTT)

t_{li} = travel time of a transit route link l_i

β_d = Marginal Utility of Travel Distance Transit (MUTDT)

d_{li} = distance of a transit route link l_i

m = number of transfers in the transit route

t_{wj} = walk time to transfer station j

t_{vj} = waiting time at transfer station j

β_s = Utility of Line Switch (ULS)

t_{wb} = walk time from last station to destination point

In the approach, time spent waiting at stations is included into the travel time transit and thus weighted with the same factor as traveling; this is a property of the underlying routing algorithm that may need revision in the future. For the present study, it is to be expected that the marginal cost of waiting is absorbed into the walk costs for access and transfer.

Other route search configurable options are:

- Initial search distance: It is a radius for stop facilities search. Its center is the starting (or destination) point location of a trip. Its lenght default value is 1,000 m.
- Extended search radius: an extra distance in meters to be added in case that an insufficient number of stops are found only with the initial distance. Its default value is 200 m.
- Transfer connection distance: radius distance in meters to search potential transferring stops in a circle around a change point. Its default value is 100 m.

The transit router finds a transit path in the transit network layer at a given time between two locations including the necessary walks to, between and from stops, and description of transit legs between starting and final stops. Once the routing process is done, the details of the found path are added to the original agent plan as new transit activities and new transit legs to depict actions like walking to stop facilities, boarding, transferring, and alighting.

3.2.1.2 Synthetic Reality (aka Network Loading)

All plans are executed by moving agents in the multimodal network simultaneously in a simulation of the physical system (synthetic reality) which includes the detailed simulation of the public transit system.

For the **traffic flow simulation**, streets are represented in the queue model by links with free speed travel time, flow capacity, and storage capacity as constraints. Vehicles are differentiated as private or public, so that bus driver agents are incorporated in the simulation to execute their own plans that consist in driving public vehicles according to route schedules.

Following the data of the transit schedule, public vehicles stop at the fixed stop facilities, where passengers wait for them in a waiting queue. Passengers try to get on the arriving vehicle, if the vehicles transit route is the one indicated by their route choice. They are allowed to board if the vehicle has not reached its maximum load capacity.

The microsimulation approach can handle and track every agent, so that the flow of both motorists and transit agents can be measured in a very precise way. This is possible with the events-based approach. Events are occurrences with temporal and spatial dimensions inside the simulation such as departure or arrival of vehicles and passengers, start or end of activities. The events triggered by the simulation are useful for modeling travel incidents such as boarding delays, failures because of overloading, delays because of late incoming vehicles, etc. For this work, events are used to track individually passengers that board and get off public vehicles. Very relevant for this study is the public vehicle depart event. After a vehicle leaves a stop, the passengers inside the vehicle are counted. Thus, simulated vehicles passenger counts per stop at a given time interval can be computed.

3.2.1.3 Plan Performance Evaluation

During the **scoring** process, each plan is evaluated quantitatively based on its own performance after their execution in the synthetic reality in each iteration.

Following a utility-based approach [CN05], the utility of a plan *V(i)* is calculated as the sum of positive utilities (in a logarithmic form) achieved by carrying out activities, plus the sum of negative utilities of traveling between activities locations.

$$V(i) = \sum_{act \in i} \beta_{perf} \cdot t^{*}_{act} \cdot \ln t_{perf,act} + \sum_{leg \in i} V_{tr,leg} \tag{3.2}$$

where:
β_{perf} is the activity marginal utility at its typical duration.
t^{*}_{act} is the activity typical duration.
$t_{perf,act}$ the activity duration in the simulation (in sec).
$V_{tr,leg}$ is the utility (typically negative) of a leg (see below).
Sometimes, there are also penalties for schedule delay, such as arriving late or departing (too) early.

3.2.1.4 Choice Set Modification

The mutation of plans is realized through adaptive strategies. The **re-planning strategies** are methods to construct new plans with mechanisms whereby some plans properties are modified, given the experience from the previous simulated day. Then, new plans created with the innovation mechanisms may be evaluated again after its performance. The strategies constitute a learning approach where synthetic travelers get some knowledge from the experience of previous iterations and accordingly, apply modification to the new ones.

The new plans are added to the agents' choice sets. The maximal number of created plans per agent is configurable. When an agent reaches the maximal number in the own choice set, usually the worst plan is removed.

A set of multiple strategies can be defined to be executed in a simulation. The definition includes the execution probability for each strategy along iterations. Some relevant strategies for the routing calibration study are:

- *TimeAllocationMutator*: Adapts randomly time dimension of plan activities according to a configurable and valid time interval.
- *ReRoute*: Regenerates routes of legs in the iteration. The MATSim modular architecture allows to implement own routing applications here.

The strategy is closely connected to the plan choice approach.

3.2.1.5 Choice.

Agents can have more than one plan. **Plan choice** is done as follows:

- If the agent has at least one non-scored (i.e. never executed) plan, a random choice between the non-scored plans is performed.
- If an agent has all plans scored, then a score-based selection between already known (executed) plans is performed, typically with a multinomial logit model [BAL85].

MATSim can implement many plan selection models. The so-called *ExpBetaPlanChanger* is used in most simulations experiments. Considering the current selected plan, this mechanism draws another random plan and changes to it, if it is better than the already selected plan, whereby the probability selection depends on the scores difference.

3.2.1.6 Iterations

After the steps of simulation execution, plan performance evaluation, and choice set modification or choice, the process goes back to the simulation execution in an iterative loop that is continued until some appropriate convergence criterion is reached. The loop describes the day-to-day learning process.

3.3 A Bus Line Scenario

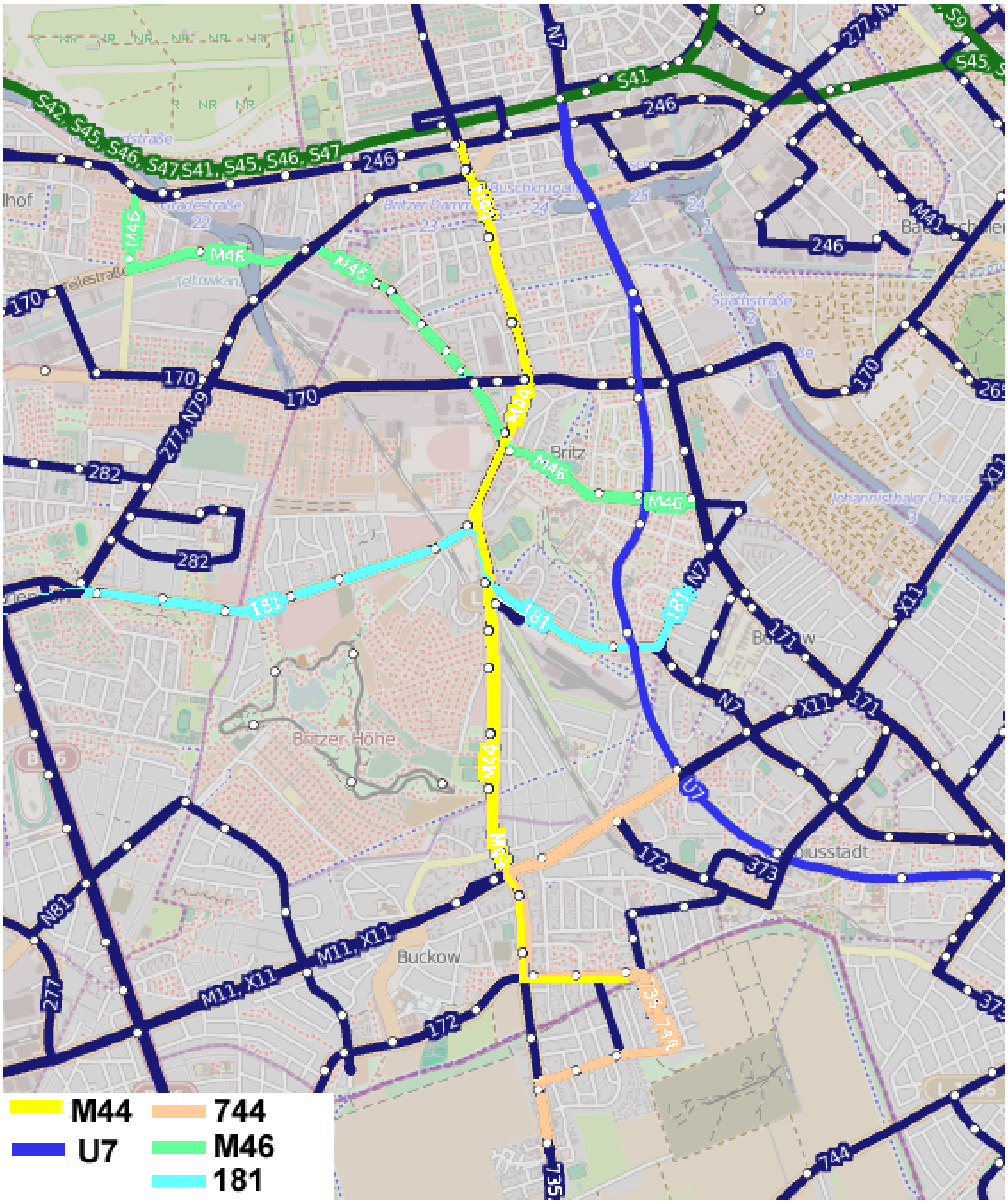
3.3.1 Supply

The transport system of the city of Berlin was chosen as scenario for estimation tests. 906 million per year, 2.4 million per day is the number of passengers that the local public transport firm BVG (*Berliner Verkehrs-AG*) reported in 2011 [BVG13]. The demand is satisfied by 10 metro (*U-Bahn*) lines, 149 bus lines, 22 tramway lines in the east districts, and 6 ferry lines. Moreover, 15 suburban metro lines[2] cover also the transit demand along the most important stop facilities in the city and its surroundings.

The *multimodal* network created for the transit simulation consists altogether of 37,591 links, where 25,704 of them represent the main avenues and 11,887 all transit links created out from the BVG timetable information. The number of nodes in the transit network representing any kind of stop facility is 4,791.

The study starts considering a small scenario that consists of the coverage area of bus line M44 in Neukölln district with persons interacting there. The passengers with activities in the area around the bus line M44 have also other alternatives. Fig. 3.1 shows the line M44 path with nearby lines: The bus line 181 that overlaps with M44 in two stations, and the bus line 744 (also named 736) that overlaps in 4 stations. The passengers located east from line M44 may be also attracted to use subway line U7. This subway runs in a parallel path to M44 with transversal distances around 900 meters. Moreover, passengers traveling from the area around bus stop Britzer Damm/Tempelhofer Weg in direction northwest (for example to S-Bahn station Südkreuz) or Schöneberg might use the line M44 and transfer to line S42 at Hermannstraße, or travel directly with line M46.

[2]The suburban metro railway system is called in german *S-Bahn (Stadtschnellbahn)* and in Berlin is not operated by BVG.



(Source: www.openmap.lt in Sep. 2013)

FIGURE 3.1: Bus line M44 and other nearby lines.

3.3.2 Demand

In order to set the demand, a synthetic population sample of agents having activities inside the bus lines M44/344 cover zone was constructed as follows (Neumann,A., unpublished data):

- The starting point is a BVG household survey from 1998 also used in other studies [KMRS02, Sch05a, RS06]. After cleaning, this survey contains the trip diaries from 57,688 persons in the Berlin-Brandenburg area and represents nearly 2% of the population.

- All persons are routed according to their selected mode. For transit mode, the aforementioned parameter default values were used.

- Passengers not having an activity in the area served by the M44/344 bus area are removed. Since in this analysis, entering/leaving a bus counts as activity, all passengers entering or leaving a bus in the M44/344 area are maintained. In contrast, passengers just traveling through the area, either by car or by other means of transport (such as longer bus lines) are removed. For the purposes of the present study, it is assumed that this is acceptable since no mode choice was considered. It is improbable (albeit not impossible) that some long-distance passenger might be available for switching to the M44/344 line; such a passenger would have been removed by the filter.

- In order to get a suitable synthetic population base of large demand, the remaining population is expanded to a "5x" sample, which means that each agent representing a passenger is copied 4 times, and these copies get their activity locations randomly relocated in a 1-kilometer radius circle around the original sites. This sample is sufficient to realize the experiments whose analysis scaled occupancy counts to 10%. After the expansion, the new synthetic travelers are routed in the same way according to their mode, and the sample is filtered again to discard new agents outside the area surrounding the line M44/344 path.

  In principle, vehicle capacities should also be scaled down to 10%. This was not done for the present studies since the Berlin transit system is rarely so crowded that this could be a reason for re-routing.

- Finally, during execution of routing processes, all agents with car mode are discarded because they do not belong to the scope of this study, which ends up with a final 5x (= 10%) population sample of 36,119 agents.

3.3.3 Counts

Data of passenger occupancy counts for 18 stops covered by the bus line M44 come from a survey by BVG realized in September 2009 and they reflect the usage of the line in a normal weekday.

The bus line M44 contains four transit routes. Two transit routes cover, in opposite directions, the complete set of 18 stops. The other two cover only 13 stops. For simulation and calibration, occupancy counts for all 18 stops in all directions and on all routes were considered. The results presented next aggregate, at each of the 18 stops, the data into hourly bins.

The occupancy is always counted after the stop, i.e. when the doors are finally closed for departure. Since the last stop of a bus line implies that all passengers must get off, no occupancy count is produced there and therefore it is not shown in the occupancy analysis.

3.4 Methodology and Results

This section describes the first methods applied to improve the transit route calculations.

3.4.1 Transit Router Adaptation

Some necessary modifications were implemented with the goal of increasing the number of found paths and add other realistic elements to the route search.

3.4.1.1 Simplified Transfer Link Creation

In the search of a transit route for an agent, a change of transit vehicle is possible thanks to the virtual transfer links created in the transit network as described earlier.

In the first network creation step, nodes stand for the stops along the transit route, and transfer links are meant to join near stops that belong to different transit lines. In the original implementation, transfer links are created between every pair of nodes within the transfer distance that

- either belong to different transit lines,
- or belong to different stop facilities.

The adaption consisted in dropping the additional condition of linking nodes of different stop facilities, thus joining nodes with the only condition that they should belong to different transit lines.

The goal was to avoid the creation of unnecessary transfer links between consecutive stops of the same transit route that are inside the transfer distance. The elimination of that requirement had the effect of reducing of transfer links in the transit network of the test scenario described in this work from 106 059 to 83 838 (almost -21%).

Moreover, in order to have a more realistic implementation of transfers, the original distance of 100 meters for the search of near stop facilities was tripled. This is in accordance with studies that suggest transfer walk distances around 300 meters or even longer [Ste96, OM96]. This radial distance expansion increased back from 83 838 to 143 154 (almost $+71\%$) the number of transfer links.

3.4.1.2 Stop Search with Progressive Radius Extension.

When a transit route search is requested, stop facilities are to be found around origin and destination points. Originally the router searches for stop facilities inside an initial given radius, but in case that the number of found stops is less than two, the radius is enlarged to the distance of the nearest stop plus an extension radius distance of 200 meters. A modification was done to guarantee a configurable minimum number of stop facilities to start the transit path, independently of their distance to the activity location. It starts with a predefined initial radius but this is enlarged progressively by the extension radius distance so many times as needed until at least the minimum number of stop facilities is found. For all runs in this section, that minimum number was set to 2. Also, instead of the standard 1000 meters distance for initial search, only 600 meters were used; this reduces the problem size in dense urban environment.

3.4.1.3 Waiting Time as Cost Component

Initially, waiting time at public transport facilities was included in the calculated travel time in vehicle. In order to be able to model travelers wait resistance, it was separated.

The waiting time at station is calculated as the difference of the departure time of the expected vehicle from the given stop and the arrival time of the passenger to the same stop. According to this formulation, two possibilities are considered as shown in Figure 3.2. There, agent's arrivals and departures from stops are represented with a blue line. Arrivals and departures of transit vehicles are represented with red lines. The interaction is shown along boarding, intermediate, and alighting stops.

- Waiting time in transit vehicle. If the passenger arrives to a stop traveling already inside a transit vehicle, the waiting time is interpreted as the time in which the vehicle stays at the stop. That is, it is the difference between vehicle departure time and vehicle arrival time at the stop.
- Waiting time off the transit vehicle. If the passenger arrives to the given stop from a mode different than transit, (commonly walk) the waiting time is calculated as the difference between vehicle departure time and passenger arrival time at the stop.

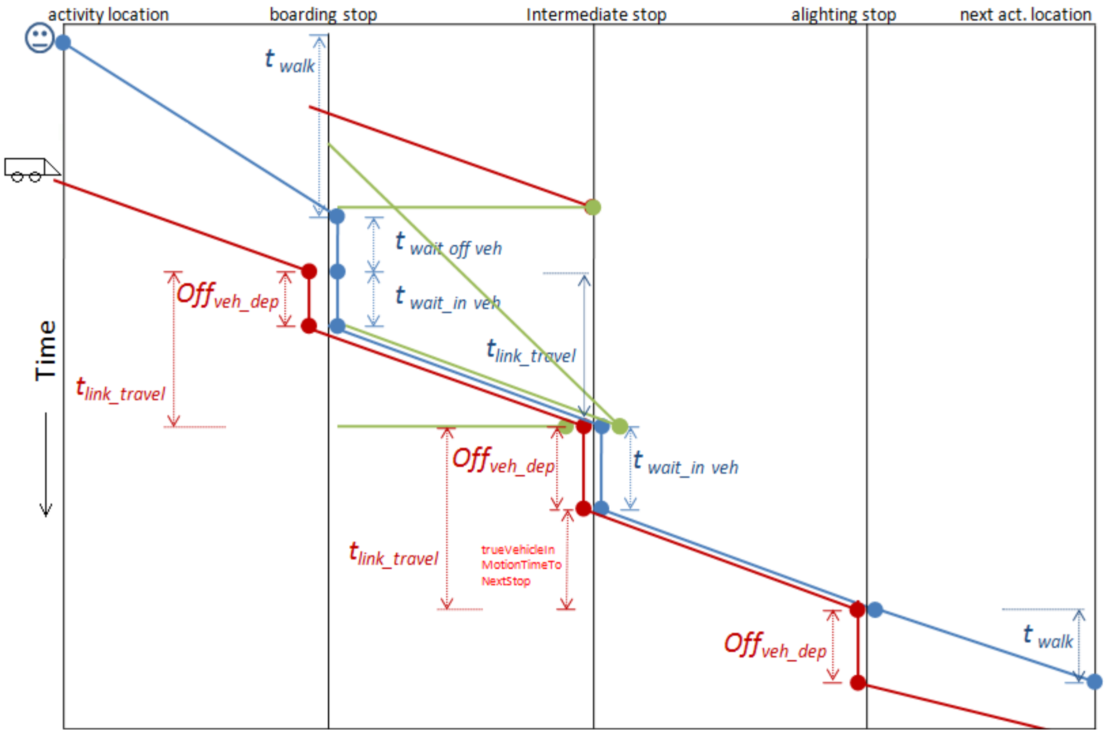


FIGURE 3.2: Distinction of passengers' waiting time **off** and **in** the transit vehicle.

The parameter Marginal Utility of Transit Waiting Time (off-vehicle) was created to add this cost to the compound cost calculation. All calibration experiments described next gave the same value from Marginal Utility of Travel Time Transit to the Marginal Utility of Transit Waiting Time. It is expected that future studies will investigate the effect of the waiting time resistance more deeply.

3.4.1.4 Results

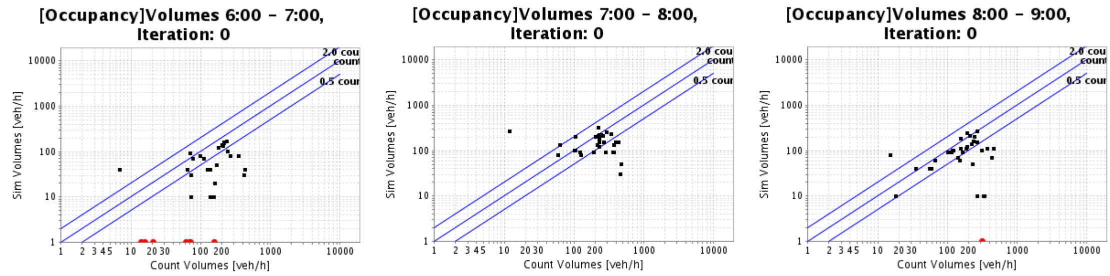
A simple comparison was done with the bus line M44 scenario before applying any calibration attempt, using the transit router default values presented before. Adapting the progressive stop search and the simple transfer link creation produced altogether more routes (almost $+12\%$) and reduced the travel time, but it increased the walk distance and walk time. The comparison of these values is shown in Tab. 3.1.

In the same way, a comparison is done in respect to the observed occupancy counts match of stops of line M44. Fig. 3.3 shows an analysis with scatter plots for 3 morning hours. In scatter plots, every dot represents both observed and simulated values for a stop at the given time bin. The observed values are in the scale of X axis, the simulated values are Y axis. Thus, a point

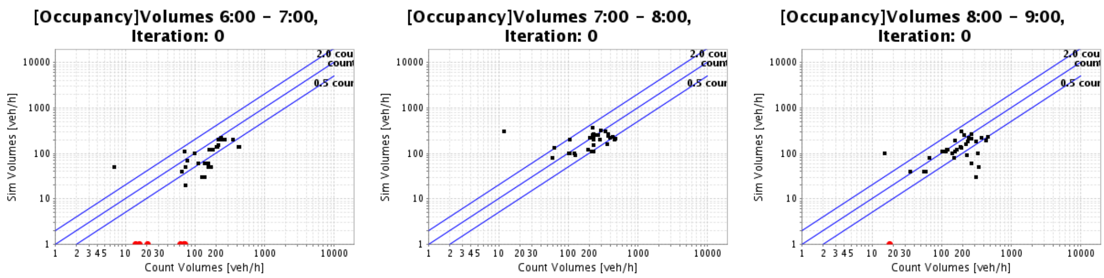
	before adaptations	after adaptations
Number of routes	86 739	97 202
Travel time in seconds	4.49E+12	3.53E+12
Number of transfers	153 644	143 022
Walk time in seconds	1.50E+10	1.72E+11
Walk distance in meters	72443	83 198

TABLE 3.1: Results of transit router adaptations.

in the diagonal would represent the state of exact match for both values. Expressed differently, for a perfect reproduction of counts in the simulation, all dots must be situated exactly over the diagonal with slope one. On the contrary, the more distant a dot from diagonal one is, the bigger is its inconsistency of observed-simulated values.



(a) before adaptations



(b) after adaptations

FIGURE 3.3: Passenger occupancy results at early hours before (a) and after (b) router adaptations.

The Mean Relative Error (MRE) is a typical quantitative analysis to evaluate the efficiency of calibration approaches. In Section 4.1 of [FCN11b] it is formulated as follows:

$$MRE(k) = \left\langle \frac{|y_a(i) - q_a(k)|}{y_a(k)} \right\rangle_a \tag{3.3}$$

where:

k = each hour of the day.

a = measurements locations.

$y_a(k)$ = observed volume on a location a in hour k .

$q_a(k)$ = simulated count on a location a in hour k .

The average $\langle\bullet\rangle$ over all stations a that are to be calibrated is evaluated separately for each k. A final plot comparison in Fig 3.4 shows the evolution of MRE along day hours for both routing mechanisms.

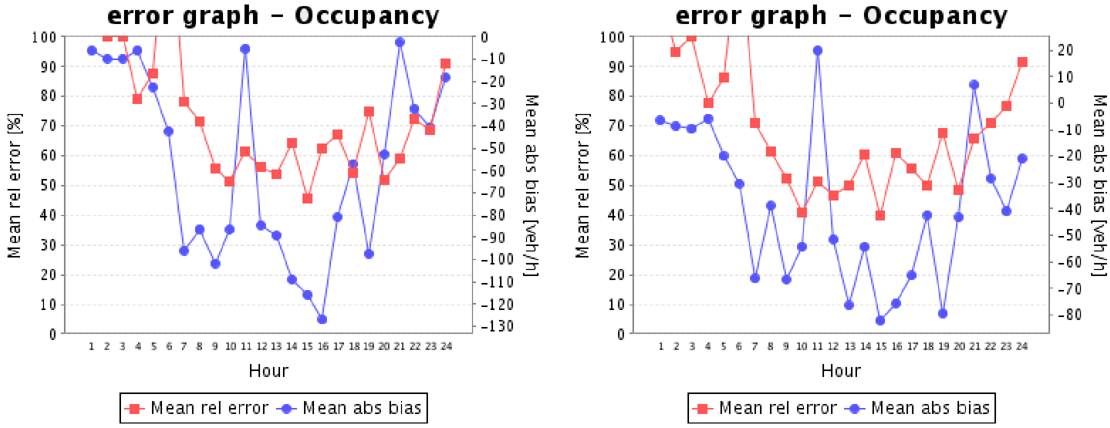


FIGURE 3.4: Mean Relative Error achieved before (left) and after (right) router adaptations.

The counts bias is the mean value of simulated minus observed counts at all stations. One can see that in both occupancy counts match analyses, a slight but distinct improvement is achieved with the adaptations too.

3.4.2 Before Calibration

A simulation run was carried out using the MATSim router travel parameters *default* values[3] (MUTTW $= -6/3600s$, MUTDT $= 0/m$, ULS $= 60s/$MUTTT). The 17 sub-figures of Fig. 3.5 show the comparison of real occupancy values (in yellow) and simulated values (in blue) for the main transit route stops in hourly bins. General occupancy analysis indicates the mean relative error (red line in last sub-figure) for the whole transit line that fluctuates around 50% and 70% before any calibration attempt.

[3]By the time of these experiments, the default values did not take into account the Opportunity Cost of Time

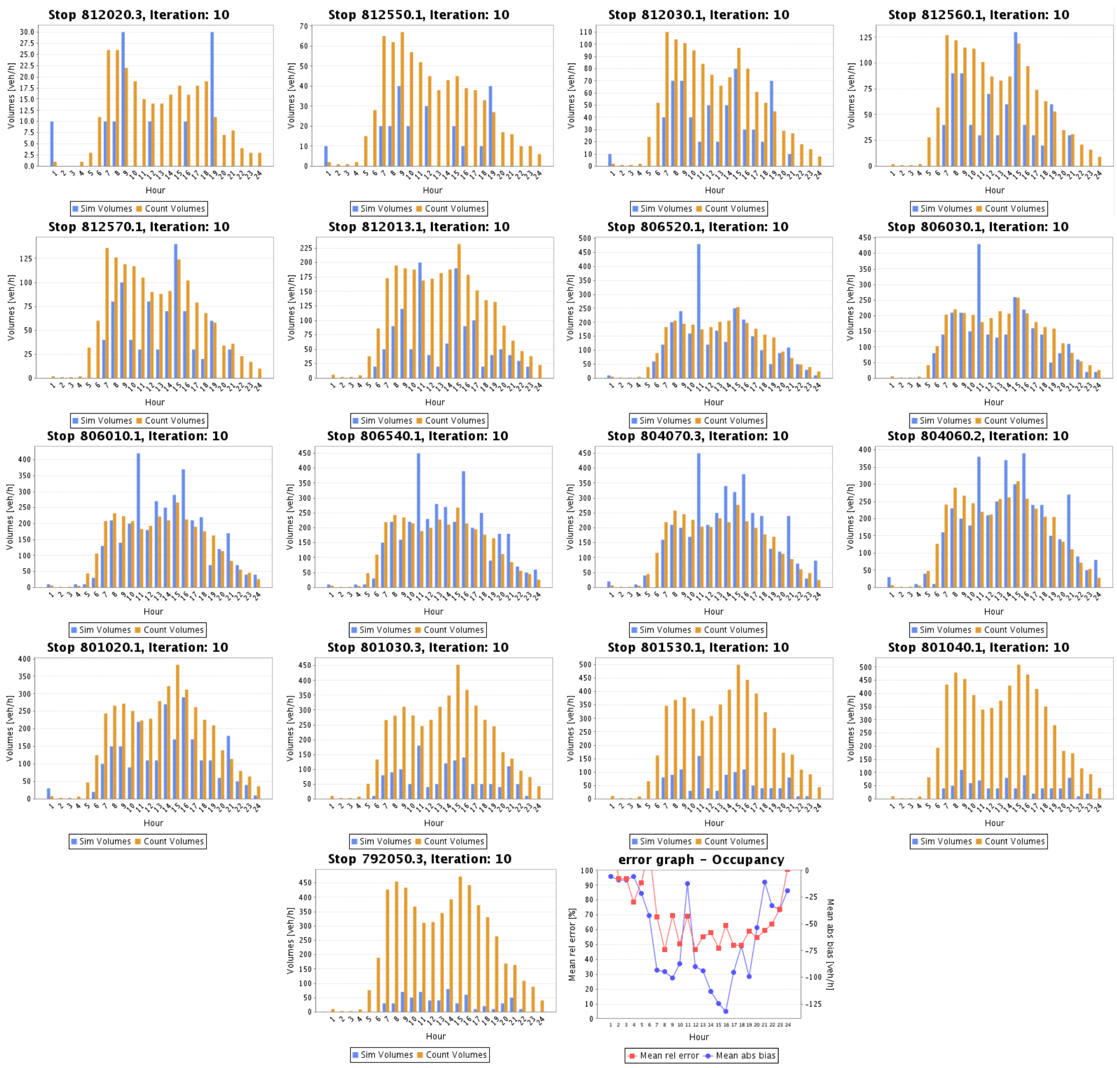


FIGURE 3.5: Per stop counts data-simulation comparison plots and general error graph before any calibration (5x expanded population).

3.4.3 Manual Calibration of the Utility Function

A first task was to find an acceptable set of parameter values that may produce close to reality occupancy simulation values. Weight variations on 3 cost variables were tested as follows:

- walking time (MUTTW from $-1/3600s$ to $-10/3600s$ in decrements of $-1/3600s$)
- transit travel distance (MUTDT from $-0/1000m$ to $-1.4/1000m$ in decrements of $-0.1/1000m$) and
- utility of line switch (ULS from $0 * \text{MUTTT}$ to $1200 * \text{MUTTT}$ in decrements of $60 * \text{MUTTT}$)

The Marginal Utility of Transit Travel Time (MUTTT) remained constant with its default (dis)utility value of $-6/3600s$.

An exhaustive search of combinations of different parameters values was done according to the mentioned range of values for each variable. That is, 3,150 parameter combinations were obtained from the number of variations of each parameter (10*15*21 = 3150). Clearly, a strongly negative MUTTW value represents a high resistance to walk to, between or from stops. A strongly negative ULS value represents a high resistance to change vehicle. A strongly negative MUTDT represents a high resistance to choose long distance routes. In every case, initial and end values were set such that the plausibility of the routing results was already obviously impaired. That is, the search interval was wide enough to contain all realistic parameter values.

Passenger routes resulting from high resistance to walk (more strongly negative MUTTW value) and also from high resistance to transfer (more strongly negative ULS value) produced simulated values closer to actual counts data. In the case of ULS, the best output was achieved with values more strongly negative than $240 * $ MUTTT (which means an equivalent penalty of 4 minutes per transfer) and in MUTTW with values lower than $-6/3600s$. Fig. 3.6 shows an example of error comparison of simulation counts data reached just by this approach. It can be seen that the MRE percentage fluctuates around 50% and 30%.

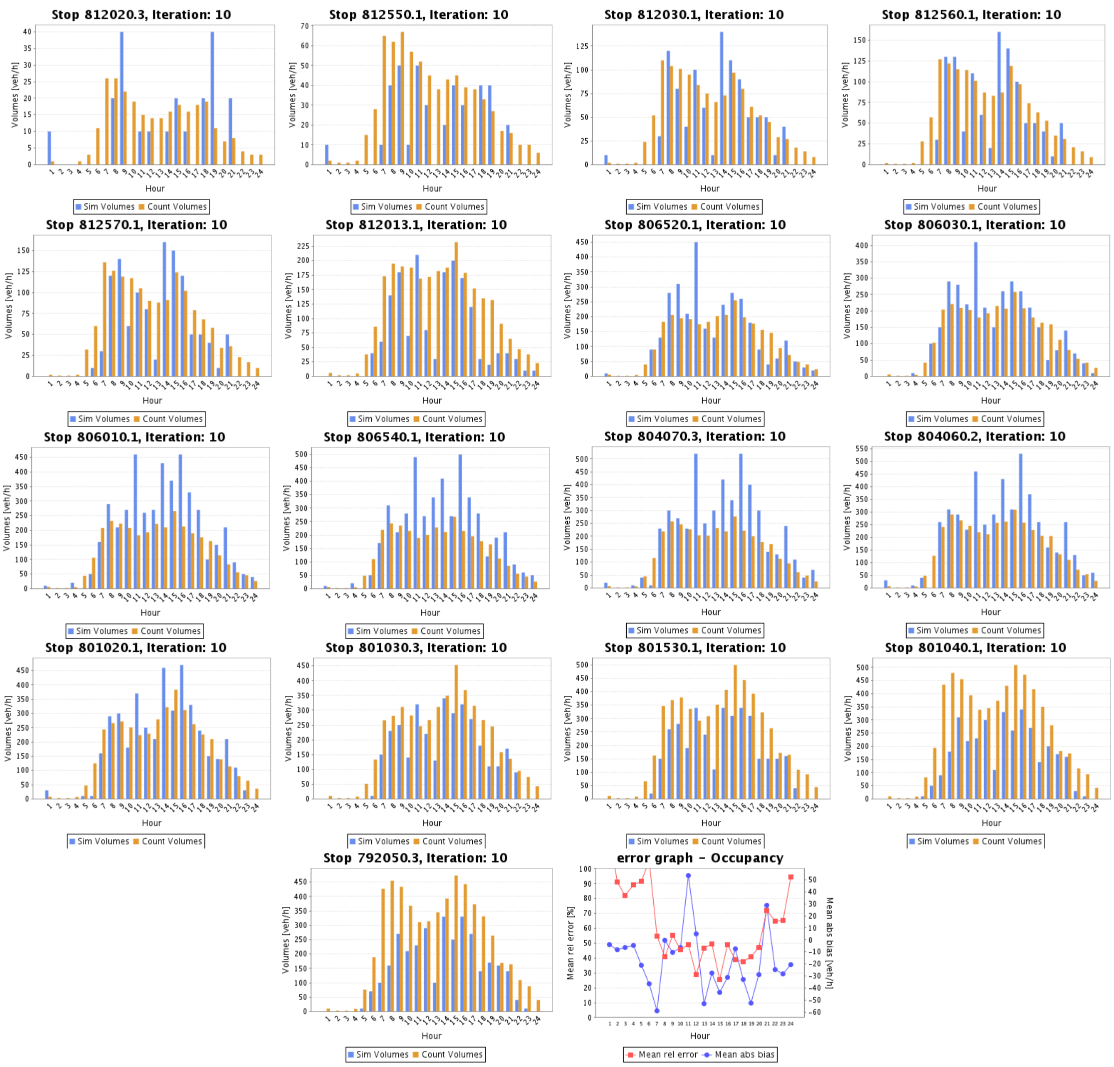


FIGURE 3.6: Per stop counts data-simulation comparison and general error graphs after manual calibration (5x expanded population).

The best combination of travel parameter values from this manual calibration is:

- Marginal Utility of Travel Time Walk (MUTTW): $-10/3600s$ (compared to $-6/3600s$ in the original router)
- Marginal Utility of Travel Distance Transit (MUTDT): $0.0/1000m$ (same as in the original router)
- Utility of Line Switch (ULS): $240 * \text{MUTTT}$ (compared to $60 * \text{MITTT}$ in the original router)

Compared with the original routing parameters, travelers attempted to reduce their amount of walk time and the number of interchanges. This suggests that in-vehicle times and in-vehicle distances should increase. And indeed, from the original routing parameters (Fig. 3.5) to the calibrated ones, the average in-vehicle travel distance for all M44 users increased from 1,804 to 2,441 meters.

As an attempt to validate these tendencies, individual transit route requests were compared with the BVG journey planner [BVG13]. It turned out that similar routes were suggested also by the BVG site.

Table 3.2 compares these values with the ones found by other mode choice and transit assignment studies in different scenarios: Florida [AAH01], the averages for a number of American cities with COMMUTER v.2 [Tra05], Toronto [Mil06], San Francisco Bay Area [CM02] and Santiago de Chile [RMd11]. The four top rows show the absolute values. The three bottom rows divide the values for walk time, switch occurrences, and wait time by the in-vehicle time coefficient, resulting in more meaningful numbers. All values seem to be in a similar range. Given the importance of the penalty for line switching in Berlin, a comparison with those models that also include a penalty for line switching seems most meaningful. Out of those, the Santiago model comes out strikingly similar to this section, while the Florida model has a relatively higher penalty on waiting and relatively less penalty on line switches. Overall, the result from this section seems to be in line with others.

Parameter	MATSim old	this section	Florida	Commuter	Toronto	San Francisco	Santiago
in-vehicle time [min]	0.1	0.1	0.02	0.025	2.0	0.023	0.119
walk [min]	0.1	0.17	0.045	0.047	1.0	0.029	0.240
line switch	0.1	0.4	0.045	./.	./.	./.	0.449
wait time [min]	0.1	0.4	0.045	0.046	2.733	0.044	0.111
walk/in-veh	1	1.7	2.25	1.88	0.5	1.26	2.02
switch/in-veh	1	4	2.25	./.	./.	./.	3.77
wait/in-veh	1	1	2.25	1.84	1.37	1.91	0.93

TABLE 3.2: Coefficient values comparison with their mode choice and transit assignment studies in different scenarios.

3.5 Conclusions

This chapter introduced the public transport microsimulation environment necessary for routing calibration investigation.

Manual calibration attempts were realized on a real small scenario represented by a bus line in Berlin. This first intent consisted in the uniform modification of travel parameters to get combinations of values that generate a big sample of routes with the goal to find the ones that match the best the observed counts in a simulation.

Chapter 4

Automatic Calibration

Calibration of transport models with systematic and automatic methods for large scenarios is nowadays possible[1]. The increasing sophistication in those methods and the current computing capacity make it possible to realize those operations within acceptable performance ranges. This chapter presents a completely disaggregated automatic calibration approach for route choice inside the transit microsimulation. The calibration of transport demand is achieved with the demand calibration tool Cadyts.

4.1 Related Works

Traffic demand calibration with systematic procedures is a prevailing topic in transport research. Chu et al. [CLOR03] proposed a traffic network-level calibration procedure for PARAMICS. Route choice diversification was achieved by costs modifications on link decreasing speed limit values, link cost factors, and link tolls. Vaze [Vaz07] used a mesosopic simulation to prove the calibration improvement with automatic vehicle identification techniques using simultaneous perturbation stochastic approximation, genetic and particle filter algorithms. Zhang et al. [ZMD08] described an implementation of genetic algorithm-based calibration tools for local, global and departure-route choice parameters.

[1]The work reported in this chapter was published at the 91th Annual Meeting of the Transportation Research Board in Washington, D.C. as Paper 12-3279, "Automatic calibration of microscopic, activity-based demand for a public transit line" [MN12] and adapted here for this dissertation format.

However, few works are found that deal directly with the estimation of passenger travel demand in transit simulation. A Fuzzy-Neuro approach is proposed by Yaldi et al. [YTY08] to improve accuracy in travel demand modeling. Tamin and Sulistyorini [TS09] used Non-Linear-Least Squares to calibrate parameters to estimate OD matrices. Li et al. [LC07] estimated also OD matrix-based route choice through passenger counts. Parveen et al. [PSW07] presented the calibration of the aggregate transit-assignment model used in EMME/2, which is based on the minimization of travel time with five parameters: boarding time, wait-time factor, wait-time weight, auxiliary time weight, and boarding-time weight. In order to match on-board counts, it uses a genetic algorithm where each chromosome represents a set of parameter values generated randomly. A more recent work by Wahba and Shalaby [WS11] presented the calibration of the transit scenario of Toronto with MILATRAS. The learning model is based on mental models for every passenger where travel experiences are updated and evaluated in order to adjust waiting and in-vehicle time. The calibration defines nine parameters related to trip purpose and transit vehicle type. It is done with the integration of a genetic algorithm engine.

4.2 Background

4.2.1 Cadyts

For transport simulations, but with the clear potential to be more general, the demand estimation problem was addressed by G. Flötteröd and co-workers (e.g. [Flö08, FBN11]). He implemented his methodological approach into the open source software Cadyts [Flö13], a calibrator for disaggregated demand models.

The core functioning of Cadyts, which is based on Bayesian principles, combines the prior agent plan choice distribution with real world measurements into a posterior choice distribution. Very intuitively, 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.

Cadyts is not a stand-alone framework, but a pluggable tool for any dynamic and iterative traffic assignment model. It has been employed for the estimation of vehicular travel demand in a number of simulators. For example, a previous interaction between MATSim and Cadyts to estimate private car traffic in the Zurich scenario is described in [FCN11a].

This chapter reports a new coupling of Cadyts with MATSim to use passenger counts at stop facilities for the microscopic public transport demand estimation.

Detailed theoretical description about Cadyts can be found in [FBN11]. Only a summary description of the calibration steps is introduced here in order to help to illustrate its integration with MATSim transit simulation:

1. **Initialization.** The calibration process starts by registering observed counts at stops. Each entry has this data structure:

   - Id: the identifier for the count station.
   - Start time: the inclusive initial time for the count time bin.
   - End time: the exclusive final time for the count time bin.
   - Value: the number of observed mobile agents during the time bin.
   - Minimal standard deviation (minStdDev): the smallest allowed standard deviation for the observed counts.

   At the beginning of the run, the calibrator method *addMeasurement* collects all available counts.

   addMeasurement(L l, int start_s, int end_s, double value, double stddev,
   Measurement.TYPE type)

   The method is called for each location *l* with available counts during the time bin specified from *start_s* to *end_s*. Counts are classified in accordance to the data structure *Measurement.TYPE* whose instance *type* may denote either the average flow rate or the total traffic count *value* during the time interval.

   Thereby, *L* is a template variable, defined by the object instantiation

   MATSimUtilityModificationCalibrator<L> calibrator = new
   MATSimUtilityModificationCalibrator<L>(...); .

   There are no restrictions to the type of *L*, which means that measurements can be attached to arbitrary objects. They just need to be the same as the objects that are traversed by the plans (see next).

2. **Plan Choice:** A MATSim-Cadyts-adapter would create instances of an interface called *Plan<L>* for Cadyts' own internal representations of travel demand. The calibration of a simulation with utility-based demand works by computing for every agent a linear plan effect. The correction information can be used in various mathematically consistent ways for calibration of the simulated travel behavior, depending on the concrete choice model at hand. For a multinomial logit model, the calibration is achieved by adding this quantity to the considered plan utility.

   The utility modification is invoked with the Cadyts method

   calcLinearPlanEffect(Plan<L> plan).

   How the choice model uses this information is left to the model, but in many cases, for every plan the utility modification is added to the uncorrected utility, and the resulting modified utilities are used for the choice model. After the agent selects a plan based on the correction, the choice is reported to the calibrator with the method:

   registerChoice(Plan<L> plan).

   Cadyts runs a regression model for every featured location l and time bin, where the number of agents that intend to cross that location is the explanatory variable and the actual flow across the same location is the dependent variable. The slope of the resulting regression line provides sensitivity information to the calibration. The *registerChoice(Plan<L> plan)* method is necessary to identify the explanatory variable. For the purpose of this work, two special implementations will be reported: Cadyts utility correction used inside the choice process, and Cadyts embedded into the simulation plan scoring module. The first approach is presented in this chapter

3. **Update:** after the simulation iteration, the calibrator reads the output network loading situation through a container *SimResults* which takes in a set of time defined resulting traffic volumes of a location *<L>*.

   afterNetworkLoading(SimResults<L> simResults)

The Cadyts posterior choice model is outlined in Sections 3.1 and 3.2 of [FCRN09]. The formulation of Cadyts posterior distribution embedded with MATSim behavioral model of multinomial logit form is presented too. It assumes moderate congestion with independently normal distributed traffic counts. The core equation for the purposes here is

$$P(i|y) \sim exp\left(V(i) + \sum_{ak \in i} \frac{y_a(k) - q_a(k)}{\sigma_a^2(k)}\right) \tag{4.1}$$

where:

y is a vector that collects all actual data.

$P(i|y)$ is the posterior plan choice distribution given y.

$V(i)$ is the MATSim score of a plan i as formulated in Eq. (3.2).

$y_a(k)$ is the actual traffic count at link a during time k.

$q_a(k)$ is the simulated traffic count at link a during simulated time k.

$\sigma_a^2(k)$ is the variance of the traffic count.

The sum $\sum_{ak \in i}$ goes over all links a and time periods k used by the plan i.

The variance $\sigma_a^2(k)$ should optimally come from specific knowledge about each sensor, but in its absence, it is calculated as: $\sigma_a^2 = \max(varianceScale * y_a(k),\ minStdDev^2)$ whereby the scale is a configurable factor for measurements without explicit variance declaration, assuming to be proportional to the measured value in order to be consistent with the assumption of Poisson distributed measurements. The `varianceScale` default value 1.0 was used for this work. In order to avoid numerical problems, Cadyts bounds the effective values of $\sigma_a(k)$ from below.

The configurable `minStddev` value defines the smallest allowed standard deviation for measurements. After some experimentation, it was set to 8 for the calibration work described in this chapter. That effectively means that relative errors below [$minStdDev^2$] ($8^2 = 64$) are under-weighted accordingly.

When the whole process is converged, *calcLinearPlanEffect* effectively returns the utility correction based on the sum of all counting stations at the time steps that are involved inside the agent plan i according to Eq. (4.1). That is, at the choice step Cadyts affects the agent plan choice in this way: The plan choice is under normal circumstances a function of the plan performance reflected on its score, but in the case of the calibration it is also a function of the real data counts reproduction. That is, the utility of a plan gets a higher value with the utility correction if the plan helps to improve the reproduce the real counts. And on the contrary, a plan receives a lower score value if it deteriorates the counts reproduction during simulation. In order to make sure that utility corrections at more representative count stations have a more significant effect than at unimportant stations, the error contributions of every individual counting station are scaled with $1/\sigma_a^2(k)$.

The combined effect of the σ_a is also that it balances between the prior utility $V(i)$ and the Cadyts utility correction: Larger σ_a mean less trust in the measurements, and thus a larger weight to the prior.

4.2.2 Coupling Microsimulation and Calibration

An integration code was written in Java to work as bridge between Cadyts and MATSim transit simulation.

The Cadyts generic network link type was originally meant to represent network links with auto traffic count stations. For the estimation of passenger travel behavior, it was adapted to represent transit stop facilities with available passenger occupancy counts instead. Thus, variables y and q of Eq. (4.1) acquire these meanings:
y is the actual occupancy count at transit facilities after unloading and loading, and
q is the simulated occupancy count after unloading and loading
$V(i)$ is set to zero for the purposes of this chapter, in order to score plans just by their consistency with real counts.

4.2.3 Automatic Calibration with Cadyts

Before applying Cadyts, the route choice generation was realized before any other process. Routes were pre-calculated in independent routing queries any simulation or calibration. The calibrator would thus select between the pre-computed plans, but not add new plans to the choice set.

The criteria to create the different plans were: variety of routes, and the search of routes with minimal number of interchanges and minimal walk distances

In the end, three different transit plans per synthetic traveler were generated. The parameter values used for optimally routing the three different public transit plans are:

- Combination 1: MUTTW= -6/3600, MUTDT= -0.0/1000, ULS= 1200*MUTTT, i.e. strong transfer penalty.

- Combination 2: MUTTW= -10/3600, MUTDT= -0.0/1000, ULS= 240*MUTTT, i.e. strong walk penalty.
- Combination 3: MUTTW= -8/3600, MUTDT= -0.5/1000, ULS= 720*MUTTT, i.e. moderate walk and transfer penalties.

In addition, in order to obtain a synthetic elastic demand, the following was done:

- All synthetic travelers (of the "5x" sample) were duplicated.
- All synthetic travelers got an extra plan in which they stayed at home.

The result is that the calibrator will not only affect the transit routing, but also the overall level of demand, which can be increased or decreased by decreasing or increasing the fraction of "stay-home" plans. See also [FL13].

Now, using the Cadyts utility modification as the basis for plan selection, a calibration run was done loading agents with those 3 different public transit plans plus the "stay-home" plan, and calibrating the period from 06:00 to 20:00 hours.

A special approach in the calibration is the use of *brute force* option. It consists in the implementation of some settings that enforce the counts reproduction with best effort. Those settings are:

1. Explicitly declaring the use of brute force in Cadyts calibrator. It is a special setting that implements a mechanism "as if" all measurements had zero sigmas.
2. Nullifying behavioral parameters with values close to zero or zero in MATSim configuration file, so that final plans scores get similar values after the scoring process.
3. Implementing a nullifying scoring function that returns value zero, no matter how plausible or poor the performance of a plan was.

For the calibration tests described in this section, the brute force was turned on applying the first two settings.

The comparison of Cadyts-enabled simulation results with real counts data are shown in Fig. 4.1.

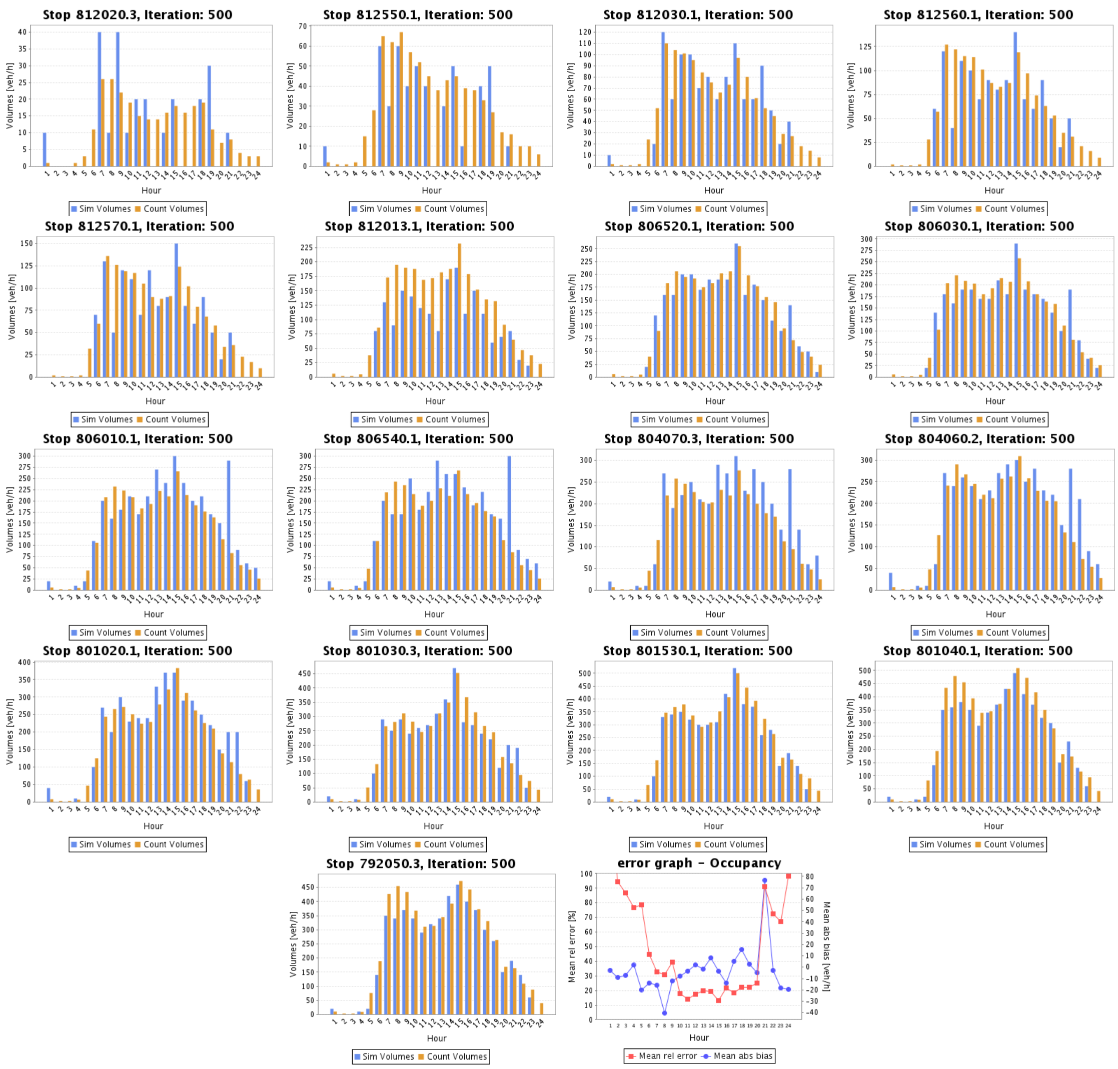


FIGURE 4.1: Per stop counts data-simulation comparison plots and general error graph after automatic calibration (5x expanded population).

The general error was reduced by around 20% in comparison with the manual calibration. Simulated and actual counts reached a suitable comparison at most stops where morning and afternoon peak hours can be identified in both counts types.

One should note, though, that the manual calibration and the Cadyts calibration attempt different things:

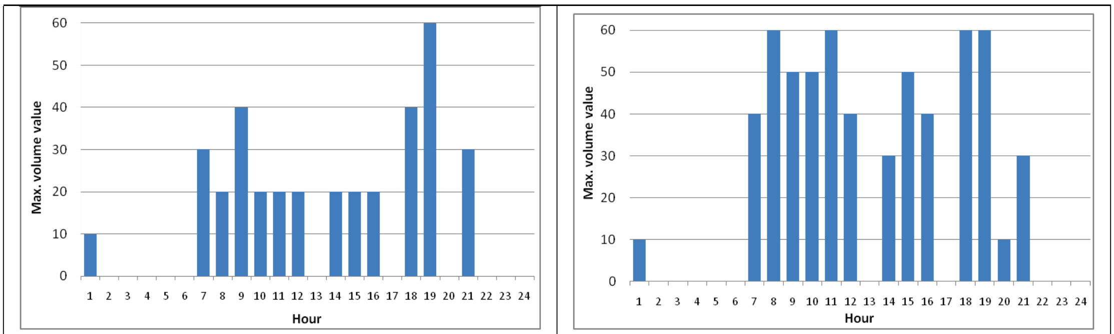
- The manual calibration attempted to find one set of behavioral parameters that would lead to realistic occupancies.
- The automatic calibration picks one out of four different route plans (one of them being the stay-home plan) in the attempt to generate realistic occupancies.

It is clear that the second approach has more degrees of freedom and thus achieves a better fit.

4.2.4 Investigation of Missing Demand Segments

The first two stops of bus line M44 showed a lower consistency with the real data than the rest of the stops, even after the calibration runs. It is quite clear that a synthetic population that is based on a simple "5x" expansion of a 2% sample may have gaps that cannot be filled by the adjustment process. The problem can already be visually taken from "Stop 812020.3" in Fig. 4.1 where one notices that the simulation can provide passengers only in increments of "10", corresponding to the 10% sample where every passenger also stands for 9 others. That is, for some hours of the day there may simply be no demand available that can be shifted to match those counts.

To investigate, occupancy counts were reviewed along the complete set of 3,150 parameter combinations to find which ones may supply higher volumes or any volumes at all for those stops. However, it was not found any combination that could be able to provide any volume for hours 2, 5, 6, 13, 17, 20, 22, 23, 24 neither at the first "Stop 812020.3" nor at the second "Stop 812550.1" for hours 2, 3, 4, 5, 6, 13, 17, 22, 23, 24, as it can be seen in their maximum volumes graph in Fig. 4.2.



Stuthirtenweg	Ringslebenstr./Mollnerweg

FIGURE 4.2: Maximum volumes per hour for the first two stops of line M44 after "manual calibration" (5x expanded population).

It means in general that the original population sample is not enough at those stops to reproduce satisfactorily the occupancy counts.

As a way to settle the insufficient demand at the first stops, a second version of the population with agents allocated at different hours was tested. It was also originated from the same 2% basis sample and prepared in the same way, but for the expansion, 9 copies instead of 4 were created. Moreover, time mutation was applied on the activities of those new agents with a random range of 7,200 seconds. To compare its effects, the same procedures of data preparation, routing, and calibration were done with the new synthetic population version. The results are shown in Fig. 4.3.

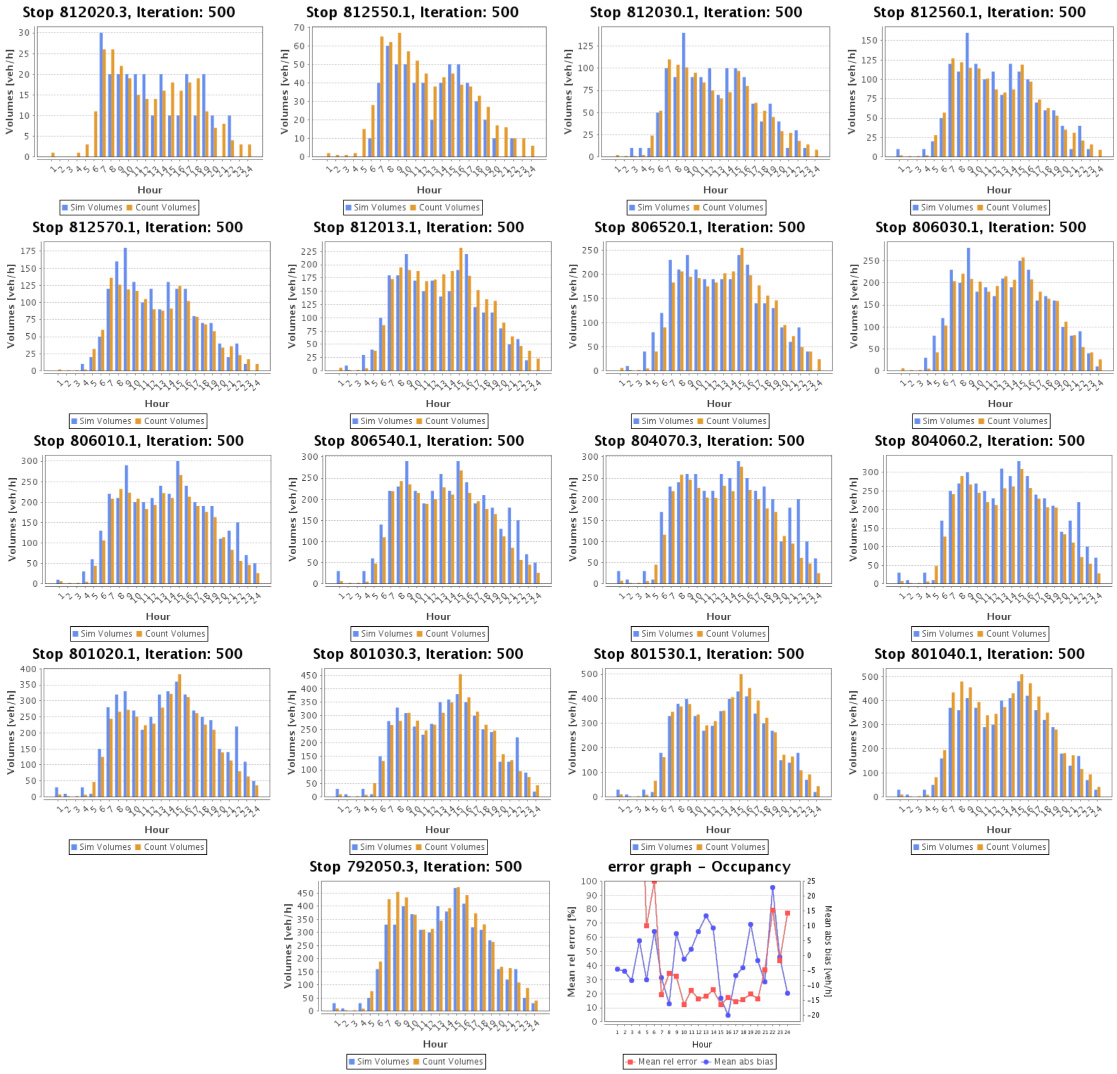


FIGURE 4.3: Stop comparison and general error after calibration of 10x expanded synthetic population (with time mutation).

It can be seen that with the time mutation of agents' activities, the calibration is able to improve the reproduction of occupancy volumes even at the bus stops with less demand. The general error also is placed between 10% and 20% for most of the calibrated hours.

4.2.5 Investigation of Residuals

Previous figures with counts comparisons help to recognize the individual contribution of each stop to the general error. However, it is tangible that some stops are more representative in terms of the error reduction than others due to their occupancy volumes magnitude. Specially in the examined bus line, last stops are presented with higher values than those of the first stops.

On these grounds, another way of analysis was done representing the error proportion for stop. It is based on the mean weighted square error calculation that indicates the average quadratic deviation between real and simulated traffic counts presented in Section 4 of [FCN11a], but in this case representing all error contributions for stop and hour. Thus, omitting the average calculation, and taking the same variable meanings as in Eq. 4.1, the weighted square error WSE of a count location a at a given time bin k is estimated like this:

$$WSE_a(k) = \frac{(y_a(k) - q_a(k))^2}{2\sigma_a^2(k)} \tag{4.2}$$

The weighted error graphs of the time-mutated synthetic population calibration are presented in Fig. 4.4. The series of graphs shows the bigger impact that middle and last stops have on the error correction in the calibration. That is, it becomes quite comprehensible that Cadyts does not attempt harder to correct the remaining errors at the first two stops: Those errors are relevant in relative terms, but not in absolute terms.

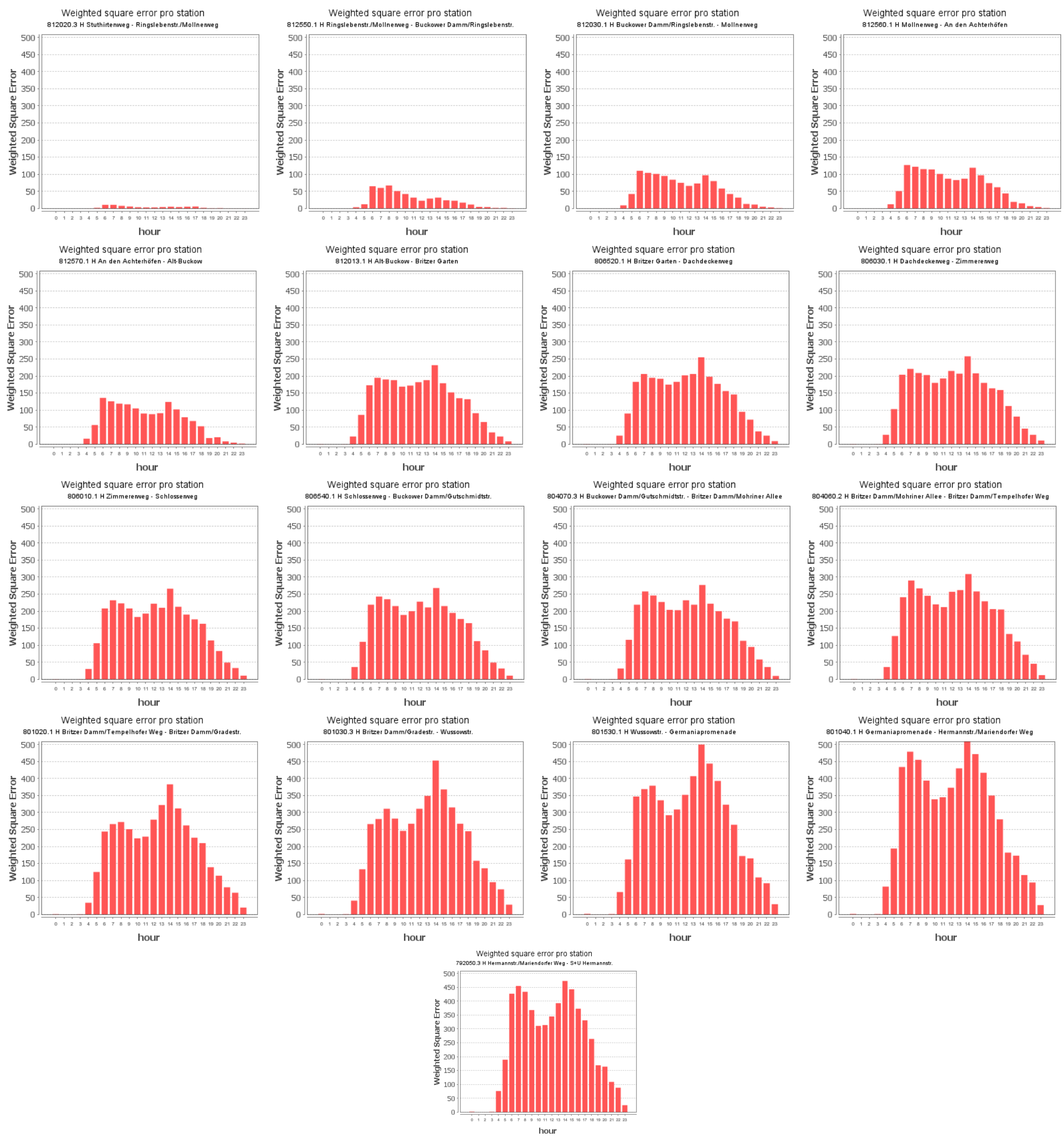


FIGURE 4.4: Weighted squared error for bus stops for calibration of 10x expanded synthetic population.

4.3 Discussion

The integration of MATSim simulation and Cadyts for transit demand estimation was presented here. The objective of the experiments on the Berlin scenario was to reproduce the actual counts of passenger occupancy inside the simulation. It had the same objective of the search of suitable travel parameter combinations during the manual calibration, but this time an automatic method was presented. In the same way as in the manual calibration, the same choice set with route diversity was considered. It consists of plans with high walk resistance, high transfer resistance, and medium values with special focus on stops with problematic counts reproduction. At the end of automatic calibration experiments, general error was reduced by 35% from about 50% to about 15%.

As stated earlier, it is no wonder that the calibrator is able to achieve a better result than the manual calibration, since it does the equivalent of modifying each individual traveler's behavioral parameters in order to reproduce the real-world counts. This is done in the choice process of synthetic travelers by selecting the most fitting plan according to the utility correction addition. Future work will have to show how this can be made behaviorally more plausible.

The most urgent task is the correct integration of the calibration into the standard MATSim travel behavioral model. Indeed, more realistic approaches should use the brute force option only for tests and create realism with other methods, e.g. by including taste variations into the synthetic travelers and then calibrating the taste coefficients.

The calibration effects were tested only on one bus line. The following step is the inclusion of more transit lines (including subway and tramway). Some studies suggest that passengers show some preference to rail-based vehicles, and it could be included inside the route choice and probed with calibration.

A more appropriate method of calibration should include the scoring function working together with Cadyts as re-planning strategy. Modifying also its parameters to find best count matches might help to reach a more complete description of passengers travel behavior. Up to now the route choice has been separated as an initial and independent step from simulation, a future task is its integration in the same re-planning process with a route diversity dynamic creation.

Chapter 5

Behavioral calibration with route choice innovation

The previous chapter presented the preliminary coupling of Cadyts with MATSim[1]. For that initial calibration implementation, the focus was set on the insertion of Cadyts in the choice process where it acted as a selector on the basis of its own internal plan evaluation. Although it accomplished plausible results, the integration of other key simulation elements (like plan generation and utility-based scoring) into the transit calibration was overlooked on purpose. Concretely, choice alternatives were reduced to a pre-calculated set of routes and the integration on the behavioral model was postponed by the use of the brute force setting to suppress the scoring of plan performance. Moreover, the test for that preparatory approach was limited exclusively to the area and stops of a reduced bus corridor.

This chapter presents further research on the behavioral transit calibration. The approach that will be presented here leaves the brute force setting aside and adds the Cadyts utility correction as an extra component of the compound MATSim scoring function. On the choice generation side, a special implementation of the transit router does the transit path search by using random travel parameter values for each agent. These adaptations are tested on a larger scenario of the Berlin transit system.

[1] The work reported in this chapter was presented at the 2nd Symposium of the European Association for Research in Transportation (hEART 2013) in Stockholm, Sweden, and also at the Conference on Agent-Based Modeling in Transportation Planning and Operations in Virginia, USA as Paper "Automatic Calibration of Agent-Based Public Transit Assignment Path Choice to Count Data" [MN13] and adapted here for this dissertation format.

This chapter is organized as follows: First, the larger transit scenario of Berlin with hundreds of thousands of agents and thousands of stop counts is introduced. In the second section, the results of a normal transit simulation with the scenario are presented. In the next section, the already known calibration approach with brute force and fixed routes is applied also over the scenario. After that, the new approach is described. The randomized transit router that generates the plan diversity is introduced. Furthermore, a different approach for the simulation-calibration integration is presented. In it, the Cadyts utility correction interacts directly into the plan performance evaluation, that is, the compound scoring function encompasses also the count match evaluation.

5.1 Related Works

Several works for demand estimation of large scenarios based on passenger counts can be found, most of them based on transit OD matrix adaptations. Rongviriyapanich et al. [RNO00] used on-off count data for two bus routes in Tokyo to evaluate OD estimation techniques used originally for road networks. The Entropy Maximization Method is found as the most practical of all considered techniques, if a priory OD matrix is available.

In the same way, Fung Wen Chi Sylvia [WC05] used boarding and alighting counts of the Hong Kong metro network for station-to-station OD matrix assignment calibration and validation. Random choice function coefficient generation methods in Monte Carlo simulation are also presented.

Farrol and Livshits [FL98] calibrated a scenario of the Greater Toronto Area based on a survey in 1996. Their results present the adjusted weights to access time, wait time, and the penalty for transfers in an EMME/2 implementation.

Lu [Lu08] used automatically-obtained passenger boarding and alighting counts for a bus line in Columbus, Ohio to review five OD flow estimation methods. The results show that the output quality depends to a great extent on the quality of the base OD matrix.

Li [Li09] presented the statistical inference of large transit OD matrices using on-off counts. Considering a given occupancy of a passenger on a stop, the probability of alighting on a posterior stop of the transit line is calculated with a Markov chain model. A Bayesian analysis draws inference about unknown parameters.

5.2 Greater Berlin Scenario

This section describes a new scenario of Greater Berlin public transport system. The steps for the preparation of the new transit demand and passenger counts are also enumerated.

5.2.1 Demand Preparation

The information about public transport demand in the Berlin and Brandenburg area was granted by the BVG. The demand was transformed from a macroscopic representation into to an activity-based model description. This was realized in a work by Neumann et al. [NBR12]. There, the plans of 598,891 persons who use all transport modes were generated. This synthetic population was adopted for the purposes of this work. In order to set the research focus on the transit calibration, these preparatory steps were realized:

- Routing: as the original passenger's survey did not include data about selected routes, the routes between agent activity locations were calculated before the simulation. In compatibility with the previous approach, basic route diversity was obtained by calculating 3 plans per agent with the usual transit travel priorities: strong walk penalty, strong transfer penalty, and moderate values of them.
- Filtering: All persons who did not include the public transport mode at all in their plans where discarded. Some persons who intended to use public transport were also discarded, namely those whom the transit router calculated a direct walk to their destinations instead of a transit route. 231,369 persons remained at the end.
- In contrast to the population preparation of the small bus corridor, the larger population did not require synthetic elasticity preparation at the beginning. That is, agents do not receive *stay-home* plans. This can be explained by the fact that demand information is consistent with passenger counts because both data sources were originated in the same study.

5.2.2 Transit Schedule

The schedule information of the scenario considers 329 transit lines. All lines were included in the simulation. Fig. 5.1 shows the public transport network of Greater Berlin area.

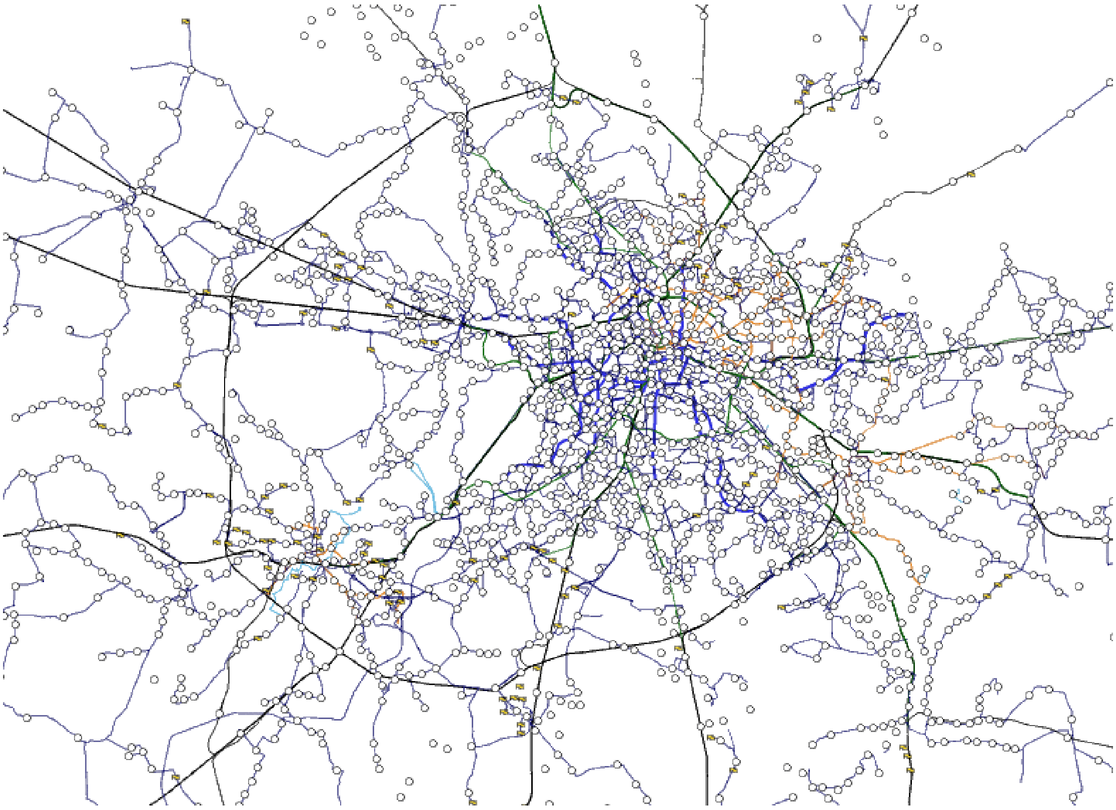


FIGURE 5.1: Public transport network of Greater Berlin area.

For the sake of convenience, not all original 329 transit lines were considered for the calibration procedure, only 218 lines that contained at least one of the considered stops with occupancy counts.

5.2.3 Counts

The availability of expanded counts for the Greater Berlin scenario was in some way the novelty for experiments described in this chapter. Although passenger boarding, occupancy, and alighting counts were granted by the BVG, only the occupancy load was considered. These preparation steps were necessary:

- Filtering: Since stops and schedule data were originated from different projects, the counts were validated to use only counts that match nominally and geographically with the stops inside the schedule file. Only 2723 from the original 7125 counts remained.[2]

[2]The big amount of discarded counts is explained by the fact that the data of aggregated counts and transit stops were not directly linked because they were generated in different projects. Some procedures were tried in order to relate each count with a stop: geographic concordance through coordinates, matching through resembling stops names and transit route pathways comparisons. At the end, only 2723 stop counts could be validated with certainty.

- 24 hours-time bin: The occupancy measurements were defined per day basis. It means that all counts from simulation were not distributed in 24 time bins, but in one single time bin for a whole day. Only with the purpose to match the compatibility of MATSim counts format, day counts were stored in the first hour and the integration code was adapted to be able to set the count back to the day period.

- Stop zone conversion: Moreover, the available counts data were not based on stops, but stop zones. A stop zone describes a set of near stops that usually have the same name but each stop can be used by different transit lines or routes in different directions. Observed stop zone-based counts were not fragmented to assign occupancy values to each component stop because there was not any reference to do it. Instead of it, the simulation worked doing normal stop-based occupancy analysis but an extra module was developed to do stop zone-based analysis by aggregating the simulated particular stops occupancies into their respective zone. A simple diagram in Fig. 5.2 represents a hypothetical zone with 4 component stops. From the calibration side, the initialization takes place inside the calibrator with the available stop zone counts. Utility correction is calculated on the own Cadyts implementation of plan that considers stop zone plans and proposed to the MATSim plan. The choice is reported to the calibrator as usual. The network load is reported to the calibrator on the basis of stop zone analysis and in one time bin per day.

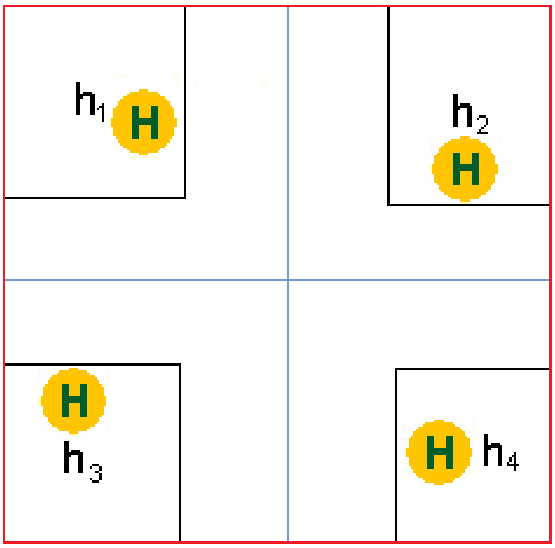


FIGURE 5.2: A stop zone with n number of stops, has its aggregated zone occupancy value Z calculated as the sum of observed individual stop occupancy values h

$$Z = \sum_{i=1}^{n} h_i$$

5.3 Initial Transit Simulation

A reasonable estimation process would have a standard simulation as starting point. But before it was launched, routes for all agents were generated. Passengers got their transit routes calculated with default parameter values of the transit router. In this regard, it is important to state that the vector of travel parameters was modified in MATSim from the time of the preliminary calibration experiments described in Chap. 3 to the time when the tests of this chapter were realized. From the values described originally in list 3.2.1.1, the ULS default value changed to -1.0. Moreover, the MUTTT and the MUTWT parameters added to their default values the Opportunity Cost of Time. The Opportunity Cost of Time represents the implicit punishment for not performing an activity and has $-6/3600$ as penalty value.[3]

After all routes for passengers were calculated, a subsequent standard simulation run was executed. The usual plan selection strategy for such standard simulation is *ChangeExpBeta* which selects a plan for the next iteration approximating the simulation to a logit model (see section 3.2.1. of [NF09]).[4]

In previous chapters, bar plots were used for the visual evaluation of the concordance between observed and simulated values. However bar plots based on hour-basis comparison as they were employed from Fig. 4.1 are not longer usable on the context of whole day counts. Instead of them, scatter plots are a more appropriate aid in this situation.

For the initial simulation analysis, Fig. 5.3 shows its respective scatter plots. One can notice that in both initial and final iterations, data points are dispersed outside the main diagonal, which is interpreted as some under- and over-occupation. The general calculated MRE for the simulated day and selected lines starts with 89.6% and ends in iteration 1000 with 97.8%. The reason why anything at all changes over the iterations lies in the fact that there is also a car traffic assignment which changes over the iterations. This can, for example, cause synthetic travelers with mixed car/transit plans to obtain a different time structure because of changing car mode travel times.

[3] Routing needs to include the opportunity cost of time, since finding a faster route does not only reduce the disutility of traveling, but also allows to make the following (or some other) activity longer. The original MATSim public transit router [Rie10], did, however, not include the opportunity cost of time. This was not an issue as long as time was the only attribute, but became an issue once time was balanced against other attributes such as the fare or the penalty for line switches. In that sense, the values of Chapters 3 and 4 would need to be corrected by the opportunity cost of time if they were to be configured by the current MATSim config file.

[4] In anticipation of a planned change in the MATSim default configuration, the `BrainExpBeta` value from that strategy was changed from 2.0 to 1.0.

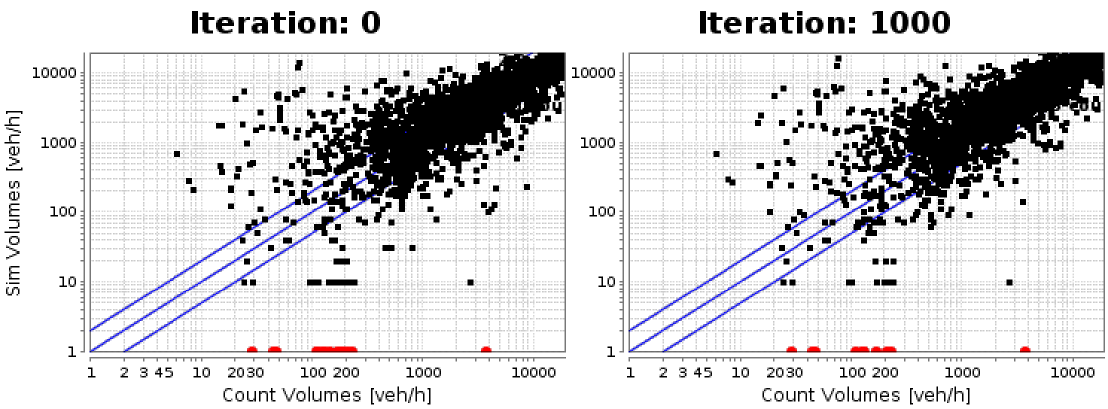


FIGURE 5.3: Scatter plot for initial situation of Greater Berlin scenario: standard transit simulation with MATSim transit router.

5.4 Initial Brute Force Calibration with Fixed Route Choice

The next step was the first calibration attempt over the big scenario. It was done following the approach described in Chapter 3, that is, the optional brute force is used. In the same way, a fixed number of transit connection alternatives per passenger were pre-calculated according to the known diverse criteria: least number of interchanges, least amount of walking, and some balance of them. For this test, unlike the small corridor scenario which got stay-home planes, for the new scenario that type of synthetic elasticity demand was not arranged. For this first calibration, Fig. 5.4 shows the comparison of counts adequacy between iteration 0 and iteration 1000 in scatter plots.

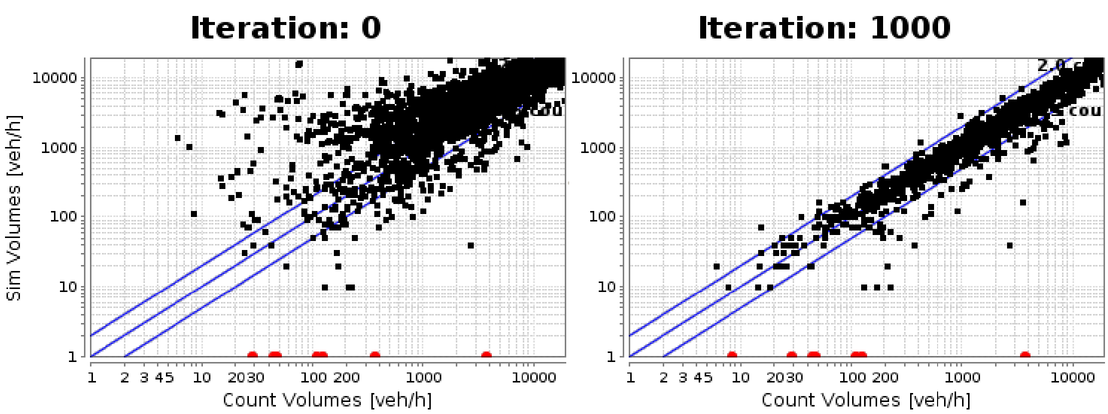


FIGURE 5.4: Count comparison for brute force calibration of Greater Berlin scenario with fixed route choice set.

One can see that the known brute force calibration finishes once again with an acceptable match of counts, even with a larger number of agents and different counts time bin to calibrate. The brute force setting pushes the simulation into the reproduction of occupancy volumes by selecting the plans most accordant with real values. The MRE starts with value 128.5 % and it is reduced to 15.3% at last iteration (1000). However, while the approach works well, the brute force option and the scoring function switching-off are incongruous from a behavioral modeling perspective. Moreover, the method depends on the fixed set of pre-calculated transit connections. Without plans mutation, Cadyts can only shift between existing plans and this would not allow the calibration procedure to guide the search into directions most consistent with the observations.

5.5 Transit Route Diversity

It is assumed that the calibration core procedure leaves the generation of choice alternatives to the simulation counterpart. Cadyts only influences the count reproductions by evaluating and preferring some alternatives that are presented to it. At the end, a favorable calibration output depends to a large extent on the generation of sufficient choice diversity. A very reduced number of routes, or a choice set that does not correspond to realistic passengers routes, will affect negatively on the expected count match.

New route generation methods were investigated in order to explore route diversity enrichment. With the goal of discarding the pre-calculation of route set and generate discretionary connections instead, a special routing module was implemented in MATSim. The "randomized transit router" takes MUTWT, MUTTW, MUTTT, MUTDT, and ULS default values to generate new random travel cost coefficients. Every time that each parameter gets a new random value, a new different route can be generated. In this way, very diverse passenger travel priorities are simulated.

The generation of route diversity from random values is illustrated with an example of a simulated person who needs to travel from the TU Transport Systems Planning and Transport Telematics Institute to the transit hub *Alexanderplatz* in Berlin. First, the transit router calculates an initial route with default parameter values (the Opportunity Cost of Time is included). With random re-routing as re-planning strategy, after 10 iterations, 11 combinations of random values are generated. In all cases the radius search for initial and final stations uses the default value, which means that initial and final walk distances are limited up to 1200 m. Table 5.1 shows the generated values in each iteration.

Random values combination	Transit Travel Parameters			
	MUTTW	ULS	MUTWT	MUTTT
Default	-12.0 / 3600	-1.0	-12.0 / 3600	-12.0 / 3600
0	-2.6 / 3600	-1.9	-4.5 / 3600	-18.3 / 3600
1	-13.0 / 3600	-1.3	-19.4 / 3600	-9.0 / 3600
2	-59.9 / 3600	-3.2	-9.6 / 3600	-43.8 / 3600
3	-39.1 / 3600	-2.6	-9.0 / 3600	-59.6 / 3600
4	-26.0 / 3600	-4.5	-29.2 / 3600	-34.3 / 3600
5	-20.7 / 3600	-3.7	-10.1 / 3600	-27.9 / 3600
6	-7.6 / 3600	-0.6	-0.3 / 3600	-2.6 / 3600
7	-46.8 / 3600	0.0	-29.7 / 3600	-18.5 / 3600
8	-33.8 / 3600	-1.9	-19.9 / 3600	-53.2 / 3600
9	-26.5 / 3600	-1.9	-14.9 / 3600	-16.0 / 3600
10	-13.4 / 3600	-3.7	-5.1 / 3600	-50.7 / 3600

TABLE 5.1: Travel parameter random value generation example.

At each iteration, the respective value combination is applied to Equation 3.1 to calculate a new additional transit route for the passenger. These 11 routes are graphically represented on Fig. 5.5.

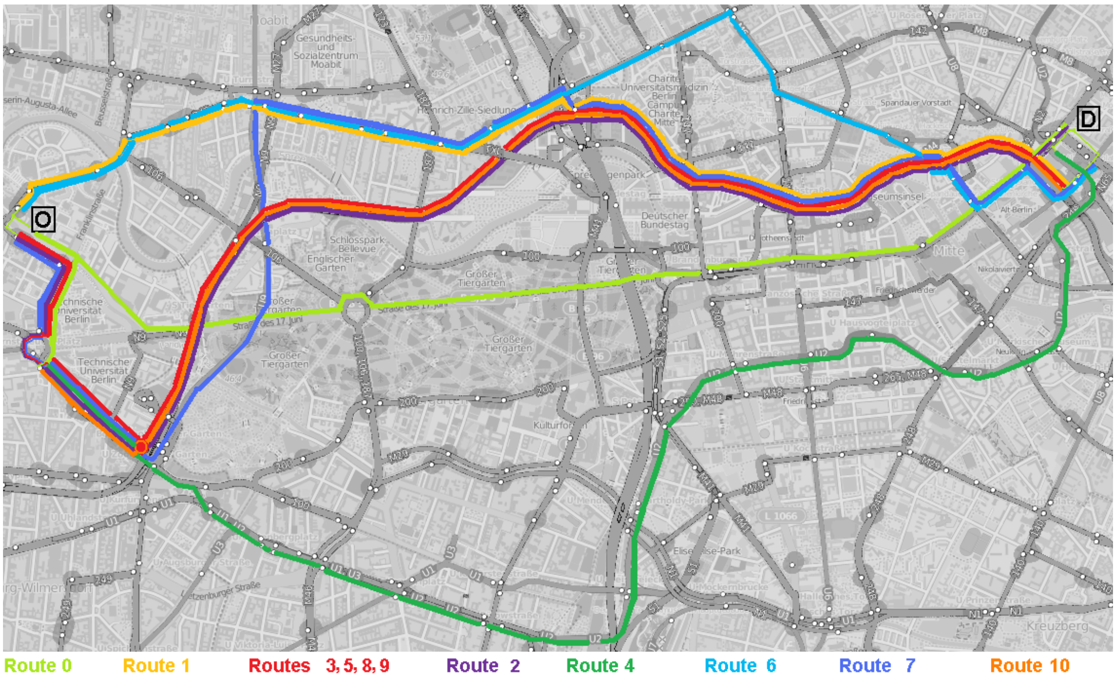


FIGURE 5.5: Randomized transit router example: 11 connections from *TU Transport Systems Planning and Transport Telematics Institute* to transit hub *Alexanderplatz* in Berlin.

The origin is marked with “0” and the destination with “D”. For 11 queries, the randomized transit router calculated 8 different routes with diversity in number of transfers and walk distances. Actually, the first light green route with number 0 is a direct walk to the destination, which means that the initial values are not good enough to find a transit path. The same color is employed for the starting and ending walking distances in the other routes.

5.6 Cadyts Calibration as Scoring Function

Cadyts calculates utility corrections for plans to guide the choice process in the direction of the counts match. Up to the last calibration attempts described in Chapter 4, the utility correction was not a part of the plan score. It was only temporarily calculated, added temporarily to the score during the choice process and then dismissed. A new approach for the integration of MATSim and Cadyts to solve this issue is presented in this section.

The new implementation of that integration presented here, consists in the integration of the calibration utility correction with the other scoring components (performing and traveling). Thus, the counts match is also included as part of the plan evaluation. More formally, Cadyts core function of posterior choice distribution presented in Equation (4.1) is not considered for utility correction calculation to be added to the utility of plan $V(i)$ (see Equation 3.2) during selection procedure anymore. Instead of it, Cadyts utility correction itself is included during scoring in the evaluation formulation as a new weighted term:

$$V(i) = \sum_{act \in i} \beta_{perf} \cdot t^*_{act} \cdot \ln t_{perf,act} + \sum_{leg \in i} V_{tr,leg} + [w \sum_{ak \in i} \frac{y_a(k) - q_a(k)}{\sigma^2_a(k)}] \tag{5.1}$$

where:

w is the weight of Cadyts correction inside the accumulated scoring function.

Having Cadyts as part of the scoring function leads to these advantages:

1. Brute force is technically abandoned which returns the calibration standpoint to a behavioral model.
2. Both plans performance and their count match contribution can be evaluated together with compound utility formulation.

3. Good plans from the calibration perspective can persist along iterations, which influences positively on the calibration feature. A scoring model based solely on travel disutility and activity performance evaluation jeopardizes the existence of plans that are plausible for the counts concordance. That is, plans that are dismissed are usually the ones that are considered the worst from the standard behavioral scoring context, overlooking their contribution to counts reproduction.

4. The calibration effect on the general model can be adjusted. Instead of an explicit brute force setting, the configurable weight can regulate the strength of the calibration in relation to the other scoring parts. The effect is comparable to the variance scale parameter in Cadyts.

5.7 Coupling Route Diversity and Cadyts Scoring Function

Achieving route diversity through random routes generation might seem inadequate from the classical assignment models perspective. Certainly it would be impractical if it were implemented as a stand-alone module for route choice model without an optimization or behavioral approach. However, its implementation is justified because random paths are created on the base of proved standard travel values as initial seed. But most important, if the search of random candidate solutions is combined with a selection mechanism (like Cadyts correction inside the scoring function) where new alternatives for each agent 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.

The integration of both approaches is outlined here:

1. **Initialization:** Usual scenario data are loaded, including the revealed occupancy counts.

2. **Settings:** Some of the configurable parameters in this step are:

    Calibration weight.

    Maximal number of plans per agent.

    Probability of execution of each strategy for choice set modification.

    Use of stop zone conversion for occupancy analysis.

3. **Initial routing:** The randomized router generates the first alternative route plan for agents and it is selected.

4. **Execution:** The selected plan of each agent is executed. The simulation includes vehicular traffic flow simulation.

5. **Scoring:** The executed plan is evaluated according to the accumulated scoring function (Equation 5.1).

6. **Re-planning:** New random routes might be calculated (according to the re-routing strategy probability) and worst plans from behavioral and counts convergence perspectives are discarded.

7. **Selection:** A plan is selected if it was never executed. If all plans are scored, the *ChangeExpBeta* strategy selects the plan (generating a logit distribution).

8. **Iteration:** The process goes back to **execution**.

9. **Analysis:** It includes the MRE calculation and generation of counts juxtaposition graphs.

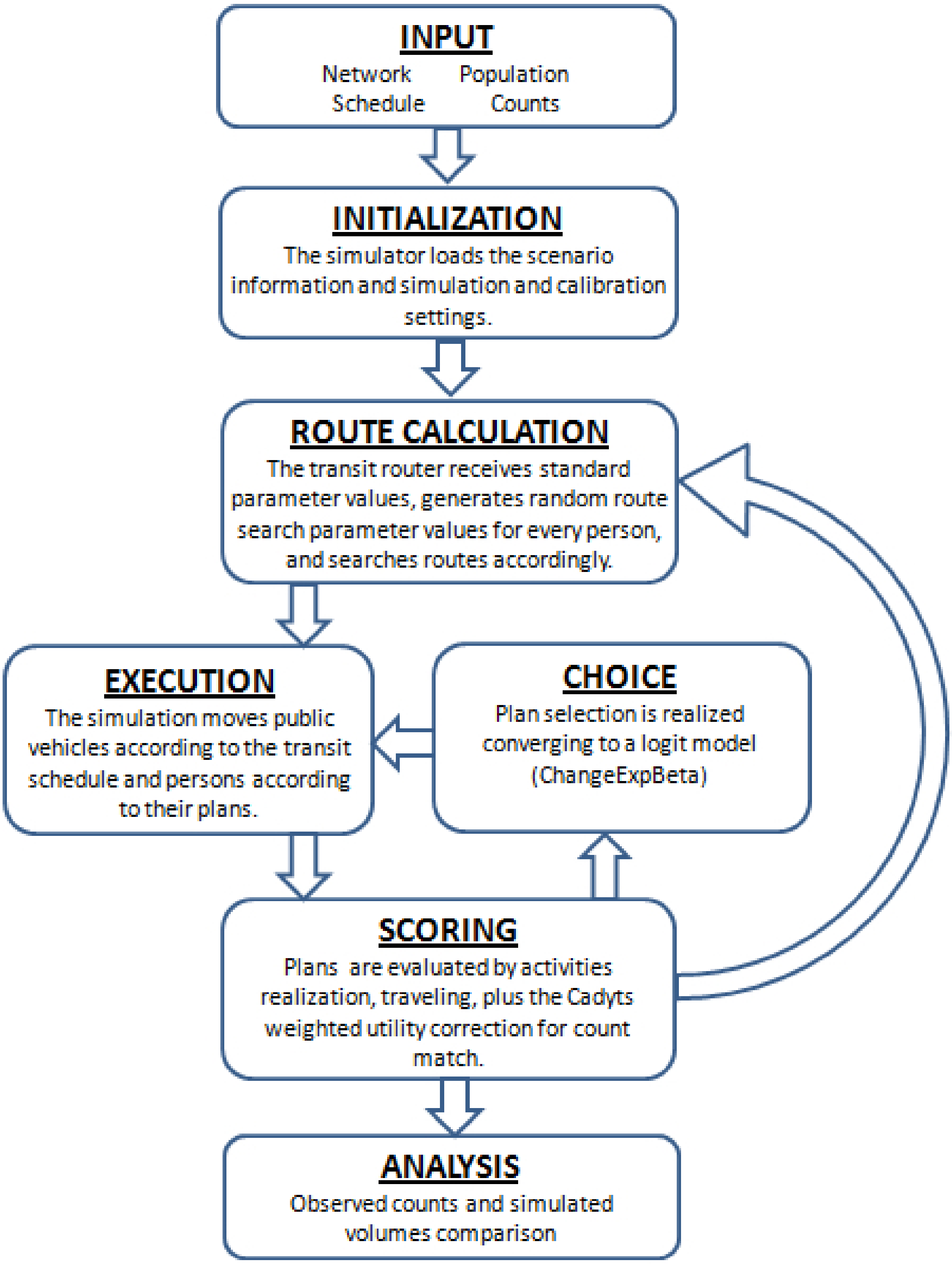


FIGURE 5.6: Diagram of randomized routing plus Cadyts inside the scoring function.

5.7.1 Implementation and Results

For the case of the Greater Berlin scenario further adaptations and settings are reported:

- Time bin size for counts is changed to be configurable. For day-based volumes, time bin size must be set to 86400 seconds instead of 3600.
- Cadyts included since version 1.1.0 a special implementation for MATSim. The so-called "*MatsimCalibrator*" is started necessarily with pre-defined and fixed time bins of 3600 seconds. For this reason its upper, more flexible instance was used instead. The "*AnalyticalCalibrator*" allowed the creation of a calibrator object with the configured 86400 seconds sized time bins per station.
- Minimal standard deviation: It is set to 4.
- Calibrated lines: Like in previous calibration runs, only the set of 218 lines with occupancy counts are considered for calibration.
- Calibrated hours: the whole day from 0 to 24 (in concordance to the 24 hours counts).
- Maximal number of plans per agent: 5
- Simulation and calibration settings: Cadyts calibration is inserted as a term inside the standard scoring function. The scoring performs as usual for each plan that is selected at a given iteration. The simulation re-planning module is configured to distribute its execution probabilities like this: randomized re-routing with 10% until iteration 400 and *ChangeExpBeta* as plan selection strategy with 90%. *ChangeExpBeta* keeps performing until iteration 1000, along the scoring approach that includes Cadyts correction utility.

In order to evaluate how Cadyts enforces the counts reproduction, a number of parametric calibration runs is realized over the scenario. Each run is done with incrementing Cadyts weights (value w from Equation 5.1), namely 0, 1, 10, 100, and 1000. Fig. 5.7 shows the analysis in scatter plots for each run. The first plot corresponds to the initial iteration of all weights, which is the same for all weights. Then, the final plot (iteration 1000) for each different calibration weight is depicted.

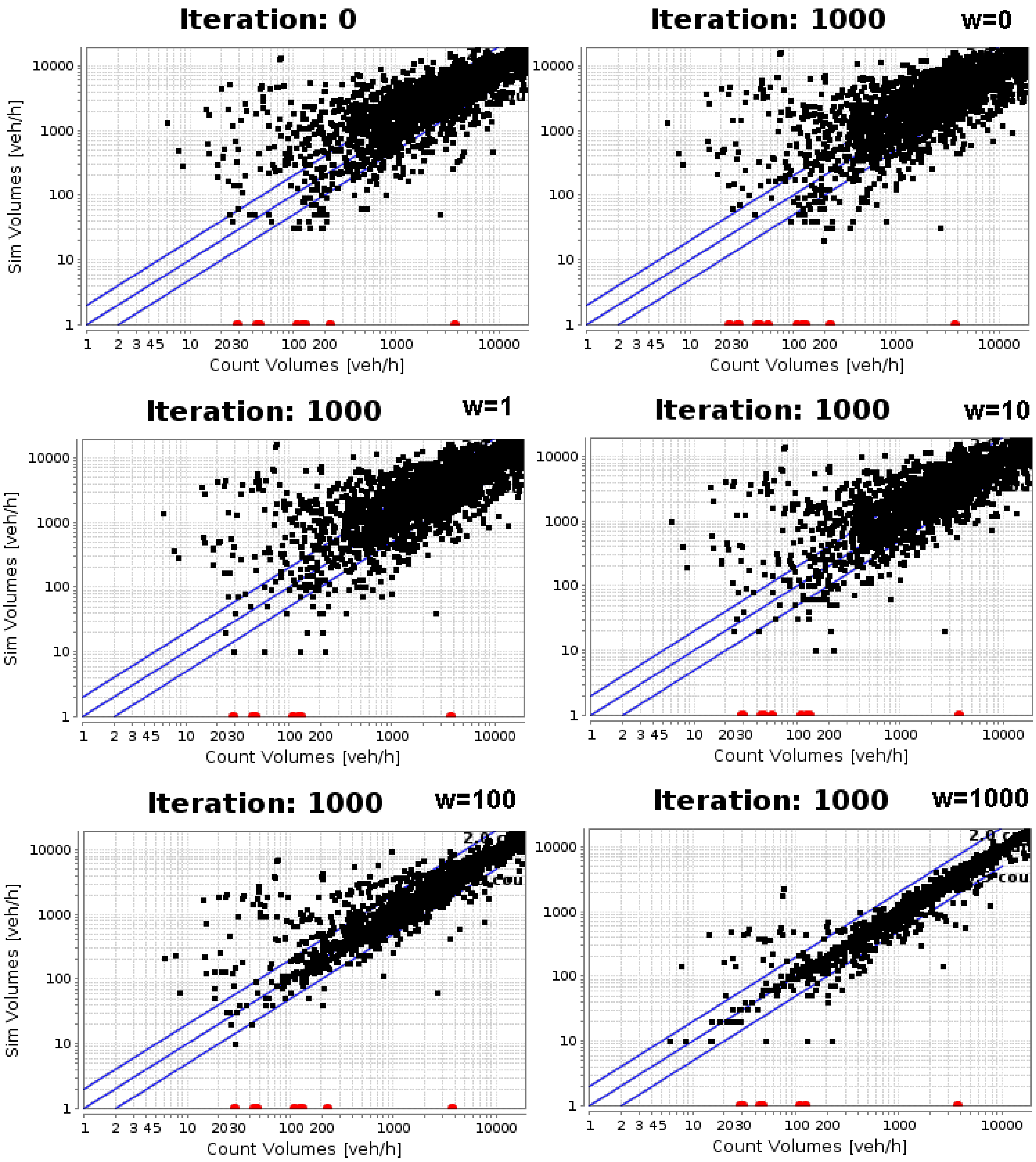


FIGURE 5.7: Calibration with randomized parameters route search and Cadyts as part of the scoring function with increasing weight.

One can see that for low calibration weights (like 0, 1, and 10), hardly any improvement is achieved regarding counts match. On the contrary, it is noticeable that a very strong weight like 1000 corresponds almost to the brute force calibration.

Another simulation exercise is described next, whereby the synthetic demand is duplicated. In concordance with the first experiments presented with fixed choice set, each agent is cloned but no geographically mutated. The goal is to show how the same calibration settings and the same observed counts can produce better affinity between observed and simulated counts. Moreover, instead of 5 plans per agent, the choice set size was increased to 10. With it, more diverse routes are available for passengers and also for the calibrator.[5]

Fig. 5.8 shows the initial and final plots for the calibration with cloned agents.

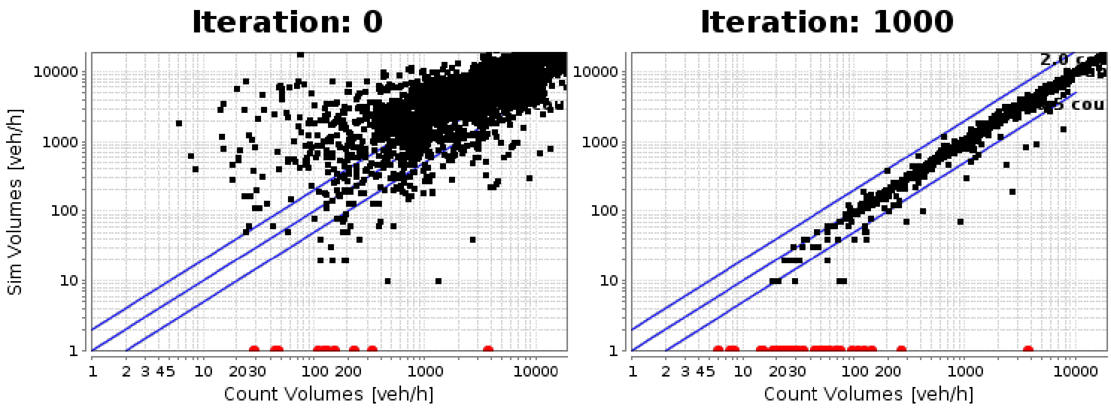


FIGURE 5.8: Calibration of Greater Berlin scenario with duplicated demand and Cadyts weight 1000.

The effect can also be seen with the MRE reduction for all the runs described in this chapter in Table 5.2.

	initial MRE	final MRE
Simulation without calibration	89.6	97.8
Brute Force and fixed choice	128.5	15.1
Random routing and Cadyts weight 0	100.0	107.2
Random routing and Cadyts weight 1	100.0	104.4
Random routing and Cadyts weight 10	100.0	89.8
Random routing and Cadyts weight 100	100.0	41.5
Random routing and Cadyts weight 1000	100.0	15.7
Random routing and Cadyts weight 1000 with agent cloning	151.3	5.0

TABLE 5.2: Comparison of initial and final MRE values for utility correction as score with increasing weight value.

One can notice that higher Cadyts weights achieve lower final MRE values. In the same way, Fig. 5.9 compares graphically the evolution of MRE values along iterations of the tests described before.

[5] Instead of creating synthetic demand elasticity with the insertion of stay-home plans, the choice set size increment is used as alternative. Choice diversity created with more random routes helps the calibrator in its tasks in this sense: If an excessive number of passenger occupancies are simulated at a stop, some of those passengers can be forced by the calibrator to travel through other stops without counts. The effect on other non-calibrated lines is still a pending study of this research.

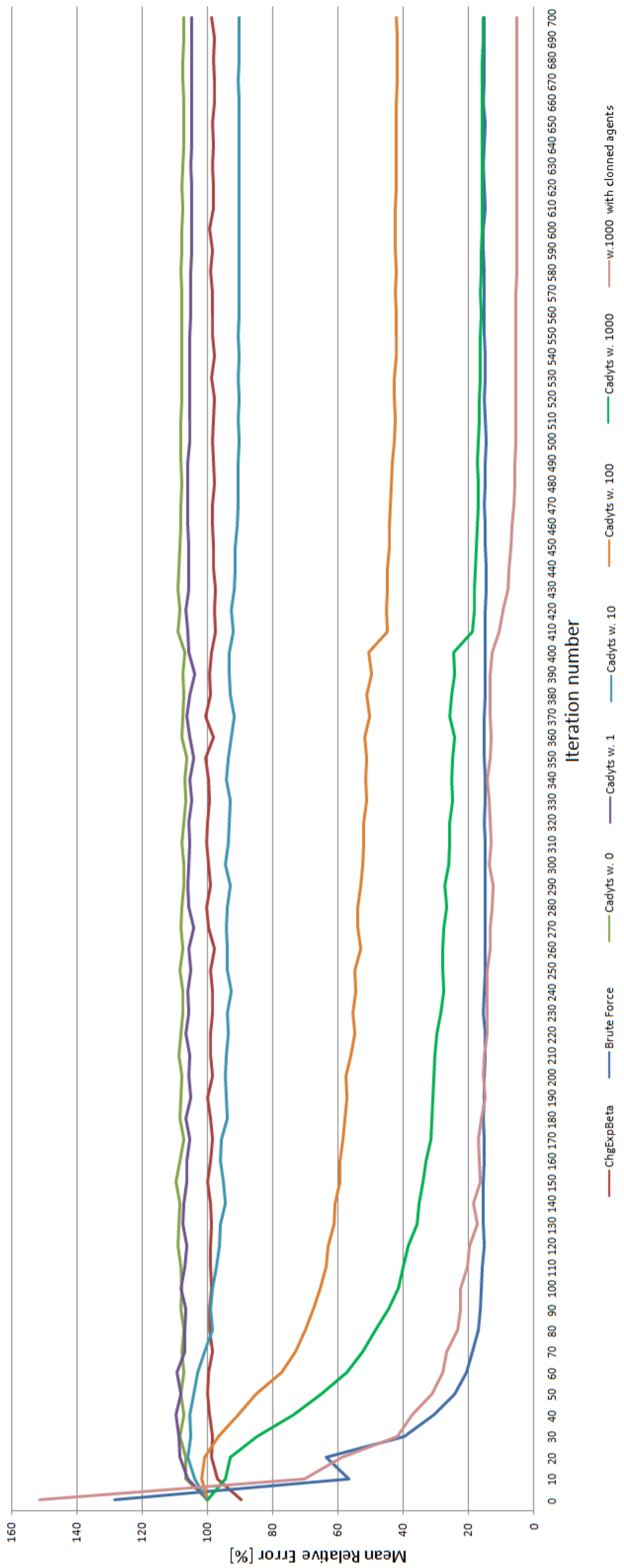


FIGURE 5.9: MRE reduction with normal simulation, brute force calibration, and Cadyts as scoring function with different weights.

The calibration with brute force with fixed choice set starts with a high MRE value (128.5%), in comparison with (100.0%) of all runs made with randomized routing. This can be explained by the fact that the fixed choice set starts always with the first plan selected, that corresponds to the pure high transfer resistance. However, the fixed plans and the plans created with random routing tend to stabilize and come relative to close values (42%, 15%) around iteration 600.

The MRE analysis shows also that low Cadyts weight values have barely a visible effect. In contrast, one may see the evident improvement for values 100 and 1000 just after the first iterations. In both strong calibrations, a sudden error reduction that happens just after iteration 400 is noteworthy. It corresponds to the stop of plan innovation (with randomized router) and the start of full calibration. The strongest weight value (1000) deserves special attention because it reaches the same MRE value of brute force calibration from iteration 600 on.

The calibration of duplicated demand starts with the worst count reproduction, but the effect of the strongest Cadyts weight value and the larger number of agents produces at the end the best output.

5.8 Conclusions

The calibration with expanded counts information is carried out, preparing the necessary input data and adapting the integration code between transit simulation and calibration. This is possible thanks to the adaptability of Cadyts (proved with its many different implementations) and the robustness of the transit calibration in MATSim.

The results demonstrate that the approach is able to work with very large scale real world scenarios, and that it is able to deal with the inter-temporal aspects implied by the available counts.

The next challenge will be how to make these findings useful for prediction. The approach for this will be to extract behavioral parameters per individual, which would explain behaviorally the choices that are most consistent with the measurements.

Chapter 6

Exploring Passengers' Taste Variations

This chapter examines the opportunity of exploiting information extracted from the transit route calibration and interpreting that knowledge as individual passengers' revealed preferences. The investigation presented here assumes that calibration output discloses passengers' travel tastes in a closer way to reality, according to the occupancy counts in the given scenarios. More conceptually, previously calibrated plans are analyzed here to calculate personalized transit travel utilities values, and in subsequent simulations use them inside the plans performance evaluation process. The individualized travel preference study presented in this chapter is tested on a small bus line scenario.

6.1 Introduction

Homogeneity in route choice preferences is far away from reality. Surveys [BNR03, NP07, TJR+07] and studies on demographic characteristics of passengers [NTM11, Wei93, War01] suggest that passengers' specific attributes may determine variations in preferences related to transit trips components like walking, changing, and traveling in public vehicles. In addition to the aforementioned investigations, the calibration experiments reported in previous chapters confirmed that diversity in route choice is a fundamental presumption on demand estimation tests.

This chapter explores the possibility of a methodological search of personalized travel preferences on the basis of calibration results. The problem is formulated like this: Is it possible to take advantage of calibration-based knowledge on an individual level in order to make route choice forecasts related to the travel behavioral model?

6.2 Background

The inclusion of taste variations in discrete choice models is a common topic in Economics. Investigation about taste homogeneity as source of differences for product developments [SB00] or the analysis of vehicle type preferences by customers [Whe03] are just some representative examples.

For transportation studies, discrete choice with taste variations is present also in travel behavior modeling. Kitamura [Kit81] enumerated three approaches for the study of taste variations: random-coefficient models, formulation of variation relevant variables and stratification according to internal homogeneity. His own work suggests that taste variations in travelers can be modeled by identifying socioeconomic values on them, and thus, trip-makers can be stratified in groups with distinguishable tastes. Other illustrative studies are: the inclusion of taste variations on individual choice stated preference experiments with hypothetical travel scenarios [FW88], route and departure time choice modeling [BAB99], simulation of passenger preferences based on their use of different transit sub-modes [Nie00], analysis on drivers' route choice preferences [HAE01], execution of distributions tests based on taste diversity premises in transportation models [HA05].

Specifically in a microsimulation environment, a previous work with MATSim [HNA12] included an random error term on the MATSim utility maximization approach in order to model the unobserved heterogeneity for destination choice investigation.

6.3 Methodology

Precedent chapters of this dissertation reported calibrations attempts whose objective was the reproduction of observed occupancy counts into the microscopic transit simulation, on the basis of evaluation and selection of those transit routes that contribute to that objective. Manual and automatic approaches were put into use on two transit scenarios of different scale. The next task is to investigate the feasibility of a methodology to deduce individual transit travel preferences from the tested calibration methods results. A procedure for this study is introduced next for an initial activity-based transport scenario without description of routes, but with passengers' counts at stops. The complete procedure has 4 steps:

1. Fixed route choice set generation.
2. Brute force calibration.
3. Individual preferences calculation.
4. Simulation with individual preferences.

The execution of steps one and two considers the use of already known techniques, namely manual or randomized generation of routes, and the routes calibration as single scoring function. But the main contribution of this section is introduced in the third step, in which individualized preferences are estimated. The fourth step is in fact the validation of preferences calculation by using the calculated preferences values as utility coefficients in the standard MATSim scoring process.

Next, steps are described in detail. After each phase specification, the corresponding implementation is made on the small scenario of bus line M44 with the simulated-versus-observed count comparison analysis, in the same way as it was done in the precedent experiments.

6.3.1 Fixed Route Choice Set Generation

The first step of the procedure is the calculation of transit routes for agent plans. If plans do not describe the routes between activity locations, MATSim can calculate automatically routes with the default values of travel parameters. Another possibility is the preparation of plans with route generation in an external module. An example of the latter is the use of uncoupled routing procedures like it was done on first calibration experiments described in Section 4.2.3. In either case, route diversity must be a key aspect to consider for the route computation in this step. If the route set is enriched with diversity of travel priorities, the probability that passengers will choose the appropriate trip according to the own preferences will increase during calibration.

For simplicity reasons, no more new transit connections are created during this first step on the test scenario on line M44. That is, the same fixed set of pre-calculated plans with travel priority diversity described in Section 4.2.3 is employed again: It is the choice set that contains plans with different route priorities: strong transfer penalty, strong walk penalty, moderate values, and an extra stay-home plan.

6.3.2 Brute Force Calibration

The second step consists in the brute force calibration which attempts to match observed passenger counts values with maximum effort inside the simulation. The objective of this step is to obtain calibrated plans with maximal possible counts reproduction whose final score contain only the Cadyts utility correction that will be a component of preferences calculation later on. In contrast to the first brute force calibration test described in Section 4.2.3 where Cadyts utility corrections were employed during the special re-planning strategy for plan selection, this section refers rather to the implementation of Cadyts as single scoring function as described in the last chapter. A reason for this implementation, is that utility corrections of all plans, including plans not selected at the last calibration iteration, will be considered for preferences calculation.

For the test scenario presented for this approach, the brute force calibration is realized with these settings:

- For effective brute force calibration, only Cadyts utility correction is started for plans scoring. Other standard behavioral components (leg, activities, and stuck agents scoring) are omitted only during this calibration step. It means, the brute force implies that Cadyts correction acts exclusively as plans performance evaluation, overriding the scoring function as it was presented previously in Equation 3.2. Moreover, the Cadyts "*useBruteforce*" option is set to *true*.
- The logit model scale parameter *BrainExpBeta* (see [Ran05]) value is set to 1.0.
- The Cadyts selector weight is a special setting that defines the influence of the utility correction during the choice process. Here, it is intentionally set to 0.0, so that the plan utility correction assignment takes place only during plan performance scoring and by no means during plan selection.

- Other known Cadyts calibration settings values for the M44 scenario are kept: Calibrated hours are set from 06:00 to 20:00, minimal standard deviation is set to 8.0, and variance scale is set to 1.0. Moreover, the calibrator is set to start performing after the first simulation iteration.

For results analysis, Fig. 6.1 shows the brute force calibration analysis of M44 bus line. Very similarly to the first calibration with Cadyts as plan selector strategy presented in Fig. 4.1, the general occupancy comparison indicates that the MRE reduction reaches also in this case values around 15% in most calibrated hours.

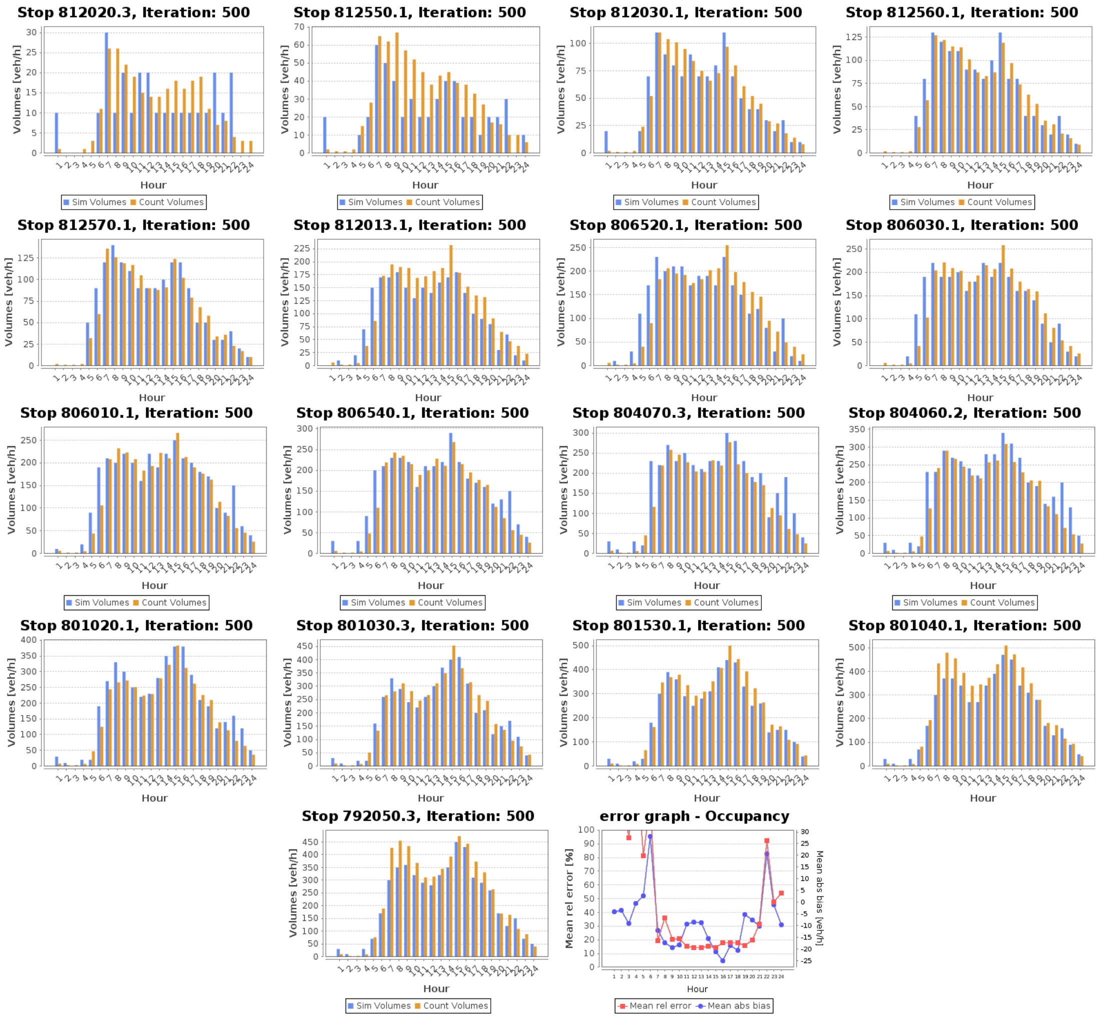


FIGURE 6.1: Brute force calibration of bus line M44 with 4 pre-calculated plans using Cadyts inside the scoring function.

6.3.3 Individual Preferences Calculation

The objective of the third step is to compute personalized travel parameter values for each agent on the basis of the calibration results. This is achieved with a) the transit trip analysis of passengers' plans and b) its use along the brute force score on a linear system solution.

6.3.3.1 Transit Trips Analysis

First, a travel analysis is realized on all calibrated plans, no matter if they ended up selected or unselected. The objective of the travel analysis is to calculate for each plan of each agent, the values of 4 transit trips attributes:

1. **Transit walk time** in seconds. After a simulation iteration, MATSim calculates the travel time of a leg and this value is attached to the leg itself as a property. Thus, the transit walk time of a plan is calculated as the sum of leg travel times, for those legs whose transport mode is labeled as *"transit_walk"*. The transit walk time includes also the time necessary to walk between transfer locations.
2. **Transit travel time** in seconds. In the same way, the transit travel time is extracted from the leg property *leg.getTravelTime()* and it is the sum of leg travel times, for those legs whose transport mode is labeled *"pt"*- public transport.
3. **Transit travel distance** (inside a pt vehicle) in meters. The distance is calculated with the transit network object. The MATSim network format (see `http://www.matsim.org/files/dtd/network_v1.dtd`) includes the property *"length"* for network links. As the transit network is also modeled in compliance with that definition, the transit travel distance is calculated as the sum of links lengths, where the links are extracted from the transit routes in which the passenger effectively traveled, according to the own transit leg information. In practical terms, the transit travel distance is not calculated on the basis of street link distances, but from stop-to-stop euclidean distances.
4. **Number of vehicle changes.** This value is calculated on the basis of *"pt interaction"* activities occurrences inside the plan element set. Since a *"pt interaction"* activity can stand for boarding and alighting a transit vehicle, a change of vehicle is deduced from a sequence of 4 *"pt interaction"* activities (which means boarding-alighting-boarding-alighting) with a *"transit_walk"* leg in the middle, which is the effective change of vehicle.

After the plans analysis, the results are stored for persistence in an object attributes file. (See `http://matsim.org/files/dtd/objectattributes_v1.dtd`).

6.3.3.2 Least Square Solution Approach

Next, available Cadyts scores and travel analysis values are used to calculate the individualized travel preferences for each agent. The calculation is proposed as the solution of a linear equations system where plans Cadyts utilities are the constant terms, plans travel values are the coefficients and the unknowns are the preferences to be calculated.

Usually, linear equations systems are represented as a matrix equation of the form $Ax = b$. A is a matrix with coefficients entries with m number of rows and n number of columns. A vector b with dimension $m \times 1$ contains the system output. A vector x with n entries contains the solution entries for the system. For the model presented here, a linear system is created for each agent. The matrix A contains all the trips attributes values a discovered by the travel analysis. It has m number of rows corresponding to the number of plans per agent. Its columns arrange the transit trip attributes entries in the order that they were enumerated in last section: transit walk time, transit travel time, transit travel distance, number of vehicle changes. The vector b contains the Cadyts utility corrections values λ_i assigned to each plan at the end of the brute force calibration. The vector x contains the still unknown β_i values of individual preferences for each travel parameter. Regardless of the number of plans, individual preferences correspond in this proposal, to the utility of 4 transit travel parameters, namely:

1. Walk: Its value will be set to β_1 for the linear system solution, and during further scoring tests, it will correspond to the personalized *utility of walk*.
2. Time: Its value will be set to β_2, and it will be the personalized *utility of traveling in public transit* value for scoring.
3. Distance: It will be the value of β_3, and it will be the *monetary distance cost rate of traveling in public transport* scoring value.
4. Changes: It will be the value of β_4, and it will be the personalized *utility of line switch* for scoring.

Altogether, the proposed linear system is shown next in a matrix representation:

$$
\begin{array}{lc}
\text{A=} & \begin{array}{cccc} walk & time & dist & changes \end{array} \\
\begin{array}{l} plan_1 \\ plan_2 \\ plan_3 \\ \\ plan_m \end{array} &
\begin{pmatrix}
a_{w,1} & a_{t,1} & a_{d,1} & a_{c,1} \\
a_{w,2} & a_{t,2} & a_{d,2} & a_{c,2} \\
a_{w,3} & a_{t,3} & a_{d,3} & a_{c,3} \\
\vdots & \vdots & \vdots & \vdots \\
a_{w,m} & a_{t,m} & a_{d,m} & a_{c,m}
\end{pmatrix}
\end{array}
\overset{x}{\begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{pmatrix}}
=
\overset{b}{\begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \vdots \\ \lambda_m \end{pmatrix}}
\tag{6.1}
$$

Solutions for linear systems are commonly computed with a) *simple* methods like Gauss elimination for systems with square matrices (where $m = n$) and b) *decomposition* methods. Decomposition is also called factorization and provides numerically stable methods for other matrix operations. Known decompositions algorithms are: Cholesky for positive definite coefficients matrices and LU for non-singular diagonally dominant square matrices. QR and Singular Value Decomposition (SVD) are algorithms that also can find solutions in least square sense for undetermined (where $m < n$) and overdetermined ($m > n$) systems.

For practical reasons, the personalized travel preferences are calculated at this point with the SVD algorithm [GK65]. The SVD is known to be a numerically robust method. Its stability is proved for example, by the fact that finding the simple SVD of a matrix is always possible. Regarding the computational performance, the SVD is the most expensive among the aforementioned algorithms, specially if it is compared with the simpler Gauss elimination. However, that should not be considered a drawback for its employment in the calculation introduced in this section. Computational efficiency is not an issue because the linear system to be solved per agent is small. One hence has a linear complexity with the number of agents; this obviously scales very well. Moreover, preferences are not calculated at each simulation iteration, but only once at the end of the calibration. Furthermore, the SVD provides the most reliable and accurate results based on the least square minimum search among those methods. Other decisive reason for its utilization is the consideration that the number of plans per agent in MATSim is variable in different types of studies and scenarios, which means that the coefficient matrix A might be under-determined, square (like in the present test of bus line M44) or overdetermined. The first and third cases make algorithms other than SVD inappropriate for the passenger preferences calculation.

Code reuse is a widespread programming guideline for software robustness and quality in computer science. For that reason, instead of programming a SVD linear system solver method from scratch, an existing library is adopted. The best alternative is the adoption of a known and well-tested component from the Apache Commons Mathematics Library (see `http://commons.apache.org/`).

The simple programming Java code implementation is like this: After assigning the travel analysis values to an array data structure named “$arrayA''$ and the Cadyts utility corrections in an array “$arrayB''$, the expected 4 solution values will be stored in an array “*arrayX*” after invoking the *Apache Commons Math* java library, like in code listing 6.1.

```
1  import org.apache.commons.math.linear.Array2DRowRealMatrix;
2  import org.apache.commons.math.linear.DecompositionSolver;
3  import org.apache.commons.math.linear.RealMatrix;
4  import org.apache.commons.math.linear.SingularValueDecomposition;
5  import org.apache.commons.math.linear.SingularValueDecompositionImpl;
6
7  ...
8
9  RealMatrix matrixA = new Array2DRowRealMatrix(arrayA, false);
10 SingularValueDecomposition svd = new
       SingularValueDecompositionImpl(matrixA);
11 DecompositionSolver svdSolver = svd.getSolver();
12 double[] arrayX = svdSolver.solve(arrayB);
```

LISTING 6.1: Java code for linear system solution with Singular Value Decomposition

- A coefficient matrix A with travel analysis values (stored previously in an array) is created (line 9).
- A compact singular value decomposition of matrix A is created (line 10).
- A solver object is created from the decomposition (line 11).

- The *solve* method finds the solution and stores the found values in an array called $arrayX$ (line 12).

The found personalized values are stored also in the object attributes format in order to be used in the next step.

6.3.4 Transit Simulation with Individual Preferences

The fourth and last step is the validation of the estimated individual preferences in a transit simulation run. This is done by just using the discovered preferences values into the standard behavioral MATSim scoring process.

The so-called personalized preferences leg scoring means basically that trips do not receive the typical negative utilities from the standard MATSim scoring. The calculated preferences are read instead. U_{ind} of a leg i is calculated multiplying travel utilities (with personalized preferences values assigned), times its corresponding travel component (with analysis values assigned) like it is seen on the first 4 terms of its formulation:

$$\begin{aligned} U_{ind,i} = \beta_1 \times t_{tw,i} \;+\; \beta_2 \times t_{tr,i} \;+\; u_m \times \beta_3 \times t_{dis,i} \;+ \\ \beta_4 \times S_i \;+\; \beta_5 \times d_{dw,i} \;+\; \beta_6 \times t_{wv,i} \;+\; c_{tm} \end{aligned}$$

where:
β_1 is the utility of walk time, whose value is set to the discovered personalized *walk* value.
$t_{tw,i}$ is the time spent on walking from and to stops during execution of leg i.
β_2 is the utility of traveling in public transit, set to the discovered personalized *time* value.
$t_{tr,i}$ is the time spent on traveling in a transit vehicle during execution of leg i.
u_m is the marginal utility of money whose default value is 1.0.
β_3 is the monetary distance cost rate of traveling in public transport, set to the discovered personalized *distance* value.
$t_{dis,i}$ is the distance traveled on a transit vehicle during execution of leg i.
β_4 is the utility of line switch, set to the discovered personalized *change* value.
S_i is a vehicle switch and it is set to 1 if the leg i represents a transfer.
β_5 is the marginal utility of distance walk whose default value is 0.0.
$d_{dw,i}$ is the distance traveled by walking in leg i.

β_6 is the marginal utility of waiting pt whose value currently is set to β_2.

$t_{wv,i}$ is the time spent waiting for a transit vehicle in leg i.

c_m is a constant value for transport mode tm whose value in all considered cases is set to 0.0.

Default values of u_m, β_5 , β_6, c_m are used and they do not have any effective influence on the leg scoring. Thus, one might realize that only the four considered utilities have an effective influence on the utility result. That creates an extra advantage, namely that for current experiments it is necessary just to adapt a very simple scoring function. Practically, it is enough to assign the personalized values to the corresponding parameter on the standard MATSim leg scoring mechanism, which conveniently let leg components values (walk time, travel time, travel distance, number of changes) be calculated from simulation events for scoring.

Formally, the plan evaluation it is expressed as the mere inclusion of U_{ind} term in the standard scoring function presented previously in Equation 3.2. For compatibility between transit individual preferences calculation and transit legs scoring, the standard activity function score is not considered for the present test. It means that the plan evaluation based on individualized preferences relies here only on the scoring of legs as shown in Equation 6.2:

$$V(i) = \sum_{leg \in i} U_{ind,i} \tag{6.2}$$

For the small scenario tests, the base population is taken from its initial state described in step 6.3.1. The base fixed route set for each agent remains the same.

- Plan strategy: *ChangeExpBeta* with probability 1.0
- *BrainExpBeta*= 1
- *maxAgentPlanMemorySize* = 4
- For behavioral parameter values, all other MATSim default values keep their default values:

    lateArrival = -18.0

    performing = 6.0

    traveling = -6.0

    travelingBike = -6.0

$waiting$ = -0.0

$waitingPt$ =-6.0

$marginalUtilityOfMoney$ = 1.0

Next, Fig. 6.2 shows the occupancy count analysis and MRE plot after the transit simulation based on personal preferences.

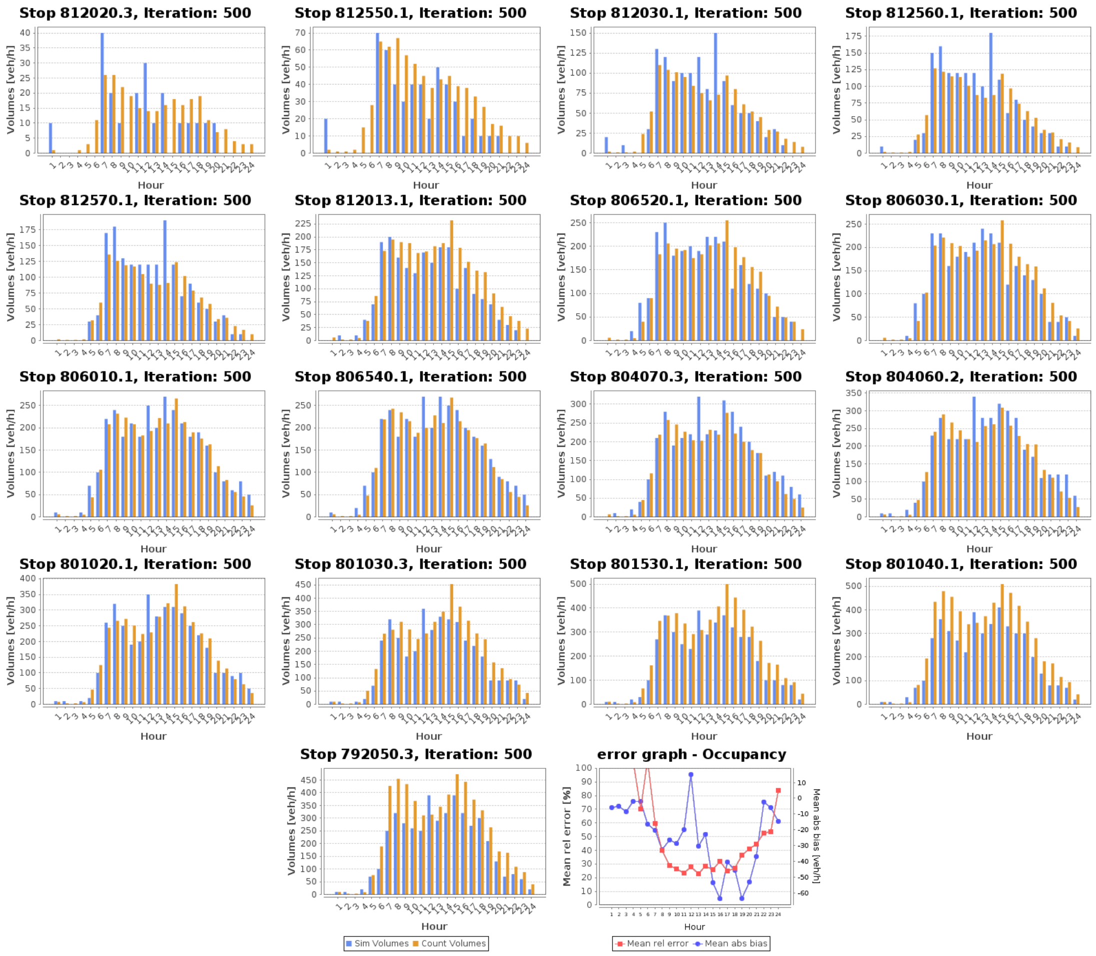


FIGURE 6.2: Stop occupancy and error comparison for transit simulation with individualized preferences.

One can see that without explicit calibration influence, but just using the knowledge obtained from a previous calibration run, the MRE reaches values between 30% and 20% at most hours that were calibrated before, between 06:00 and 20:00. That represents only a difference between 5% and 15% in relation with the error reduction achieved with brute force calibration.

6.4 Further Experiment with Larger Choice Set

For the preferences-based scoring presented in the last section, it is important to remark that it is a coincidence that the number of plans is the same as the numbers of unknown values of travel preferences. For that test, the choice consisted of the 4 known plans with basic route diversity that included also a stay-home plan for synthetic demand elasticity.

In experiments with fixed route choice sets like in the method described in this chapter, route diversity becomes even more determining in the demand estimation. This section presents again the application of the proposed individualized preferences study procedure, but the focus is set on route diversity. This time, agents traveling inside the bus line M44 coverage area receive a more heterogeneous and larger choice set. A larger choice set implies that the linear system presented in Section 6.3.3.2 does not consider a square matrix A anymore. This new case with an overdetermined linear system reinforces the decision to implement the SVD method as solution tool in this proposed procedure. And generally speaking, overdetermined linear systems do not have an exact solution, but an approximate solution that might be found with least squares methods.

6.5 Larger Choice Set Creation

The main adaptation for the execution of a second test was the creation of 20 plans with diverse travel priorities for each passenger. The higher number of plans is achieved applying random routing costs with the special transit router implementation introduced in Section 5.5. Concretely, a special simulation run is executed setting the $randomized\ router$ as default transit router with the only goal to generate 20 diverse plans during 20 iterations. Some other relevant settings for this simulation oriented to route diversity creation are:

- *firstIteration* = 0
- *lastIteration* = 20
- strategy *ReRoute* with probability 1.0
- *maxBeelineWalkConnectionDistance* = 300.0

- *searchRadius* = 1000.0
- *extensionRadius* = 200.0
- default MATSim score values:

  BrainExpBeta = 1

  waitingPt = -6.0

  utilityOfLineSwitch = -1.0

  travelingPt = -6.0

  travelingWalk = -6.0

After the randomized router generates 20 diverse plans, this new routed synthetic population base is used to launch a standard transit simulation with strategy *ChangeExpBeta* and default MATSim travel parameter values. This simulation is taken as new "initial situation" to be used as comparison point in further results analysis. The new "initial situation" counts comparison and MRE state is presented in Fig. 6.3.

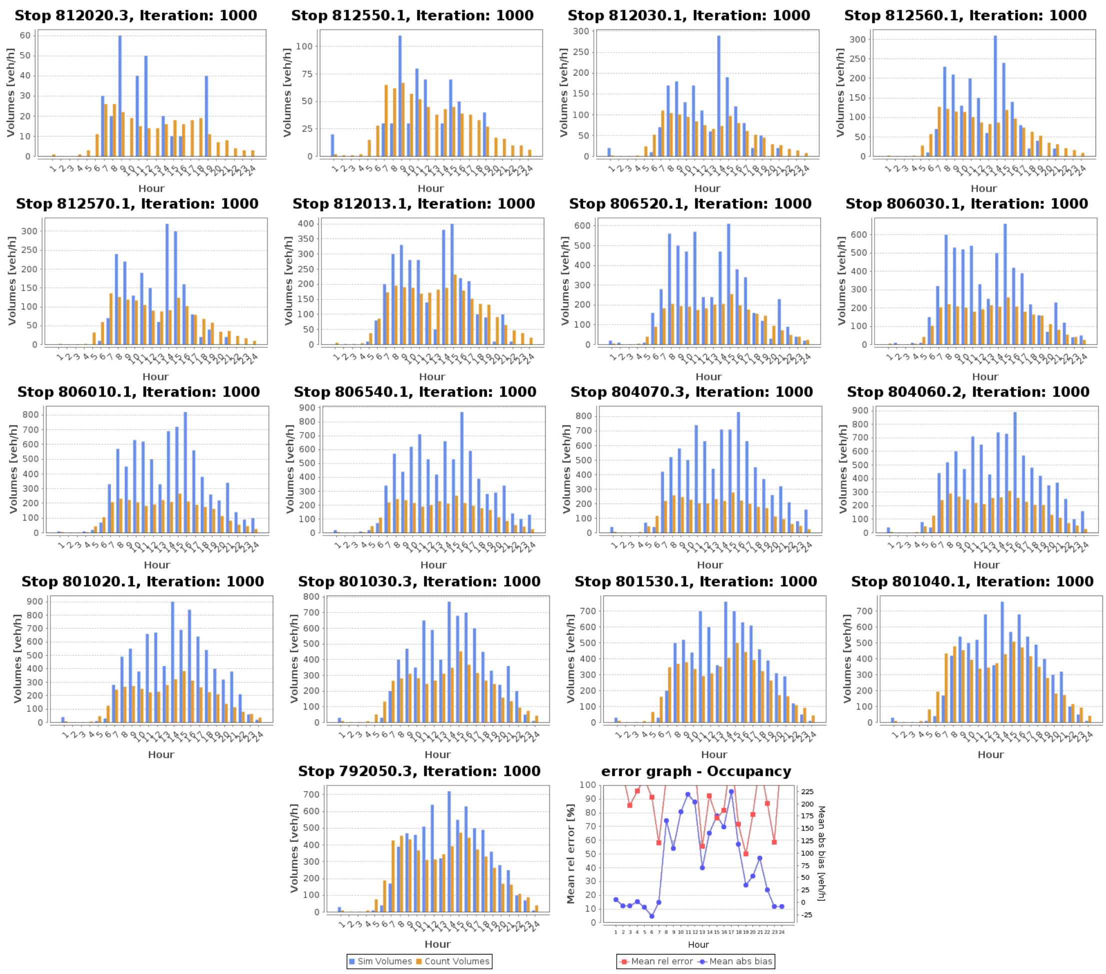


FIGURE 6.3: Stop occupancy and error comparison for initial situation of transit simulation with 20 plans.

For calibration, the weight value for calibration is set again to 1 for this new scenario and all others settings stay the same as in last run with only 4 plans. For the brute force calibration, Fig. 6.4 shows the counts comparison and the respective MRE.

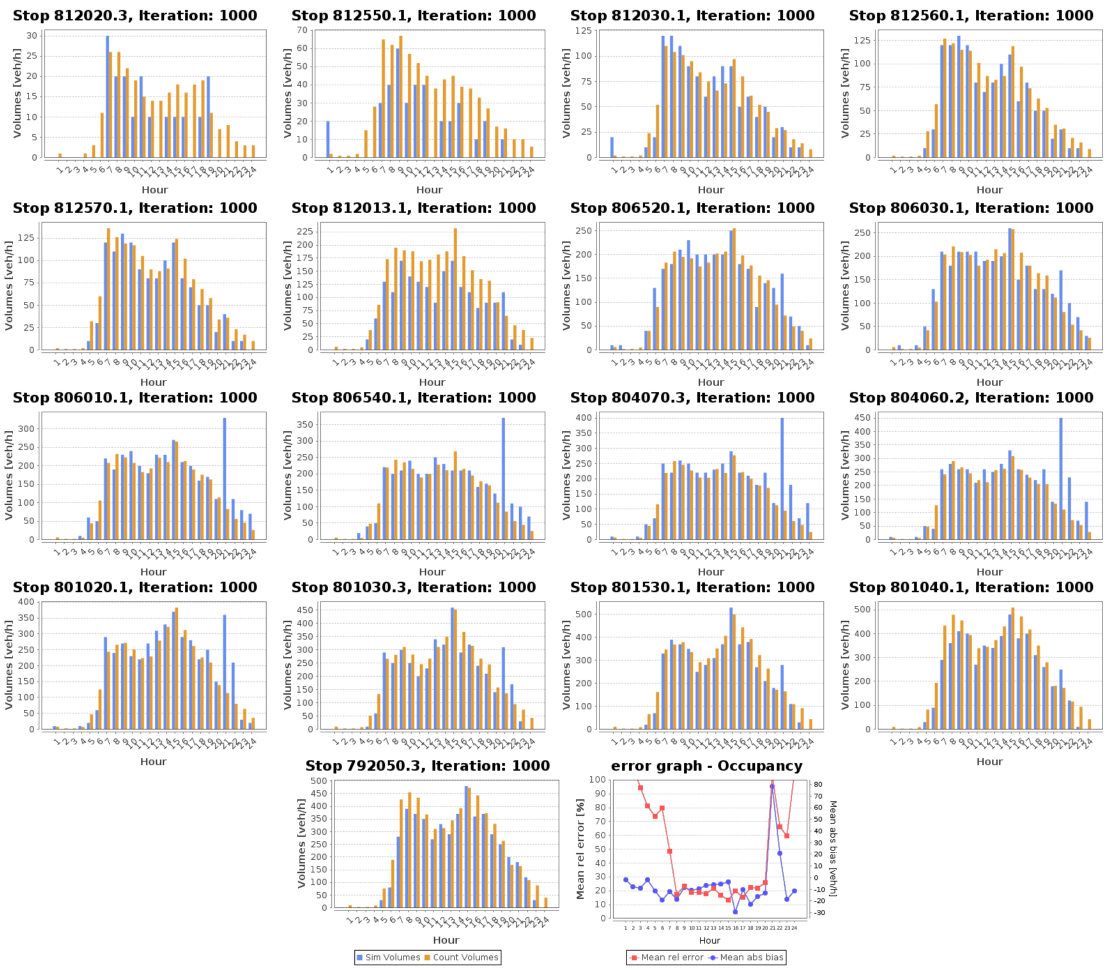


FIGURE 6.4: Stop occupancy and error comparison after brute force calibration of 20 plans.

Very similarly to previous calibration attempts on bus line M44 scenario, Cadyts achieves also improvement in the MRE reduction with values between 20% and 10% in most calibrated hours. A first impression could be also the overfitting. That is, that the approach increases the error outside the calibrated time period or that the error could be incremented for non-calibrated lines. Fig. 6.4 compared with Fig. 6.3 shows, however, that the error during the non-calibrated periods (0–6 hrs. and 20–24 hrs.) is not increased as a consequence of the calibration during the daytime hours.

The third step, individualized preferences calculation, requires the considerations of all plans, which means that this time the computation is realized with a set of 20 rows matrices A and b. Vector x remains without changes as the set of unknown preferences is the same.

The calculated individualized preferences frequency distribution is represented in histograms in Fig. 6.5 for each travel parameter.

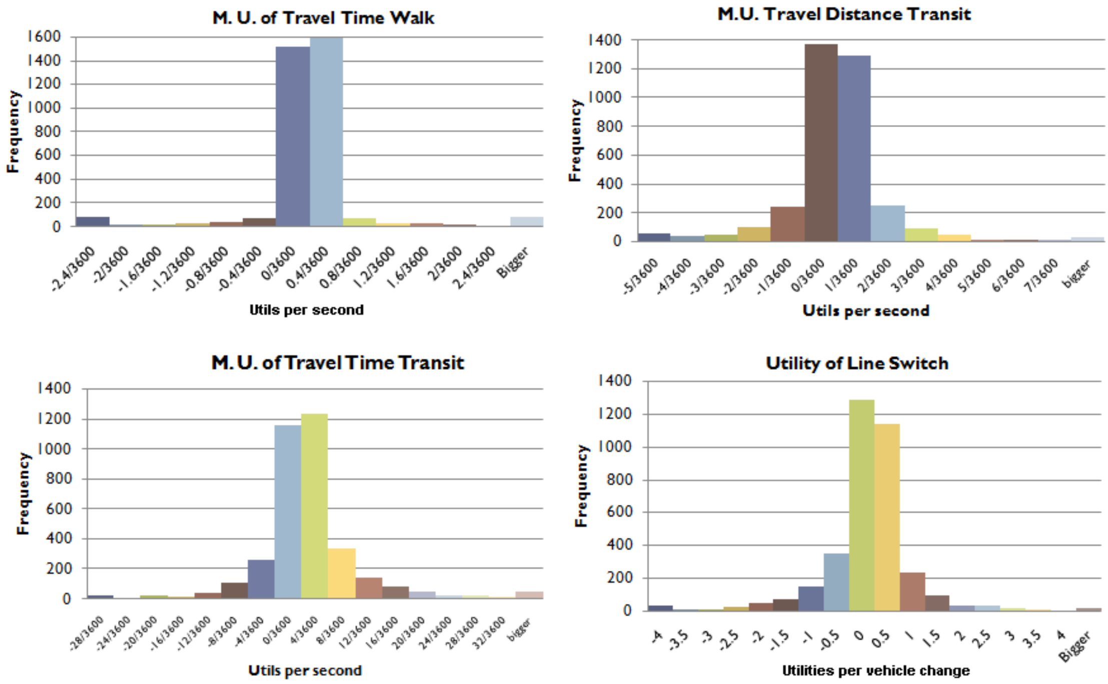


FIGURE 6.5: Individualized parameter value histograms calculated from 20 plans.

One can notice that in the four cases, the values come together around the value zero. This can be explained by the fact the SVD tries to find the solution with least values.

After preferences calculation, the final simulation with leg scoring based on preferences values is executed without any other special change besides the consideration of maximal number of plans set to 20. The final occupancy counts analysis per bus stop is shown in Fig. 6.6.

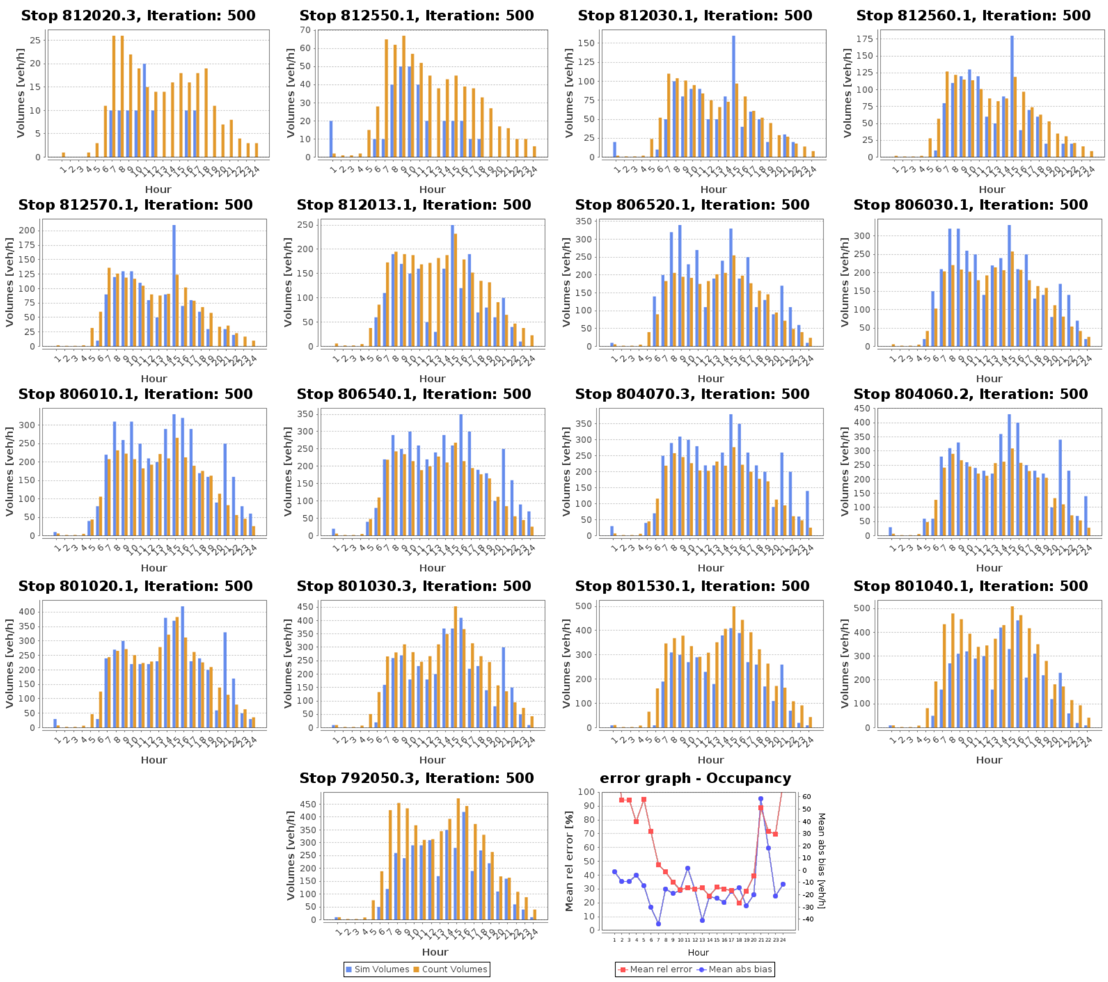


FIGURE 6.6: Stop occupancy and error comparison for 20 plans after simulation with individualized preferences scoring.

For this experiment with larger choice set, the MRE reaches also values around 30% and 20% in previously calibrated hours (06:00 to 20:00). It is important to remember that in contrast with the manual creation of the shorter set of 4 plans, this population did not get elasticity on the form of stay-home plans.

6.6 Conclusions

The contribution of this chapter was the proposal of a methodology that takes advantage of the calibration-based knowledge availability to deduce individual travel preferences. A procedure was presented that employs the known automatic demand estimation methods oriented to passengers counts reproduction. The procedure deduces individual utilities at the disaggregated level and makes use of them inside the existing behavioral model to bring normal simulation results closer to reality.

The validation of the presented procedure reveals an approximation to observed counts close to calibration results, although the calibrator is no more inserted in the simulation.

It is important to emphasize that the use of calculated individualized preferences should not be considered as a replacement for a scoring mechanism based on behavioral model. Experimental runs just proved that the computed travel parameter values produce approximations to real travel patterns. Future work should use the predictive potential of the individualized preferences. Obviously, they should be implemented in a fully behavioral approach.

Chapter 7

Discussion and Conclusions

This last chapter recapitulates the dissertation work, enumerates the main findings and discusses possible future research work directions.

7.1 Recapitulation

This investigation started from the need to estimate the travel demand for large public transport scenarios. The still present (exponential) computational capability growth [Moo65] makes now detailed simulation operations feasible. However, relative little work has been realized outside aggregated flow simulation environments.

The main aim of this thesis was to present the calibration methodology that can be applied to a real public transport system simulation. It was realized with different approaches implemented on an agent-based microsimulation framework and with data of a real world scenario. Its integration with a high-level abstraction demand calibrator allowed a better approximation from the simulation to observed available passenger measurements.

The research started with a literature review on classical and up-to-date optimization studies. The purpose was to introduce the foundations, the evolution, and state of art of optimization techniques in engineering, specially those related to optimal route search. The review confirms the increasing interest of the scientific community on optimization models. Special attention has been given to evolutionary algorithms. They represent up to now one of the most promising ways for optimization resolutions. The constant increment of computing capability has opened the possibility for more exact and complex implementations based on natural evolution processes.

The transport system simulation background was introduced in Chapter 3. The chapter presented the microsimulation, agent-based approach along its implementation in a small real scenario. A primary calibration attempt carried out through enumeration of all plausible parameter value combinations was also introduced. The combinatorial search pursued a uniform behavioral parameters disclosure and it represented a preliminary empirical transit path choice model. Nonetheless, the results showed some foreseeable results, like high walk and transfer resistances in simulated passengers. Moreover, the analysis of output parameters revealed many similarities with other analogous studies around the world.

The integration of both simulation and calibration tools was presented in Chapter 4. The first automatic calibration approach for a small scenario was introduced. Routes were calculated before the calibration process starts. Although the scenario was constructed with real information, the data provided from different sources, which was not a serious drawback, considering the adaptability of both simulation and calibration tools. Concretely, the simulation was guided only to match passenger occupancy measurements with brute force calibration. This was just an attempt to create a reliable baseline to conduct the following calibration attempts.

The objective to integrate more closely the calibration into the transport simulation behavioral model was achieved in Chapter 5. There, an improved implementation was presented where the calibrator acts inside the plan performance evaluation process. Furthermore, the tested Berlin transit scenario was expanded to a larger number of agents and the complete public transport system was used for the experiments. The implementation was able to solve the predicament of having available only occupancy data with longer time intervals. With some adaptations, the larger number of agents was calibrated without considering the whole-day aggregation of the counts as a serious obstacle.

A taste variation study was presented in Chapter 6. It consisted in a preliminary exercise of individual parameter estimation based on calibration output. The calculation of individualized preferences is done according to each passenger's selection and performance score during previous calibration runs. The simplicity of the presented procedure should assist further demand prediction exercises.

7.2 Contribution of this Research

The main contributions of this thesis are enumerated next:

- The simulation of passengers' route decision on an individual level was manually calibrated by taking advantage of a public transport microsimulation paradigm. A parametric search generated realistic results comparable to other more advanced methodologies.
- This work managed to couple a microsimulation framework with a transport demand calibrator originally presented for the demand calibration of motorist routes. The coupling approach was able to calibrate a large public transport scenario from the fully disaggregated perspective, which has been hardly investigated up to now.
- In order to make demand prediction approximations with personal taste adjustments, a computation method of individualized travel parameters was presented. It exploits the results of calibration to calculate choice model coefficient values for each passenger taking their own calibrated plans.
- The application of the calibration as a criterion for agent plan performance evaluation, as well as the introduction of randomized route diversity generation helped to implement Cadyts in a variable choice set specification, as it was discussed in Section 6.4.5.1 of [Flö08].

7.3 Discussion

Realistic simulations or transport studies should be based on a deep knowledge of passengers travel behavior. Understanding passengers travel behavior is crucial for public transport operators. Public transport microsimulation and transit assignment are important specifications to reveal passengers decisions patterns, specially if they are based on detailed behavioral rules. The routing calibration is a decisive step that can help to achieve the goals of representing passenger travel decisions in a more realistic way.

In an activity-based model, calibration is usually achieved by generating the set of public transport routes for the fixed OD pairs and selecting the appropriate alternatives that are more in concordance with stated preferences.

The results of this research work were achieved with simulation and calibration tools that separately have proved their plausibility on many other previous studies.

An open question is how this microsimulation and calibration coupling would look like in a project application. The less speculative answers seem to say that it makes sense to first do something similar to what is done in the present work, and then adjust the behavioral parameters to better explain it. The taste variation approach presented here is a way to address this issue.

Some of the work in this research had to do with preparation of the tested scenario input data, like synthetic elasticity generation or code adaptation to daily counts. The employment of synthetic procedures was necessary to test the calibration approach with actual public transport supply and demand information. The calibration experiments conducted on the Greater Berlin area demonstrate that its application on large scenarios with real, complete and validated input data could help to make adequate demand estimation.

In the meantime, it should be pointed out that the methods presented here have their applications. Further studies can see themselves benefiting, for example those that look at the interaction between schedule stability measures and demand for a single line in much more detail. For such investigations, it is useful to have a demand that is as close as possible to the actual counts. Clearly, for this it is possible just to use the boarding and alighting counts directly as demand (see, e.g., [NN10]). Yet, for many investigations it is desirable to have that demand embedded in the remainder of the system in order to investigate interactions such as, say, demand shocks from subway lines. For such investigations, the presented approach seems very appropriate.

7.4 Directions for Future Work

The calibration results and the work itself raised questions that are still open and should be addressed:

7.4.1 Data Collection

A defined guideline from the beginning of the research work was the application of the calibration experiments on a real public transport system scenario. As it was stated in the scenario description, most input data were collected from different sources and generated at different times. The gap between different surveys methodologies resulted on the need of data preparation. The preparation included some known techniques like population filtering, expansion, and synthetic elasticity generation. Running again the calibration experiments on scenarios with more uniform and consistent information would be a valuable comparison point.

In the same direction, data collection methods might consider the compilation of more precise and extended revealed preference data. Modern mobile data techniques and their subsequent analysis could be a decisive factor to achieve a more realistic route choice modeling.

7.4.2 Routing

Realism in route calculation is key to get plausible simulation results. Up to now, 5 cost components have been considering for calculation of transit routes. Indeed, the characteristics of the optional pre-paid fare system in the scenario of Berlin have allowed to omit the monetary cost criterion in routing. However, the inclusion of pricing as optimization objective should be considered for realistic modeling in other transport systems. That could be said not only for the simulation of nearby scenarios in Europe but also for other transit system around the world.

The inclusion of effective waiting time value as route factor and the generation of random routes have been some efforts that have been undertaken to improve the routing implementation. However, more systematic research should be done in these existing procedures, and also in new potential routing-related procedures. The presentation of Multi-Objective Transit Routing state of art investigation in Section 2.3.4.2 showed for example, that current tendencies include speed-up techniques like pre-calculation and transit network clustering.

7.4.3 Analysis of Worst Plan Elimination

It is necessary to conduct further investigation on the current MATSim worst plan elimination mechanism. A special concern is the fact that "worst plans" are discarded only from the standard scoring perspective. This might affect directly plans that have some plausibility from a view other than performance. For example, plans with the worst performance scoring, but with excellent contribution to counts match in the calibration environment, were discarded in the first calibration experiments. When that happens in any other transport simulation study, the contribution of all those eliminated plans is wasted, which is reflected on the results.

The desired route diversity can be also affected during the scoring process. In evolutionary algorithms, individuals[1] with high fitness score are the ones that tend to prevail along the evolutive process. As they share the caracteristics of a high score, they tend to be similar among them. This represents a conflict between fitness and diversity. If nothing is done to avoid it, agents end up with very similar solutions, which might compromise some investigation efforts like demand estimation.

7.4.4 Individual Preferences Calculation

7.4.4.1 Dynamic Random Route Generation Inclusion

More work is necessary to integrate effective plan innovation for individual preferences calculation. Up to the present experiments, previous randomized route generation and individualized preferences-based scoring approaches proved reasonable stability separately. But a pending task is to bring out further theoretical investigation about route diversity validation which can be close connected with the taste variation evaluation approach.

7.4.4.2 Performance

The small bus line M44 scenario with 4 fixed plans was calibrated in 500 iterations in 06:30 hours in a computer cluster node with 8 core lx-amd64 architecture and 23.6G RAM without parallelization. Although the computation time seems to be reasonable for calibration purposes, its performance optimization has not been exhaustively studied. Special attention should be given to the generation of routes, which consumed much of the processing time during the simulation start-up.

The same could be said for the individualized parameter calculation. The efficiency of other least square solution methods should be tested from the performance perspective. A prospect is the use of QR decomposition for least square calculation as alternative for the SVD method. For example, a performance comparison between both decomposition methods suggested that QR improves slightly the performance on a sinusoidal frequency estimation method [SS93].

[1] in MATSim evolutionary approach, the plans of each agent constitute the individuals that evolve along the simulation.

7.4.4.3 Behavioral Model Extension

For the application of the calibration in further studies, a closer integration of the calibration into the behavioral model is suggested. Specially in the personalized parameter calculation, the inclusion of activity scoring into the complete plan performance evaluation should be resumed. Specifically, a connection between personal attributes and found parameters should be investigated.

7.5 Pre-publications

The manual and calibration methods presented in Chapters 3 and 4 were published [MN12] in the TRB 91st Annual Meeting.

The calibration of Greater Berlin scenario of Chapter 5 was presented in the 2nd Symposium of the European Association for Research in Transportation (hEART 2013) in Stockholm, Sweden and also in the Conference on Agent-Based Modeling in Transportation Planning and Operations in Virginia USA in 2013.

The pre-publications were adapted here for this dissertation format.

7.6 Acknowledgements

MATSim is an open source software framework distributed under the terms of the GNU General Public License (GPL).

Cadyts (Copyright 2009, 2010, 2011 Gunnar Flötteröd) is distributed under the terms of the GNU General Public License as published by the Free Software Foundation, version 3 or later.

All the programming code necessary for this dissertation was developed in Java, (http://www.java.com) a programming language of Oracle Corporation. Oracle and Java are registered trademarks of Oracle and/or its affiliates. Other names may be trademarks of their respective owners.

Andreas Neumman prepared the scenario data. The code for the generation of randomized public transport routes used in Chapter 5 was developed by Prof. Kai Nagel. The randomized router was tested for the first time by Graf [Gra13].

Commons Math, the Apache Commons Mathematics Library was used to perform linear square solution. Commons Apache is distributed under the Apache License (http://www.apache.org/licenses/LICENSE-2.0.txt).

Maps of the Berlin scenario presented in this thesis (Figures 3.1, 5.5, and 5.1) were taken and adapted from www.openmap.lt. The site is based on www.openstreetmap.org (©OpenStreetMap contributors), which consists of open data licensed under the Open Data Commons Open Database License (ODbL) (http://opendatacommons.org/licenses/odbl/) and whose cartography is licensed under the Creative Commons Attribution-ShareAlike 2.0 license (CC-BY-SA) (http://creativecommons.org/licenses/by-sa/2.0/).

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Appendix A

Behavioral Parameters in MATSim Configuration

The MATSim config object (see http: http://www.matsim.org/files/dtd/config_v1.dtd) defines necessary configuration values to run a simulation. This appendix shows an extract of "*plan-CalcScore*" module that contains the behavioral parameters used for routing and scoring processes. Here, parameters are presented with their default values (see [CN05] [CN05][Kic09]) as they are at the day of the submission of this dissertation.

```
    ...
<param name="learningRate" value="1.0"  />
<param name="BrainExpBeta" value="2.0" />
<param name="PathSizeLogitBeta" value="1.0"  />
<param name="lateArrival"  value="-18.0" />
<param name="earlyDeparture" value="-0.0" />
<param name="performing" value="6.0" />
<param name="traveling"  value="-6.0" />
<param name="travelingPt"  value="-6.0" />
<param name="travelingWalk" value="-6.0" />
<param name="travelingOther"  value="-6.0" />
<param name="travelingBike"  value="-6.0" />
<param name="waiting" value="-0.0" />
<param name="waitingPt" value="-6.0" />
<param name="marginalUtlOfDistanceWalk" value="0.0" />
```

```
<param name="marginalUtlOfDistanceOther" value="0.0" />
<param name="marginalUtilityOfMoney" value="1.0" />
<param name="monetaryDistanceCostRateCar" value="0.0" />
<param name="monetaryDistanceCostRatePt" value="0.0" />
<param name="utilityOfLineSwitch" value="-1.0" />
 ...
```

LISTING A.1: Behavioral parameters in MATSim configuration file

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