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Development of a Multi-Criteria Optimization Model Based on Floating Truck Data for Individual Truck Parking Recommendations

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Executive Summary

Trucks are the most important mode of freight transport, apart from container ships, and the backbone of the economy. However, a major issue is the lack of overnight parking spaces along major freight corridors. The increasing availability of Floating Truck Data offers new possibilities to match parking demand and supply.

This thesis proposes a novel Truck Optimization Parking System (TOPTIPS), which provides truck-specific parking recommendations. Demand and supply are optimally matched by balancing the interests of truck drivers and road authorities. Whereas the drivers often face pressure to generate revenue miles and prefer to have some amenities (shower, food, fuel) at the end of a working day, road authorities are mostly concerned with avoiding overcrowding and maintaining safety for all traffic participants. Complicating the matter, truck drivers must comply with Hours of Service regulations.

The central idea of the thesis is to model truck parking mathematically with a bipartite graph and to solve the resulting Mixed-Integer Programming optimization problem. A multi-criteria optimization approach is chosen to account for the different objectives of drivers and road authorities. To evaluate the proposed model, a large-scale microscopic traffic simulation is set up. The simulation is calibrated and validated with real data from induction loops/overhead detection and specialized truck detectors. The results show a well-calibrated model. The Squared Inverse Mean Percentage Error metric indicates small spatio-temporal speed deviations ($f \approx 0.89$), and the Travel Time Difference Index underscores well-matching travel times ($f \approx 0.96$).

The evaluation of TOPTIPS shows that both truck drivers and road authorities can be supported in achieving their goals. The uneven filling of the rest areas is reduced by $59.0\,\%$, and, at the same time, the productivity of the drivers is increased by $16.7\,\%$ compared to the status quo. Second, it is shown that equipment levels of only $30\,\%$ already have a significant impact. Third, tests with inaccurate travel time predictions indicate that only $4.0\,\%$ of the trucks exceed their driving time. Fourth, in case of a large traffic jam, TOPTIPS can increase the average velocity of the affected trucks by $39\,\%$ by recommending temporary stops.

Summarizing, the current truck parking situation is transformed into a controlled environment. The parking search is simplified, the traffic safety is increased, and construction costs can be saved.

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Chapter 1

Introduction and Motivation

Freight transport is indispensable for our society as it connects supply and demand over large distances [TAVASSZY and JONG, 2014]. Over the past ten years, the use of freight transport has increased [TAVASSZY and JONG, 2014; KOUROUNIOTI et al., 2020] and is projected to increase further in the future [ZEIMPEKIS et al., 2018]. Using the example of the US and Germany, the growing demand for freight transport will be illustrated with concrete figures. The examples are representative of global growth in freight shipping [KOUROUNIOTI et al., 2020]. In order to quantify freight transport activities, the weight and value of the transported commodities are often used.

In the US, the tonnage and value of shipments increased by 9.8 % and 6.6 %, respectively, from 2012 to 2018 [BUREAU OF TRANSPORTATION STATISTICS, 2020]. For the future, the authors expect further growth in terms of tonnage from 18 616 Mt in 2018 to 25 472 Mt in 2045 (+36.8 %). Regarding the value of shipments, an increase from $18 907 billion to $37 064 billion (+96.0 %) is predicted. A similar situation is reported for Germany, where freight transport is projected to rise by 38 % in terms of Tonne-kilometre (tkm) from 2010 to 2030 [BMDV, 2014]. The tkm metric not only takes into account the weight but also the distance. It is another frequently used freight activity metric. The average transport distance is also expected to increase over the same period (+17 %). The reason for this global upward trend is deeply rooted in our socioeconomic development. Concretely, KOUROUNIOTI et al. [2020] cite the following causes: population growth, falling trade barriers, reduced transport costs, increased consumption, customized products, and better transport infrastructure.

Having outlined the general importance of freight transport, the next step is to obtain a clear picture of the modal split. The modal split, also called modal share, is defined for passenger transport as the "distribution of traffic relations among the different modes of transport" [KIRCHHOFF, 2002, p.78]. For freight traffic, metrics such as the tonnage, value of transported goods, and tkm can be used to calculate the modal split. Again, the situation is explained using the US and Germany as examples. A generalization is then made based on data from the European Union (EU). For the US, the modal split with respect to the shipped values is depicted in Figure 1.1. The figure shows that trucks are the most important mode with a share of 60.9 % [BUREAU OF TRANSPORTATION

STATISTICS, 2020]. When the weight metric is analyzed, the percentage share remains approximately the same. The multimode category accounts for the second-largest portion with 17.7 %. This category includes not only movements using two or more modes but also mail. The remaining four modes, rail, water, air, and pipeline, add up to just 20.9 %. Looking at Germany, the situation is similar. According to the BAG [2020], the modal share of trucks is at 86.8 % and 76.3 % with regard to weight and tkm, respectively. However, the figures do not include freight transport by air, as is the case for the statistics from the US. In summary, it can be stated that trucks are the most important mode of freight transport regardless of which metric is used. This is underscored by an analysis from the EU which states that road freight transport accounts for 76.0 % (with respect to tkm) [EUROSTAT, 2021]. In conclusion, freight transport is already at a high level and is predicted to grow significantly in the future. The majority of freight is transported by trucks, which represent the backbone of our economy. Therefore, it is pivotal to ensure efficient, reliable, and sustainable road freight transport.
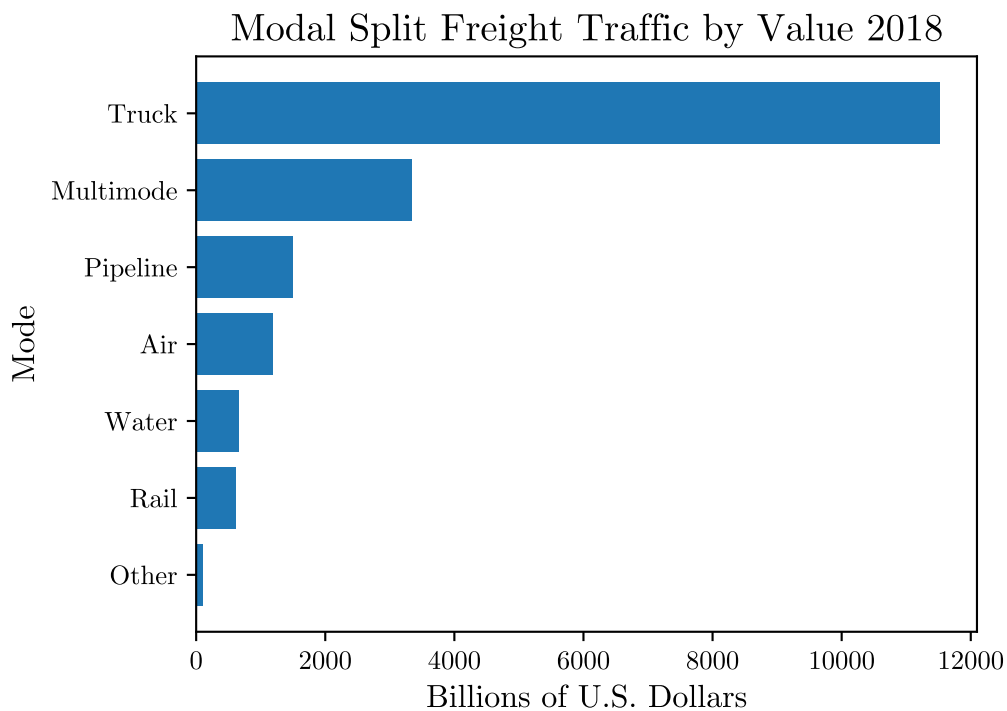

Figure 1.1: Modal split freight traffic US - data: Bureau of Transportation Statistics

1.1 Truck Parking Problem

Increasing road freight traffic poses challenges in several areas. At the strategic level, it uses infrastructure that often operates at its capacity limit. This, in turn, makes the road-based transport system more susceptible to congestion, wear-related physical deterioration, and rising maintenance costs. Heavy vehicles are a major cause of pavement and bridge damages, and there is a great amount of research being done to mitigate the effects [COLE and CEBON, 1991; GREEN and CEBON, 1997; AGOSTINACCHIO et al., 2014]. Furthermore, environmental aspects are becoming increasingly important. Trucks account for 60 % of greenhouse gas emissions in freight transport in Germany [ALLEKOTTE et al., 2021] and are still responsible for 6 % of the country's total CO_2 emissions [LÉONARDI and BAUMGARTNER, 2004]. At the operational level, road freight traffic faces challenges such as time pressure for drivers, driver shortages, high turnover rates, driver health issues, and fatigue-induced crashes [GARBARINO et al., 2018; WILLIAMS et al., 2017; SIEBER et al., 2014; ADAMS-GUPPY and GUPPY, 2003].

Another major issue is the lack of parking spaces, in particular for long-haul drivers along major freight corridors [SMITH et al., 2005; BORIS and BREWSTER, 2018; FHA, 2012]. In the US, numerous studies about the shortage of truck parking spaces have been conducted in the past. One of the most comprehensive reports was published by the Federal Highway Administration. In comparison to many other studies that were conducted by the individual states in the US, the "Jason's Law" report covers the entire National Highway System (NHS) [FHA, 2015]. The study concludes that most states experience truck parking shortages. Only the ones in rural areas appear to have sufficient parking spaces. Furthermore, the study found that peak demand for parking is during night hours on weekdays. The findings are in line with a report from IRZIK et al. [2019] of the Federal Highway Research Institute, which investigated the parking situation along the German highway system in 2018. The study found that 94 100 trucks require parking every night, whereas only 70 800 parking spaces are available. Hence, 23 300 parking spaces are missing every night. The study design covers all available parking spaces along the German motorway network by on-site counts. It is conducted regularly every five years. A comparison of the two most recent reports shows that the parking shortage has worsened. In 2012, there were "only" 10 900 parking spaces missing, which results in an increase of 12 400 missing spaces. On some motorway sections, the parking pressure is so high that trucks are even forced to park at rest areas where it is prohibited. For example, at the rest area *Holledau* on the A9 this can be seen frequently. Figure 1.2 shows the situation on Wednesday, September 11, 2019 at about 7:30 p.m.

Sufficient parking supply is of the utmost importance as truck drivers are required to comply with the Hours of Service (HOS) regulation. The HOS regulation limits the

Figure 1.2: Parking pressure along the A9 between Nuremberg and Munich

maximum amount of time a driver may work and drive and sets minimum rest periods. In most industrialized countries, HOS regulations exist, which aim to improve safety by reducing fatigue [JENSEN and DAHL, 2009]. While HOS regulations reduce the risk of fatigue and improve working conditions, the truck drivers can be put in a conflict of objectives when looking for a parking space at the end of a shift. The first decision to be made by the driver is how early he or she starts looking for a parking space. A large time buffer reduces the productive time behind the wheel, but increases the likelihood of finding a suitable and legal parking space. The second decision to be made is when no proper parking space is found. Stopping at on-ramps, off-ramps, or on the shoulder ensures that HOS regulations are followed, but this is usually illegal, unsafe, and affects the rest quality. The other option is to continue driving and hope that a parking space can be found somewhere downstream but at the cost of violating HOS regulation and being fatigued. This situation can lead to additional stress for drivers, who may already be under time pressure. CHEN et al. [2015], for example, surveyed more than 1000 long-haul truck drivers and found that 73 % considered their delivery schedules unrealistic. Of the respondents, 37 % admitted to not complying with HOS regulations (violation: often or sometimes).

In summary, road freight traffic is pivotal for the economy to function as it is the major mode of freight traffic. Steadily increasing freight traffic poses serious challenges, particularly with regard to adequate and safe parking. It is widely recognized that there is a lack of parking along major freight corridors in many industrialized countries. However, truck drivers rely on legal parking to avoid fatigue, improve traffic safety, and to comply with HOS regulations [GUTMANN et al., 2021].

1.2 Research Gap and Solution Approach

Truck parking literature can be divided into two groups. The first group deals with methods to identify locations where truck parking expansions are required. In the last five years, considerable progress has been made in using Floating Truck Data (FTD) samples to prioritize infrastructure investments [Haque et al., 2017; Corro et al., 2019; Nevland et al., 2020]. This enables fast and cost-effective data-driven spending decisions. However, building and expanding parking supply is still expensive, time-consuming, in competition with other land-use types, and has negative environmental impacts [Smith et al., 2005; Adams et al., 2009]. Moreover, construction-based approaches are not sufficient because road freight traffic increases faster than new parking spaces can be built [Irzik et al., 2019].

Therefore, the second research group deals with improved matching of supply and demand [Nagy and Sandor, 2012; Cheng et al., 2020; Sadek et al., 2020; Yang et al., 2021; Gutmann et al., 2021]. It is argued that parking information systems, sometimes also called intelligent truck parking, are required to provide real-time or even predicted occupancy information. The underlying assumption is that truck drivers can use this kind of information to make improved parking choices. Improved parking decisions are supposed to result in less parking search traffic, better-matched parking supply and demand, and higher compliance with HOS regulations. However, first results from the literature show only minor effects with respect to reduced parking search traffic and better-matched supply and demand [Monninger et al., 2021].

This thesis takes a new approach to mitigating the parking issue by better considering the truck driver's perspective. The parking search process is simplified by providing individual parking recommendations. Even if real-time/accurately predicted occupancy information was broadly available, drivers would still need to undertake mental efforts to decide on the parking locations — probably using some mobile device while driving and being fatigued at the end of a working day. This search process is complex as the drivers have to consider multiple alternatives along the route, need to maximize productivity, stay within the allowed HOS regulations, consider traffic conditions, and take into account preferences for amenities. Regarding the productivity aspect, literature shows that truck drivers face pressure to generate revenue miles (about 70 % are paid by the mile [Boris and Brewster, 2018; Lemke et al., 2021]). However, each driver has an individual remaining driving time at the end of his or her shift, which limits revenue miles and parking choices. Parking early results in decreased revenue miles [Boris and Brewster, 2018]. Not finding parking in time violates HOS regulations. The aspect of amenities is also often reported to influence parking choice. Adams et al. [2009], for example, describe that truck drivers prefer certain amenities for overnight rests and select rest areas accordingly.

In summary, there can be multiple reasons why a truck driver is not able/willing to park at a rest area with free spaces. Just providing the current or expected occupancy may only help a little in these situations. Research on providing real-time/predicted occupancy information of rest areas often neglects this fact [GARBER et al., 2004; BAYRAKTAR et al., 2015; CHENG et al., 2020; SADEK et al., 2020; YANG et al., 2021]. Prior research has focused on overcrowding, but it has overlooked the fact that truck drivers have their individual objectives and restrictions. The literature also shows that drivers do not or cannot plan parking well in advance and make their parking choice towards the end of their shift [SMITH et al., 2005; GOLIAS et al., 2020; METZGER and SPANGLER, 2021]. This, in turn, means that individual parking recommendations, which are updated as the driver approaches the end of his or her allowed driving time, could be very valuable.

Therefore, the aim of this thesis is to better consider the truck driver's perspective by using FTD to provide individual parking recommendations. Truck-specific recommendations are valuable to the drivers because the recommendations free them from the parking search task and allow them to focus entirely on driving. However, if only the truck drivers' perspective is considered, this does not necessarily lead to optimally matched parking demand and supply. As a consequence, the perspective of road authorities, which are interested in better utilizing existing parking infrastructure and increasing traffic safety [FLEGER et al., 2002; ADAMS et al., 2009; FHA, 2015], also needs to be taken into account. This is particularly important when demand surpasses supply and safety-critical situations have to be handled. Therefore, an integrated approach is proposed in this thesis, which considers the objectives of the two main stakeholders, provides individual parking recommendations for the truck drivers, and has the potential to be infrastructure-independent.

1.3 Research Questions

As outlined above, there are system objectives (road authorities) and individual objectives (drivers), which can conflict with each other and need to be balanced. This leads to the first research question:

Q1: What impact can truck-specific parking recommendations have for drivers and road authorities?

To answer this research question, a parking recommendation system is developed and tested using a traffic simulation. For the development of the parking recommendation system, it is pivotal to understand the global and individual objectives of the two main stakeholders in detail. The objectives will be derived from an extensive literature review.

Furthermore, individual recommendations require truck driver-specific data, which is provided by FTD. Even though FTD is becoming increasingly available, it has to be assumed that the parking recommendation system cannot start with penetration rates of 100 %. This leads to the second research question:

Q2: What are the effects of different penetration rates?

The recommendation system is to be developed detached from any potential technical limitations of current FTD. However, which data requirements exist and whether these can be realistically met within the next ten years should be analyzed.

Traffic is inherently stochastic and delays are inevitable. This is a challenge for truck drivers who must adhere to strict HOS regulations while being unsure when they will arrive at a particular rest area. Reliable travel time predictions are necessary for many applications and also play an important role for the parking recommendation system. However, real-world travel time predictions are inaccurate to some extent. This leads to the third research question:

Q3: What are the effects of different levels of travel time prediction accuracy?

Travel time prediction is a broad field and attracts much research attention with numerous models being proposed in the literature. A good overview can be found in MORI et al. [2015]. In this thesis it is assumed that travel time predictions are given, but the impact of typical prediction errors on the parking recommendation system should be evaluated. The two terms predicted and estimated travel time are used interchangeably.

Large traffic jams, also called mega jams by KESSLER et al. [2020], can happen from time to time on motorways. For any driver, these situations lead to substantial travel time increases and delayed arrivals. However, for truck drivers there is another undesirable impact: reduced remaining driving time with only a few driven revenue kilometers. In order to avoid these productivity losses, it can be advantageous to stop temporarily at the next suitable rest area and to wait until the jams has dissolved. Therefore, the fourth research question is:

Q4: In case of large traffic jams, can the productivity be increased?

1.4 Structure

The structure of the thesis is shown in Figure 1.3 and briefly summarized in the following. Chapter 2 presents an overview of the parking literature and introduces the required optimization theory. It begins with Section 2.1, which introduces the general parking search theory. Section 2.2 deals exclusively with truck parking and summarizes proposed solutions as well as challenges. With a deep understanding of the current situation, the derivations from the literature are presented in Section 2.3. Identifying the two main stakeholders with their respective objectives lays the foundation for the design of the parking recommendation system. The recommendation system is based on Mixed-Integer Programming (MIP) modeling, for which the required theory is covered in Section 2.4.
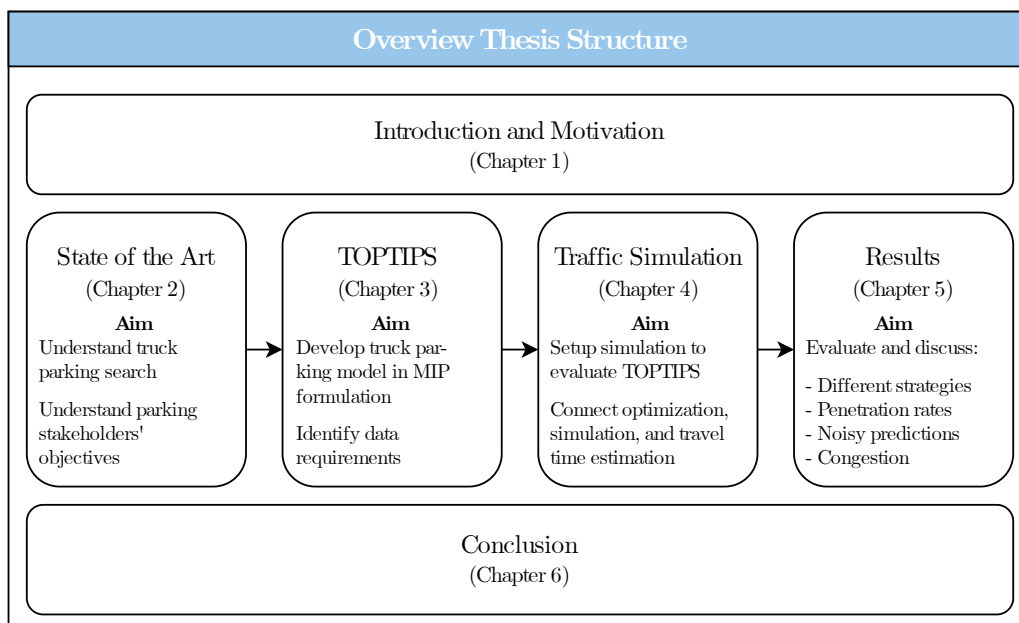

Figure 1.3: Structure of the thesis

The recommendation system, called Truck Optimization Parking System (TOPTIPS), is developed in Chapter 3. A high level overview of the system, its boundaries, and the required assumptions are presented in Section 3.1. In Section 3.2, first, the motivation behind choosing a MIP approach for truck park modeling is explained. Second, the foundation for truck parking modeling is laid with the help of a simplified example. Third, the entire full-scale model is developed step by step.

TOPTIPS is evaluated using a microscopic traffic simulation, which is covered in Chapter 4. As a prerequisite for the simulation, truck parking data is collected from a parking guidance system. The minute-by-minute data is analyzed in Section 4.1. Subsequently, the modeling of the road network as well as the traffic detectors is explained in Section 4.2. Next, the general traffic demand and the truck parking demand are covered in Section 4.3. After setting up the simulation, the calibration and validation results are presented and discussed in Section 4.4. Lastly, in Section 4.5, the simulation is connected to the optimization and the travel time estimation modules.

Chapter 5 evaluates TOPTIPS in different scenarios and discusses the results. It begins with an explanation of the metrics that are used to quantify the outcomes in Section 5.1. Section 5.2 compares different recommendation strategies with each other and with the status quo. Subsequently, different penetration rates (Section 5.3) and noisy travel time predictions (Section 5.4) are tested. Section 5.5 shows the potential of TOPTIPS to increase productivity in congested situations. The results and their transferability are discussed in Section 5.6.

The work is concluded in Chapter 6 by summarizing the results with respect to the original research questions. In addition, the contributions of TOPTIPS to the state of the art in truck parking are presented. Finally, the outlook puts this work in the broader context of making freight transport safer, more reliable, and more environmentally friendly in the future.

Chapter 2

State of the Art

In the first section, the theory of parking, developed and applied primarily in urban contexts, is presented. This provides a solid theoretical background on how parking search works. Further, the overall impacts of parking search are explained by summarizing the most important studies in the field. Second, key parking search factors are described, and it is discussed how they influence the search likelihood. In the next section, the focus is on truck parking literature. First, studies with respect to the truck parking shortage and the overall impacts thereof are presented. Second, the individual perspective of the drivers is covered as they are directly confronted with the shortage. Third, important literature on proposed solutions is reviewed. In the following section, the extensive literature review is clustered based on system and user objectives. Ultimately, the clustering serves as the basis for the development of the parking recommendation system because the objectives play a key role in the design of the mathematical model. The last section introduces the optimization theory for solving the mathematical model.

2.1 Parking Search Theory

Parking in cities can be divided into two categories: on-street parking and off-street parking [RAJABIOUN and IOANNOU, 2015]. On-street parking, also known as curb parking, means that vehicles park at a street level in designated areas. It can be free or paid, for example, via meters or apps. Many municipalities issue resident parking permits allowing residents to park at reduced rates. Typically, there are parking regulations that set a maximum time or provide incentives for specific parking hours. In most cases, on-street parking is publicly owned and managed. In contrast, off-street parking means that vehicles park in garages or dedicated enclosed parking lots. Off-street parking can be owned publicly or privately. Sometimes, off-street parking is closely associated with businesses that aim to provide convenient parking for their customers. Typically, off-street parking has some type of access restriction to ensure that only authorized vehicles enter, parking hours are respected, and fees are paid.

In most cases, the prices for off-street parking are higher than for on-street parking. SHOUP [2006] collected data on parking near city hall in 20 cities across the US and

found that the cost of off-street parking is, on average, five times higher than the cost of on-street parking. With a mathematical model, he quantified the impacts of parking search traffic. He argues that cruising for parking is the driver's response to the public parking policy and that underpriced on-street parking has many negative effects. The next subsection summarizes the current state of knowledge on parking search traffic and related impacts.

2.1.1 Parking Search Process

The search for parking in cities is an issue that has been known for a long time. Shoup [2006] even claims that parking search traffic must have emerged shortly after the invention of the wheel. Parking search is defined as "the process by which drivers are able to reconcile their parking intentions with the actual availability of parking opportunities" [Polak and Axhausen, 1990, p. 3]. Typically, parking search is associated with on-street parking [Brooke et al., 2014], but there may be instances where cruising for off-street parking is necessary. It leads to congestion, increased fuel consumption, noise, pollution, and causes accidents [Shoup, 2006; Arnott and Inci, 2006; Caicedo, 2010; Waterson et al., 2001]. The first studies were published at the beginning of the 20th century. Simpson [1927] concluded that on-street parking can lead to parking search traffic, particularly when there are only few spaces available. He argues that off-street parking garages need to be built because street space is very valuable and should be used to keep traffic moving. According to him, parking search traffic accounts for 19.3 % to 34.4 % of total traffic in Detroit. In the following years, many more studies analyzed the share of cruising vehicles for parking. A good overview can be found in Shoup [2006], who calculated the average share of cruising vehicles in a meta-analysis. He reports that cruising vehicles account for 30 % of the overall traffic and that drivers spend 8.1 min searching on average.

In addition to the traffic share, Axhausen et al. [1994] investigated the time required for searching compared to the overall travel time in different cities. The parking search accounts for 4.9 % to 40.3 % and varies between the survey locations. However, it should be noted that the most widely used methodology in terms of search time is the survey. Therefore, the self-reported values have to be treated with caution. Drivers may not properly distinguish between driving and searching or may simply recall incorrect numbers as each driver has different perceptual errors. Another effect that can be observed is reduced speed during parking search. According to Benenson et al. [2008], drivers drive at speeds between 20 km/h to 25 km/h when looking for parking and slow down further to 10 km/h to 12 km/h when an immediate parking decision is expected to be made.

Parking search traffic is the result of how drivers choose to park. The parking search

behavior is a complex process dependent on many different parameters, which may even be perceived differently by the drivers. THOMPSON and RICHARDSON [1998] suggested a parking search process that is based on a series of linked decisions. The process is shown in Figure 2.1 and briefly summarized in the following.
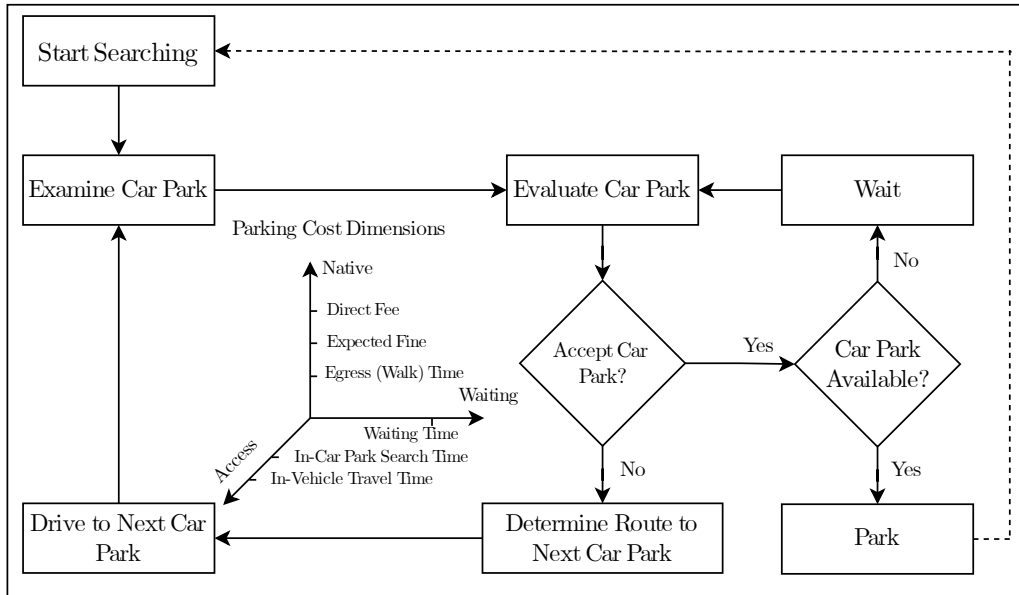
Figure 2.1: Parking search process - adapted from Thompson et al. 1998

The process starts with the examination of parking attributes while moving. Attributes are, for example, fees, walking time to destination, in-vehicle travel time, waiting time, and may also include expected fines. The attributes are used to evaluate specific parking options. It should be kept in mind that the attributes can be evaluated differently by drivers depending on trip purpose, gender, weather conditions, and income. BARATA et al. [2011], for example, report that lower income drivers are less willing to pay for parking and that gender plays an important role as female drivers are more likely to pay. In addition, VAN OMMEREN et al. [2012] analyzed cruising depending on trip purpose. They found that cruising times are substantially higher for leisure and shopping activities than for working. Moreover, their results are in line with BARATA et al. [2011] with respect to income. A more detailed explanation of relevant attributes and their perception is given in the next subsection. For now, the focus is on the overall parking search process. In general, each driver uses his or her own specific cost function to evaluate parking options. THOMPSON and RICHARDSON [1998] clustered the parking attributes into three cost dimensions, which can also be seen in Figure 2.1. The outcome of the evaluation is a binary decision whether to accept or reject the specific parking option. If the parking is accepted, it is still not guaranteed that it is actually available, and the driver may have to wait. After waiting, the parking is reevaluated with the updated knowledge

and a new decision is made. If the parking is rejected, the driver needs to determine a route to the next parking, drive there, and start again with the examination subtask. The parking search process defined by Thompson and Richardson [1998] provides a sound theoretical background for how drivers choose parking. The most important part of the search process is the parking attributes and their individual evaluation because they determine whether a specific parking option is accepted or rejected.

2.1.2 Parking Search Factors

Brooke et al. [2014] extended the idea of parking attributes to a more general concept of factors influencing the parking search likelihood. With this approach, it is possible to partially disentangle individual perceptions of parking attributes and to examine personal characteristics that influence parking. The result is a list of parking search factors, each of which has an impact on the search likelihood. Table 2.1 shows the relevant parking search factors grouped into six major categories according to Brooke et al. [2014]. In addition, the influence of each factor with respect to the search likelihood is shown. If the direction of influence can go in both ways, which is the case, for example, for factors in the group individual characteristics, it is indicated with "Both." In the following, the most important factors are briefly explained with examples from the literature.

Time-related factors are defined as search time and observed or experienced queuing and waiting times. It is obvious that more search time will lead to increased parking search efforts. However, it is important to understand why some drivers take more time for search than others. van Ommeren et al. [2012], for example, found that the trip duration as well as the expected parking duration increase search times. Parking search time is also important for parking choice modeling, and the literature in this domain supports van Ommeren et al. [2012] findings. It is known from parking choice modeling that the trip purpose can also influence parking search time [Van Der Goot, 1982; Axhausen and Polak, 1991]. More recent parking choice models are often developed using stated preference methods [Chaniotakis and Pel, 2015; Axhausen and Polak, 1991; Ibeas et al., 2014] because scenario approaches can be used and the actual choice set does not necessarily have to exist. Van Der Waerden et al. [1993] used this method to research parking search in congested situations where drivers must adapt to an occupied primary parking intention by using the following options: waiting, continue searching, illegal parking, or other. The key findings are that drivers tend to wait less when the expected waiting time is higher. In addition, the probability of waiting decreases the more parking lots were previously visited without success.

Shoup [2006] developed an analytical model to quantify the benefits and costs associated with cruising for parking. Important factors that enter the model are the price of curb

Category	Factor	Parking Search
Time-related	Search time	More
	Queuing and waiting time	More
Price-related	Parking charges	More
	Increased willingness to pay	Less
Area-wide traffic and parking policy	Parking control and enforcement	Both
	Parking guidance information	Less
	Park and ride	Less
	Car-sharing	Less
	Technology	Less
Parking characteristics	Type	Both
	Capacity	Both
	Vegetation and shade	Both
	Occupancy and turnover	Both
Individual characteristics	Trip purpose	Both
	Personal	Both
	Sociodemographic	Both
	Socioeconomic	Both
Other	Weather condition	Both
	Unobservable Preferences	Less

Table 2.1: Factors influencing parking search - adapted from Brook et al. 2014

parking and the price of off-street parking among other variables such as number of passengers, time value, fuel cost, and parking duration. He concludes that cheap on-street parking compared to more expensive off-street parking leads to significantly increased parking search traffic. Similarly, ROTH [1965] argue that subsidized or free on-street parking results in queues in front of parking lots, making a common good unavailable. In addition, the willingness or the financial means to pay for parking are another important factor of the price-related category. Many studies have found that lower income drivers are more likely not to pay for parking and instead seek for other alternatives [VAN OMMEREN et al., 2012; BARATA et al., 2011]. IBEAS et al. [2014] explicitly accounted for the heterogeneity of drivers and modeled parking choice by including variables such as residency and income level. In line with the other studies, higher-income drivers are more willing to pay. The same applies to non-residential drivers.

The third category is concerned with area-wide traffic and parking policies. One of the

most prominent examples is parking guidance information, which aims at reducing the search for parking. Axhausen et al. [1994] evaluated the effectiveness of a parking guidance information system in the city of Frankfurt am Main. The authors report high awareness rates of about 80 % three months after the system was in operation. Further, 20 % of drivers that prefer parking off-street may use the system. However, only a few drivers use the system as their primary source of information. In most cases, the system supports previously made decisions or serves as a fall-back solution if the desired parking option could not be found. Thompson and Bonsall [1997] conducted a meta study with respect to the response of drivers to parking guidance systems. The purpose of those systems is clearly stated as reducing parking search times as well as queues at the entrance of garages. The authors reviewed studies from 11 different cities and concluded that, although parking guidance systems are widely used in cities, studies on the effects are rare. The few studies that exist suggest that the systems can alter parking choice, but in most cases the usage rates are low. The other factors park and ride, car-sharing, and technological advances toward real-time occupancy of this category reduce the search likelihood. With respect to parking control and enforcement, the literature generally suggests less parking search likelihood [Cullinane and Polak, 1992]. Concretely, May and Turvey [1984] found that the usage of wheel clamps reduces the percentage of drivers searching from 15 % to 10 %, which may be due to higher turnover rates [Brooke et al., 2014]. However, the literature also reports cases in which stricter enforcement increases the likelihood of search [Brooke et al., 2014].

The factors grouped under physical parking characteristics are the type of parking, capacity, vegetation, and current occupancy. Some drivers have preferred parking types such as conveniently located on-street parking [Brooke et al., 2014]. It was mentioned earlier that limited on-street parking supply or cheaply priced on-street parking can increase the search likelihood. A much researched parking type is employee parking. It decreases on-street occupancy rates, increases congestion, and generally provides incentives to use the car to commute to work [Wilson, 1992; Mehranian et al., 1987]. Wilson [1992] came to the conclusion that if employees had to pay for parking, up to 34 % fewer cars would be used. Furthermore, he stresses that municipalities should be aware of this powerful mode choice instrument, which often conflicts with the goal of increased public transport usage. On the other hand, minimum on-site parking requirements can free-up on-street parking spaces and prevent on-street parking from overcrowding [Jia and Wachs, 1999]. This might be the reason why many cities ask for minimum parking requirements. However, increased supply may also lead to increased ownership in the mid-term [Guo, 2013]. In summary, there is much debate in the literature whether and how parking supply affects car ownership [Guo, 2013]. As there is evidence for parking search likelihood in either direction, the parking type factor is marked with "Both" in Table 2.1. This is a modifica-

tion compared to the original table by Brooke et al. [2014]. The original work primarily refers to on-street parking. This work includes literature regarding off-street parking.

Individual characteristics such as trip purpose and personal preferences play an important role for the parking search likelihood. van Ommeren et al. [2012] demonstrated that the trip purpose has a significant effect on cruising times. Work-related trips have the least cruising time, whereas leisure and shopping activities exhibit longer search times. It is assumed that there is greater pressure for some trip purposes (e.g., work-related trips, doctor's appointment) than others. However, there is newer evidence from Assemi et al. [2020], who did an empirical study of cruising factors in the CBD of Brisbane, that suggests that work-related trips exhibit the highest cruising times. The contradicting results show that it remains a challenge to separate the many influencing factors of search likelihood. Moreover, studies are conducted using different methods in different cities, which makes the transferability of the results difficult. However, there seems to be a good transferability across different countries and cities with respect to the socioeconomic factor income [van Ommeren et al., 2012; Barata et al., 2011; Ibeas et al., 2014; Anastasiadou et al., 2009]. Higher incomes are generally associated with a greater willingness to pay for parking, which results in less parking search efforts. This also shows that the factors defined by Brooke et al. [2014] are interrelated. The socioeconomic factors influence the willingness to pay, which is grouped under the price-related category. The willingness to pay, in turn, is affected by the socioeconomic status of the driver, but may also be affected by other factors such as the number of passengers in the car [Shoup, 2006].

In summary, the factors influencing parking search are a valuable framework. For the development of a parking recommendation system, it is pivotal to understand the underlying parking search theory in depth. However, truck parking is unique. Therefore, the next section provides a literature overview of truck parking. Finally, it should be noted that the impact of parking on traffic flow and network capacities is receiving increasing attention from research [Arnott and Inci, 2006; Boyles et al., 2015]. More recently, this has led to Macroscopic Fundamental Diagram (MFD)-based approaches [Liu and Geroliminis, 2016; Geroliminis, 2015]. This aspect of parking is not addressed here because it is considered less important for truck parking on motorways.

2.2 Truck Parking Literature

This section provides an overview of truck parking literature at rest areas and truck stops. A rest area is a parking facility at or very close to the motorway where truck drivers can legally stay overnight. A truck stop is similar to a rest area, but it is privately operated and usually offers more amenities. It should be noted, however, that in some countries there may be differences and subtleties in what is meant by rest area and truck stop. If not otherwise stated, the two terms are used interchangeably. In general, truck drivers are much more restricted when it comes to parking compared to private drivers in cities. First, there are often tight schedules and Just-In-Time (JIT) delivery requirements to be fulfilled [CHATTERJEE and WEGMANN, 2000]. Second, Hours of Service (HOS) regulations do not allow for long search times when the allowed driving time is (almost) exceeded [CORRO et al., 2019]. Third, illegal parking can potentially have more severe impacts for drivers than a parking ticket: The consequences range from sleep deprivation (e.g., improper sleep conditions) to severe accidents [BOGGS et al., 2019]. The literature is clustered into the following three categories: First, truck parking shortage literature with respect to causes and effects is presented. Second, studies on drivers and their specific issues are summarized. Third, proposed solutions for the facility and corridor level are reviewed.

2.2.1 Truck Parking Shortage

An insufficient supply of parking infrastructure can lead to unauthorized parking. BORIS and BREWSTER [2018] studied the frequency of unauthorized parking and found that the majority of drivers park illegally at least once a week. Figure 2.2 shows that only 11 % of drivers never park in an unauthorized location. Illegal parking is, however, not only the result of parking shortage but also of a "lack of awareness of available nearby parking [...] or HOS constraints" [BORIS and BREWSTER, 2018, p. 244]. The issue of unauthorized parking demonstrates that parking shortage, HOS violation, fatigued driving, and the lack of knowledge of nearby parking are interrelated and require systematic research.

In general, truck parking shortage has been documented for more than 20 years [BORIS and BREWSTER, 2018]. One of the first comprehensive studies on truck parking was conducted by FLEGER et al. [2002] in the US. The authors found that the lack of truck parking can lead to fatigue-related crashes and that the problem is not simply a supply and demand issue but one that requires more in-depth analysis. To better understand the problem, the researchers surveyed more than 2000 truck drivers, gathered data on parking supply, and developed a nationwide parking demand model. With this approach, it is possible to compare estimated demand with the known supply on a corridor level. In the case of
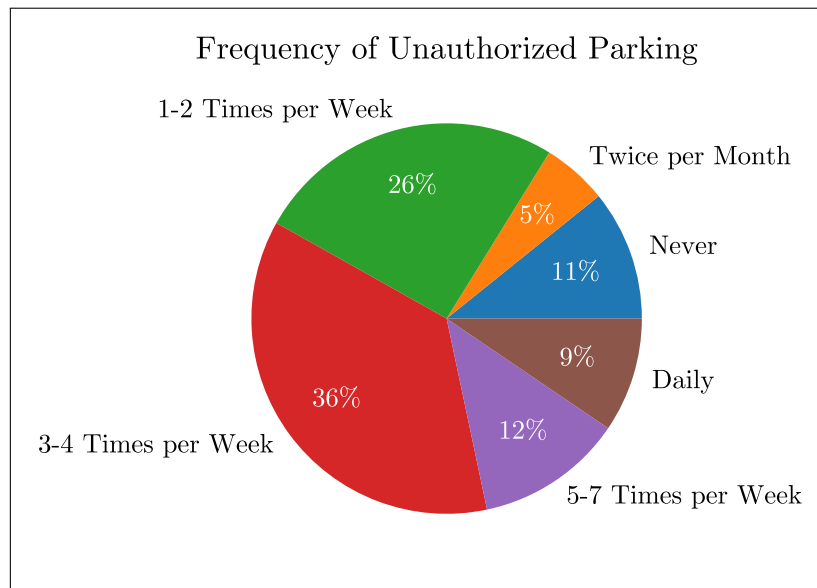
Figure 2.2: Frequency of drivers parking in an unauthorized location - adapted from Boris and Brewster 2018

this study, a distinction between public rest areas and private truck stops is made as it is important with respect to the results. The authors report that 35 states experience shortage of truck parking at public rest areas, and eight states show a lack of parking supply at private truck stops. However, it is also acknowledged that the model outcomes are not fine-grained enough to identify shortages of specific parking facilities. With respect to the conducted survey, only 11 % of the drivers indicate that they frequently or almost always find available parking at public rest areas. 34 % report the same answer regarding commercial truck stops. One interesting aspect concerns parking amenities. Besides the expected amenities, such as showers, restrooms, and food, well-lit parking lots are ranked among the top five attributes. A more detailed investigation demonstrates that the attribute well-lit parking is perceived differently by sex. 92 % of female drivers indicate that the feature is frequently or almost always important, whereas only 75 % of male drivers answer the same way, respectively. In summary, the work of FLEGER et al. [2002] documented the parking issue in unprecedented detail almost 20 years ago and led to a reassessment in 2012.

The "Commercial Motor Vehicle Parking Shortage" report confirms the findings of 2002 and concludes that the shortage is still widespread and in some areas acute [FHA, 2012]. Moreover, it predicts further growth in road freight traffic, which is in line with the forecast from 10 years ago [FLEGER et al., 2002], which will exacerbate the issue unless there are parking infrastructure expansions and improved matching of supply and demand. Capacity expansions and other measures are funded through national grant programs.

However, the authors report that the requested project costs of $231 million exceeded the available funds eight times. Another important aspect that is mentioned is road safety. Preliminary data on HOS violations and illegally parked trucks are also presented, yet, the authors acknowledge that data collection is difficult. In Idaho, for example, 25 % of drivers who park illegally report that they are out of HOS. In other states, the numbers are as low as 2 % (Maine), as high as 73 % (Nebraska), or no data is available (e.g., Kentucky and Virginia). This indicates that more attention needs to be paid to quantitative truck parking research in terms of safety. In general, the issue of HOS violation and illegally parked vehicles is further exacerbated by the pressure to maximize productivity [Boris and Brewster, 2018]. The authors support this fact by concluding that "drivers do not want to lose time diverging from their route" [FHA, 2012, p. 9] when they search for overnight parking. In summary, the situation between 2002 and 2012 did not improve considerably despite the research undertaken. However, efforts to understand and improve truck parking were intensified, which resulted in the most current and detailed nation-wide study to date. This study is presented in more detail because of its importance in truck parking research.

The report "Jason's Law Truck Parking Survey Results and Comparative Analysis" was published by the FHA [2015] in 2015. The study is named after the truck driver Jason Rivenburg who was murdered after failing to find safe parking. The incident has led to numerous efforts to "push forth legislation to focus national attention on the issue" [FHA, 2015, p. 1] and resulted in section 1401 of the Moving Ahead for Progress in the 21st Century Act (MAP-21), widely known as "Jason's Law." The authors state that truck parking shortage is a national safety concern. To get a full understanding of the current situation, surveys were not only conducted among each state's department of transportation officials but also among motor carrier safety officials, rest area operators and owners, fleet managers, and drivers. Each stakeholder group provided insights from a different perspective. The key findings of the study are summarized in the following. Parking shortages are reported by most states; however, rural states seem to be less affected. The shortages happen mostly at night times during the week when there is peak demand for parking. This leads to illegal parking primarily on hard shoulders, motorway interchanges, and ramps. Furthermore, 90 % of the drivers report that they have issues finding appropriate parking for the night's rest, with weekdays being the most difficult. The peak demand during weekdays seems to correlate with popular delivery windows. However, further research is required to fully understand whether the correlation is due to causality. Capacity expansions of rest areas are clearly seen as a potential solution, but challenges such as zoning laws and lack of funding are reported to be impediments. Finally, the authors acknowledge that the truck parking shortage is the result of many stakeholders and that more data is required to address the challenge. As a result, they

categorize data requirements by difficulty of acquisition:

- Tier I data: Basic level, easily obtainable, and currently in use on a national level (e.g., truck travel demand on national highway system, parking space inventory).

- Tier II data: Intermediate level, more difficult and costly to obtain, and possibly in use by different stakeholders (e.g., hourly parking utilization, origin-destination information, amenities at facilities, HOS violations).

- Tier III data: Advanced level, limited or no data currently available. Research and development needed to obtain data (e.g., impact of congestion on parking demand, use of technology by drivers to locate parking, environmental impact).

In conclusion, the "Jason's Law Truck Parking Survey Results and Comparative Analysis" report provides a comprehensive background of the current truck parking situation and necessary data requirements. Besides the large nationwide studies over the last two decades, some states conducted their own research on the issue. In the following, key findings of selected studies are summarized to understand the situation more in detail.

ADAMS et al. [2009] researched truck parking in Wisconsin and found that outskirts of metropolitan areas are often hotspots for truck parking issues as truck drivers park and wait for their delivery windows. This finding supports the conclusion of the FHA [2015], which argues that many rest areas were originally located in exurban or rural areas along the interstates but due to ongoing urbanization are now located in urban neighborhoods. This, in turn, leads to competing land-use between truck parking and other activities, which exacerbates the situation. In addition, ADAMS et al. [2009] confirm that shortages happen primarily during evening and night times when there is peak demand for parking. The design of rest areas also plays a role in that poor design makes maneuvering more difficult or impossible, which leads to fewer usable spaces. Moreover, it is reported that physical parking capacity is sometimes reduced by passenger cars blocking truck parking spots or other vehicles that need more than one parking space. It is not always clear how design and parking discipline interact, but the result is usually reduced capacity. This is supported by findings of FLEGER et al. [2002]. Of the surveyed truck drivers, 50 % indicate that the reason to park on ramps and shoulders is blocked access of nearby rest areas, even though there are still free spaces. Similar results are also found in SUN et al. [2018]. BAYRAKTAR et al. [2012] investigated truck parking in Florida by conducting field research. Their findings confirm the already mentioned lack of parking spaces. However, their work reveals effects of illegal parking on shoulders that are rarely mentioned. Issues with respect to erosion, drainage system blockage, and pavement deterioration are mentioned. GOLIAS et al. [2020] examined truck parking in Tennessee using Global Positioning System (GPS) data and a driver survey of 311 respondents. Forty percent of the drivers report changing their routing due to expected parking challenges. Another

interesting fact is that truck drivers rarely plan parking well in advance. Only 17 % of the respondents say that they plan parking before they start. The majority (51 %) states that they plan to park 1 h to 3 h in advance. In addition to the survey, the authors describe a methodology how to use GPS data, which was provided by the American Transportation Research Institute, to study truck parking. The study demonstrates that the use of GPS data allows for easier calculation of performance metrics such as traffic-to-capacity ratios and the number of violations on ramps. In Figure 2.3, an example of derived truck parking from GPS data is shown. Through the use of polygons, GOLIAS et al. [2020] can identify parking on ramps. However, as the GPS data only represents a sample of the population, extrapolation is required to make statements for the entire truck parking population.

Figure 2.3: Derived truck parking from GPS data - source: Golias et al. 2020

In conclusion, the shortage of truck parking poses serious challenges and is expected to worsen as road freight traffic increases. The BUREAU OF TRANSPORTATION STATISTICS [2020] predicts an increase of road freight traffic in terms of tonnage (+31.1 %) and value (+62.2 %) by 2045. The focus of the literature on truck parking is on the US as the lead market. However, as previously mentioned in the introduction, the problem exists in many industrialized countries [SEYA et al., 2020; HEINITZ and HESSE, 2009; IRZIK et al., 2019; AARTS and DE SUTTER, 2014; NAGY and SANDOR, 2012; SOCHOR and MBIYDZENYUY, 2013; NEVLAND et al., 2020].

2.2.2 Studies on Drivers

One of the most comprehensive studies on truck drivers is by APOSTOLOPOULOS et al. [2016] because the authors performed in-depth interviews and collected blood as well as

urine samples. The data covers 90 respondents, including truck drivers, prostitutes, and drug dealers. The study aims at better understanding the psychological impacts of the occupation as well as coping strategies. The strength of the study is the unique insights from the affected individuals. The results show that truck drivers are exposed to serious strains every day. These include isolation and long times away from home, family, and friends. Further, important events such as weddings, funerals, birthdays are often missed. Besides the social isolation, drivers face stressful working environments due to long working hours, dense and congested traffic conditions, pay by the mile compensation schemes, and JIT delivery requirements. Drivers are also exposed to risks such as traffic accidents, being sick without access to healthcare resources, chronic fatigue, and making deliveries in unsafe suburban industrial neighborhoods. Another important aspect is discrimination because of their profession, which exacerbates depressions, anxiety, loneliness, and in general mental health. Some drivers can count on social support from their families to deal with their loneliness and mental strains, whereas others cannot. The latter tend to use forbidden substances or random sexual encounters as coping strategies. In order to improve the situation, the authors propose to strengthen support systems, such as counseling, social media, and company help hotlines.

A more recent study by HEGE et al. [2019] relied on statistical models to quantify the overall impact of work organization on truck drivers. In contrast to APOSTOLOPOULOS et al. [2016], who focused on individual programs, the authors aimed to get insights into which organizational changes could support the drivers. Data from a cross-sectional survey with 260 long-haul truck drivers from a truck stop in North Carolina was the basis for their analyses. Logistic regression models were studied with work organization variables, such as work hours, daily schedule routines, perceived stress, sleep duration, and sleep quality, as independent variables and alcohol consumption, exercise, smoking, caffeine intake, and cooking as dependent variables. Two models are significant at a significance level of $\alpha = 0.05$. Caffeine intake can be predicted by the work hours variable ($OddsRatio(OR) = 2.34$). More than 11 h daily work increases caffeine consumption. Cooking/eating for more than 1 h is 52 % less likely when high stress levels are perceived and 58 % less likely when poor sleep quality is reported. Further, two more models were developed with physical health complications and mental health complications as dependent variables. Both models are significant at a significance level of $\alpha = 0.01$. If drivers sleep less, they experience more physical health issues ($OR = 2.55$) such as high cholesterol, diabetes, hypertension, and cardiovascular issues. Increased mental health problems, such as fatigue syndromes, depression, and anxiety, are predicted by high stress levels ($OR = 3.58$) and poor sleep quality ($OR = 2.22$). As solutions, the authors propose making full use of revised HOS regulations, giving drivers greater degrees of flexibility and self-determination, and avoiding schedules with overnight appointments.

ANDERSON et al. [2018] conducted a survey among 201 truck drivers in Washington State, Oregon, and Idaho with respect to their perceived likelihood of finding adequate and safe parking. The authors built a random parameters binary logit model with 134 indicator variables, 11 of which were statistically significant. The advantage of their approach is that the model parameters are not fixed but are drawn from a probability distribution to account for heterogeneity of the respondents. The study demonstrates that truck drivers who perform Less-Than-Truckload (LTL) shipments have a 32 % lower probability of experiencing parking issues. The authors speculate that these drivers are generally more likely to comply with HOS regulations because of smaller travel distances. The results further suggest that issues with parking are 50 % more probable during weekdays compared to non-weekdays, which is in line with studies from SMITH et al. [2005], YANG et al. [2021], and FHA [2015]. Interestingly, the age also seems to play an important role. Older drivers (60–69 years) have a 29 % lower probability to encounter parking issues. The results could reflect the work experience or that safe and adequate parking is simply perceived differently by this age group. Lastly, the authors found that there is no one-size-fits-all approach with regard to real-time occupancy dissemination. While some drivers prefer information via GPS, some others prefer different means.

LEMKE et al. [2021] studied factors that are associated with HOS compliance. Further, they investigated how HOS regulations impact traffic safety. The authors used the same data set as HEGE et al. [2019], which consists of 260 interviewed truck drivers, and created HOS violation and a sleep-related safety risk composite variables. The HOS violation variable consisted of four subvariables asking about violating specific rules (i.e., 14-hour rule, 10-hour rule, and 70-hour rule) and under-reporting work hours. The sleep-related safety risk variable subsumed questions concerning, for example, frequency of falling asleep while working and how and whether sleepiness impacts job performance. Other questions about whether a driver has ever had a near miss, an accident, or made a serious error due to sleep deprivation were also integrated. An ordinal logistic regression with the HOS violation variable as dependent variable shows that drivers with reduced weekly mileage (< 2500 miles) are 47 % less likely, drivers who work less than 11 h daily are 81 % less likely, drivers who report less fast pace work are 58 % less likely, and drivers with longer sleep duration are 20 % less likely to have high composite HOS violation scores. Moreover, the authors applied a multinomial logistic regression model with the sleep-related safety risk composite variable as the dependent variable. Significant predictor variables are increased supervisor support ($OR = 0.17$), fatigue announcement to supervisor ($OR = 0.42$), and working less than 11 h ($OR = 0.37$). Interestingly, none of the HOS compliance variables are significant. This may indicate that HOS regulation compliance alone does not have the assumed strong effect on traffic safety, but other factors such as pace of work and relationship between drivers and supervisors should be given greater consideration.

Whereas all previous studies on drivers are survey-based, BORIS and BREWSTER [2018] pointed out weaknesses of methods based on questionnaire responses and conducted a travel diary study. 148 truck drivers filled out a 14-day travel diary and reported detailed information about, for example, parking locations, search time, number of rest areas visited, and stop reason. The results show that only 11 % of the drivers never park in an unauthorized location. The majority (36.5 %) must park illegally three to four times per week. With respect to search times, drivers typically need more time (more than 15 min) during peak times between 4pm and midnight. In order to reduce search time, parking reservations could be a solution. However, only about one in two drivers is willing to pay for such a service [BORIS and JOHNSON, 2015]. Most interesting are the findings with respect to lost productivity due to early parking. About 74 % of the drivers are payed by the mile, which confirms findings from LEMKE et al. [2021] (about 70 %), and, thus, have incentives to drive as long as possible. However, 40 % of the drivers have between 30 min to 60 min remaining driving time left and approximately 45 % more than 60 min when they park. Stops where drivers pick up or deliver shipments are not included in the remaining driving time analysis so as not to distort the figures. The median of lost productivity is at 56 min per day and adds up to more than 9300 revenue miles per year and driver. Lastly, the authors investigated the location (distinction is made between rest area and truck stop) and amenity preferences. More than 70 % use truck stops for the night's rest, which is most likely due to the offer of amenities and the high supply of parking spaces. Through additional questions, factors influencing location choice were studied. Most drivers (96.5 %) favor locations which are close to the route, equipped with restrooms and showers (79.8 %), and offer free parking spaces (75.5 %). It is known from other studies that truck drivers typically value amenities most for their night's rest [FHA, 2015].

2.2.3 Proposed Solutions

After having outlined the truck parking issue with its causes and effects from both state and driver perspective, proposed solutions are presented at the facility/corridor level. Literature on methodological advances to estimate or predict truck parking demand is also included.

Data-Driven Approaches

Data-driven approaches range from on-site parking detection, using specialized detector equipment, to analysis of Floating Truck Data (FTD) trajectories. Better matching of parking demand and supply through the collection of real-time occupancy data is often

considered a promising research direction [GARBER et al., 2004; SMITH et al., 2005; NAGY and SANDOR, 2012; BAYRAKTAR et al., 2015; CHENG et al., 2020]. For this approach, occupancy detection technology is pivotal. SUN et al. [2018] evaluated in-pavement parking detection technology at two rest areas along the I-75 in Florida. All sensors show high event accuracy rates ($> 95\%$) as well as occupancy accuracy ($> 97\%$), which only deteriorate slightly during adverse weather conditions. Event accuracy tests the capability to identify ingress and egress maneuvers correctly, whereas occupancy accuracy tests the correctness of the reported status: occupied or free. However, spacing of the sensors remains an important issue because smaller vehicles that occupy designated truck parking spaces need to be reliably detected. In addition, installing detection devices at each parking lot can be costly. Therefore, COOK et al. [2014] proposed a camera-based approach where cameras are mounted on poles facing the parking area. The authors used structure from motion techniques, which are able to reconstruct a 3D representation from multiple 2D images. The advantage of this approach is a more robust detection in adverse weather conditions compared to 2D image processing. The results show an overall detection accuracy of 99% and a classification accuracy of 95%. During night times, the performance decreases slightly. Wrong classifications are primarily due to low-light conditions and dark-colored vehicles. In general, however, the results are very promising and show that non-intrusive camera-based systems can be reliably operated in all weather and light conditions.

Besides the presence detection, also known as direct detection, count-in and count-out systems, also known as indirect detection, exist [SMITH et al., 2005; COOK et al., 2014]. Indirect detection is usually less expensive than direct detection with respect to equipment and installation [SMITH et al., 2005]. GERTLER and MURRAY [2011] investigated a count-in and count-out system, which uses cameras at the entrance and exit ramps of the rest area. Figure 2.4 shows an example of the detection of an incoming truck. An important requirement for this type of systems is not only the detection of incoming and outgoing vehicles but also the correct classification of the vehicle type. The classification must distinguish at least two types: truck-like and car-like vehicles. With the use of image processing software, GERTLER and MURRAY [2011] achieve vehicle detection rates of 97.7%. However, the performance deteriorates during night times and leads to multiple detections. In terms of classification accuracy, the system only achieves 91.7% during the day. The authors report a higher classification accuracy for night times (96.6%), but they also acknowledge that this is probably due to the over-detection of vehicles. In general, count-in and count-out systems also suffer from another issue: additive errors [PFANNERSTILL et al., 2020; SMITH et al., 2005; COOK et al., 2014]. Detection and classification errors add up over time and periodical re-calibration is necessary. The interested reader is referred to MAGET et al. [2020], where a good overview of possible

detection technologies with their respective advantages and disadvantages can be found.
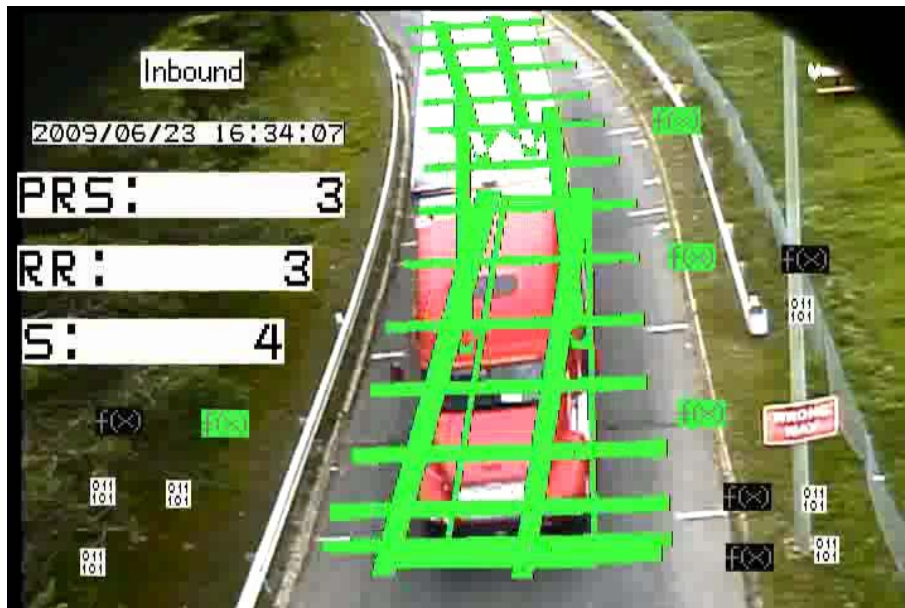

Figure 2.4: Camera-based vehicle detection and classification -
source: Gertler and Murray 2011

Data-driven approaches are applied not only for providing real-time occupancy levels but also for estimating parking demand and prioritizing infrastructure investments. Increasing penetration rates of trucks that send GPS position data allow new data-driven methodologies to be applied. HAQUE et al. [2017] used GPS data for the estimation of parking demand. In addition, they were interested in what factors are important for truck parking and what effects they have. The authors developed different count models, i.e. Poisson, binomial and generalized ordered-response probit models, and compared their performance in terms of data fit. The results indicate that the Poisson model outperforms the other models using the Bayesian information criterion (BIC) as thr quality metric. Important factors for the models are truck volumes and average truck speeds on the freeway as well as on-ramp and off-ramp parking. CORRO et al. [2019] studied expansion factors for GPS data in order to estimate truck parking occupancy. The authors state that insight from GPS data may be more cost-effective and can cover greater spatio-temporal regions compared to field observations or surveys. However, key challenges were low penetration rates, which had to be extrapolated. They used two methods for extrapolation. The first one was based on manual on-site counting. The second one was based on traffic volumes at nearby weight-in-motion stations. The results show that the Mean Absolute Percentage Error (MAPE) ranges from 46 % to 58 % for the first method and from 144 % to 307 % for the second method. This indicates that more research is required to achieve an extrapolation accuracy which is applicable in practice. Yet, the methodological con-

tribution of how to use GPS data for truck parking investment prioritization is valuable. In terms of investment prioritization, SRIVASTAVA et al. [2012] stress the importance of appropriate clustering as infrastructure expansions have effects on neighboring rest areas. Therefore, the authors propose a nearest-neighbor hierarchical clustering method that shows good results when being validated with expert knowledge from highway officers and freight planners. NEVLAND et al. [2020] pursued another interesting approach using GPS data for identifying truck parking locations. They argue that systematic investigations of available truck parking is missing because typically only parking spaces at rest areas, truck stops, and sometimes weight stations are considered. However, parking is also available, for example, at publicly accessible business locations and on commercial property with restricted access. The researchers developed a classification scheme with nine different parking categories (5 legal and 4 illegal) and matched parked trucks to the respective category. The results show that parking supply is significantly increased when parking on commercial property with limited access is considered. However, it is also noted that unauthorized parking accounts for about 11 %. Similar to CORRO et al. [2019], the authors conclude that GPS can be useful to identify locations where parking supply expansions are most needed. Interestingly, they also consider the functional conversion of shopping center parking lots to truck parking during nighttime hours.

In contrast to the previous studies, MAHMUD et al. [2020] applied machine-learning-based techniques to analyze GPS data. With the help of a bi-level unsupervised learning approach, the authors studied how the offered amenities influence parking usage patterns. A k-means clustering algorithm was used to group the 11-dimensional input vectors in three clusters. The algorithm exhibits a classification accuracy of 57 %. It is concluded that full-service rest areas are predominantly used for shorter parking durations (3 h to 5 h) and partial-service facilities for long overnight rests. Further, the authors note that restrooms have higher priority for overnight breaks than fuel or shower offers. The results are partially inconsistent with findings from driver surveys and logbook analyses [BORIS and BREWSTER, 2018; SMITH et al., 2005; SRIVASTAVA et al., 2012]. Here, drivers indicate preferring more amenities for overnight rests. The rising popularity of machine-learning algorithms and increased availability of trajectory data require systematic approaches for data processing and feature extraction. YU et al. [2021] proposed a data processing scheme and applied it to FTD to infer parking locations, similar to NEVLAND et al. [2020]. In addition, the authors studied parking rules such as which parking combinations have a higher probability of occurrence or which origin-destination pairs are associated with specific rest areas. Another important aspect is data protection as trajectory data can be linked to individual drivers. Additionally, trucking companies are in competition with each other and aim to avoid disclosing business operations. The proposed processing scheme addresses these concerns.

Intelligent Truck Parking

The availability of real-time occupancy data of multiple rest areas along a corridor makes it possible to operate parking information systems. GARBER et al. [2004] are one of the first to describe the essential building blocks for a truck parking information system. They state that truck parking information systems are different from urban parking systems in that "different system users, different geographic scale, and different parking facilities' geometric design" [GARBER et al., 2004, p. 30] have to be considered. The vehicle detection, for example, needs to be able to classify vehicle types in all weather conditions and during night times. In addition, the objectives differ. Whereas in urban environments the objectives include reduced congestion and increased mobility, truck parking information systems aim at improved safety, full capacity use, and higher convenience for drivers. The proposed system consists of four components: data collection, data transmission, data management, and data display. SMITH et al. [2005] follow the argumentation of GARBER et al. [2004] by stressing the need for parking information systems. They argue that there are only two other options that have only limited effects in mitigating the parking issue or are not always feasible. The first option is to make underutilized facilities more attractive, but this may not be feasible because in some cases there are (almost) no free capacities. The second approach is to invest in new facilities, which can be expensive or is difficult because of residents' concerns. The authors recommend that matching supply and demand with real-time information should be pursued by considering the general standards of the National ITS Architecture. These may have to be adapted to be applicable for truck parking. NAGY and SANDOR [2012] propose a similar parking information system architecture as SMITH et al. [2005] and extend it by booking and payment capabilities. Another aspect they consider as important is the way information is displayed. Among other dissemination means, Variable Message Signs (VMSs) play an important role and should not only show the occupancy of the immediate downstream rest area but also the following ones. As SMITH et al. [2005] only describe information dissemination theoretically, an example of truck parking availability dissemination via VMSs from a German research project on the A9 is shown in Figure 2.5. Not only information on the availability but also on the distance to the downstream rest areas is provided. In summary, the key idea of the authors is to develop an integrated parking information and booking system, which conforms to standardized interfaces to be operable across national borders.

Whereas current literature about intelligent truck parking is primarily theoretical and conceptual, CHENG et al. [2020] report initial results from the first network-wide parking information system actually in operation. Wisconsin, Minnesota, Ohio Kansas, Iowa, Michigan, Indiana, Wisconsin, and Kentucky participate in the Truck Parking Information Management System (TPIMS), which started operation on January 4, 2019. The TPIMS

Figure 2.5: Research project truck parking availability dissemination via VMSs on the A9 - source: Lukas Kremtz

uses both direct and indirect detection and provides real-time information every 5 min via different communication means, including VMSs along the network and smartphone applications. Additionally, the information is sent to dispatchers, traffic management centers, and a database for archiving. Data accuracy plays a significant role and much emphasis is placed on the need for manual calibrations. This can be labor intensive and is in line with findings from other studies [PFANNERSTILL et al., 2020; SMITH et al., 2005; COOK et al., 2014]. The performance of the system is monitored continuously to gain more insight. The metrics aimed to be studied are reliability, utilization, and safety. The reliability metric is a combination of accuracy measures and system availability. The utilization metric is reported for peak times, which are defined as the period between 10 p.m. and 4 a.m. The authors note that the safety metric is the most difficult to study as it requires additional data sources such as parking violations and crash reports. To date, no results have been published apart from statistics of manual validation checks. With respect to safety metrics, the work of BOGGS et al. [2019] is one of the few that attempts to quantify accidents on ramps and to find associated attributes. The authors analyzed 179 crash data records of illegally parked trucks on ramps together with utilization rates of nearby rest areas. Three Bayesian binary logit models with different prior distributions were used to study cash occurrence odds related to ramp attributes. Bayesian approaches allow statistically valid conclusions with smaller sample sizes due to the specification of a prior distribution. The study found that crash odds at exit ramps increase significantly

when parking facilities are located at the exit, which, when overcrowded, can lead to parking on ramps. Furthermore, ramps with illegally parked trucks or wider shoulder width are also positively associated with crash occurrences. 33 % of crashes happen on interchange ramps where parking facility utilization is higher than 90 %. In conclusion, the work of BOGGS et al. [2019] provides crucial details of how parking shortages are associated with increased crash occurrences on ramps. However, coming back to the TPIMS studied by CHENG et al. [2020], and the difficulty of calculating safety-related metrics, studies of intelligent truck parking systems on crash occurrences remain a great challenge and research gap. BOGGS et al. [2019] studied accidents on ramps in general, but the impact of intelligent truck parking systems on accident occurrences was not considered.

Parking Prediction

Parking prediction is a logical step that builds upon the work of truck parking information systems. Drivers need to know not only the current utilization but rather the expected occupancy level when they arrive at a rest area. One of the first integrated studies was done by BAYRAKTAR et al. [2015]. The authors propose a parking information system based on direct spot detection. Similar to SUN et al. [2018], the researchers used three detector units per parking spot, which were installed intrusively in the pavement. As already described theoretically in SMITH et al. [2005], the authors studied possibilities to not only provide real-time information but also predictions. A Kalman Filter with real-time measurements updated to the last hour was used to predict parking occupancy for the next hour. The predictions of the Kalman Filter were compared with a regression model based on the Root Mean Square Error (RMSE) metric. The results show that the Kalman Filter approach underpredicts only 20 % of the time and the RMSE stays below four trucks. However, the proposed solution was only tested with limited data at a small rest area with 13 parking spots.

A Fourier prediction model was suggested by SADEK et al. [2020], which is based on one year of occupancy data from a trucking logistics facility with a maximum capacity of 800 trucks. Four models were developed: static regular model, trend switching model, trend shifting model, and hybrid model. The underlying assumption was that truck parking activities follow certain trends, which can serve as a baseline. If necessary, different corrections based on current occupancy measurements were applied. The static regular model assumes a regular trend without taking new information into account, whereas the hybrid model is the most complex approach based on trend switching and trend shifting. The RMSE of the different models ranges between 13 and 40 trucks, which corresponds to 5 % of the maximum capacity. Finally, the Fourier approach shows superior performance and higher computational efficiency when compared with an Long Short-Term Memory

(LSTM) neural network.

GUTMANN et al. [2021] studied the potential of model fusion by combining predictions from an Extreme Gradient Boosting (XGB) and an LSTM model with the help of a feed-forward neural network. Both models were successfully applied to other traffic prediction tasks, e.g., traffic flow and trajectory predictions [ZHAO et al., 2017; ALTCHÉ and LA FORTELLE, 2017; MEI et al., 2018]. The researchers collected one year of data from a high accuracy truck parking detection system in Bavaria to test their model, which is called Truck Parking Prediction (TPP) model. The results show small RMSEs of 2.1, 2.9, 3.5, and 4.1 trucks for 30, 60, 90, and 120 min ahead predictions. The TPP model outperformed all tested benchmark models, which can be seen in Figure 2.6. Another
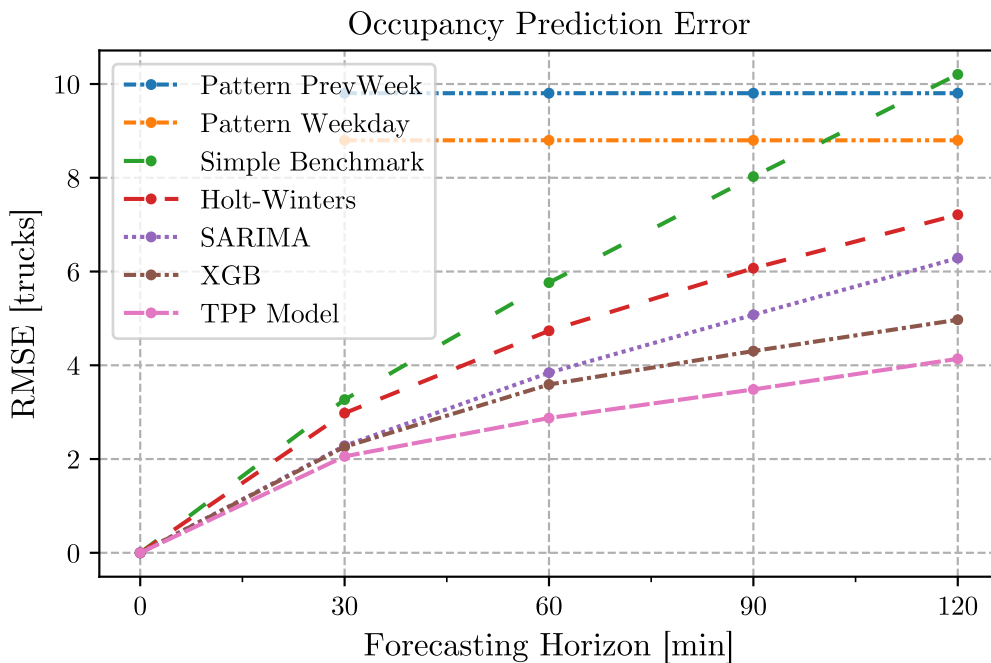

Figure 2.6: Truck parking occupancy prediction with the TPP model - adapted from Gutmann et al. 2021

contribution is the methodology of data preprocessing, which can handle outliers, occupancy jumps due to calibration activities, and arbitrary prediction horizons. In addition, the regression task of forecasting numerical occupancy levels was transformed to a binary classification problem to study how often the proposed model incorrectly predicts free spaces. For this, type I (incorrectly predicting fee spaces) and type II (incorrectly predicting a full rest area) errors were evaluated. The proposed model is the only model that can keep the type I error, which is more severe from the truck driver's perspective, below 7 % for prediction horizon of two hours.

YANG et al. [2021] gathered parking occupancy data of radar-based spot detection sen-

sors from two rest areas along the I-5 interstate. Furthermore, weather data was collected from the nearest weather station. First, the authors studied whether prevailing patterns in truck parking activities can be found by introducing a novel Advanced Sequence Alignment Method. The new method introduces a "subtract" operation besides the known operations: "insert", "delete", and "identify". The results show that daily and weekly patterns exist with peak times on weekday nights. This is known from other studies [BAYRAKTAR et al., 2015; GOLIAS et al., 2020], but the research contribution is the sound mathematical method used to identify the patterns. Patterns based on weather conditions do not seem to exist. In the second step, an occupancy prediction architecture was developed. The core consists of an LSTM network similar to GUTMANN et al. [2021]. Additionally, the authors included an embedding module for weather data and an attention layer. The results show small MAPEs of 5.82%, 5.07%, 4.84%, and 4.19% for $16\,\text{min}$, $8\,\text{min}$, $4\,\text{min}$, and $2\,\text{min}$ ahead predictions, which outperform the tested benchmark models. The sensitivity analysis of the attributes reveals that the elimination of the weather attribute has no significant effect on the prediction accuracy. However, the authors note that this may be different for truck parking in other locations and further research efforts are required to fully understand this.

Simulation and Optimization

The last category of the literature review on proposed solutions is simulation and optimization approaches. In terms of methodology, this category is most closely related to the approach of this work. Yet, the research objectives in the literature, ranging from optimized capacity expansions to truck dispatching, differ significantly from the parking recommendations in this thesis.

MAHMUD et al. [2021] proposed a combination of Agent-Based Simulation (ABS) and optimization to prioritize investments in capacity expansions. The authors built parking profiles based on origin and destination information, typical rest periods, and HOS regulations. The parking profiles were then assigned to the agents. The authors differentiated two types of agents: risk-takers and risk-averse agents. Risk-takers start later with the search for parking and are more likely to park illegally if they do not find a parking space compared to the risk-averse drivers. Risk-takers were assumed to account for 20% of the total population. The output of the simulation was parking utilization for all considered rest areas. The simulated parking demand was then used in a maximum coverage capacitated facility location problem to identify locations where new facilities or expansions of existing rest areas are needed. Different service levels were considered ranging from no-service to full-service, each with respective estimated costs. The validation of the model was done for the state of Arkansas. The model captures parking utilization well

with Mean Absolute Error (MAE) of 15 % between simulated and real (extrapolated from GPS data) relative occupancy data. Further, the authors show that investments above $13 million do not significantly improve the situation. The curve levels off and there are no more options to build or expand facilities in the regions with high demand.

THOMPSON et al. [2015] also used ABS but pursued completely different research objectives compared to MAHMUD et al. [2021]. The researchers studied how different payment regimes affect fatigue, crash risk, and responses of enforcement agencies. The authors argue that crashes are rare events and, thus, very difficult to study with statistical methods of real data. Further, data on mean speed or mean time between rest periods could mask rare but extreme driving behavior. The hypothesis of the authors was that different compensation regimes can lead to riskier driving behavior resulting in higher fatigue levels and increased crash risk. An ABS was proposed where three different driver payment methods are implemented: per-km, per-trip, and flat-rate. In general, the simulation shows realistic driving and resting patterns. Drivers that are payed by the per-km compensation regime are more likely to drive while fatigued and experience higher crash risks. Furthermore, they face higher fines and are more likely to lose their license. Drivers payed by a flat-rate remuneration regime are on the opposite side compared to the per-km regime. The per-trip payment method lies between the two regimes. One of the key contributions is the modeling of pressure, which increases due to, e.g., falling behind schedule, traveling below mean speed, earning less money than the peer group, and experienced delays at loading and unloading locations. Drivers under pressure are less likely to follow rules and regulations. As expected, the drivers of the per-km payment regime experience the highest amount of pressure. Another interesting effect that was studied is the number of deployed enforcement units. It was assumed that crashes increase the number of enforcement units deployed by regulators. In line with the previous findings, the per-km and per-trip remuneration regimes show the highest levels of enforcement needs. However, it is also stated that there are also lengthy periods without enforcement increases but high fatigue levels, high pressure levels, and high productivity. In summary, THOMPSON et al. [2015] took a new research direction by linking payment structures to pressure on drivers, which, in turn, influences compliance with rules and regulations.

GARCÍA et al. [2017] proposed another interesting ABS approach by developing a distributed negotiation protocol. The authors pursued two objectives: reducing the number of illegally parked trucks and increasing the satisfaction of drivers. Driver satisfaction was measured by the extent to which their individual preferences for specific rest areas were met. The ABS consisted of rest area agents and truck agents, which sent reservation requests to rest areas. If a rest area was full, a negotiation process was initiated between all trucks that currently had a reservation for that rest area. The trucks involved in the negotiation process sent an ordered list of their preferred rest areas. The rest area agent

computed a solution set that consisted of all possible combinations of parking permutations. Truck agents voted on the combinations using a Borda count system, which was adapted for the case of truck parking. For example, votes of trucks with lower remaining driving time were weighted higher. At the end, one truck lost the negotiation and made a reservation for the second rest area in the preference list. The authors call this procedure cascade negotiations, which were repeated until a free space was found or the truck that lost the final negotiation was notified that no spaces were available. The cascade negotiation procedure was evaluated using a simulation. Illegal parking is reduced by 40 % and driver satisfaction is increased by 10 % compared to a first come first serve basis. Additionally, the scalability of the proposed algorithm was studied. It is shown that the number of trucks affects the time complexity of the algorithm linearly. Simulations for the largest truck stop in the world (Iowa80 with 900 parking spaces) show that solving times remain below 2 s. The proposed approach seems robust and not too complex, which makes it a candidate for implementation in practice. However, the simplistic approach also has various disadvantages in real-world scenarios. Congestion and other traffic disturbances are not considered. Even filling of rest areas, when all of them are fully occupied, was not studied.

The work of VITAL and IOANNOU [2019] is probably most closely related to this thesis. The authors studied long-haul truck scheduling constrained by HOS regulations and parking availability. A complex Mixed-Integer Programming (MIP) model was developed where parking availability of a rest area is modeled as a set of time-window constraints. The time window starts at 5 a.m. (normally distributed with standard deviation 0.5 h) and ends at 8 p.m. (normally distributed with standard deviation 1 h). With respect to the HOS regulations, three different types were considered. The daily driving limit restricts driving time to 11 h between two daily rests. The elapsed time limit ensures that a driver may not drive after 14 h since the end of the last daily rest. In addition, drivers may not be on duty and driving more than 60 h for any consecutive seven days. The model was tested with a trip from San Diego to Seattle (1960 km) with 94 parking facilities along the route. As a baseline, the researchers used a model without parking availability constraints. Both models were solved using CPLEX, and the mean trip duration was compared. The newly developed model produces significantly more feasible solutions than the baseline model. This means that no schedules were proposed that would lead to rest periods within time windows when there were no free parking spaces assumed. However, the average trip duration could not be improved. The limits of the study are that only one truck trip with known and fixed route for several days was considered. Furthermore, travel times between the rest areas were assumed to be time-invariant. As already mentioned, parking availability was modeled by drawing from a normal distribution and is therefore quite general. Individual driver preferences regarding rest areas with food, fuel,

and shower facilities were not considered. These restrictions need to be overcome to use this scheduling model in practice.

2.3 Derived User and System Objectives from the Literature

The literature review focused on a deep understanding of the current situation and proposed solutions. The next step is to derive underlying objectives from the literature to improve the status quo and cluster them. The clustered objectives are the cornerstone for developing a parking recommendation system that is tailored to the needs of the key stakeholders. An overview of the reviewed literature is presented in Table 2.2. There are seven key objectives found in the literature. Ultimately, these objectives are the answer to the question: *What should be done in order to make truck parking efficient, convenient, safe, and readily available?* The objectives are:

- Use full capacity. Optimally match demand and supply.

- Reduce building cost. Expansion of parking supply is expensive, needs time-consuming planning and approval procedures, consumes land, and is in competition with other land-use types (particularly near urban environments).

- Increase traffic safety. Illegally parked trucks are a safety issue for drivers and other road users.

- Comply with HOS. Drivers must not drive longer than HOS regulations allow.

- Maximize productivity. Parking too early translates into lost revenue-km.

- Reduce stress and improve working conditions. The parking shortage makes the job of truck drivers, which is often stressful and already has poor working conditions, more stressful and unpredictable.

- Find amenities. Help drivers to find parking according to their individual preferences.

In addition, the two main stakeholders are identified: truck drivers and road authorities. Both stakeholders have different motivations with respect to truck parking. Therefore, the seven objectives are clustered into *System Objectives (collective)* and *User Objectives (individual)*. As is often demonstrated in traffic, user objectives may not be the same as system objectives. Probably, the most well-known study in this domain dates back to the 1950s and is from WARDROP [1952], who studied a user equilibrium and a system optimum. He derived a mathematical model for drivers who want to get from a fixed origin to a fixed destination and have multiple route options. His work demonstrates that

if all drivers choose the fastest route (i.e., user equilibrium), link travel times are higher compared to a system optimal state (i.e., system optimum). There is a similar situation for truck parking. If each truck driver chooses the "best" rest area for him or her, this does not necessarily lead to an optimal match of parking supply and demand; rather, it results in overcrowding. The term "best" is elaborated later.
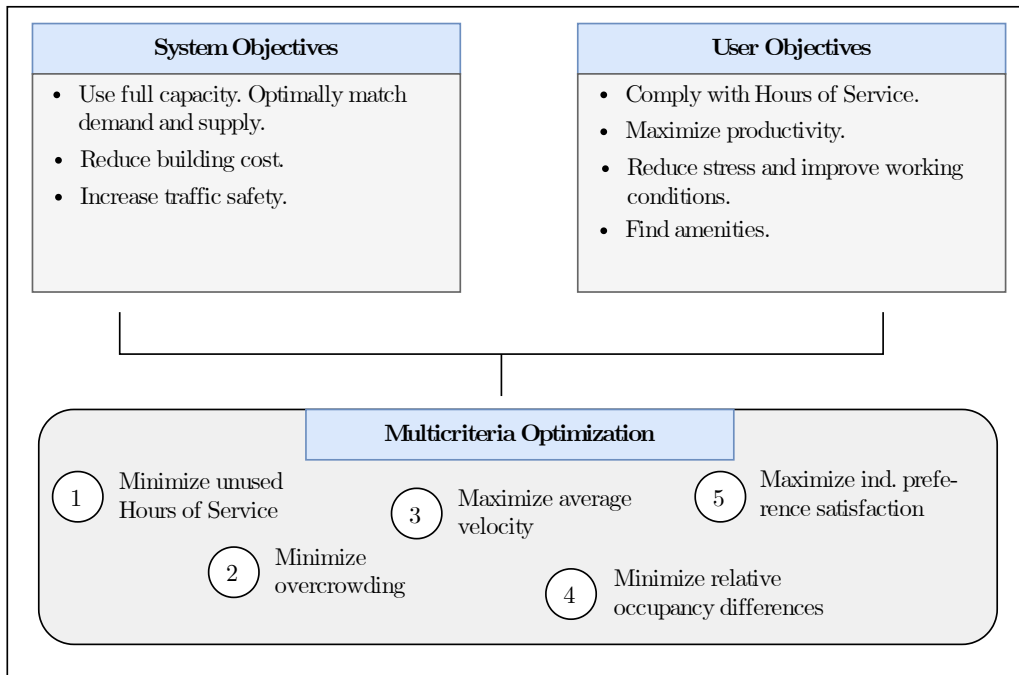

Figure 2.7: Objectives translation from the literature

Figure 2.7 summarizes the objectives derived from the literature and translates them into five distinct minimization or maximization formulations. The respective mathematical formulations are explained in Section 3.2.3 TOPTIPS Modeling.

Objectives	Use full capacity	Reduce building cost	Increase traffic safety	Comply with HOS	Maximize productivity	Red. stress, improve work conditions	Find amenities (e.g., shower, food, fuel)
Type	System Objectives (collective)			User Objectives (individual)			
Fleger et al. 2002	X	(X)	X	X			X
Garber et al. 2004	X	X	X				(X)
Gaber et al. 2005	X		X	X			
Smith et al. 2005	X	X	X	X	X		(X)
Adams et al. 2009	X	X	X	X	X		X
Gertler and Murray 2011	X		X				
Bayraktar et al.[1] 2012	X	X	X	X			
Srivastava et al. 2012	X	X	X	X			X
Nagy and Sandor[2] 2012	X	X	X	(X)		X	X
FHA 2012	X	(X)	X	X	(X)		
Cook et al. 2014	X	X	X	X			
FHA 2015	X	X	X	X	X	X	X
Thompson et al. 2015			X	X	X	X	
Bayraktar et al. 2015	X	X	X	X	(X)		
Apostolopoulos et al. 2016			X	X	X	X	X
Haque et al. 2017	X		X	X		X	
García et al. 2017	X	(X)	X	X	X		X
Sun et al. 2018	X					X	
Anderson et al. 2018	X	X	X	X	(X)		
Boris and Brewster 2018		(X)	X	X	X		X
Corro et al. 2019	X	X	X	X	(X)		
Boggs et al. 2019		X	X	X	(X)		X
Hege et al. 2019			X	X	X	X	(X)
Vital and Ioannou[3] 2019	X	X	X	X	X		
Cheng et al. 2020	X		X	X	X		
Nevland et al. 2020	X	X	X	X		(X)	X
Golias et al. 2020	X	X	X	X	X		(X)
Sadek et al. 2020	X	X	X	X			
Mahmud et al.[4] 2020	X	(X)	X	X	X		X
Gutmann et al. 2021	X		X	X	X		
Yang et al. 2021	X		X			X	
Mahmud et al. 2021	X	X	X	X			X
Lemke et al.[5] 2021			X	X	X	X	
Yu et al. 2021	X	X	X		X		(X)

X Covered   (X) Partially covered
[1] Detailed information on pavement and drainage   [2] Additional information about emissions due to building activities   [3] Detailed HOS consideration
[4] Additional information about environment and air pollution   [5] Detailed study of HOS and traffic safety relationship

Table 2.2: Literature overview: system vs. user objectives

2.4 Optimization Theory

The truck parking recommendation system, which is described in the next chapter, is based on MIP modeling. In order to solve the MIP model, the mathematical programming solver Gurobi was used. In this section, a brief introduction to the two fundamental algorithms for Linear Programming (LP) and MIP programming is given: Simplex and Branch&Bound algorithm. For more details and the underlying mathematical proofs, the reader is referred to GRITZMANN [2013] and ARORA [2012].

2.4.1 Simplex Algorithm

The simplex algorithm was proposed by George B. Dantzig in 1947 and is a widely used method to solve LP problems. The following explanation of the algorithm is based on HURLBERT [2010], PAN [2014], and ARORA [2012]. Geometrically, the constraints of an optimization problem define the feasible set, which is called a polyhedron in $\mathbb{R}^n$. A polyhedron is defined as "the intersection of finitely many half-spaces" [HURLBERT, 2010, p. 29]. A half-space, in turn, is a region which is defined by a linear inequality. The overall idea of the simplex algorithm is to move from one vertex to an adjacent vertex of the polyhedron to improve the objective function. It can be proven that if an optimal solution exists, it can be found at a vertex. This means that the search is narrowed down from infinitely many points in the feasible region to a finite subset (i.e., the vertices of the polyhedron). The simplex algorithms always aims to move to vertices which improve the objective function and, thus, does not need to explore all vertices. The vertices represent basic feasible solutions. By moving from vertex to vertex, the simplex algorithm searches the basic feasible solutions for the optimum.

In general, there are two types of the algorithm: primal and dual simplex. The primal simplex algorithm can be used on the standard form of the LP problem. Whereas the dual simplex algorithm works on the dual representation of the standard LP problem. In the dual representation, the number of constraints is changed to the number of variables, and the number of variables is changed to the number of constraints. The primal and dual representations are shown in Table 2.3. It should be noted that the number of constraints impacts the computational complexity more than the number of variables [DIWEKAR, 2020]. Therefore, the dual simplex method can be advantageous for problems with many constraints. In conclusion, the simplex algorithm is an important prerequisite for the branch-and-bound algorithm, which is briefly described in the next section.

Primal Problem	Dual Problem
$\max\ Z = \sum_{i=1}^{n} c_i x_i$	$\min\ Z_d = \sum_{j=1}^{m} b_j \mu_j$
x_i for $i = 1, \ldots, n$	μ_j for $j = 1, \ldots, m$
$\sum_{i=1}^{n} a_{ij} x_i \leq b_j$	$\sum_{j=1}^{m} a_{ij} \mu_j \geq c_i$
$j = 1, \ldots, m$	$i = 1, \ldots, n$
$x_i \geq 0$	$\mu_j \geq 0$

Table 2.3: Primal and dual representations - adapted from Diwekar 2020

2.4.2 Branch-and-Bound Algorithm

The simplex algorithm requires the design variables to be continuous. However, the Truck Optimization Parking System (TOPTIPS) model also has integer variables. Consequently, it can not be directly solved with the simplex method. Nevertheless, the simplex algorithm is pivotal because it can be used to determine lower and upper bounds, thus complementing other techniques. According to Arora [2012], mixed variable problems can be divided into five classes. The classification considers the following aspects: Is the objective function twice differentiable? Is the objective function continuous? Are the variables purely discrete or mixed? Can discrete variables have non-discrete values during the solution process? Are some of the discrete variables linked to others?

An overview of methods to solve discrete variable optimization problems is given in Table 2.4. The details of how the mixed variable types in the second column are defined are not directly relevant. The interested reader is referred to Chapter 15.1.2 "Classification of Mixed Variable Optimum Design Problems" in Arora [2012]. It is only important to note that the first three methods provide the greatest flexibility as they are able to solve all five defined types. The methods to solve discrete variable problems can be divided into enumerative and stochastic approaches. Enumerative approaches usually do not perform a full enumeration, but only need to perform a partial enumeration since some enumeration branches can be excluded (e.g., by known upper or lower bounds). Stochastic methods use randomness to find an optimal solution and can be inspired by nature (e.g., genetic algorithm) or physics (e.g., simulated annealing). For this thesis, the enumerative branch-and-bound method is chosen because it guarantees to always find an optimal solution, if one exists. In addition, fast and efficient mathematical programming solvers are available that can be leveraged.

Subsequently, the branch-and-bound algorithm is briefly explained based on Arora [2012]. It is assumed that a MIP problem should be maximized. First, LP relaxation is performed, which removes all integer constraints. The relaxed problem is solved with

Method	Mixed-variable types solvable?	Can find feasible discrete solution?	Can find global optimum for convex problem?	Needs gradients?
Branch-and-Bound	1–5	Yes	Yes	No/Yes
Simulated Annealing	1–5	Yes	Yes	No
Genetic Algorithm	1–5	Yes	Yes	No
Sequential Linearization	1	Yes	Yes	Yes
Dynamic Round-off	1	Yes	No guarantee	Yes
Neighborhood Search	1	Yes	Yes	Yes

Table 2.4: Overview of discrete variable optimization methods - adapted from Arora 2012

the simplex algorithm and denoted as the root node. The objective value of the relaxation is the upper bound of the optimization problem. There will be no better solution because restricting the design variables can only lead to equally good or worse objective values. If it happens that all variables were to be integer values, no further steps would be required, and the algorithm would terminate. Most likely, however, some variables are continuous and further branching is necessary by restricting a non-integer variable. The problem is split into two sub-problems (i.e., child nodes) by defining one additional constraint for each sub-problem. The value of the variable x_i which is branched on is between the next lower and upper integer values $d_{ij} < x_i < d_{ij+1}$. The values d_{ij} and d_{ij+1} are used to define the respective constraints of the sub-problems. The new LP problems are solved again with the simplex algorithm.

If a solution fulfills the integer constraints (and is better than any previous feasible completion), it is called current feasible completion and it is fathomed. The objective value of the current feasible completion is a lower bound. Any other node which has an objective value lower than the current feasible completion can be fathomed. Fathoming means that no feasible completion with a better objective value can be found by branching further. Fathoming is a very powerful concept as it avoids the need for full enumeration. The algorithm continues by branching and fathoming until all nodes are fathomed or a defined

threshold is reached. In summary, the branch-and-bound algorithm takes advantage of the simplex algorithm and uses branching, bounding, and fathoming to find a solution. Good bounds are important because they can reduce the solution space to be searched. Therefore, additional techniques such as heuristics and cutting planes are used to increase the efficiency of mathematical programming solvers [GUROBI OPTIMIZATION, LLC, 2022; ABHISHEK et al., 2010].

Key Takeaways: State of the Art

This chapter has three main aims: First, the research gap is identified. Second, the system and user objectives are determined. Third, the required optimization theory is introduced.

- Current research concerning better matching of demand and supply often neglects the truck driver's perspective.

- Many truck drivers have a stressful job with poor working conditions. There is a lack of healthcare access, drivers suffer from loneliness and mental strains, and the occupation is one of the most deadliest. Parking shortage is another stressor for the occupation.

- Illegal parking can have more severe impacts for drivers than a parking ticket: the consequences range from sleep deprivation to severe accidents.

- Parking search is a complex process as drivers have to consider multiple alternatives along the route, need to maximize productivity, stay within allowed HOS regulations, consider traffic conditions, and take into account preferences for amenities.

- The majority of the drivers do not have information on free parking spaces, do not plan where to park before they start a trip, and decide where to park towards the end of a trip.

- -

Research Gap

- There is a need for individual parking recommendations that better consider the truck driver's perspective (user objective). At the same time, the road authority's perspective (system objective) needs to be considered to ensure balanced use of the parking infrastructure.

- An integrated approach based on Floating Truck Data is missing.

For designing the parking recommendation system, the main objectives of the two stakeholders are identified (see Table 2.2).

Chapter 3

Truck Optimization Parking System

This chapter introduces the Truck Optimization Parking System (TOPTIPS), which is a parking recommendation system intended to close the research gap. It begins with a high-level introduction of the system. After having outlined the key components, necessary assumptions and system boundaries are explained. In the next section, the inner workings of the mathematical model are covered. First, the motivation behind choosing a Mixed-Integer Programming (MIP) approach for truck park modeling is explained. Second, the foundation for truck parking modeling is laid with the help of a simplified example. Third, the entire full-scale model is developed step by step. It should be noted that the terms TOPTIPS model and mathematical truck parking model are used interchangeably.

3.1 TOPTIPS Description

This section describes TOPTIPS, which generates the parking recommendations for the truck drivers. First, an overview of the entire framework with necessary input and expected output data is given. Next, the system boundaries are described. Third, the assumptions are explained and reference is made to relevant literature that leads to a particular assumption. It should be noted that the terms truck and truck driver are used interchangeably, since they are considered a combined truck-driver unit.

3.1.1 High-Level System Overview

The system overview, which is depicted in Figure 3.1, consists of three parts: the input data, TOPTIPS, and the output part. The input data involves primary and secondary data. Floating Truck Data (FTD) provides the necessary primary data, which consists of the current Global Positioning System (GPS) position, the desired route, and the remaining driving time, also called Hours of Service (HOS). FTD is defined as a superset of Floating Car Data (FCD) as it provides additional information about the route and the remaining HOS. The GPS position locates the truck in space and time. Moreover, it provides occupancy information for the rest areas. A non-moving truck located at a rest area is assumed to occupy a parking space. The route information is used to figure

out the upcoming potential rest areas and their amenity offers. A distinction is made between the set of potential and feasible rest areas. Feasible rest areas are a subset of the potential ones. In order to get the feasible rest areas, the set of potential rest areas has to be further constrained by the remaining driving time (HOS). The HOS information is important as it restricts the time the driver is allowed to drive before he or she must rest. In other words, the data fusion of the current position with the route and the remaining driving time allows to determine the feasible rest areas. The described primary data set is the minimum which is required. Usually, FTD provides additional information about velocity and driving direction which can be processed to identify stopped trucks at rest areas better.

With the primary data, only undisturbed traffic conditions can be handled. Secondary data can be fed into TOPTIPS from any source and enhances the capabilities of TOP-TIPS. For example, disturbed traffic states can be handled with secondary data. The system needs predicted travel times for the set of potential rest areas, which can be provided by any supplier of Real-Time Traffic Information (RTTI).
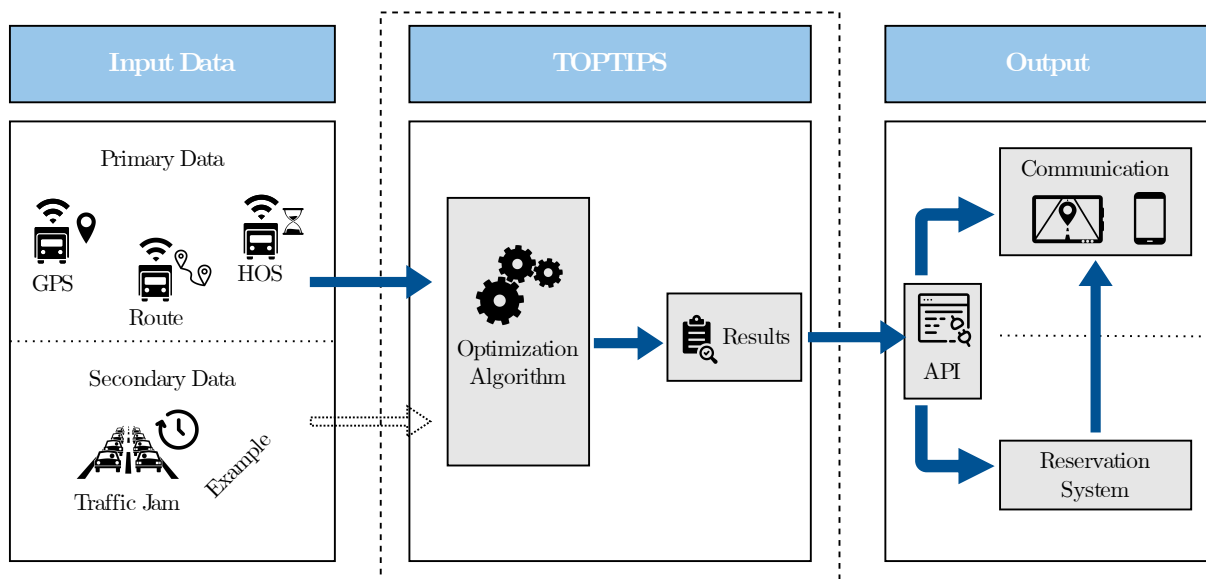

Figure 3.1: System overview TOPTIPS with input and output

Both primary and secondary data are provided to TOPTIPS. At its core, TOPTIPS consists of a multi-criteria MIP model. The mathematical modeling will be described in Section 3.2. For now, it suffices to note that TOPTIPS runs in the backend, and the results are individual parking recommendations. Because the system is based on multi-criteria optimization, the objectives of truck drivers and road authorities are considered at the same time. Without going into detail yet, this means that the user and system objectives can be weighted arbitrarily depending on what has been defined as "optimal" a priori. However, it should be noted that there are numerous (physical) restrictions that

limit the degrees of freedom of the optimization model. This aspect will be explained in more detail in the mathematical modeling section. The results (i.e., individual parking recommendations) are then distributed via an Application Programming Interface (API). First, this ensures that TOPTIPS can be integrated in any existing navigation system, smartphone App, or fleet management system. Further, truck drivers' attention is not distracted as the recommendations are seamlessly integrated with devices they are already familiar with. Second, there could be an interface with parking reservation systems. Currently, truck parking reservation and enforcement are only feasible at some locations (i.e., mostly on private property), but could make truck parking more convenient in the future. TOPTIPS has the flexibility to fully or partially connect to parking reservation systems.

3.1.2 System Boundaries and Assumptions' Assessment

The previous section explained which data sources are required for TOPTIPS and how the results can be communicated to the drivers. This section defines the system boundaries and discusses the assumptions made. The thesis deals exclusively with the development of TOPTIPS, which is indicated with a dashed frame in Figure 3.1. The other two parts *Input Data* and *Output* are assumed to be given. However, these assumptions are discussed in the following with respect to whether they can be fulfilled within the next five years. It begins with the assumptions of the output side. The connection via a defined API and the passing on of parking recommendations to navigation systems, smartphone apps, or online reservation systems is a standard task where no major problems are expected. Therefore, this part is not further elaborated. The only underlying assumption which needs to be checked is whether truck drivers have internet connection. According to a survey from METZGER and SPANGLER [2021] with 140 truck drivers, 94 % have internet connection when driving through Bavaria. The responses may differ between countries, but, generally, the availability of internet access can be assumed for the majority of drivers. This is also supported by HEATON et al. [2017]. The authors researched how truck drivers use the internet for both personal and job-related reasons. According to their research, about 70 % even have a laptop with them to access the internet.

Primary Data

The assumptions regarding the *Input Data* are more complex. First, the hypotheses with regard to the primary data are described by the example of GPS location data. The transferability to the remaining primary data types will be explained later. The input GPS data is assumed to be given with sufficient accuracy and frequency. In order to estimate parking trucks at rest areas correctly, the location accuracy should be less than 10 m. The update frequency should be at least every minute. According to Neuhold et al. [2017], who investigated different GPS receivers on different road types for the purpose of FCD provision, the accuracy requirement is met. The authors report that the average location accuracy is 5 m or less on freeways, even for low-cost smartphone positioning. Additionally, there are studies which show that the identification of parked trucks is highly possible with GPS data [Nevland et al., 2020; Corro et al., 2019; Golias et al., 2020]. The update frequency of the tested devices is reported with at least 1 Hz [Neuhold et al., 2017]. This is not necessarily the frequency with which data is sent to the backend where TOPTIPS is assumed to run. However, in studies for incident and congestion detection, transmission frequencies of every 10 s to 15 s are reported [Houbraken et al., 2017; Liang et al., 2017]. Houbraken et al. [2018] define low frequency transmission as every 30 s to 60 s and high frequency transmission as every 1 s to 10 s. Consequently, current transmission frequencies are sufficient for TOPTIPS.

Further, the re-transmission needs to be considered as the parking recommendations have to reach the driver. In 2012, Rémy et al. [2012] demonstrated that FCD re-transmission to connected cars via 4G LTE is possible in under 1 s. Ten years later and with the rise of 5G, even safety critical applications are becoming feasible with end-to-end latency in the order of magnitude of 1 ms [Parvez et al., 2018]. This is much faster than what is required for TOPTIPS. In summary, the entire round trip communication-wise can be safely assumed to take not more than 30 s. The only missing part is the runtime of the TOPTIPS optimization algorithm. It will be shown later that runtime is upper bounded by 15 s. Hence, it can be safely assumed that the entire process of sending FTD and receiving a recommendation takes not more than 1 min. Consequently, the assumptions for TOPTIPS are met with current technology. The assessment of the update frequency was conducted using the GPS data type as an example, but there is no indication that it does not apply to the other primary data types. For example, accurate data on remaining driving time is already collected via electronic logging devices [Miller et al., 2020], which is assumed to be transmitted to the backend via the same means as the GPS data. However, it must be considered that driver-specific HOS data sent to the backend could potentially cause privacy issues. It is an important aspect to be accounted for but it is not focus of this study.

Another key assumption concerns the penetration rates of TOPTIPS trucks. A TOP-TIPS truck is defined as sending FTD and receiving recommendations. The study assumes 100 % penetration rates to test the overall performance of the proposed approach. Obviously, this does not correspond to the current reality. Therefore, experiments with lower penetration rates are conducted to estimate the impacts when only a proportion of the trucks is equipped. As mentioned earlier, the GPS location data is used in two ways. First, the feasible rest area set is computed by taking the GPS location data and connecting it with HOS and route information for each truck. Second, GPS location data of stopped trucks at rest areas is processed to get the current occupancy levels. For the latter use-case, lower penetration rates require estimating occupancy levels based on a sample or to collect the information from physical on-site detectors. For this thesis, it is assumed that occupancy data is available for penetration rates below 100 % through physical on-site detectors, which corresponds to the setup in the study area on the A9 between Munich and Nuremberg.

Secondary Data

Secondary data can be supplied by any source. A straightforward use case of secondary data is RTTI. For methods concerning how the quality of RTTI information can be evaluated, the interested reader is referred to HUBER et al. [2014]. In order to provide parking recommendations that neither exceed remaining HOS nor suggest parking too early, travel time predictions based on RTTI are required. Travel time predictions are not a focus of this study and assumed to be provided as secondary data. However, travel time predictions exhibit uncertainties. Therefore, experiments are conducted with different levels of travel time prediction accuracy. The order of magnitude of uncertainty is based on the literature. RILETT and PARK [2001], for example, studied spectral basis neural networks for freeway corridor travel time prediction. The results indicate that 25 min ahead forecasts can be achieved with a Mean Absolute Percentage Error (MAPE) of 13 % for non-congested periods and 22 % for congested periods. More recently, ZHANG and HAGHANI [2015] showed similar results for a gradient boosting method that achieves a MAPE of 15 % or less for prediction horizons of 30 min on freeways during non-peak hours. For peak hours, the authors report a MAPE of 30 % or less for the same horizon. With respect to 15 min horizons, the MAPE reduces to 20 % or less. For a good overview of the extensive literature on travel time prediction, the reader is referred to VLAHOGIANNI et al. [2014] or BAI et al. [2018]. In conclusion, the literature suggests that assumptions regarding travel time predictions errors should be in the range of 20 % to 30 %.

3.2 Mathematical Modeling

This section presents the mathematical foundation of TOPTIPS. The overall idea is to model truck parking with a bipartite graph and solve the resulting MIP problem.

3.2.1 Mixed Integer Linear Programming

"A mixed integer linear program (MIP) is an optimization program involving continuous and integer variables, and linear constraints" [POCHET and WOLSEY, 2006, p. 78]. It is explained briefly in the following according to POCHET and WOLSEY [2006]. Vectors are denoted using bold font. Written in general MIP form, Equation 3.1 and Equation 3.2 denote the objective function and the feasible set S, respectively.

$$Z(S) = \min_{\boldsymbol{x},\boldsymbol{y}}\{\boldsymbol{c^T}\boldsymbol{x} + \boldsymbol{h^T}\boldsymbol{y} : (\boldsymbol{x},\boldsymbol{y}) \in S\}, \quad \text{with} \tag{3.1}$$

$$S = \{(\boldsymbol{x},\boldsymbol{y}) \in \mathbb{R}^n_+ \times \mathbb{Z}^p_+ : A\boldsymbol{x} + B\boldsymbol{y} \geq \boldsymbol{b}\} \tag{3.2}$$

- $\boldsymbol{x} \in \mathbb{R}^n_+$ denotes a n-dimensional column vector of non-negative, continuous variables.

- $\boldsymbol{y} \in \mathbb{Z}^p_+$ denotes a p-dimensional column vector of non-negative, integer variables.

- S is the feasible set, which consists of continuous and integer variables.

- $\boldsymbol{c} \in \mathbb{R}^n$ and $\boldsymbol{h} \in \mathbb{R}^p$ are the column vectors of the objective coefficients.

- $\boldsymbol{b} \in \mathbb{R}^m$ is the right-hand side vector of the m constraints.

- $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{m \times p}$ are the constraint matrices.

- $Z(S)$ denotes the optimal objective value for respective variable values $\boldsymbol{x}^*$ and $\boldsymbol{y}^*$.

A special case is when the integer variables $\boldsymbol{y}$ can only take values 0 or 1. This often occurs when modeling decision or assignment problems, where $\boldsymbol{y} \in \{0,1\}^p$ denotes a column vector whose entries a binary. This binary modeling approach is applied for TOPTIPS because parking choices can be well captured with it.

3.2.2 TOPTIPS Modeling Overview

In order to provide the reader with more understanding about the mathematical modeling, a simplified version of the parking problem is presented in Figure 3.2. This should help to gain a basic understanding before the actual, more complex model is presented. The most basic version of truck parking modeling considers a motorway stretch with rest areas and trucks looking for parking. Mathematically, this can be modeled with a bipartite graph
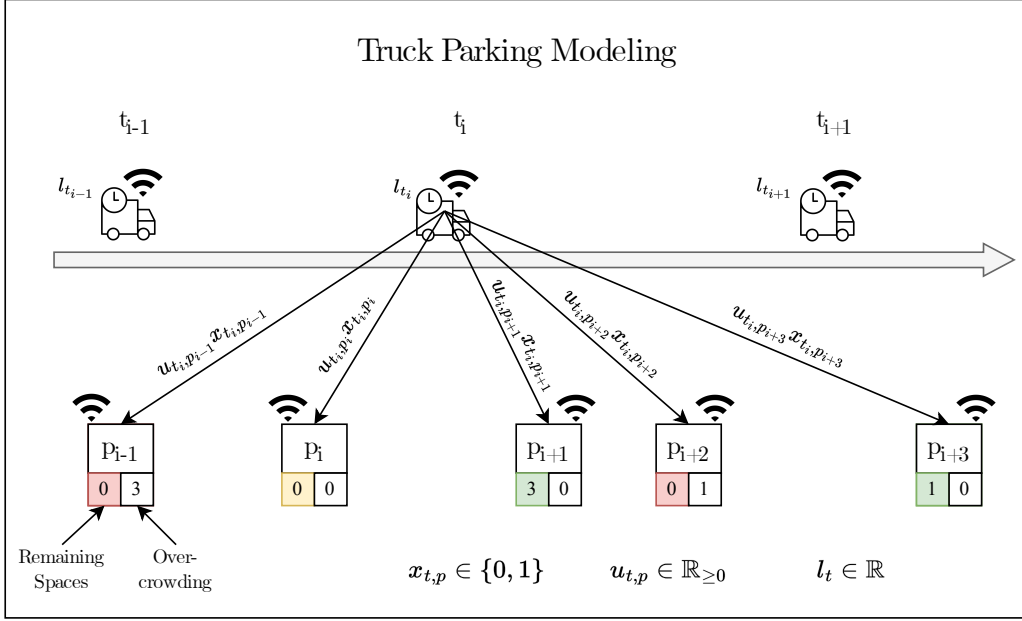
Figure 3.2: Basic understanding truck parking modeling

$\mathcal{G} = (T, P, E)$, where T and P are disjoint and independent sets of vertices representing trucks $t \in T$ and rest areas $p \in P$. E denotes the set of edges, each connecting a vertex in T to a vertex in P. It should be noted that only the connections of one truck to all possible parkings are shown in Figure 3.2 in order not to overload the figure. Rest areas can be in one and only one state at a time: fee, full, overcrowded. For the first and third state the number of free spaces or the degree of overcrowding is specified in units of trucks. It is important to model the possibility of overcrowding because this happens frequently in practice as the literature review showed. The three states are depicted with green, yellow, and red in Figure 3.2. The remaining driving time of a truck is modeled with the parameter $l_t \in \mathbb{R}$. A negative value of l_t indicates that the driving time is exceeded and the truck driver violates HOS regulations. The decision variable whether a truck t chooses rest area p for parking is modeled with $x_{t,p} \in \{0, 1\}$. When $x_{t,p}$ is set to 1, it means that truck t is going to park at rest area p. However, a truck can only park at one rest area at a time. This is ensured by adding constraints, which will be explained later. The weight of an edge (t, p) is denoted by the parameter $u_{t,p} \in \mathbb{R}_{\geq 0}$. $u_{t,p}$ is used as a container parameter for a wide variety of modeling purposes. The purposes can be divided into two groups. The first group is static where the container parameter $u_{t,p}$ does not change with time. For example, the preference degree of truck driver t for rest area p, which is assumed to be time-invariant, can be captured. The second group is dynamic and models time-variant situations. For example, $u_{t,p}$ can be used to reflect the predicted travel time for truck t to arrive at rest area p. This parameter is updated with time as the truck moves through space-time. Finally, the linear combination $\sum_t \sum_p u_{t,p} x_{t,p}$ can

be used as the objective function to maximize or minimize the amount of the container parameter. The advantage of this modeling approach is that it is flexible, transparent, and efficiently solvable with state-of-the-art MIP solvers. Moreover, conflicting objectives of road authorities and truck drivers can be balanced by multi-criteria optimization.

3.2.3 TOPTIPS Modeling

After having gained a basic understanding with a simplified model of truck parking, the actual TOPTIPS is described. First, the nomenclature is defined, which consists of sets and indices, parameters, and variables. Second, the individual objectives are explained, which are then combined into one overall objective through weighting. Third, the constraints are described. Lastly, dynamic constraint and objective extensions are presented, which are applied if the model is not feasible. For example, this can happen in practice when truck drivers violate HOS regulations. TOPTIPS should be able to cope with all types of real-world situations.

Sets and Indices

$t \in T$	Set of trucks and respective index
$p \in P$	Set of rest areas and respective index
R_T	Set of reachable rest areas

The set of trucks is denoted by $T = \{t_1, t_2, \ldots, t_n\}$ and comprises all TOPTIPS trucks that are willing to park. Non-TOPTIPS trucks or TOPTIPS trucks that are not looking for parking are not part of the set T. Rest areas along the motorway are denoted by the set $P = \{p_1, p_2, \ldots, p_k\}$. It should be noted that the term rest area is used for any type of parking facility that is appropriate for overnight stays. R_T denotes the set of reachable rest areas of the trucks in T. Concretely, let F_t denote the set of rest areas that truck t can reach, then $R_T = \bigcup_{t \in T} F_t$. R_T equals P most of the time, but there exist situations where $R_T \subset P$. In this case, only the reachable rest areas should be considered.

Parameters

$K = \|P\|$	Total number of rest areas
$R = \|R_T\|$	Number of reachable rest areas for trucks $t \in T$
o_p^{ext}	Current occupancy (from external system) for rest area p
cap_p	Maximum official parking capacity for rest area p

cap_p^{close}	Closing capacity for rest area p
o^{max_ovld}	Closing rest area factor, i.e., $\max(\{cap_p^{close}/cap_p \mid p \in P\})$
l_t	Remaining driving time for truck t
$s_{t,p}$	Driving distance from truck t to rest area p
$c_{t,p}$	Predicted travel time from truck t to rest area p
$v_{t,p}$	Predicted average speed of truck t to rest area p
$h_{t,p}$	Predicted unused HOS for truck t arriving at rest area p
$i_{t,p}$	Individual preference of truck (driver) t for rest area p
$v_t^{pull\_over}$	Pull-over velocity threshold for truck t in case of a traffic jam
d	Maximum allowed relative occupancy difference between rest areas $p \in P$
M	Big positive constant (e.g., $10\,000$)
δ	Small positive constant (e.g., 0.1)

The total number of rest areas considered is denoted by $K \in \mathbb{N}$, the number of reachable rest areas by $R \in \mathbb{N}$, respectively. The current occupancy of rest area p is modeled with $o_p^{ext} \in \mathbb{N}$, the maximum official capacity with $cap_p \in \mathbb{N}$, and the closing capacity with $cap_p^{close} \in \mathbb{N}$. The closing capacity does not necessarily need to be the physical capacity limit. For example, it can also be the maximum tolerated number of trucks at a rest area. The distinction between maximum official capacity and closing capacity is essential because TOPTIPS should be applicable in practice. An analysis of rest area occupancy data from the A9 was conducted to estimate cap_p^{close} in comparison to cap_p, which is defined as closing rest area factor $\frac{cap_p^{close}}{cap_p}$. The results show that closing rest area factors of $140\,\%$ can be observed. Many aspects may influence the extent to which overcrowding can happen. For example, the layout of a rest area or temporal parking signs can have an impact. The closing rest area factor can vary between rest areas. The maximum factor of all rest areas $\max(\{cap_p^{close}/cap_p \mid p \in P\})$ is defined as $o^{max\_ovld} \in \mathbb{R}_{\geq 0}$. This factor is essential for modeling even filling beyond the maximum official capacity by normalizing the closing capacity.

Another pivotal parameter is $l_t \in \mathbb{R}$, which denotes the remaining driving time for truck (driver) t. Negative values indicate that the driver violates HOS regulations. $s_{t,p} \in \mathbb{R}_{\geq 0} \cup \{-1\}$, $c_{t,p} \in \mathbb{R}_{\geq 0} \cup \{-1\}$, and $v_{t,p} \in \mathbb{R}_{\geq 0} \cup \{-1\}$ denote driving distance, predicted travel time and predicted average speed of truck t to rest area p. A negative value of -1 indicates that a particular rest area is already passed by a truck or should not be considered for parking. The parameter $h_{t,p} \in \mathbb{R}_{\geq 0}$ denotes the predicted unused HOS for truck t when arriving at rest area p. Any predictions which would lead to HOS violations are modeled with $h_{t,p} = 0$. Only rest areas which do not violate HOS are considered as feasible, which is ensured by appropriate constraints. These constraints are explained later. The parameter $i_{t,p} \in [0, 1]$ captures the individual preference of a truck (driver) t for rest area p. Generally,

$i_{t,p}$ can be the output of a utility function $u : \mathbb{R}^n \mapsto [0, 1]$ which models utility based on, for example, showers, food, and perceived security. $v_t^{pull\_over} \in \mathbb{R}_{>0}$ denotes a truck-specific pull-over velocity threshold in case of traffic disturbances. The parameter ensures that trucks avoid congestion by recommending a temporary stop. After the traffic jam has dissipated, the trucks can continue their journeys. The relative occupancy difference between the rest area with the highest occupancy $\max(o_p^{rel} \mid p \in P)$ and the one with the lowest occupancy $\min(o_p^{rel} \mid p \in P)$ should not be more than $d \in \mathbb{R}_{>0}$. M and δ are technical parameters used to model logical expressions. It should be noted that care needs to be taken in selecting these parameter values because numerical issues can occur.

Decision Variables

$x_{t,p}$	Binary decision variable for truck t going to rest area p

Further Variables

o_p^{curr}	Current occupancy estimation for rest area p
o_p^{crowd}	Overcrowd occupancy for rest area p
a_p^{crowd}	Auxiliary variable indicating overcrowding for rest area p
o_p^{srrl}	Surcharge variable relative occupancy for rest area p
o_p^{rel}	Relative occupancy for rest area p
o_{avg}	Average occupancy of reachable rest areas
o_p^{diff}	Occupancy difference from average occupancy for rest area p
$o_p^{diff\prime}$	Auxiliary variable for modeling absolute values of o_p^{diff} for rest area p
$s_{t,p}^{l_t}$	Slack variable remaining driving time of truck t to rest area p
s_p^{close}	Slack variable closing capacity for rest area p
o_{avg}^{cl}	Average closing capacity violation
$o_p^{cl\_diff}$	Closing capacity violation difference from average violation for rest area p
$o_p^{cl\_diff\prime}$	Auxiliary variable for modeling absolute values of $o_p^{cl\_diff}$ for rest area p
s^{spread}	Slack variable maximum allowed relative occupancy difference

As previously mentioned in Section 3.2.2 TOPTIPS Modeling Overview, the binary variable $x_{t,p}$ is used to model whether a truck t parks at rest area p. In addition to the decision variables, there are a number of supporting variables that are only briefly introduced here since their meaning will only become clearer when the constraints are explained. However, a basic understanding is needed at this point because some of them are already being used in the objective functions. The domains of the variables are specified in the

constraints section. o_p^{curr} denotes the current occupancy estimation of rest area p. a_p^{crowd} is an auxiliary variable that indicates whether rest area p is overcrowded, i.e., the official maximum capacity cap_p is exceeded by o_p^{crowd}. The surcharge variable o_p^{srrl} normalizes the relative occupancy o_p^{rel}, which, in turn, is used to calculate the average occupancy o_{avg}. The occupancy difference of rest area p from the average occupancy is denoted by o_p^{diff} and the absolute difference by $o_p^{diff\prime}$.

TOPTIPS should be able to deal with a variety of real-world situations. One such situation is that a truck t does not have sufficient remaining driving time l_t to reach any rest area. Such a state can happen, for example, if earlier travel time predictions underestimated the actual required time to arrive at a particular rest area. This results in an infeasible model which cannot be solved. HOS must be violated to be able to park at the next downstream rest area. The purpose of the remaining variables is to overcome infeasible model states, which is explained in more detail in Section 3.2.3 Treatment of Infeasible Model States. $s_{t,p}^{l_t}$ is a slack variable to allow HOS violations. s_p^{close} can deal with closing capacity violations. In the very rare cases this is needed, violations should happen evenly distributed. For this, the variables $o_p^{cl\_diff}$, $o_p^{cl\_diff\prime}$, and $o_p^{cl\_diff}$ are introduced, similarly to o_p^{diff}. Lastly, s^{spread} can relax the defined maximum relative occupancy difference.

Objectives

The system and user objectives are derived from the literature and translated into five distinct maximization and minimization formulations (see Section 2.3 Derived User and System Objectives from the Literature). For convenience and a better overview, the five formulations are repeated again:

1. Minimize unused HOS

2. Minimize overcrowding

3. Maximize average velocity

4. Minimize relative occupancy differences

5. Maximize individual preference satisfaction

Their mathematical formulations are shown in Equation 3.3 to Equation 3.7 and explained in the following:

$$\min f_1(\boldsymbol{x}) = \sum_{t \in T} \sum_{p \in P} h_{t,p}^2 \, x_{t,p} \tag{3.3}$$

$$\min f_2(\boldsymbol{x}) = \sum_{p \in P} \max(\sum_{t \in T} x_{t,p} + o_p^{ext} - cap_p, 0) \tag{3.4}$$

$$\max f_3(\boldsymbol{x}) = \sum_{t \in T} \sum_{p \in P} \min(v_{t,p}, v_t^{pull\_over}) \, x_{t,p} \tag{3.5}$$

$$\min f_4(\boldsymbol{o}^{diff\prime}) = \sum_{p_r \in R_T} o_{p_r}^{diff\prime} \tag{3.6}$$

$$\max f_5(\boldsymbol{x}) = \sum_{t \in T} \sum_{p \in P} i_{t,p} \, x_{t,p} \tag{3.7}$$

Equation 3.3 maximizes the productivity of the truck drivers by minimizing the predicted unused HOS $h_{t,p}^2$ upon arriving at parking p. It should be noted that $h_{t,p}$ is squared. This is a small but important detail. First, squaring $h_{t,p}$ makes sure that the unused driving time (i.e., productivity loss) is distributed as fairly as possible among the trucks. Second, it ensures that TOPTIPS is more robust regarding travel time prediction errors. Since the two claims are not immediately obvious, they are illustrated using a simplified, concrete thought experiment with only two trucks and two rest areas. The situation is shown in Figure 3.3.
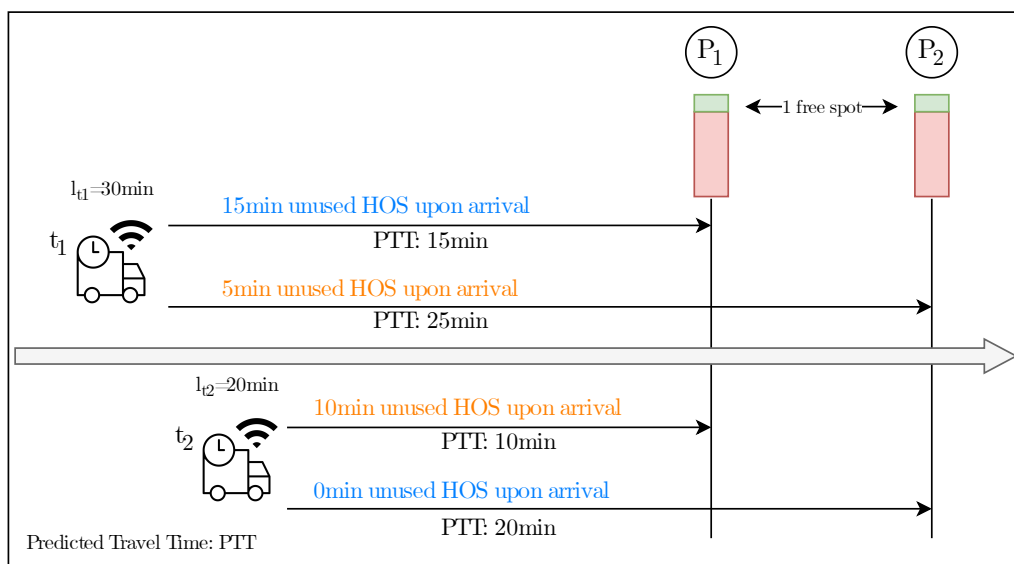
Figure 3.3: Thought experiment regarding unused HOS

There are two trucks t_1 and t_2 with remaining driving time $l_{t_1} = 30\,\mathrm{min}$ and $l_{t_2} = 20\,\mathrm{min}$

and two rest areas p_1 and p_2 with one free parking space each. The remaining driving times are sufficient for both trucks to park at either one of the rest areas. In situation *blue*, truck t_1 goes to p_1, and truck t_2 goes to p_2. In situation *orange*, truck t_1 goes to p_2, and truck t_2 parks at p_1. Both situations have in common that the total unused driving time upon arrival is 15 min (assumed that the travel time predictions are correct). However, in situation *blue* truck t_1 loses the entire 15 min and truck t_2 looses 0 min. In situation *orange*, truck t_1 has 5 min unused driving time and truck t_2 exhibits 10 min unused driving time. The situation *orange* is fairer as both trucks share the unavoidable productivity losses. Furthermore, 0 min predicted unused driving time poses the risk of violating HOS regulations. In situation *blue*, 5 min predicted unused driving is a safety buffer and makes the model more robust with respect to erroneous travel time predictions. In conclusion, situation *orange* is preferable because of fairness and robustness. However, minimizing $\tilde{f}_1(\boldsymbol{x}) = \sum_{t \in T} \sum_{p \in P} h_{t,p} x_{t,p}$ does not distinguish between the two situations. Both of them result in $h_{t_1,p_2} + h_{t_2,p_1} = h_{t_1,p_1} + h_{t_2,p_2} = 15$ min total unused driving time. Minimizing $f_1(\boldsymbol{x}) = \sum_{t \in T} \sum_{p \in P} h_{t,p}^2 x_{t,p}$ results in picking the preferred *orange* situation, i.e., $h_{t_1,p_2}^2 + h_{t_2,p_1}^2 = 125$ min versus $h_{t_1,p_1}^2 + h_{t_2,p_2}^2 = 225$ min.

After having studied the problem with a concrete thought experiment, a mathematical proof for the case of $n = 3$ trucks is conducted.

Proposition. *Let x_1, x_2, and x_3 be non-negative real numbers which denote the unused driving time of three trucks. Suppose that the total unused driving time is constant $x_1 + x_2 + x_3 = c$. Then $\min f(x_1, x_2, x_3) = x_1^2 + x_2^2 + x_3^2$ results in $x_1 = x_2 = x_3 = \frac{1}{3}c$.*

Proof. Since $x_1 + x_2 + x_3 = c$ by assumption, it follows that

$$x_3 = c - x_1 - x_2.$$

Using the multinomial theorem,

$$(x_1 + x_2 + \ldots + x_m)^n = \sum_{k_1 + \ldots + k_m = n} \binom{n}{k_1, \ldots, k_m} x_1^{k_1} x_2^{k_2} \ldots x_m^{k_m}$$

, we can write

$$\begin{aligned} f(x_1, x_2, x_3) = f(x_1, x_2) &= x_1^2 + x_2^2 + (c - x_1 - x_2)^2 \\ &= x_1^2 + x_2^2 + c^2 + x_1^2 + x_2^2 - 2cx_1 - 2cx_2 + 2x_1 x_2. \end{aligned}$$

To find the minimum, we set

$$\nabla f(x_1, x_2) = 0.$$

We can expand using partial differentiation

$$\text{I} \quad \frac{\partial f(x_1, x_2)}{\partial x_1} = 4x_1 - 2c + 2x_2 = 0$$

$$\text{II} \quad \frac{\partial f(x_1, x_2)}{\partial x_2} = 4x_2 - 2c + 2x_1 = 0.$$

Solving the system of linear equations gives

$$x_1 = x_2 = \frac{1}{3}c.$$

This, in turn, gives

$$x_1 = x_2 = x_3 = \frac{1}{3}c.$$

Lastly, the stationary point needs to be classified as minimum using second derivatives

$$\text{I} \quad \frac{\partial^2 f(x_1, x_2)}{\partial x_1^2} = 4$$

$$\text{II} \quad \frac{\partial^2 f(x_1, x_2)}{\partial x_2^2} = 4$$

$$\text{III} \quad \frac{\partial^2 f(x_1, x_2)}{\partial x_1 \partial x_2} = 2.$$

As $f_{x_1 x_1} f_{x_2 x_2} - f_{x_1 x_2}^2 > 0$, $f_{x_1 x_1} > 0$, and $f_{x_2 x_2} > 0$ for the entire domain of f, the point

$$x_1 = x_2 = x_3 = \frac{1}{3}c$$

is the minimum point. $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\square$

The proof was carried out for the case of three trucks. A generalization of the proof to an arbitrary number of n trucks remains subject to researchers with a strong background in mathematics.

Equation 3.4 minimizes overcrowding, i.e., trucks that park in excess of the official maximum capacity cap_p. The max function ensures that the minimization objective is only active for trucks beyond the official capacity. Equation 3.5 maximizes the average velocity of truck t to parking p. Concretely, it means that trucks are penalized for driving into a traffic jam. The min function inside the double summation ensures that the objective only gets activated when the average velocity falls below the velocity threshold $v_t^{pull\_over}$. Furthermore, small velocity variations can be filtered out and do not affect TOPTIPS, which would be undesirable in practice. If not otherwise stated, $v_t^{pull\_over}$ is set to $60 \, \text{km/h}$. Equation 3.6 is responsible for minimizing the absolute relative occupancy difference between the reachable rest areas $p_r \in R_T$. The auxiliary variable $o_p^{cl\_diff'}$ is used instead

of the squared relative occupancy difference $o_p^{cl\_diff^2}$ because the latter would result in a quadratic objective function. Quadratic multicriteria objective functions cannot be solved with the Gurobi solver (version 9.1) at the moment. Therefore, the fourth objective is linearized. It is the only objective where $x_{t,p}$ is not involved directly but indirectly through constraints. Yet, ultimately the objective also depends on $x_{t,p}$ and is therefore treated as a function of $\boldsymbol{x}$. The fifth objective is shown in Equation 3.7 and maximizes the individual driver preferences. It should be noted that the parameter $i_{t,p}$ is kept generic and that any appropriate utility function $u : \mathbb{R}^n \mapsto [0, 1]$ can be used to specify it.

Linear Objective Scalarization

The simultaneous optimization of the five objective functions (Equation 3.3 to Equation 3.7) leads to a Multi-Criteria Optimization Problem (MOP). For a MOP, it is generally not possible to find a unique optimum solution but many optimum solutions points, which form the Pareto-optimal set [EHRGOTT, 2005]. Pareto optimality is defined as [ARORA, 2012, p. 663]:

> "A point $\boldsymbol{x}^*$ in the feasible design space S is Pareto optimal if and only if there does not exist another point $\boldsymbol{x}$ in the set S such that $f(\boldsymbol{x}) \leq f(\boldsymbol{x}^*)$ with at least one $f_i(\boldsymbol{x}) < f_i(\boldsymbol{x}^*)$."

Methods to solve MOPs include *weighted sum, weighted Tchebycheff, weighted global criterion, lexicographic, ϵ-constraint,* and *goal programming* [ARORA, 2012]. Here, the *weighted sum* approach is chosen because it allows setting the weights of the objective functions by a domain expert, thus achieving transparent balancing. Further, the approach guarantees to find a Pareto-optimal solution, whereas other methods sometimes only find a weakly Pareto-optimal solution [ARORA, 2012]. However, the downside is that the computational complexity increases as the utopia point $\boldsymbol{f}^\circ$ needs to be found. The scalarized objective function F is shown in Equation 3.8.

$$\min F(\boldsymbol{x}) = w_1\, f_1(\boldsymbol{x}) + w_2\, f_2(\boldsymbol{x}) - w_3\, f_3(\boldsymbol{x}) + w_4\, f_4(\boldsymbol{x}) - w_5\, f_5(\boldsymbol{x}) \tag{3.8}$$

$$\sum_{i=1}^{5} w_i = 1 \tag{3.9}$$

$$\boldsymbol{w} > \boldsymbol{0} \tag{3.10}$$

It should be noted that the objective functions f_3 and f_5 are multiplied with -1 in order to convert the maximization formulation into a minimization equivalent. Equation 3.9 makes sure that the weights sum up to 1, which helps the domain expert to express his or her preferences. Equation 3.10 constrains the weights to positive values.

However at this point, the five objective function values have different orders of magnitude. For example, the function f_1 might be expressed in seconds or minutes squared, while the function f_2 is expressed in number of trucks. This would make the choice of the weights $w_1, \dots, w_5$ difficult and not intuitive. Therefore, the objective functions have to be normalized with the help of the utopia point $\boldsymbol{f}^\circ$. The i-th entry of the utopia point is defined as $f_i^\circ = \min f_i(\boldsymbol{x})$ such that $\boldsymbol{x} \in S$. Concretely, this means that each objective function f_i is minimized separately considering only the constraints but without considering the remaining objective functions. In general, the utopia point is not in the feasible criterion space and is therefore unattainable [ARORA, 2012]. With the number of objective functions, the complexity to compute the utopia point increases as the optimization of each function has to be performed. The utopia point is used to get the normalized i-th objective function $f_i^{norm} : \mathbb{R}^n \mapsto [0,1]$. Normalization is computed as follows [ARORA, 2012]:

$$f_i^{norm} = \frac{f_i(\boldsymbol{x}) - f_i^\circ}{f_i^{\max} - f_i^\circ}.$$

$f_i^{\max}(\boldsymbol{x}) = \max_{1 \le j \le 5} f_i(\boldsymbol{x}_j^*)$ is the maximum value f_i where $\boldsymbol{x}_j^*$ denotes the point that minimizes the j-th objective function. Concretely, f_i is evaluated at all $\boldsymbol{x}_j$ and the maximum is taken as upper bound for the normalization. In conclusion, TOPTIPS needs to run six optimization cycles (one more than the number of objective functions): five pre-optimization runs in order to get the utopia point $\boldsymbol{f}^\circ$ and the upper bound vector $\boldsymbol{f}^{norm}$ and one final optimization run to obtain the actual results.

Constraints

Lastly, the constraints are explained which describe physical circumstances, driving restrictions, and auxiliary variables that are primarily used in the fourth objective function.

$$\sum_{p \in P} x_{t,p} = 1 \qquad\qquad \forall t \in T \qquad\qquad (3.11)$$

$$-s_{t,p}\, x_{t,p} \le 0 \qquad\qquad \forall t \in T,\, p \in P \quad (3.12)$$

$$c_{t,p}\, x_{t,p} \le l_t \qquad\qquad \forall t \in T,\, p \in P \quad (3.13)$$

$$\sum_{t \in T} x_{t,p} + o_p^{ext} = o_p^{curr} \qquad\qquad \forall p \in P \qquad\qquad (3.14)$$

$$o_p^{curr} \le cap_p^{close} \qquad\qquad \forall p \in P \qquad\qquad (3.15)$$

$$o_p^{crowd} = \max(o_p^{curr} - cap_p, 0) \qquad \forall p \in P \qquad\qquad (3.16)$$

$$M \, a_p^{crowd} \geq (o_p^{curr} - 1 + \delta) - cap_p \quad \forall p \in P \tag{3.17}$$

$$M \, (1 - a_p^{crowd}) \geq cap_p - (o_p^{curr} - 1 + \delta) \quad \forall p \in P \tag{3.18}$$

$$\frac{o_p^{curr}}{cap_p^{close}} o^{max\_ovld} - \frac{o_p^{curr}}{cap_p} = o_p^{srrl} \qquad \forall p \in P \tag{3.19}$$

$$\frac{o_p^{curr}}{cap_p} + a_p^{crowd} o_p^{srrl} = o_p^{rel} \qquad \forall p \in P \tag{3.20}$$

$$\sum_{p \in R_T} \frac{1}{R} o_p^{rel} = o_{avg} \tag{3.21}$$

$$o_p^{diff} = o_p^{curr} - o_{avg} \qquad \forall p \in P \tag{3.22}$$

$$o_p^{diff\prime} = \begin{cases} -o_p^{diff} & \text{if } o_p^{diff} < 0 \\ o_p^{diff} & \text{otherwise} \end{cases} \quad \forall p \in P \tag{3.23}$$

$$\max(o_p^{rel} \mid p \in P) - \min(o_p^{rel} \mid p \in P) \leq d \tag{3.24}$$

$$x_{t,p} \, , \, a_p^{crowd} \in \{0, 1\} \qquad \forall t \in T \, , \, p \in P \tag{3.25}$$

$$o_p^{crowd} \, , \, o_p^{curr} \in \mathbb{N}_0 \qquad \forall p \in P \tag{3.26}$$

$$o_p^{diff} \in \mathbb{R} \qquad \forall p \in P \tag{3.27}$$

$$o_p^{diff\prime} \, , \, o_p^{srrl} \, \mathbb{R}_{\geq 0} \qquad \forall p \in P \tag{3.28}$$

$$o_{avg} \in \mathbb{R}_{\geq 0} \tag{3.29}$$

Equation 3.11 ensures that each truck can only park at one and only one rest area. A truck cannot be at two rest areas at the same time. The equal sign means that all considered trucks must park at one rest area. A "$\leq$"-sign would be a less restrictive modeling approach because some trucks could park at different parking facilities (e.g., at an industrial area) not specified in the set P. In this thesis, the restrictive approach is chosen as it makes sure that each truck gets a parking recommendation. However, this makes the handling of the model more complex and can lead to infeasible model states that need to be overcome. Details on infeasible model states are explained later in Section 3.2.3 Treatment of Infeasible Model States. Equation 3.12 restricts trucks from driving backwards. The parameter $s_{t,p}$ can also be used to exclude specific truck rest area combinations. A theoretical use case could be that a rest area is closed for heavy trucks because of pavement issues. However, these types of use cases are not the

focus of the study and should only show the flexibility of the MIP modeling approach. Equation 3.13 ensures that a truck driver does not exceed his or her allowed remaining driving time. This constraint is very important as it restricts the set of potential rest areas to the set of HOS feasible rest areas. Equation 3.14 captures the current occupancy estimation o_p^{curr} for each rest area by summing trucks that already park there and the ones that get a recommendation for it. The next constraint makes sure that the current occupancy estimation o_p^{curr} does not exceed the closing capacity. Equation 3.16 defines the overcrowding for each rest area. If there is no overcrowding, the max function ensures the lower bound of 0 for the variable o_p^{crowd}. Equation 3.17 and Equation 3.18 use the big M trick to define the auxiliary variable a_p^{crowd}. It is either 1 or 0 and indicates whether a rest area is overcrowded or not. It is essential for the calculation of the normalized relative occupancy o_p^{rel} in Equation 3.20. Normalization is necessary because each rest area has its own closing rest area factor $\frac{cap_p^{close}}{cap_p}$. Concretely, this means that some rest areas may close at $120\,\%$ while others close at $140\,\%$ of the official maximum capacity. In order to model even filling of the rest areas up to the closing capacity, the relative occupancy (when in an overcrowding state) needs to be normalized. First, the surcharge o_p^{srrl} is calculated in Equation 3.19. In Equation 3.20, the normalized relative occupancy is calculated considering the surcharge variable o_p^{srrl} only when the rest area is in an overcrowding state. The last two constraints are pivotal for modeling even filling. In non-overcrowding states, even filling up to the official maximum capacity cap_p is ensured. Here, no normalization is desired. In an overcrowding state, proper filling up to the closing capacity cap_p^{close} with normalization is guaranteed. The average occupancy o_{avg} is calculated in Equation 3.21. It should be noted that the average only considers the set of reachable rest areas R_T, as the occupancy of the other rest areas $P \setminus R_T$ cannot be influenced by trucks $t \in T$. Equation 3.22 captures the occupancy difference from the average. Its absolute value is calculated in Equation 3.23. The absolute values are minimized in the fourth objective (see Equation 3.6), which results in even filling of the rest areas. The occupancy difference between the rest area with the highest demand and the one with the lowest demand is upper bounded by Equation 3.24. This constraint is also referred to as maximum allowed relative spread and can be made optional by setting a large value for d (e.g., $d = M$). It is only needed if relative occupancy values should not deviate more than d. Equation 3.25 restricts the variables $x_{t,p}$ and a_p^{crowd} to be binary. The remaining Equations 3.26 to 3.29 define the domains of the respective variables, which is particularly important when these need to be defined in a MIP-solver environment.

Treatment of Infeasible Model States

As previously mentioned, there are situations in which the described mathematical model cannot be solved because real life does not always follow the rules and regulations. Therefore, the model is equipped with an extra layer of flexibility. For example, if the predicted travel time $c_{t,p}$ for the next rest area is greater than the remaining driving time l_t, HOS regulations must be slightly violated so that the truck does not have to stop on the shoulder. The following slack variables and objectives are added to the model when an infeasible model state is detected. With this approach, specific hard constraints can be relaxed and turned into soft constraints.

$$c_{t,p}\, x_{t,p} - s_{t,p}^{l_t} \leq l_t \qquad\qquad \forall t \in T_{inf}, p \in P \quad (3.30)$$

$$\frac{\max(o_p^{rel} \mid p \in P)}{- \min(o_p^{rel} \mid p \in P) - s^{spread}} \leq d \qquad\qquad (3.31)$$

$$o_p^{curr} - s_p^{close} \leq cap_p^{close} \qquad\qquad \forall p \in P \quad (3.32)$$

$$\frac{\sum_{p \in P} s_p^{close}}{K} = o_{avg}^{cl} \qquad\qquad (3.33)$$

$$o_p^{cl\_diff} = s_p^{close} - o_{avg}^{cl} \qquad\qquad \forall p \in P \quad (3.34)$$

$$o_p^{cl\_diff\prime} = \begin{cases} -o_p^{cl\_diff} & \text{if } o_p^{cl\_diff} < 0 \\ o_p^{cl\_diff} & \text{otherwise} \end{cases} \qquad \forall p \in P \quad (3.35)$$

$$o_p^{cl\_diff} \in \mathbb{R} \qquad\qquad \forall p \in P \quad (3.36)$$

$$s_{t,p}^{l_t}, o_p^{cl\_diff\prime} \in \mathbb{R}_{\geq 0} \qquad\qquad \forall t \in T_{inf}, p \in P \quad (3.37)$$

$$s_p^{close} \in \mathbb{N}_0 \qquad\qquad \forall p \in P \quad (3.38)$$

$$o_{avg}^{cl}, s^{spread} \in \mathbb{R}_{\geq 0} \qquad\qquad (3.39)$$

Equation 3.13, which ensures that a truck driver respects his or her remaining driving time, is relaxed by introducing the slack variable $s_{t,p}^{l_t}$ in Equation 3.30. It allows reaching the next rest area. It should be noted that the slack variable $s_{t,p}^{l_t}$ needs only to be added to the constraints that involve trucks that make the model infeasible (i.e., $t \in T_{inf}$). Equation 3.31 contains the slack variable s^{spread}, which softens constraint Equation 3.24 and allows greater spreads than defined by d. In Equation 3.32, s_p^{close} gets added, which relaxes constraint Equation 3.15 and allows to exceeding cap_p^{close}. Equations 3.33 to 3.35 are required to compute the absolute closing capacity violation difference $o_p^{cl\_diff\prime}$.

The aim is to distribute closing capacity violations evenly between the rest areas. The remaining constraint Equations 3.36 to 3.39 define the domains of the respective variables.

Turning hard constraints into soft constrains also involves objective extensions in order to penalize the slack variables. This leads to the following additional objective functions:

$$\min f_6(\boldsymbol{s}^{l_t}) = \min \sum_{t \in T_{inf}} \sum_{p \in P} s_{t,p}^{l_t} \tag{3.40}$$

$$\min f_7(s^{spread}) = \min s^{spread} \tag{3.41}$$

$$\min f_8(\boldsymbol{s}^{close}) = \min \sum_{p \in P} s_p^{close} \tag{3.42}$$

$$\min f_9(\boldsymbol{o}^{cl\_diff\prime}) = \min \sum_{p \in P} o_p^{cl\_diff\prime} \tag{3.43}$$

Equation 3.40 minimizes the HOS violation necessary to reach an open rest area, i.e., TOPTIPS recommends the next non-closed rest area downstream. Equation 3.41 minimizes the allowed relative occupancy difference violation. Closing capacity violation minimization is shown in Equation 3.42. However, minimizing closing capacity violation does not automatically lead to evenly distributed violations, which is modeled in Equation 3.43. The four objective functions for constraint relaxation are also scalarized with the weighted sum approach. Smaller weights can be used for those objectives which are considered least harmful to violate. The weights are defined depending on the magnitude of the slack variables as no normalization is conducted.

$$\begin{aligned} \min F_{relax}(\boldsymbol{s}^{l_t}, s^{spread}, \boldsymbol{s}^{close}, \boldsymbol{o}^{cl\_diff\prime}) = {} & w_6 \, f_6(\boldsymbol{s}^{l_t}) + w_7 \, f_7(s^{spread}) \\ & + w_8 \, f_8(\boldsymbol{s}^{close}) + w_9 \, f_9(\boldsymbol{o}^{cl\_diff\prime}) \end{aligned} \tag{3.44}$$

In summary, this leads to two scalarized objective functions: I (Equation 3.8) and II (Equation 3.44). For the solution, a lexicographic approach is chosen. A lexicographic approach assigns priorities to the objective functions and optimizes according to the resulting priority order [ARORA, 2012]. This means that the highest priority function is solved first. Then, the second highest priority function is solved but with the constraint that the previous objective function does not degrade. The procedure is repeated until all objectives are considered. For lower priority objectives, all previously solved objectives are not allowed to degrade. The advantages of this approach are that it always leads to a Pareto-optimal solution and that the objective functions do not need to be normalized [ARORA, 2012]. The priority ordering is ideal for infeasible truck parking model states. If objective function II is given higher priority, a solution that leads to the least regulation violations is found first. Then, the actual solution of the objective function I is computed by considering the feasible design space that does not lead to any additional violations.

In summary, overcoming infeasible model states may seem a theoretical exercise, but it helps to make the model more robust for all kinds of real-world situations. Furthermore, the lexicographic approach keeps the model interface simple for the domain expert as he or she only needs to weight the five primary objectives without worrying about infeasible model states. To conclude, the mathematical modeling of TOPTIPS offers the following advantages:

- Weighting of objectives is intuitive and easy (no need to know the modeling details).

- Tolerated overcrowding is explicitly considered as it happens frequently.

- Ready to be applied in practice as infeasible model states can be overcome without manual intervention.

- Well extendable to accommodate possible future needs (e.g., parking preference for electric charging, advanced routing).

- Model design allows using fast and efficient MIP solvers.

A potential disadvantage is the complexity of the approach. It remains the subject of further research under which circumstances simpler heuristics can be used and how close they are to an optimal solution. The results of this thesis could be used as a benchmark.

> ### Key Takeaways: Truck Optimization Parking System (TOPTIPS)
>
> The TOPTIPS chapter introduces the mathematical modeling of the parking recommendation system.
>
> - First, the system boundaries, assumptions, and required input data are investigated. It is shown that the required input data is technically available through Floating Truck Data today.
>
> - The central idea to model truck parking is based on a bipartite graph representation of the problem.
>
> - A multi-criteria approach is chosen to address the different objectives of drivers and road authorities.
>
> - To find a Pareto-optimal solution of the Multi-Criteria Optimization Problem, the weighted sum method is chosen. It allows defining a priori preferences for the respective objectives. However, the approach requires finding the utopia point to normalize the single objectives.
>
> - The resulting discrete variable optimization problem is solved with the Branch&Bound algorithm.
>
> - Infeasible model states, which can happen in practice due to, for example, inaccurate travel time predictions, are explicitly considered by turning hard constraints into soft constraints if required.

Chapter 4

Microscopic Traffic Simulation

Truck Optimization Parking System (TOPTIPS) is evaluated with a microscopic traffic simulation. This chapter deals with the steps to set up, calibrate, and validate the simulation. Furthermore, the interplay between the optimization and the simulation is described. As research on how to simulate large-scale microscopic truck parking is still in its infancy, current simulation guidelines [FGSV, 2006; GEISTEFELDT et al., 2017; FHA, 2019] are only partially applicable but still very valuable. Therefore, advanced approaches to simulate truck parking are explored in this thesis. This upstream work is a prerequisite to thoroughly validate the proposed TOPTIPS model. The microscopic traffic simulation SUMO [LOPEZ et al., 2018] is chosen as simulation environment because it is open source, is capable of simulating large road networks with many vehicles, and has a mature Python Application Programming Interface (API) that is well documented. Moreover, additional tools and scripts are available, which can be modified, customized, and extended. However, some disadvantages come with this choice: lack of user-friendliness and the need for highly specialized expert knowledge, both of which make scenario setup non-trivial. All software and key libraries used for the thesis can be seen in Appendix D: Calibration and Validation in Table A.2.

The structure of the chapter is as follows: First, the truck parking data itself is described to gain a better understanding of the parking characteristics. The second and third section cover modeling traffic supply and demand. In the fourth section, calibration methods and validation results are presented. The fifth section explains the custom modules for multi-destination routing and travel time prediction. Lastly, the entire evaluation framework is summarized by explaining the interplay of the microscopic traffic simulation, the optimization framework, and the custom modules for routing and travel time prediction.

4.1 Truck Parking Data

The truck parking simulation is different from the ordinary traffic simulation. In addition to general traffic demand, truck parking demand must be modeled. This section describes the truck parking data collection process, analyzes the data, and discusses its characteristics.

4.1.1 Truck Parking Data Collection

Truck parking occupancy data was collected from the parking guidance system on the A9 between Munich and Nuremberg, which is part of the digital testbed A9 [BASt, 2021] and extends over a length of 140 km (one-way). In total, the system consists of 22 rest areas that are equipped with sensor units at the entrance and exit. A sensor unit is composed of radar and laser detectors. In-pavement radar sensors measure the length and the velocity of the vehicles. The laser scanners are mounted on poles and measure the height and width. Through sensor fusion, vehicles are detected and classified into trucks and non-trucks. The relevant motorway section with the locations of the rest areas is shown in Figure 4.1

The truck detection and classification accuracy is high. Supported by regular calibrations from operators, occupancy errors should not exceed three to five trucks at any given time [SSP Consult, 2015]. The threshold depends on the size of the rest area. As the vehicle counting happens at the entrance and exit of the rest areas, the system belongs to the category of indirect detection systems. For more details concerning the different detection principles and their respective advantages and disadvantages, see Section 2.2.3 Proposed Solutions. Occupancy levels are updated every minute and stored on a server. It is the first and largest motorway truck parking guidance system in Germany. In summary, the infrastructure of the digital testbed A9 provides an unprecedented opportunity for truck parking research. For the first time, historical truck parking occupancy data by the minute is available for a 140 km motorway stretch.

The northbound direction of the digital testbed was selected as the study area. The reasons for the decision are explained in the following. In traffic simulation, a distinction is made between the study and model area [FGSV, 2006]. The study area is smaller than the model area in terms of the spatio-temporal extent that is simulated. Concretely, this means that both temporal and spatial lead and lag need to be added to the study area to obtain the model area. In truck parking simulation, the spatial and temporal lead is more important than the lag because trucks must be taken into account when they are upstream of potential rest areas. As mentioned in the literature review, drivers start to consider parking options 1 h to 3 h in advance [Golias et al., 2020; Smith et al., 2005].
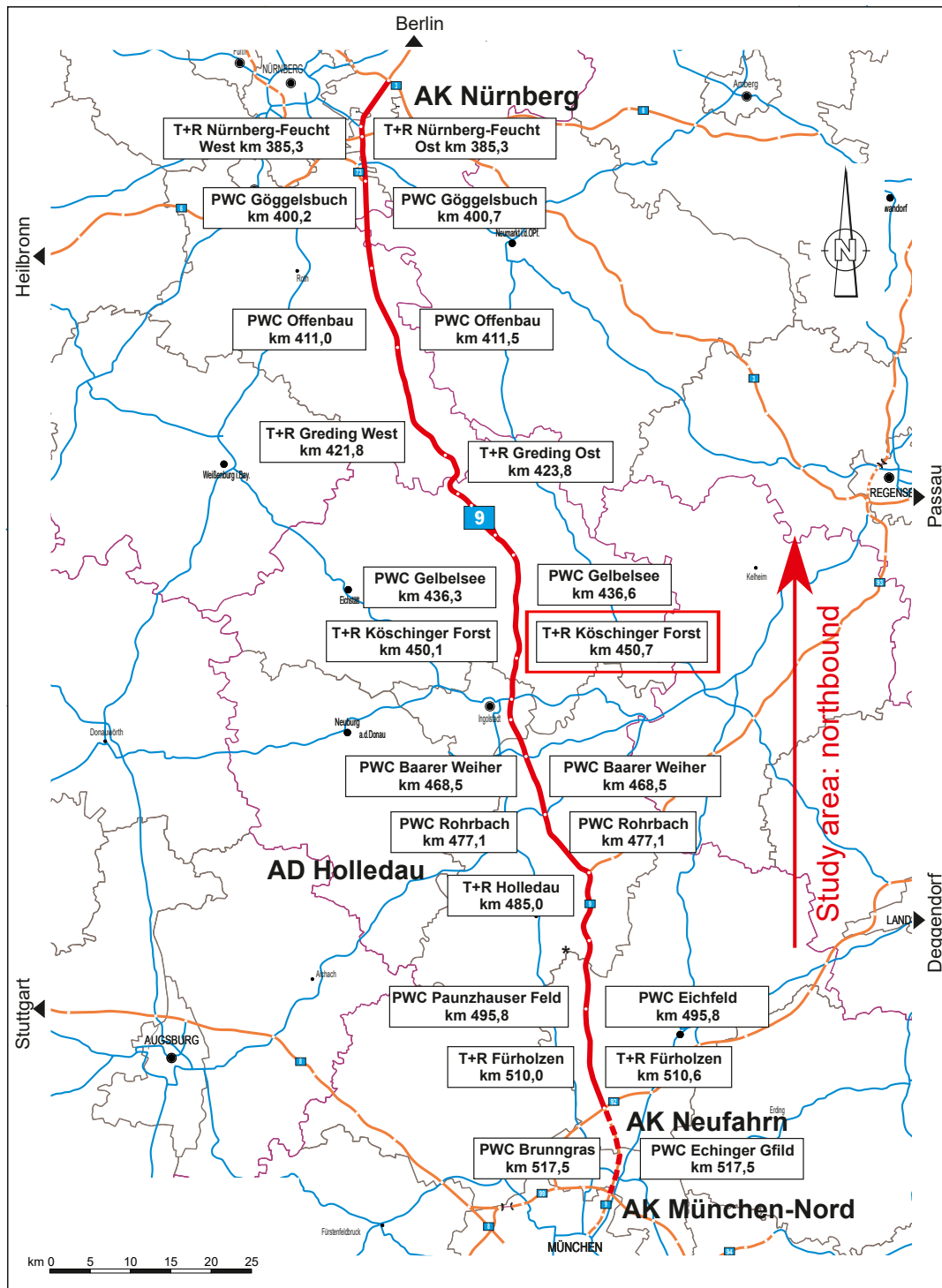
Figure 4.1: Truck parking data collection from the digital testbed A9 - source: ZVM

Assuming truck velocities of 80 km/h, at least a 1 h temporal and 80 km spatial lead have to be modeled. Traffic demand data for the simulation is derived from traffic detectors (induction loops and overhead detection). In the south of the digital testbed A9, there

is a dense coverage with traffic detectors on the A99 and the A8 East. Therefore, the northbound direction with 11 rest areas was selected as the study area for evaluating TOPTIPS.

4.1.2 Parking Data

Minute-by-minute parking occupancy data was collected from January 15, 2020 at midnight to March 16, 2020 at midnight. The occupancy raw data on the server is stored as Extensible Markup Language (XML) files (one per day and rest area), which is not convenient to work with. Therefore, the data is extracted from the XML files and a relational database (PostgreSQL) is set up. In theory, there should be 966 240 data records (61 days × 24 hours × 60 minutes × 11 rest areas = 966 240), but only 867 667 data records are available (90 %). The data analysis reveals that the rest area *PWC Rohrbach FR Berlin* did not send valid data because it was closed due to construction. As occupancy data for each rest area is required, data from 2019 for the same period is used as a surrogate. Additionally, implausible occupancy values from the rest area *PWC Gelbelsee FR Berlin* between February 10, 2020, and February 15, 2020, are excluded. There is no (Bavarian) public holiday during the investigated period. Therefore, no additional days have to be excluded. However, it should be noted that trucking can be affected by public holidays outside of Bavaria. This will not be investigated further and remains the subject of future research. Finally, there are 945 049 data records available for the study corresponding to data availability of 98 %.

As an example of the data, the occupancy levels of the second-largest rest area *Köschinger Forst* northbound are shown in Figure 4.2 from two different perspectives. The upper part of the figure illustrates the occupancy over time. Sundays are shaded in gray, and the official maximal capacity of 140 truck parking spaces is depicted with a black horizontal line. In general, a weekly pattern can be observed with five peaks followed by a flat plateau. The peaks represent weekday nights from Monday to Friday where the utilization of the rest area is well above the maximal capacity. It can reach more than 140 %. Between the peaks, there are valleys which represent times when trucks are on the road. The last peak of the weekly pattern is of particular interest because it shows the situation from Friday night to Saturday morning. On Saturday mornings, the occupancy declines but usually not as much as during the week. This can be observed from the sixth valley in each week, which is higher than the previous valleys. The hypothesis is that some trucks do not drive on Saturdays. The plateaus show that trucks are generally (with exceptions) not allowed to drive on Sundays. They remain parked at the rest area, and new trucks do not enter either. The occupancy stays below the maximal capacity threshold, which indicates that sufficient parking spaces are available for long weekend rests.
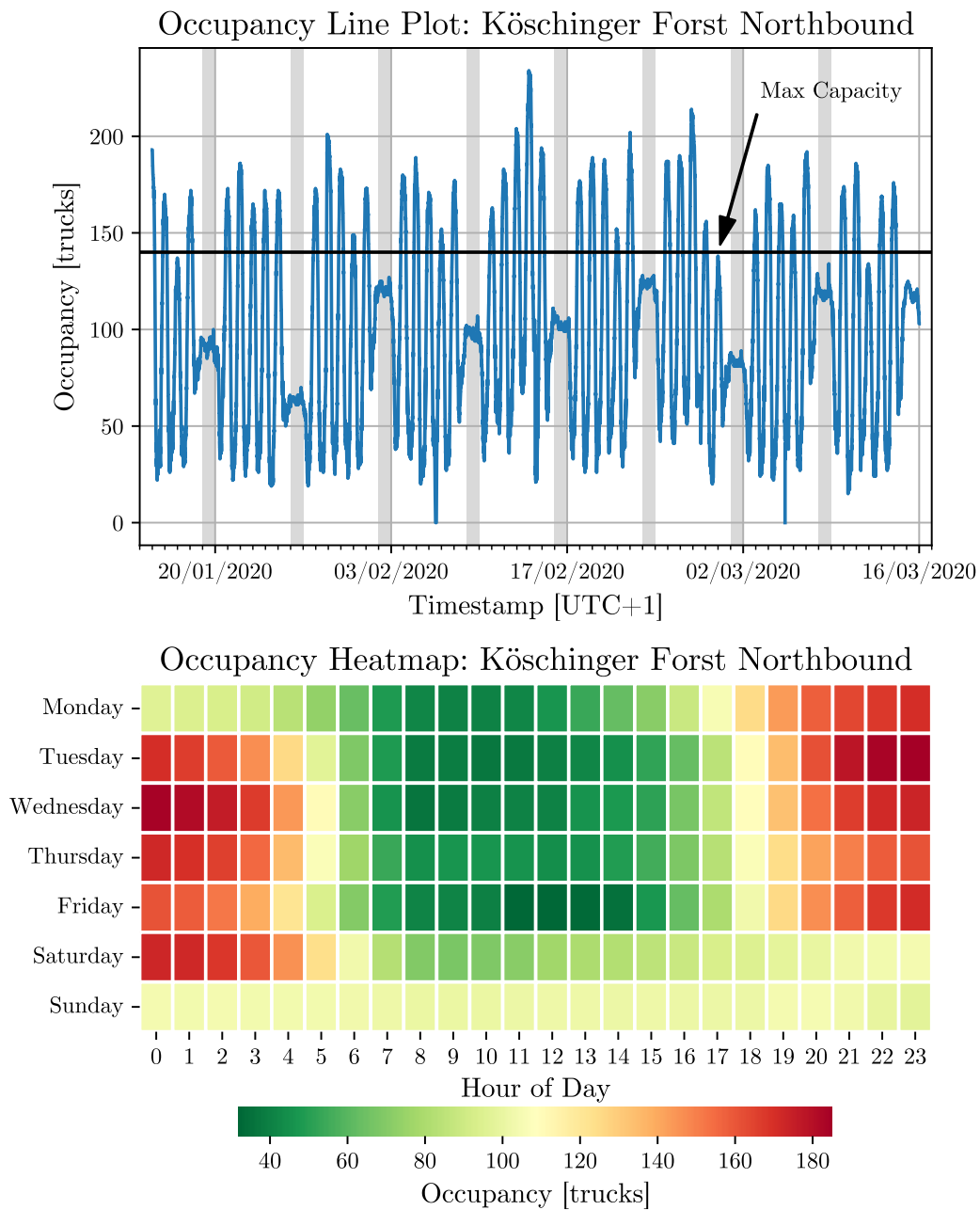
Figure 4.2: Occupancy data from Köschinger Forst northbound

The lower part of Figure 4.2 aggregates the same data by days of the week and time of day and calculates the respective mean values. The result is a heat map where each patch represents the mean occupancy for a particular hour of the day on a specific day of the week. Times of high occupancy are depicted in red, and times of low occupancy are shown in green. This perspective supports some of the observations made earlier but also reveals more details. The weekly pattern with five peaks is now illustrated by red patches. For example, occupancy from Monday night to Tuesday morning is shown by red

patches at the end of the first row and the beginning of the second row. However, with the help of the heat map, the start of the filling and the onset of the emptying can be more precisely determined. Generally, filling starts between 4 p.m. and 6 p.m., and emptying begins between 3 a.m. and 5 a.m. The almost constant occupancy levels on Sundays can be observed well in the last row.

The remaining rest areas show similar characteristics. Heatmaps of the raw data for all rest areas can be found in Appendix A: Raw Data in Figure A.1. In summary, the data confirms the findings in the literature that the truck parking issue is most pressing during weekday nights. In addition, the data suggests studying the time between 4 p.m. and 12 a.m. on weekdays for evaluating TOPTIPS as truck drivers need parking recommendations the most during this time. From now on, this timespan is also called the study period. The truck parking data is used to derive the parking demand in Section 4.3 Modeling Demand. Before the demand is explained, the supply modeling is described.

4.2 Modeling Supply

In traffic simulation, two major sub-areas are distinguished: supply and demand [FHA, 2019]. This section describes the traffic supply, i.e., the road network and network elements. The next section deals with the traffic demand. In terms of network elements, a further distinction can be made between static and dynamic elements [FGSV, 2006]. Static elements capture road attributes such as curvature, inclination, and static speed limits, whereas dynamic elements typically include traffic lights and Variable Message Signs (VMSs).

4.2.1 Modeling the Road Network

The road network can be modeled as a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ represents the set of vertices and $\mathcal{E}$ is the set of directed edges. The edges connect the vertices, also called nodes or junctions in the SUMO terminology. Edges are defined by attributes such as the number of lanes, position, shape, and the connected nodes at the head and tail. It should be noted that, typically, junctions in SUMO correspond to junctions of the modeled street network. However, there can be more junctions in SUMO because when static network elements change, for example, when the number of lanes or the road class changes, an artificial node is added. In general, there are two possibilities to model a real-world road network in SUMO. Netedit, a graphical tool provided by the SUMO community, can be used to draw the road network and assign the respective attributes for the edges and nodes. Nodes have attributes such as shape, position, right-of-way as

well as incoming and outgoing edges. However, this approach is infeasible for large-scale networks. The second option is to obtain a street network in a suitable format and convert it to use in SUMO. This approach is more complex and briefly explained in the following. The result is shown in Figure 4.3. On the left, the entire road network is depicted. For better orientation, major roads of the metropolitan areas Munich and Nuremberg and the relevant rest areas are included. On the top right, a close-up view of Munich with the end of the A8 East, A99 East, and the start of the A9 is shown. On the bottom right, a detailed view of the rest area *Echinger Gfild Ost* with off-ramp and on-ramp is presented.
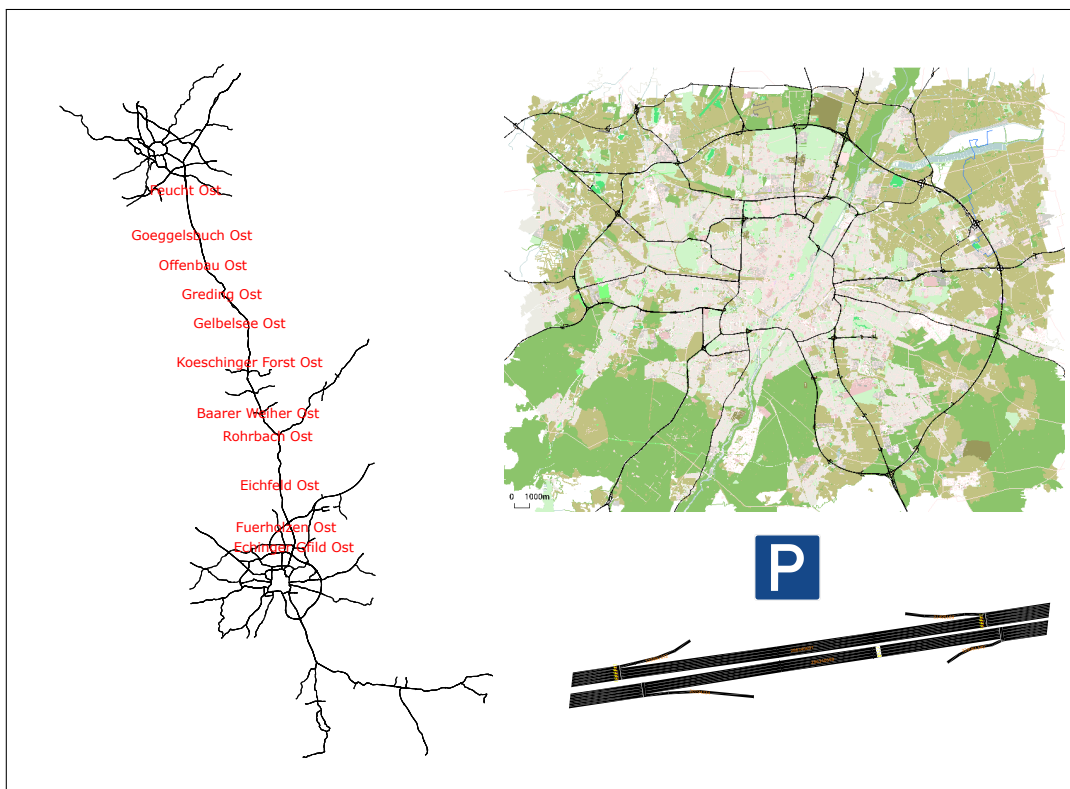
Figure 4.3: Exported road network from OSM (left). Close-up view of the metropolitan area Munich (top right). Example of a rest area with ramps (bottom right).

First, the road network, ranging from the *Dreieck Inntal* via A8 East, A99 East, and A9 up to the *Kreuz Nürnberg-Ost*, with all on-ramps and off-ramps as well as motorway interchanges, is exported from Open Street Map (OSM). This route is also called the main trunk in the following. OSM is a free and editable map of the world built by the community [HAKLAY and WEBER, 2008] and a valuable source for basic road network data. The OSM map can be thought of as a very big database where all types of objects are stored (e.g., museums, restaurants, shops, streets, rail tracks). Only the motorway street network needs to be exported. However, OSM has a vast amount of road classes.

For example, on-ramps and off-ramps have a different category than the main motorway trunk. Additionally, the users mapping the streets have their own understanding of road categories. Therefore, care must be taken to consider all relevant road classes and rather err on the side of caution by exporting too many roads. Unnecessary road classes can then be removed manually. A specialized query language (Overpass Query Language) is used to query road edges belonging to the categories: motorway, trunk, primary, motorway_-link, trunk_link, and primary_link. Furthermore, the respective nodes are exported with a recursive query on the filtered edges.

Second, the raw data from OSM is converted to a SUMO network file with the help of *netconvert*, which is a command line application. This application reads an OSM file, type files, and additional parameters. Type files are necessary because OSM raw data may miss some important information, e.g., speed limit or number of lanes. The type files define default values that are applied if some required information is missing. For this thesis, the officially provided type files are used without modification. Additional parameters give processing instructions. Usually, OSM data does not include on-ramps and off-ramps but instead models the situation with simple junctions. Therefore, the parameter *–ramps.guess* can be supplied, which inserts additional acceleration and deceleration lanes. Another important parameter is *–geometry.remove* which simplifies the network by joining edges if nodes are only present because of geometrical reasons. The geometry itself is preserved with the help of geometry points. A reduced number of edges makes the simulation and the data aggregation based on edges faster.

Third, manual corrections of the road network are conducted. The OSM map may contain inaccuracies. Any model of the real world is just a model with (simplified) assumptions. Additionally, maps need continuous updating efforts to incorporate changes in the real world. The third reason for manual corrections is the processing heuristics of *netconvert*. Guessing ramps is a difficult task in and of itself and which does not always succeed. In conclusion, manual corrections are time-consuming work, in particular, for large-scale networks as in the present case. Sometimes network inaccuracies can only be detected iteratively. For example, when peak times are simulated and congestion forms at unexpected locations, it can be due to network errors, among other reasons. The motorway access *Aschheim*, for example, requires manual corrections because ramp guessing does not work properly, and unexpectedly long jams form in the morning peak hours. The interested reader is referred to Appendix B: Modeling Supply, Figure A.2 to Figure A.5, where OSM views, satellite images, and the resulting SUMO network are shown. In the evening peak hours, the ramp modeling error would not have been noticed. In summary, it can be useful to load large networks with peak traffic demands (even if they are not part of the actual study period) to detect inaccuracies in the network that are otherwise difficult to identify by visual inspection of the static network elements alone.

4.2.2 Modeling Traffic Detectors

Traffic data was provided by *Die Autobahn GmbH* from the south and north offices of their respective areas of responsibility. Concretely, the traffic demand is derived from lane-fine traffic detectors, gathered from induction loops and overhead sensors. Both types are modeled as E1 detectors in SUMO. Before the actual modeling can be described, some naming conventions need to be introduced to avoid confusion. Usually, the term induction loop/overhead sensor location refers to a Global Positioning System (GPS) position of a group of neighboring detectors. There is no lane-fine position data for each detector. Generally, two aggregation levels are distinguished: Permanent Counting Location ("Dauerzählstelle") (DZ) and Cross-Section Measurement ("Messquerschnitt") (MQ). The DZ has only one GPS position for both directions of travel and is usually pointing between the two directional roadways of a motorway [BASt, 2020]. The MQ has a GPS position pointing to a specific direction of travel.

Analyzing the data, the aggregation level DZ is mostly found outside of VMS-controlled areas. Within VMS-controlled areas, the aggregation level MQ is identified. The detector locations are visualized in Figure 4.4 to get a better insight into the raw data.
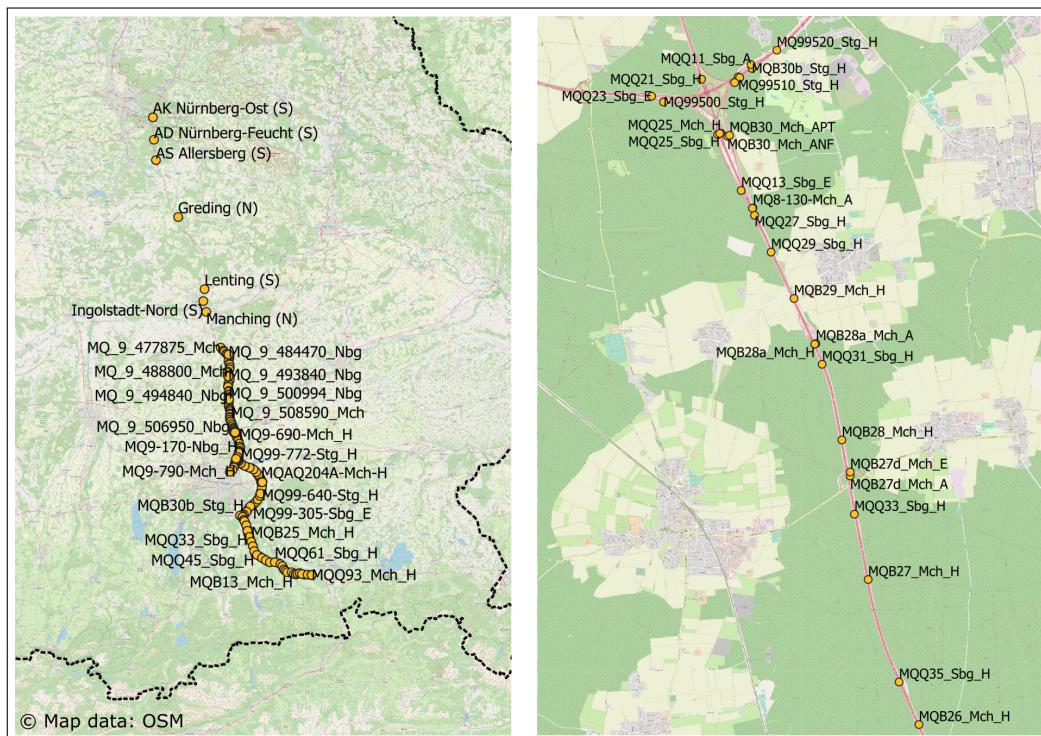
Figure 4.4: Detector locations (left). Close-up view A8 East end (right).

In south Bavaria, there are considerably more detector locations because of the VMSs on the A8 East, A99, and A9. Moreover, the MQ data provided for south Bavaria includes

both directions of travel, but only one is needed. In total, more than 300 GPS records are processed and the relevant ones are filtered out. Upfront filtering based on the name is difficult and error-prone due to inconsistent naming conventions. Therefore, the idea is as follows: First, all GPS positions are map-matched, and then the relevant detectors are extracted. With this approach three goals are achieved:

- Detector locations (WGS84) are located in the SUMO network (UTM-based custom coordinate system).

- Each lane of an edge is equipped with its own detector from a single DZ or MQ GPS position record.

- Relevant detectors (lane-fine) on the main trunk can be extracted.

A script is developed to automatically locate the detectors in SUMO and to save the metadata as an XML file. The script draws a radius of 10 m around each GPS position and the lanes are queried that fall within the circle. For each lane, it is computed to which edge it belongs. The most probable edge (for DZ locations, the most probable edge for each direction) is selected and the number of lanes is queried again. Finally, one detector is modeled on each lane.

With this approach, it is ensured that the right number of detectors is located on the main trunk for each cross-section from a single GPS position even if the record is not pointing on the trunk or is closer to other roads (i.e, ramps and neighboring streets). The script works well, but there are two caveats. First, sometimes, GPS positions are off by more than 10 m. It is not possible to increase the radius because this would cause problems for map matching of the remaining detector locations. Second, the script has difficulties locating detectors in special locations. Detectors on motorway feeders, e.g., on the connections of A8 East and A99 or A99 and A9, are not properly located. For the two aforementioned reasons, manual checks and corrections are required.

The last step is to build a route in SUMO to represent the trunk from *Dreieck Inntal* up to the *AK Nürnberg-Ost*. Dijkstra's algorithm with free-flow speeds as edge weights is used to compute the shortest path. Trucks are not allowed to use the *Mittlerer Ring* to cross Munich. Therefore, the algorithm is forced to visit one edge close to *AK München Ost* on the trunk, which ensures that the route follows the A99 instead of using the inner ring road. Finally, all edges of the route are traversed and checked for detectors. The output is an ordered list of detectors. Not all of the detectors in the list can send data in reality; therefore, only the ones for which data is provided can be used. There are multiple reasons why detectors do not send data. Technical failure is only one of them. Because of traffic works on the A99 (8-lane expansion between *AK München Nord* and *Aschheim*) and A9 (conservation works between *AS Langenbruck* and *AD Holledau*), there is no data

for some detector locations. How the effects of missing data are mitigated, and how many cross-sectional measurements can be ultimately used, is explained in the next section.

4.3 Modeling Demand

The overall aim of the simulation is to evaluate TOPTIPS on a typical workday when there is truck parking peak demand in the afternoon and evening. For the large-scale network under consideration, it is difficult to find a representative workday in the data. Therefore, the available data is averaged based on weekdays to approximate a typical workday. Tuesday, Wednesday, and Thursday are generally considered typical workdays because they are least affected by weekend commuters and other weekend-related patterns. It should be noted that the general term data refers to both the detector data and the truck parking occupancy data. The next section describes how the general traffic demand is derived. Afterwards, assumptions and derivations with respect to the truck parking demand are explained.

4.3.1 General Traffic Demand

As previously mentioned, the traffic demand is derived from short-term detector data. Short-term data is defined as data that captures traffic state variables in short aggregation intervals, typically 1-minute [BASt, 2012]. The minute-by-minute detector data is provided by the *Autobahn GmbH* for the same period as the truck parking occupancy data (January 15, 2020 at midnight to March 16, 2020 at midnight). The data provides basic, lane-fine information about the average velocity (time-mean speed) and the number of vehicles per time interval, differentiated by vehicle type (car and truck). The number of vehicles per time interval is traffic flow. It should be noted that the flow measurements are only an approximation of the actual demand. Particularly in congested situations, the actual demand can be higher than what is measured. Analyzing velocity and flow data at the same time helps to get a deeper understanding of the traffic states. This leads to the topic of traffic flow theory and Fundamental Diagrams (FDs), which were pioneered by GREENSHIELDS [1935]. For a good introduction, the interested reader is referred to TREIBER and KESTING [2013]. In the following, first, the data preprocessing methodology is described. As the data handling requires considerable computational resources, a brief explanation of the data preprocessing environment follows. Third, the derivation of the SUMO demand input from the preprocessed data is described.

Data Preprocessing Methodology

In general, the data differs slightly between the different business entities north and south Bavaria of the *Autobahn GmbH*. In addition, differences are noted with respect to the data source (DZ or MQ). In the first step, the data is unified to conform to a common scheme. It should be noted that erroneous and missing data is encoded by the value 255 according to the Technical Delivery Requirements for Roadside Units ("Technische Lieferbedingungen für Streckenstationen") (TLS) [BASt, 2012]. Even tough velocities of 255 km/h are theoretically possible, all values of 255 in the data are excluded and treated as erroneous.

Additionally, with respect to the DZ data sources, the data records for the correct direction of travel need to be selected, which can be done with the information of the Data Device ("Daten-Endgerät") (DE) channel. The German Federal Highway Research Institute ("Bundesanstalt für Straßenwesen") provides recommendations in the TLS on the numbering of DE channels [BASt, 2012]. Each motorway is considered either a north-south (e.g., A9) or west-east connection (e.g., A8). The direction of travel 1 is north or east and numbered with the DE channels 1 to 31. It is recommended to start with 1 in the rightmost lane. The direction of travel 2 (either south or west) is numbered with DE channels 33 to 63. It is recommended to start with 33 in the rightmost lane. Consequently, the data records for the A9 need to lie within 1 to 31 (direction of travel 1) and for the A8 within 33 to 63 (direction of travel 2).

Moreover, there are traffic works along the trunk which cause construction-related congestion and data gaps. Obviously, both effects are not desired. In the north of the *AD Holledau*, phase 1 of the construction project, called conservation works, lasted from December 2019 until November 2020. To address the issue of missing data and construction-related congestion patterns, data from 2019 for the same period is used as a surrogate. Unfortunately, this approach does not work for the construction project on the A99. In conclusion, a total of 79 cross-sectional measurements along the trunk can be used in the calibration procedure.

After having consolidated all relevant data and having put it into a common format, the minute-by-minute lane-fine flows and velocities are aggregated per measurement cross-section. In terms of the velocities, the weighted average $\bar{v}_{cross-section} = \frac{\sum_{i=1}^{l} n_i * \bar{v}_i}{\sum_{i=1}^{l} n_i}$ is computed. The number of lanes is denoted with l. The reported velocity $\bar{v}_i$ of lane i is weighted with the number of vehicles n_i. This results in velocity values for each cross-section in 1-minute intervals, which are then averaged for each day of the week. The output is typical minute-by-minute velocity values for each day of the week and measurement cross-section, which can be analyzed using contour plots [TREIBER and KESTING, 2013]. Contour plots for specific weekdays will be shown when the calibration and valida-

tion results are discussed in Section 4.4 Calibration and Validation. For a first impression, a heatmap representation can be found in Appendix C: Modeling Demand in Figure A.6.

With regard to the flows, the lane-fine values are summed up in order to obtain the total flow per cross-section in 1-minute intervals, and they are then further aggregated into hourly flows. The flows are used to approximate demand in SUMO with the help of the *routeSampler* script, which is explained later. For now, it is only important to group the hourly flows by measurement cross-section, day of week, and hour of day before they are averaged. This results in typical hourly flow values for each day of the week and measurement cross-section, which is shown in Figure 4.5. A version including detector locations that do not send data can be found in Appendix C: Modeling Demand in Figure A.7.

Some general observations can be made with respect to the flows. The vertical stripes in bright and dark show the variation of flows during the weekdays. Higher flows are observed between 6 a.m. and 6 p.m. (on Sundays later). The horizontal darker strip at the MQB30_Mch represents the two-lane feeder from the A99 to the A9. Another location with lower flows throughout the day is between the MQ9-350-Nbg_H and the MQ_-9_51..00_Nbg. The MQ9-361-Nbg_H is located inside the *AK Neufahrn* after the A92 branches off to *Deggendorf* and before the A92 branches in. In-depth investigation shows that it has the same GPS coordinates as the MQ9-360-Nbg_H and that the two lie on top of each other. However, the MQ9-361-Nbg_H only consists of two lane-fine detectors, whereas the MQ9-360-Nbg_H is linked to three. Most probably this is an error in the raw data, which is very difficult or even impossible to spot visually when the detectors are map matched. As the A9 has three lanes inside the motorway interchange, the MQ9-361-Nbg_H, which is responsible for the dark horizontal stripe, is excluded. Another interesting phenomenon is the outbound evening peak from Munich on the A9. The pattern is clearly visible and similar for Tuesdays, Wednesdays, and Thursdays. On Saturdays, there is considerable demand on the entire trunk, which could partially be due to ski traffic returning home. On Sundays, demand seems to occur somewhat later than on the other days of the week, which can be seen from the wider dark vertical bar between Saturdays and Sundays.

In summary, the processed velocities and flows are a prerequisite to setting up the simulation. The flows are used, among other things, to derive the demand input for SUMO. It should be noted that the composition of the traffic is important [GEISTEFELDT and SIEVERS, 2017; FGSV, 2015]. Therefore, not only the total flows are calculated, as just described and shown in Figure 4.5, but also the flows with respect to the vehicle types: car and truck. This allows modeling the demand in SUMO considering the real traffic composition.
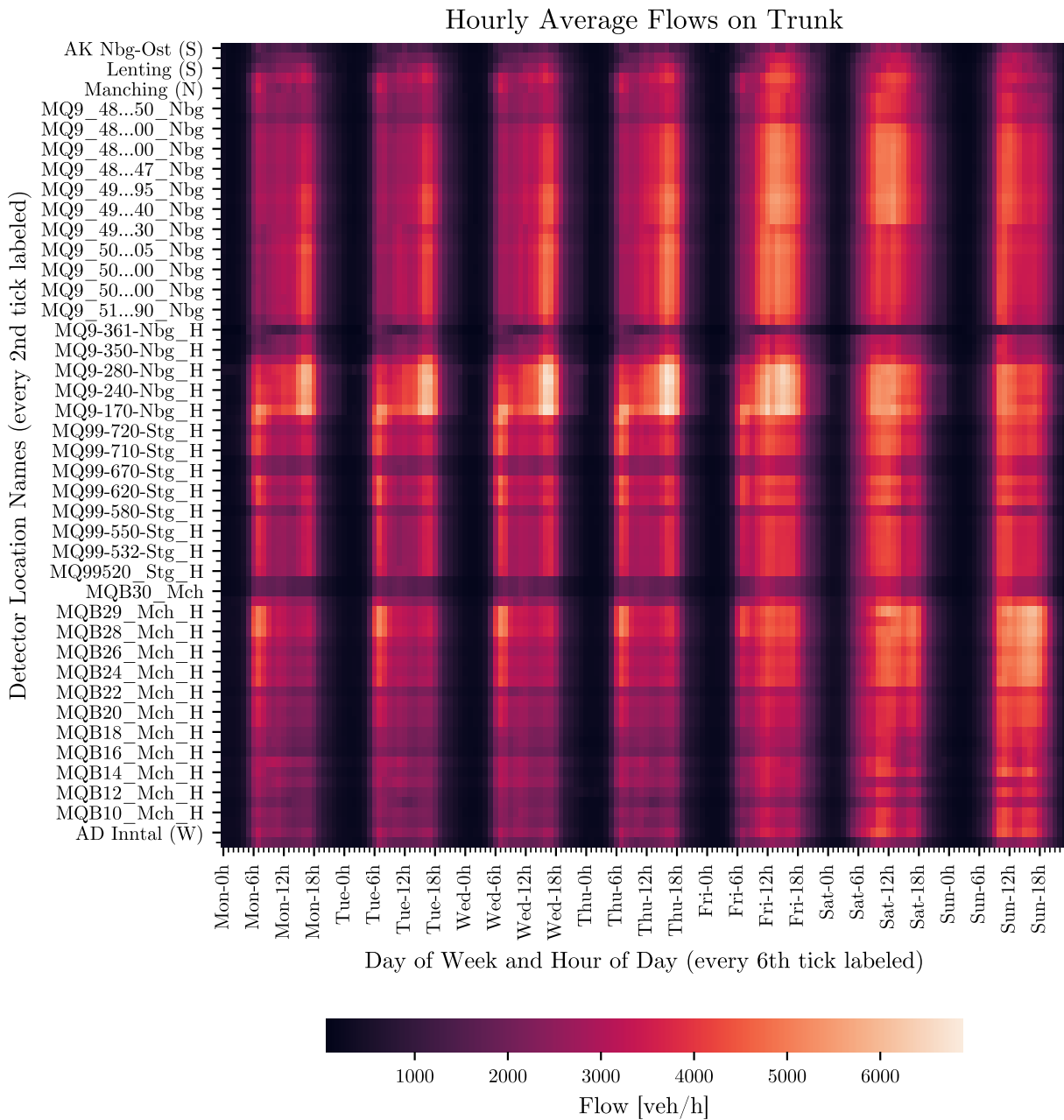
Figure 4.5: Hourly averaged flows on trunk

Data Preprocessing Environment

The preprocessing of the large amount of data requires considerable computational resources. Roughly speaking, there are more than 20 million data records for every two months. Therefore, a server with docker technology is used to process the data. In Figure 4.6, an overview of the preprocessing environment is shown. The raw data is either sent to a private laptop or a server running docker technology. Prototyping, development,
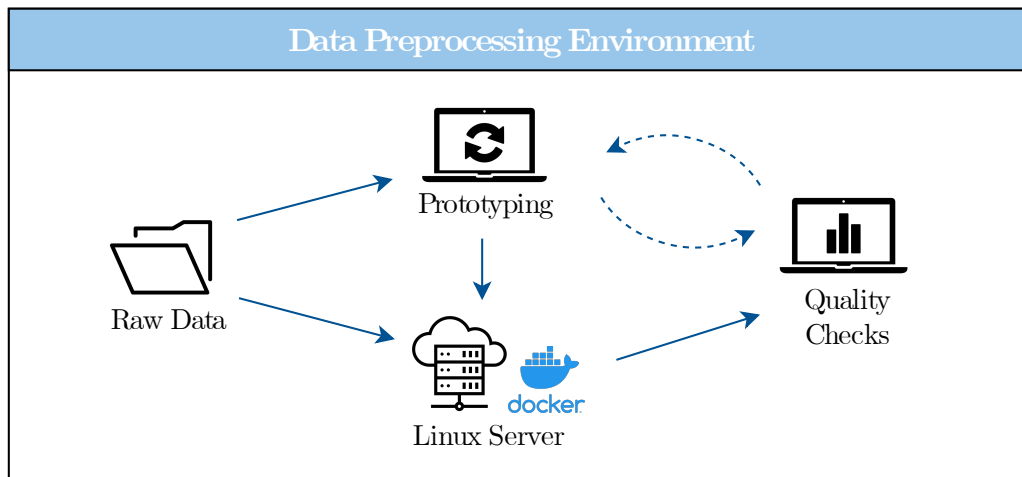
Figure 4.6: Resource efficient data preprocessing

and testing is conducted on the laptop. Concretely, this means that the preprocessing code is developed and tested using only a subset of the data. It allows for flexible development and fast bug fixing but comes at slower processing times. Although many steps of data preprocessing can rely on fast implementations in the C programming language through Cython, some critical steps cannot. The weighted mean implementation in pandas for averaging the velocities, for example, cannot take advantage of fast C building blocks. Therefore, the computational resources of a server are used. Once the code is mature, it is packaged up through a docker image. The image can be sent to the server and run as a container. This not only allows for leverage of the computational resources of the server, but also keeps the operational overhead of the server low at the same time. Moreover, the docker approach ensures that the same library versions and dependencies that are used for prototyping are used on the server as well. Thus, no dependency conflicts or unexpected code behavior is encountered. The results of the container are written to a persistent storage and sent back to the laptop with a graphical user interface. It is used for final quality checks, calculation of aggregated statistics, and plotting.

General Traffic Demand Generation for SUMO

At this point, the hourly flows for the detector locations for typical Mondays through Sundays are available. TOPTIPS should be evaluated for a typical workday. Therefore, data for a typical Tuesday is used to derive the demand and calibrate the SUMO simulation. A typical Wednesday serves for simulation validation. As mentioned earlier, the *routeSampler* script plays an important role in generating the SUMO demand from the hourly detector location flows. The script is open source and needs a set of predefined SUMO routes as input [Lopez et al., 2018]. Routes are drawn from the input set to best

fulfill the edge counting data.

Edge counting data is defined as counts on an edge per time interval in SUMO. The hourly flows of the detectors need to be converted to this format. The detector location is mapped to the respective edge on which it is located, and the hourly flows are assigned to it. However, there is a caveat to consider. Two or more detector locations can end up on the same edge in SUMO, in particular when the distance between the locations is small. As the name suggests, there cannot be different counts for an edge. If two or more detectors are located on the same edge, one is chosen randomly. In total, 66 detector locations can be processed to edge counting data and are used as input for the *routeSampler* script.

A set of predefined SUMO routes is the second required input. Therefore, source and sink edges are defined for the trunk. Each on-ramp of the trunk is considered a possible source, and each off-ramp is considered a possible sink. An additional source is located at the beginning of the trunk and an additional sink at the end of the trunk. At motorway interchanges, respective sources and sinks are also identified. In total, there are $|S_{sources}| = 43$ sources and $|S_{sinks}| = 40$ sinks. Each source is connected to all sinks ahead and routes are built. Obviously, each sink i must not be connected to the sources ahead, represented by the set $S^i_{sourcesAhead}$. This results in 875 possible source-sink pairs, which is shown in Equation 4.1.

$$\underbrace{\binom{83}{2}}_{A} - \underbrace{\binom{43}{2}}_{B} - \underbrace{\binom{40}{2}}_{C} - \underbrace{\sum_{i \in S_{sinks}} |S^i_{sourcesAhead}|}_{D} = 875 \tag{4.1}$$

The first part A captures the number of combinations that two items can be drawn from the set $S_{total} = S_{sources} \cup S_{sinks}$. Part B and C subtract the number of combinations for the instances that the two items are either two sources or two sinks. Part C further reduces the number of combinations because there must not be tuples with a sink and a downstream source. Routes are built for all possible source-sink pairs with Dijkstra's algorithm. Ultimately, it is sampled from this set of routes to best match the edge counting data. Additionally, weights can be assigned to the routes to increase the probability of being sampled. This is useful during the calibration process because some routes may be more likely than others. In summary, the route sampling approach helps to set up large-scale traffic simulations, but upfront possible routes need to be created. It should also be noted that the aim is to match real-world countings and velocities on the motorway trunk, but this does not necessarily mean that route lengths or origin-destination pairs match. However, this advanced level of detail is not required for the purpose of evaluating TOPTIPS. The used simulation parameter settings can be found in Appendix C: Modeling Demand in Table A.1.

4.3.2 Truck Parking Demand

Truck parking demand is derived from the parking occupancy data, which was introduced in Section 4.1 Truck Parking Data. As for the general traffic demand, data for a typical Tuesday is the basis for calibrating the SUMO simulation. How the demand is derived is explained with the help of an example.
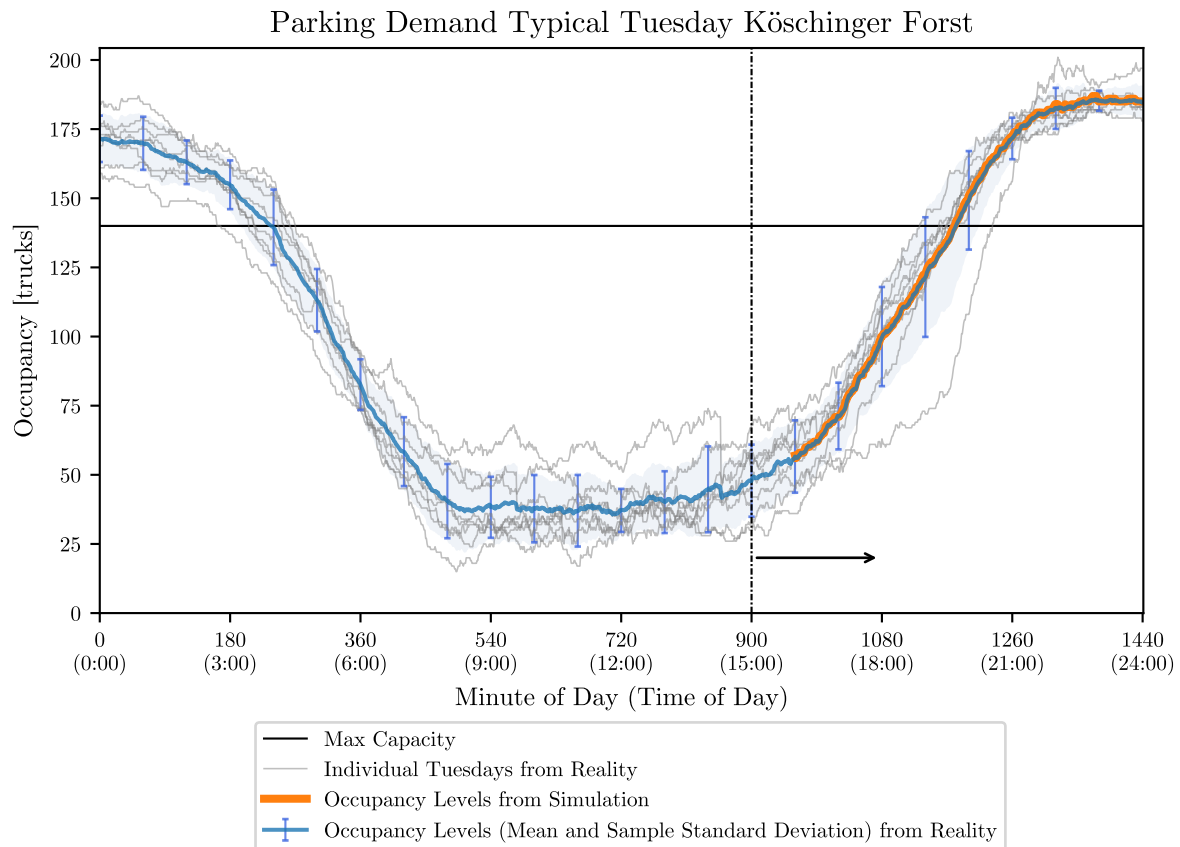
Figure 4.7: Truck parking demand reality vs. simulation - example Köschinger Forst

Figure 4.7 shows the occupancy over time in gray for each of the eight Tuesdays in the available data set. The average occupancy of a typical Tuesday is plotted in blue with error bars for every hour and error band (shaded area) for every minute. As previously mentioned, TOPTIPS should be evaluated between 4 p.m. and midnight; therefore, the SUMO truck parking demand needs to be generated for this period. Generally, the demand derivation requires some simplifying assumptions, which are covered in the next section. The result is truck parking demand that can be simulated in SUMO, which is shown in orange and will be explained in more detail in the next section as well.

Simulating truck parking requires modeling the current occupancy of a rest area in every simulation step. Therefore, a custom occupancy detection module is developed that keeps

track of the current occupancy. For each rest area and simulation step, the module needs to check whether incoming trucks or leaving trucks are detected. Even though it is difficult to see in Figure 4.7, trucks departing from a rest area not only occur in the early morning hours but also, albeit to a much lesser extent, in the evening hours. In summary, the occupancy detection module is computationally expensive as the custom code has to interface with the simulation in every simulation step. However, it is essential to simulate truck parking.

Truck Parking Demand Generation for SUMO

The aim of truck parking demand generation is that the current occupancy shown by the occupancy detection module in the simulation should correspond to the occupancy curve of a typical Tuesday between 4 p.m. and 12 a.m. as closely as possible. In other words, trucks should enter and leave the rest areas as they do in reality. To achieve this goal, the occupancy curve is traversed minute-by-minute and three cases are distinguished: declining, constant, and rising occupancy levels. For declining values, the respective number of trucks is subtracted in the occupancy detection module in the respective minute. Constant levels imply that no trucks entered or left the rest area. However, this is not quite true. If the same number of trucks enter and leave a rest area within 1 min, the occupancy data shows no change. The same logic applies to the other two cases of rising and declining levels. Consequently, the occupancy curve is only an approximation of the real in- and outflow subject to the sampling rate of 1 min. In the third case, the values are increasing, which means that the corresponding number of trucks must be inserted into the simulation at some point in advance.

At this point, some assumptions are necessary because the occupancy data neither identifies individual trucks nor includes the origin and the route of a truck. However, it turns out that the origin of a truck is only of minor importance because the literature suggests that drivers do not or cannot plan to park well in advance and choose where to park towards the end their shift [SMITH et al., 2005; GOLIAS et al., 2020; METZGER and SPANGLER, 2021]. Concretely, GOLIAS et al. [2020] found that the majority of truck drivers plan parking 1 h to 3 h in advance. In order to evaluate TOPTIPS with fewer degrees of freedom (conservative approach) and to reduce the uncertainty of the route choice, one hour is chosen as the temporal lead. With regard to the spatial lead, the following assumptions are made. As the route of the trucks within the last hour is not known, any location in the network with a travel time of 1 h is theoretically possible. Complicating the matter, the travel time is dependent on the traffic states along the possible routes. Consequently, the traffic states for each rest area within a catchment area of 1 h would be required, which is almost impossible to obtain. In conclusion, the actual routes taken by the parking trucks

are not known and cannot be derived from the available data. However, the following observation is made: The actual routes do not necessarily have to be known because only the Estimated Travel Time (ETT) is required for TOPTIPS. Consequently, the trucks can be assumed to be on the trunk 1 h in advance of parking and are assumed to follow the trunk route. It should be noted that the terms ETT and predicted travel time are used interchangeably.

The assumption that the trucks follow the trunk is also useful because of another reason. In Section 3.1.1 High-Level System Overview, it is explained that ETT information can be provided by any supplier of Real-Time Traffic Information (RTTI) and is considered to be given. For the present simulation study, the ETTs need to be reconstructed from the traffic states of the simulation using virtual trajectories. The details are explained later in Section 4.5.2 Travel Time Estimation. For now, it suffices to note that ETT information can be derived from the simulation as a surrogate for externally provided RTTI.

Another important assumption concerns the unused Hours of Service (HOS) when the trucks park. In a joined project of the Technical University of Munich (TUM) and the Competence Centre for Traffic Management ("Zentralstelle für Verkehrsmanagement") (ZVM), 140 truck drivers were surveyed on the A9 [METZGER and SPANGLER, 2021]. According to the responses, the drivers have 36 min left on average when parking. As survey data might be subject to bias, the literature is consulted for further evidence. The work of BORIS and BREWSTER [2018] provides additional valuable insight as the authors used travel diary data from 148 truck drivers to investigate unused HOS time. The results show that the majority of drivers (86 %) have more than 30 min left when they park. For the simulation study, 30 min of unused HOS when parking is assumed for each truck driver. This again follows the conservative assumption approach since TOPTIPS gets fewer degrees of freedom. As a consequence, trucks need to be inserted into the simulation with 90 min of remaining HOS.

In conclusion, rising occupancy levels in the data lead to the respective number of trucks being inserted 1 h in advance, 80 km upstream, and with 90 min remaining HOS of the respective rest area. The result is shown for the example rest area in Figure 4.7, where the orange line matches the blue line quite well. For an overview of the simulated filling curves of all rest areas, the interested reader is referred to Appendix C: Modeling Demand, Figure A.8. It should be noted that the approach may lead to a slight overestimation of trucks on the trunk (general traffic demand). A truck that is traveling on the trunk, for example, is already accounted for by the detector data. However, the overestimation is considered to be negligible since a total of 806 trucks are added in this way over nine hours.

4.4 Calibration and Validation

"Essentially, all models are wrong, but some are useful" [Box and Draper, 1987, p. 424]. This famous quote by George Box underscores the fact that a model can never be an exact representation of the real world but only an approximation. Further, the approximation does not include all aspects of reality but only those that are of interest to the study objective. Treiber and Kesting [2013] emphasize this fact well by focusing on the intended use of a model: "Validation is the process of determining the reliability of a model, i.e., the degree to which it is an accurate representation of the real world from the perspective of the intended uses" [Treiber and Kesting, 2013, p. 333].

In this section, the question is answered how well the simulation reproduces real traffic for the study objective of truck parking. The aim is to evaluate TOPTIPS on a typical working day between 4 p.m. and midnight. A typical Tuesday between 3 p.m. and midnight is used to calibrate the simulation. The validation is based on a typical Wednesday for the same period. With regard to TOPTIPS, the ETTs for a truck to reach potential rest areas are critical input parameters that depend on the traffic states along the route. Most importantly, the realized speeds within the traffic states are of interest as they translate directly into travel times. In order to quantify the correspondence between reality and simulation, the chosen assessment criteria must particularly take into account velocities. Therefore, metrics that are based on the comparison of spatio-temporal velocity patterns and travel time differences are included. The following four metrics are selected in order to determine the goodness of fit:

- Traffic flow deviation at detector locations (quantitative)

- Contour Plot Analysis (qualitative)

- Squared Inverse Mean Percentage Error (quantitative)

- Travel Time Difference Index (quantitative)

The traffic flow deviation is a standard metric mentioned in simulation guidelines [FGSV, 2006; FHA, 2019] and should provide a first impression of the goodness of fit. It is followed by a visual qualitative analysis of contour plots which focuses on the realized velocities in space and time. In order to harden the qualitative assessment, the metrics Squared Inverse Mean Percentage Error (SIMPE) and Travel Time Difference (TTD) index are evaluated. They were originally developed for RTTI quality assessment by Huber et al. [2014] and are applied in a modified form for calibration and validation. Coincidentally, this opens up new areas of application for these metrics in the field of traffic simulation. Both measures rely upon traffic state reconstruction. Therefore, the chosen reconstruction approach is briefly explained in the following before the evaluation of the metrics is presented.

Adaptive Smoothing Method by Treiber and Helbing

Stationary traffic detectors can capture traffic state variables only at fixed locations in space. Traffic state reconstruction aims to obtain the desired variable in the entire space-time region of interest as function $Z(x,t)$ with $x \in [x_{first}, x_{last}]$ and $t \in [t_{start}, t_{end}]$, i.e., for any point between the first and the last detector and any time between the start and the end of the measurement period. For this thesis, the robust and well-established Adaptive Smoothing Method (ASM) from TREIBER and HELBING [2003] is applied to the measured velocities v_i from any detector at time t_i and location x_i for $i = 1, \ldots, n$. One of the main advantages of the method is the an-isotropic smoothing between detector locations in space and time which considers general traffic properties. In free flow conditions, perturbations propagate into the direction of travel with almost constant velocity of $c_{free} \approx 80\,\mathrm{km/h}$ on motorways. In congested states, perturbations move upstream with almost constant velocity of $c_{cong} \approx -18\,\mathrm{km/h}$. The main idea of the ASM is the superposition of the free flow speed field V_{free} and the congested speed field V_{cong} by weighting the two fields with $w(V_{free}(x,t), V_{cong}(x,t)) \in [0,1]$:

$$V(x,t) = w(x,t)\, V_{cong}(x,t) + (1 - w(x,t))\, V_{free}(x,t) \tag{4.2}$$

$$w(V_{free}(x,t), V_{cong}(x,t)) = \frac{1}{2}\left[1 + \tanh\left(\frac{V_c - \min(V_{free}(x,t), V_{cong}(x,t))}{\Delta V}\right)\right] \tag{4.3}$$

The weight $w(V_{free}(x,t), V_{cong}(x,t))$ should be close to 0 for free flow states and close to 1 for congested traffic states. The two speed fields are obtained by spatio-temporal interpolation using the kernel ϕ_0 and the respective normalization constants $\mathcal{N}_s$ with $s \in \{free, cong\}$:

$$V_{free}(x,t) = \frac{1}{\mathcal{N}_{free}(x,t)} \sum_i \phi_0\left(x - x_i, t - t_i - \frac{x - x_i}{c_{free}}\right) v_i \tag{4.4}$$

$$V_{cong}(x,t) = \frac{1}{\mathcal{N}_{cong}(x,t)} \sum_i \phi_0\left(x - x_i, t - t_i - \frac{x - x_i}{c_{cong}}\right) v_i \tag{4.5}$$

$$\mathcal{N}_s(x,t) = \sum_i \phi_0\left(x - x_i, t - t_i - \frac{x - x_i}{c_s}\right) \quad \text{with } s \in \{free, cong\} \tag{4.6}$$

$$\phi_0(x,t) = \exp\left[-\left(\frac{|x|}{|\sigma|} + \frac{|t|}{\tau}\right)\right] \tag{4.7}$$

The result is a smooth filter function $V(x,t)$ that accurately captures the underlying traffic states and propagates perturbations in the respective directions. When solving the ASM numerically, the filter function is discretized in Δx and Δt. An overview of the parameters, which are based on SCHREITER et al. [2010], is given in Table 4.1. In general, TREIBER and KESTING [2013] note that the ASM is very robust with regard to the specific values

Parameter	Value	Description
c_{free}	$80\,\text{km/h}$	Free flow propagation
c_{cong}	$-18\,\text{km/h}$	Congestion propagation
σ	$500\,\text{m}$	Spatial kernel length
τ	$60\,\text{s}$	Temporal kernel length
V_c	$70\,\text{km/h}$	Cross-over speed (free-congested)
ΔV	$10\,\text{km/h}$	Length of transition region
Δx	$200\,\text{m}$	Spatial discretization
Δt	$60\,\text{s}$	Temporal discretization

Table 4.1: Parameters used for ASM smoothing

of the parameters as long as they are in the correct order of magnitude. Moreover, the required processing times can be significant, in particular for large spatio-temporal regions, as it is the case in this thesis. Therefore, the enhanced implementation by SCHREITER et al. [2010] using cross-correlation is applied. It is based on fast matrix calculations instead of looping over the data. The resulting velocity field V can be visualized using contour plots and provides a qualitative way of assessing the simulation quality. The contour plots can be seen in Section 4.4.2 Contour Plot Analysis for both real and simulated data.

4.4.1 Analysis of Traffic Flow Metric

The flow deviation metric is intended to evaluate the extent to which the traffic volumes of the simulation match the flows measured in reality. The hourly flow values of the reality are already available due to the data preprocessing described earlier. The respective flow values of the simulation need to be aggregated from the minute-by-minute SUMO raw data output of the detectors. The absolute relative flow deviations $q_{i,h}^{absdiff} = \frac{|q_{i,h}^{simulation} - q_{i,h}^{reality}|}{q_{i,h}^{reality}}$ for the detector locations $i = 1, \ldots, 66$ and the hours of interest $h = 15, \ldots, 23$ are shown in Figure 4.8. It can be observed that the calibrated simulation exhibits vehicle flows that match the real data quite well. $90.0\,\%$ of the hourly detector flows have an absolute relative deviation of less than $20\,\%$. With regard to the validation, still $87.0\,\%$ fall in the same range. In general, the two histograms of calibration and validation show similar shapes. Yet, not surprisingly, the validation histogram exhibits some more absolute relative deviations in the region of $40\,\%$. To provide some more quantitative figures, the RMSE $= \sqrt{\frac{\sum_{h=15}^{23} \sum_{i=1}^{66} (q_{i,h}^{simulation} - q_{i,h}^{reality})^2}{66 \times 9}}$ of the simulated and real flows is calculated. The calibration has a Root Mean Square Error (RMSE) of $181\,\text{veh/h}$. The validation exhibits
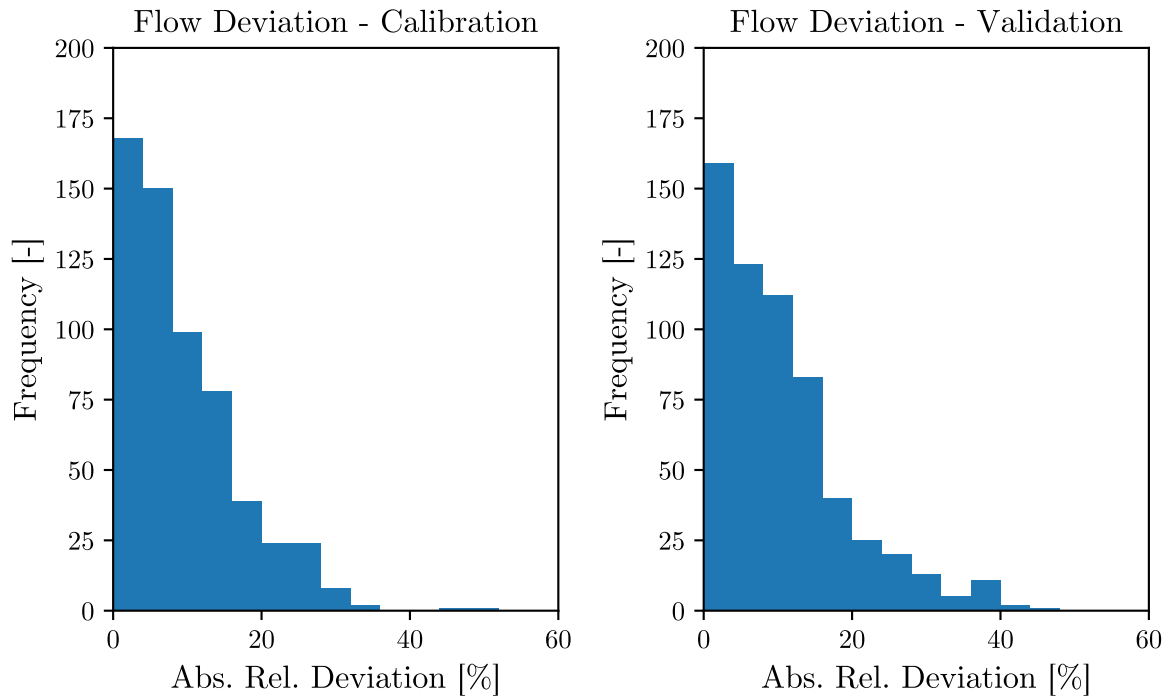
Figure 4.8: Calibration and validation metric: absolute relative flow deviation

slightly increased values with 244 veh/h. Another approach to compare the flow values is proposed by LOPEZ et al. [2018]. The authors suggest that the 85th percentile of the flow differences between simulation and reality should be 15 % or less. The 85th percentile of the calibration is 17.7 % and the respective value for the validation is 18.8 %. The reference from the literature is almost matched. Given that the present large-scale microscopic simulation is subject to research, the figures are acceptable. In summary, the three different sub-metrics (I) absolute relative flow deviations, (II) RMSE, and (III) 85th percentile give a first hint of a sufficiently calibrated and validated traffic simulation for the purpose of the TOPTIPS evaluation.

4.4.2 Contour Plot Analysis

The visual inspection of the contour plots shifts the focus from the flows to the realized velocities, which are of greater interest for the TOPTIPS evaluation. The calibration contour plots for reality and simulation are shown in Figure 4.9 and Figure 4.10. It should be noted that the names of the detector locations are simplified, shortened, and only a selection is displayed. It is intended to give the reader an orientation by mentioning the respective motorway or DZ name and, at the same time, to leave enough space to display an entire day. For completeness, the contour plots are shown for an entire day, but only the time after 3 p.m. is relevant, which is indicated by the vertical dash-dotted

black line and an arrow pointing to the right.
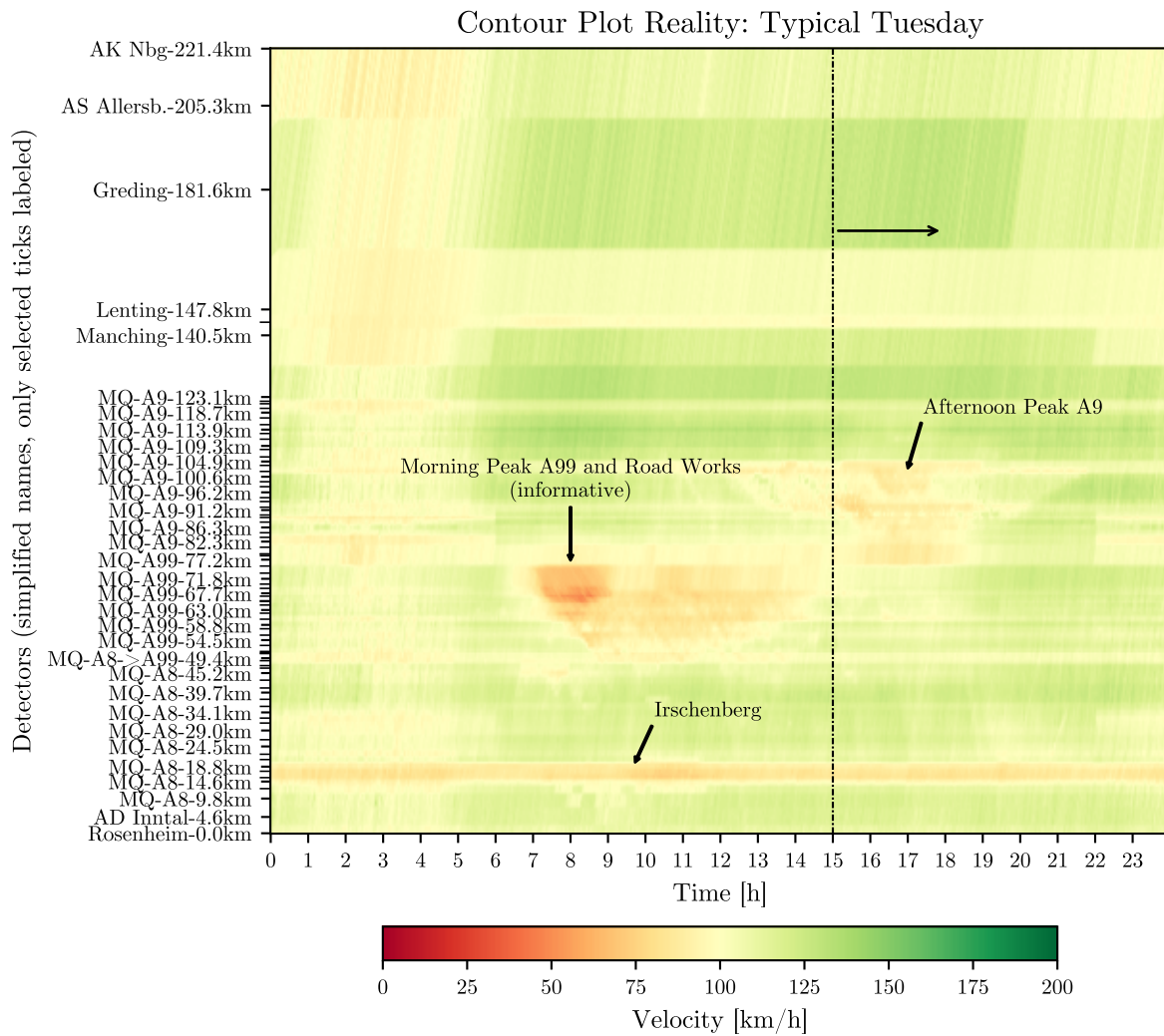
Figure 4.9: ASM smoothed contour plot reality of a typical Tuesday

With regard to the contour plot of reality, some general observations can be made. If they are relevant for the TOPTIPS simulation, reference is made to the contour plot of the simulation.

- Slower speeds can be observed on the entire trunk in the early morning hours. This is mainly due to higher heavy vehicle shares in this period. In Appendix D: Calibration and Validation in Figure A.9, average hourly heavy vehicle shares are shown for a typical week. The bright vertical stripes represent higher heavy vehicle shares in the early morning hours.

- A morning peak on the A99 can be observed. Presumably, there are several reasons for this pattern: First, the A99 exhibits a very high demand in general with up to 150 000 veh/day [DIE AUTOBAHN, 2022]. Second, there were smaller road works

on some of the days that could be identified using Consyst, which is an internal tool of *Die Autobahn GmbH*. This phenomenon is not relevant for the TOPTIPS simulation.

- There is an afternoon peak on the A9 between 3:30 p.m. and 6 p.m. which is relevant for the TOPTIPS simulation. The observed reduced velocities are modeled with VMSs set to 100 km/h. The results are noticeable in the SUMO contour plot.

- A horizontal stripe with reduced speeds can be observed in the lower part of the figure which represents a motorway stretch on the A8 East with steep inclination (more than 5 %) and VMSs, called *Irschenberg*. From earlier research in the direction of travel *Salzburg*, it is known that the inclination can lead to lower average velocities [GEISTEFELDT et al., 2017]. As the SUMO simulation does not consider inclination, VMSs set to 85 km/h are used to model the effects on this stretch.
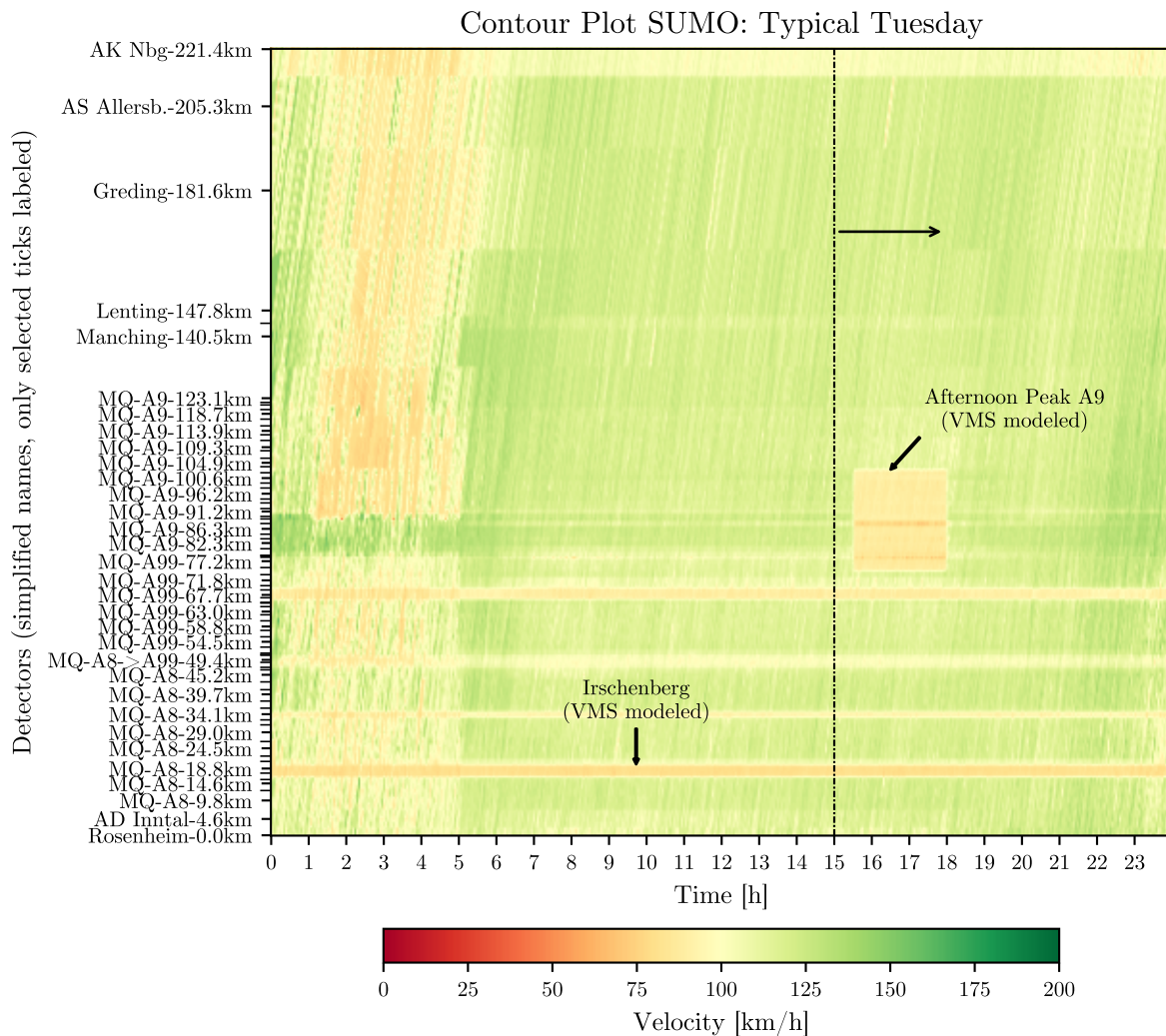
Figure 4.10: ASM smoothed contour plot SUMO of a typical Tuesday

For the validation, the simulated results are also compared to the real data of a typical Wednesday, which can be seen in Appendix D: Calibration and Validation in Figure A.10. In summary, the qualitative contour plot analysis shows a good match of real and simulated velocities during the relevant times in the afternoon and evening. The next section aims at analyzing the velocities more rigorously using a quantitative metric.

4.4.3 Analysis of SIMPE Metric

The SIMPE metric is well-suited to quantify the spatio-temporal velocity deviations between real and simulated data. For a detailed explanation of the SIMPE metric within the context of RTTI quality assessment, the reader is referred to Huber et al. [2014]. Only parts of the procedure are required when applying SIMPE for calibration and validation of traffic simulations. The novelty is to apply the methodology to a different field in traffic research, which is briefly explained in the following.

The trunk motorway stretch between the first and the last detector $x \in [x_{first}, x_{last}]$ is discretized by x_i for $i = 1, \ldots, n$, each with length Δx defined by the spatial resolution of the ASM. Likewise, the time period of interest $t \in [t_{start}, t_{end}]$ is discretized by t_j for $j = 1, \ldots, m$, each with length Δt defined by the temporal resolution. Further, let $X = \{x_i\}_{i=1}^n$ and $T = \{t_j\}_{j=1}^m$ define the sets of all x_i and t_j, respectively. The main idea is to compare the piece-wise constant reconstructed speed functions $V_{real} : \mathbb{R} \times \mathbb{R} \mapsto \mathbb{R}_{>0}$ and $V_{sim} : \mathbb{R} \times \mathbb{R} \mapsto \mathbb{R}_{>0}$, obtained by the application of the ASM, with the SIMPE metric for all $(x_i, t_j) \in X \times T$. It should be kept in mind that there are actually two different V_{real}, one for the calibration and another one for the validation, i.e., V_q with $q \in \{cal, val\}$. The SIMPE metric (modified for simulation assessment) for a grid cell (x_i, t_j) is given by

$$\text{SIMPE}_q(x_i, t_j) := \left(\frac{\frac{1}{V_q(x_i,t_j)} - \frac{1}{V_{sim}(x_i,t_j)}}{\frac{1}{V_q(x_i,t_j)}} \right)^2 \qquad q \in \{cal, val\} \tag{4.8}$$

The overall SIMPE error metric is defined by the weighted average over all cells as follows:

$$\text{SIMPE}_q := \frac{1}{w} \sum_{i=1}^n \sum_{j=1}^m w_{x_i,t_j} \, \text{SIMPE}_q(x_i, t_j) \tag{4.9}$$

$$w_{x_i,t_j} := \Delta x \, \Delta t \tag{4.10}$$

$$w := \sum_{i=1}^n \sum_{j=1}^m w_{x_i,t_j} \tag{4.11}$$

The weight of a cell is defined by the spatial and temporal area covered. For the case of simulation assessment, the weighting simplifies because of the constant grid cell area $\Delta x \Delta t$ induced by the ASM. In general, the SIMPE metric penalizes large errors more severely.

Values close to 0 are desirable as it is an error metric. Figure 4.11 shows the color-coded SIMPE values for a typical Tuesday and Wednesday. As with the contour plots, only the
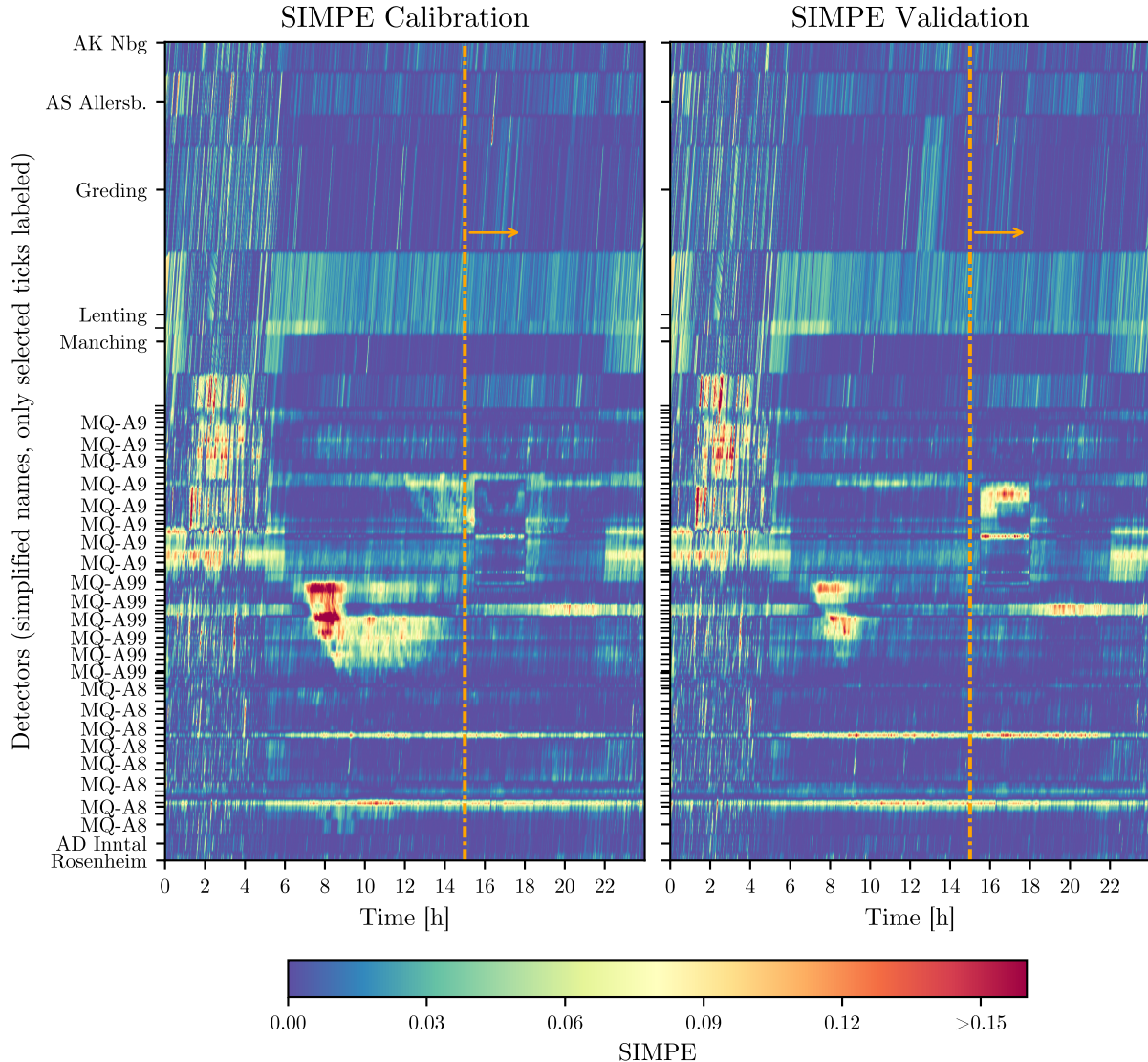
Figure 4.11: SIMPE calibration and validation metric

period after 3 p.m. (shown by the orange dash-dotted lines) is relevant for which almost similar SIMPE metrics result for calibration and validation. Concretely, calibration has a SIMPE value of 0.013 and validation of 0.011. Small and close SIMPE values are desirable because they show that the simulation models velocities in the afternoon and evening of a typical working day well. Visually, the biggest deviations (> 0.15) can be seen during the morning peak on the A99. However, this region is not in the relevant time span and not of interest for the TOPTIPS evaluation. It simply demonstrates the applicability of the SIMPE metric for the calibration and the validation of microscopic traffic simulations. In general, the SIMPE metric is a "very abstract measure" [HUBER et al., 2014, p. 16]

and difficult to interpret. Therefore, the authors derive a formula with which the SIMPE metric can be converted to a constant relative speed relation $f > 0$ between V_q and V_{sim}:

$$f_q = 1 - \sqrt{\text{SIMPE}_q} \tag{4.12}$$

The SIMPE values for both validation and calibration translate to $f \approx 0.89$, which is a good result. It suggests that velocities are slightly higher in the simulation than in reality. This is further investigated with the TTD index.

4.4.4 Analysis of TTD-Index Metric

Besides the highly technical and difficult to interpret SIMPE metric, HUBER et al. [2014] also propose the TTD index, which takes into account the customer perspective. Within the context of RTTI, customers are ultimately interested in the accuracy of the ETT. Since TOPTIPS requires ETTs as important input information for recommending rest areas, this metric is particularly suitable. The overall idea of the TTD index is to use virtual trajectories that start, for example, every five minutes and move through V_{real} and V_{sim}. The resulting travel times can then be compared and converted to an error metric.

First, the concept of virtual trajectories is explained. Then, the actual TTD index is described. Let a velocity field be given by $V(x, t)$ for $x \in [x_{first}, x_{last}]$ and $t \in [t_{start}, t_{end}]$. A virtual vehicle vv is defined as a vehicle that always travels with the speed given by the velocity field, i.e., $v_{vv}(t) = V(x_{vv}(t), t)$. Let a virtual vehicle start at t_{insert} at position $x_{first} = x(t_{insert})$ and travel up to x_{last}. In order to get the estimated travel time $t(t_{insert})$, the first-order ordinary differential equation

$$\frac{dx}{dt} = V(x(t), t) \tag{4.13}$$

is integrated numerically until the termination condition $x_{last} = x(t_{insert} + t(t_{insert}))$ is reached. An example of virtual trajectories is shown in Figure 4.12. The figure only serves to illustrate the general idea of virtual trajectories, and the selected time span is not of interest for TOPTIPS. Therefore, a spatio-temporal region during the morning peak is chosen that exhibits speed drops. Virtual trajectories are the basis for the TTD index. Applying the TTD index for simulation calibration and validation requires some modifications compared to the original use case. Three virtual vehicles depart at starting times t_i for $i = 1, \ldots, n$ and drive through the velocity fields V_{cal}, V_{val}, and V_{sim}, where V_{cal} denotes the field of a typical Tuesday and V_{val} of a typical Wednesday. For this thesis, virtual vehicles depart every five minutes, i.e., $t_{i+1} - t_i = 300\,\text{s}$. It should be noted that the entire space-time region $[x_{first}, x_{last}] \times [t_{start}, t_{end}]$ needs to be covered by the virtual trajectories. This implies that some trajectories lie partially outside of the defined
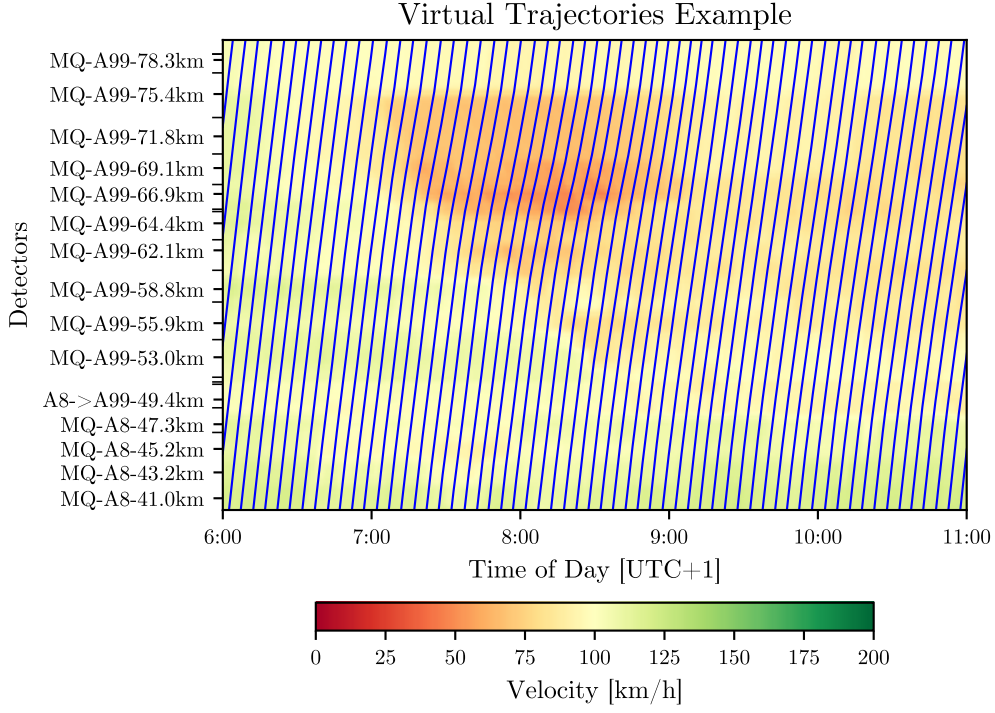
Figure 4.12: Example of virtual trajectories

region. Hence, the three velocity fields are extended, and free flow speeds of 130 km/h are assumed in the added regions:

$$V_{cal}(x,t) = V_{val}(x,t) = V_{sim}(x,t) := v_{free} \quad \forall (x,t) \notin [x_{first}, x_{last}] \times [t_{start}, t_{end}] \qquad (4.14)$$

The first and last virtual trajectories, which depart at t_1 and t_n, are chosen in such a way that they do not touch the relevant region and do not need to be considered. The TTD index aggregates the travel time differences into a scalar metric by calculating the Mean Square Error (MSE) of the relative travel time differences for $t_2, \ldots, t_{n-1}$.

$$\text{TTD}_q := \frac{1}{n-2} \sum_{i=2}^{n-1} \left(\frac{t_q(t_i) - t_{sim}(t_i)}{t_q(t_i)} \right)^2 \qquad \text{for} \ \ q \in \{cal, val\} \qquad (4.15)$$

As with the SIMPE index, the TTD index is only applied for the time of interest in the afternoon and evening. The results are $\text{TTD}_{cal} = 0.00135$ (calibration) and $\text{TTD}_{val} = 0.000688$ (validation). As the numbers are difficult to interpret, the authors provide a formula for conversion to a constant relative speed relation f. The TTD index for both calibration and validation translates to $f \approx 0.96$, which is a good result.

Before the derived travel times are aggregated into the TTD index, they can be visualized. For completeness, the travel times for the entire typical Tuesday and Wednesday are shown in Figure 4.13.
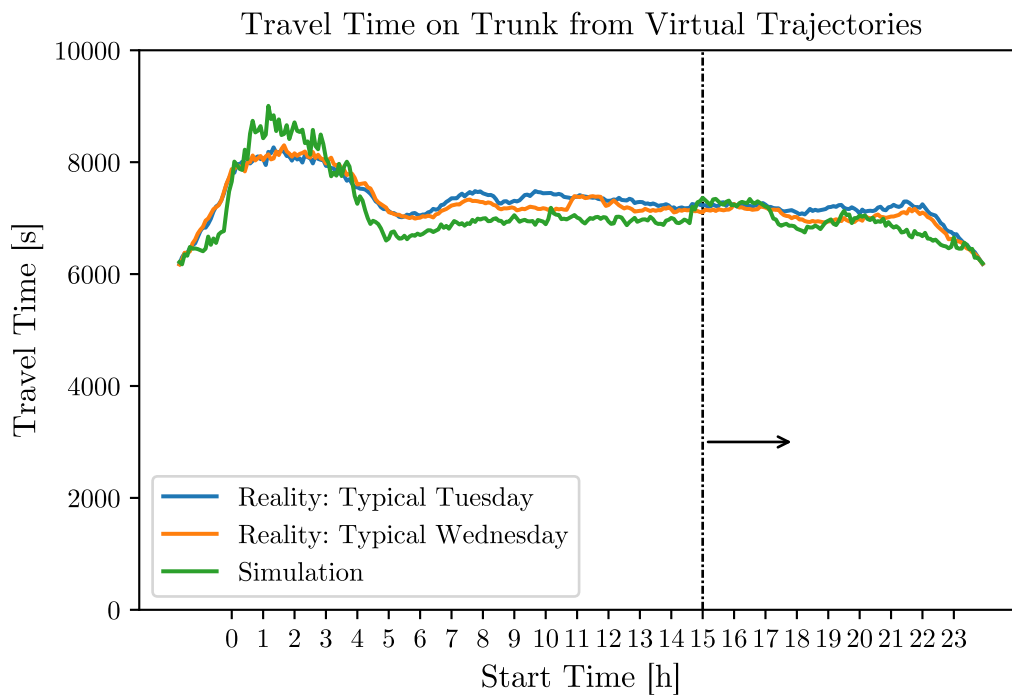
Figure 4.13: Travel times from virtual trajectories

The relevant time of the day is indicated with a vertical dash-dotted line. Even though the early morning hours are not of interest for TOPTIPS, the increased travel times during the night hours are interesting to study. Longer travel times are observed, which are primarily caused by higher heavy vehicle shares. This finding is in line with the contour plot shown in Figure 4.9 and the hourly heavy vehicle share plot in Appendix D: Calibration and Validation in Figure A.9. Moreover, the result suggests that the real vehicle composition is well matched in the simulation.

4.5 Interplay of Optimization, Simulation, and Travel Time Estimation

The validated simulation is one part of the TOPTIPS evaluation framework. The purpose of this section is to connect the dots between the optimization, the simulation, and the travel time estimation for TOPTIPS trucks. After this section, all prerequisites are in place to proceed to the results.

4.5.1 Overview Evaluation Framework

Figure 4.14 shows an overview of the evaluation framework. In the middle, the main module is depicted, which interfaces with the SUMO simulation, the optimization module, and the travel time estimation module. It is mainly responsible for four tasks: First, it conducts traffic state estimation, which is a prerequisite for the derivation of ETTs. Second, it monitors the occupancy of the rest areas. Third, it is responsible for handling all data flows within the application, logging events for error reporting, loading external data, and saving results. Lastly, it controls the simulation via the traci API. Concretely, for example, it controls the destinations of the TOPTIPS trucks or the speed limits shown on the VMSs. The traci interface also allows retrieving simulation variables. Important simulation variables are the position and the remaining driving time of the TOPTIPS trucks. Further, the current occupancy of the rest areas needs to be queried.
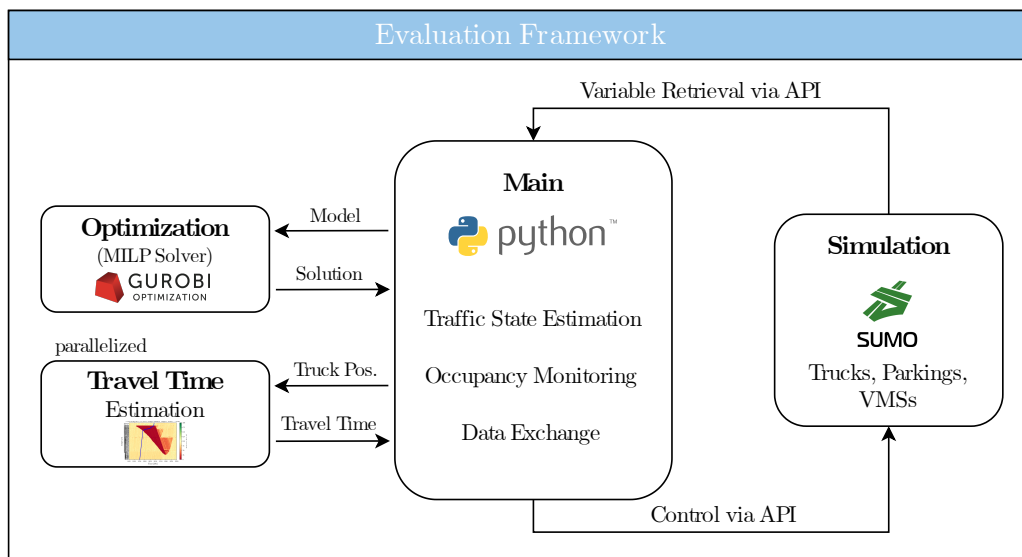
Figure 4.14: Main modules of the evaluation framework

The arrows on the right side connecting the main module and the simulation represent

a loop. After each simulation step, data is queried and transferred to the main module where various processing steps are carried out. The result is a set of new control inputs which are sent back from the main module to the simulation, represented by the arrow on the bottom right. The control commands such as the parking recommendations rely upon the modules on the left, which are called with optimization frequency f (e.g., $1.1\,\mathrm{mHz} \,\widehat{=}\,$ every 15 min). The retrieved data from the simulation is used to set up the mathematical optimization model. The model is sent to Gurobi, which tries to solve the optimization problem, and returns a solution. If a model is infeasible, the model is relaxed within the main module and the modified version is resent. Infeasible model states are explained in Section 3.2.3 TOPTIPS Modeling. The running time of the optimization depends mainly on the weighting combination, the number of trucks, and the current occupancy levels (the latter two depend on the time of the day). By and large, the running time is in the order of magnitude of some seconds. Occasionally, specific situations may take longer to solve. Therefore, the running time is upper bounded by 15 s, which ensures that TOPTIPS is applicable in practice. The best solution found within this given time limit is applied. Finally, one important input parameter to set up the optimization model has not yet been explained: ETTs for TOPTIPS trucks to reach potential rest areas. The interplay between the travel time estimation and the traffic state estimation module is explained in the following section.

4.5.2 Travel Time Estimation

Travel Time Estimation

Travel time estimation is based on traffic states. For the application of TOPTIPS in reality, it is assumed that ETTs are provided by a specialized RTTI provider. In the simulation, the ETTs for TOPTIPS trucks to reach potential rest areas need to be derived from the traffic states of the simulation. The ETTs should be as accurate as possible to obtain a baseline for the evaluation. Thereupon, it can be researched how TOPTIPS performs when ETTs exhibit typical real-world inaccuracies by adding noise.

As already demonstrated, travel time estimation can be conducted using virtual trajectories and a velocity field, represented by a contour plot. In order to achieve the highest traffic state representation accuracy possible, a velocity field is constructed from lane-based mean speeds (i.e., lane-specific space-mean speed) with a temporal resolution of 30 s and spatial resolution corresponding to the edge/lane lengths (mean length: 398 m) of the trunk. This velocity field captures more details than the velocity field reconstructed from the detectors. Further, no ASM is applied. It should be noted that edge-based mean speeds are less accurate because every on- and off-ramp distorts the edge measurements.

As trucks are most often found on the right lane, a heuristic is developed to always pick the rightmost lane of an edge. When on- and off-ramps are present, the first lane to the left of the ramp lane(s) is chosen. The result is a high accuracy contour plot, which is obtained by running the simulation once without any TOPTIPS control inputs to collect lane-based speeds. In subsequent runs, the current TOPTIPS truck positions are used to insert the trucks into the high accuracy contour plot and to derive the ETTs by means of virtual trajectories. The virtual trajectories take into account the maximum allowed velocity for trucks with the parameter v_{truck}^{max}, which is set to $22.22\,\text{m/s}$. The differential equation shown in Equation 4.13 is adapted respectively as follows:

$$\frac{dx}{dt} = \min(V(x(t), t),\ v_{truck}^{max}) \tag{4.16}$$

In summary, the high spatial and temporal resolution allows approximating travel times within the simulation well. Another advantage of this approach is explained in the following.

Multi-Destination Estimation

TOPTIPS requires ETTs for all trucks to all potential rest areas. Only rest areas that can be reached within the remaining driving time are considered feasible. This means
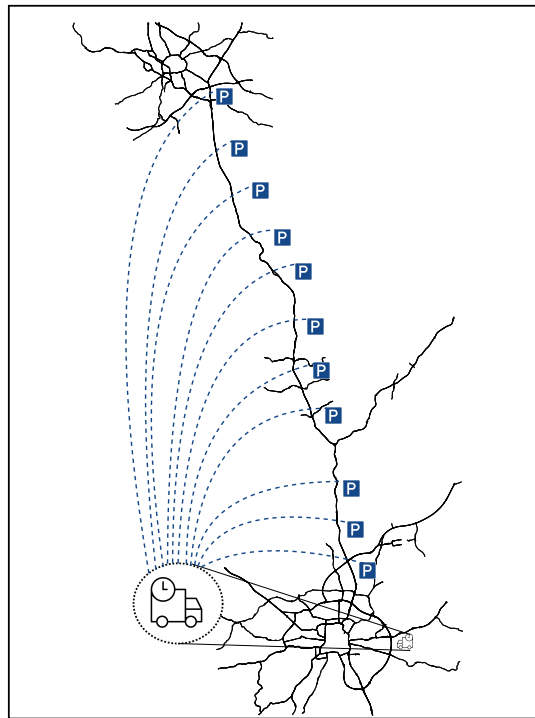
Figure 4.15: Visualization of multi-destination travel time estimation

that for each truck multiple virtual trajectories need to be constructed, i.e., one for each potential rest area. In the following, this is also called multi-destination estimation, which is sketched for a single TOPTIPS truck on the A99 in Figure 4.15. The approach with virtual trajectories and a priori constructed velocity field allows to estimate travel times for any truck at any position in space and time to any potential rest area. Traffic jam avoidance is a scenario where this is of particular interest. In case of a traffic jam, it can be advantageous to stop temporarily and wait until the jam dissolves. It will be shown that TOPTIPS is capable of recommending pull-over stops and sending trucks off again to a final rest area for the overnight stay. In this scenario, travel times can be "easily" obtained for restarted trucks with virtual trajectories and a priori constructed velocity field.

Virtual trajectories for all trucks to all potential rest areas are based upon numerical solutions of the ordinary differential equation shown in Equation 4.16. This is a computationally expensive procedure and slows down the simulation considerably. However, to account for randomness, ideally, multiple simulation runs of a scenario can be performed. To overcome this issue, the travel time estimation module is parallelized. Usually, Python applications run on a single core unless the code is optimized to use multi-core processors. The result is a travel time module that runs on all available cores and improves simulation speeds considerably. This allows investigating multiple simulation runs for each scenario.

Key Takeaways: Microscopic Traffic Simulation

This chapter describes the setup, calibration, and validation of the traffic simulation. The simulation is required to evaluate the proposed Truck Optimization Parking System (TOPTIPS).

- Parking demand is derived from occupancy data which is collected through specialized truck detectors along the A9 between Munich and Nuremberg.

- General traffic demand is derived from induction loops and overhead detection. Data is collected on the A8 East (from Rosenheim), A99, and A9 (up to Nuremberg). Due to the special nature of truck parking, the model area must be significantly larger than the study area.

- The traffic supply data is exported from Open Street Map. Numerous manual corrections are required to overcome OSM network simplifications. Manuel corrections are also required for map matching of lane-specific traffic detectors.

- The large-scale traffic simulation is calibrated and validated for a typical weekday. Qualitative (Adaptive Smoothing Method contour plot analysis) and quantitative (flow deviations, Squared Inverse Mean Percentage Error, and Travel Time Difference Index) metrics are used.

- All metrics indicate a well-validated model for the purpose of TOPTIPS evaluation. 87.0 % of the hourly detector flows have an absolute relative deviation of less than 20 %. The SIMPE metric shows small spatio-temporal speed deviations ($f \approx 0.89$) between reality and the model. The TTD index underscores well-matching travel times ($f \approx 0.96$).

- The evaluation framework is an interplay between simulation, optimization, and multi-destination travel time estimation based on virtual trajectories.

Chapter 5

Results

This chapter aims at answering the four research questions, described at the beginning in Section 1.3. It begins with a brief introduction of the evaluation metrics. There are five different evaluation metrics that correspond to the five optimization objectives, which are derived from the literature in Section 2.3. Next, for each research question, there is a subsection that motivates the specific research goal of the scenario, describes the simulation approach and assumptions, and explains the results. Each subsection concludes with a reference to the original research question. It addresses to which extent the original research question could be answered and what new questions arose in the course of the work. In the sixth section, the results are summarized and discussed with the help of a graphical overview. Moreover, the transferability of the results into practice is investigated.

5.1 Evaluation Metrics

Most of the optimization objectives are already formulated in such a way that they can easily be converted into the respective evaluation metric. As the literature showed, some rest areas may be overcrowded, while others still have free capacities. Moreover, when multiple rest areas are in an overcrowded state the demand needs to be balanced to avoid excessive overcrowding of some parking facilities. In other words, the relative occupancy levels should be similar. To evaluate the relative occupancy differences, the Mean Absolute Relative Occupancy Difference (MAROD) metric is defined as follows:

$$\text{MAROD} := \frac{1}{|P|} \sum_{p \in P} \left| \frac{o_p}{cap_p} - \bar{o}_{rel} \right| \tag{5.1}$$

The set P comprises all rest areas, o_p divided by cap_p denotes the current relative occupancy of rest area p, and $\bar{o}_{rel}$ stands for the current average relative occupancy over all rest areas. The unused Hours of Service (HOS) metric is defined as the sum of unused driving time hos_t^{unused} of the trucks that have reached their destination. For some evaluations,

instead of the sum the mean is more suitable.

$$\text{HOS}_{\text{sum}} \coloneqq \sum_{t \in T_{arr}} hos_t^{unused} \tag{5.2}$$

$$\text{HOS}_{\text{mean}} \coloneqq \frac{1}{|T_{arr}|} \sum_{t \in T_{arr}} hos_t^{unused} \tag{5.3}$$

Overcrowding of rest areas can result in safety issues for truck drivers as well as other traffic participants. Therefore, overcrowding should be avoided. However, this is not always possible due to the higher parking demand than supply. Additionally, the remaining driving time of some drivers may not allow them to reach a non-overcrowded rest area. The overcrowding metric is defined as the sum of overcrowding trucks over all rest areas as follows:

$$\text{CROWD} \coloneqq \sum_{p \in P} o_p^{overcrowd} \quad \text{with } o_p^{overcrowd} = \max(o_p - cap_p, 0) \tag{5.4}$$

The literature also showed that truck drivers have preferences for certain types of rest areas. To quantify the degree to which preferences are satisfied, the individual preference satisfaction metric is defined as the percentage of trucks that park at rest area p, which is within their set of preferred rest areas Y_t, i.e., $p \in Y_t$.

$$\text{MATCH} \coloneqq \frac{1}{|T_{total}|} \sum_{t \in T_{arr}} m_t \quad \text{with } m_t = \begin{cases} 1 & \text{if } p \in Y_t \subset \mathcal{P}(P) \\ 0 & \text{otherwise} \end{cases} \tag{5.5}$$

Any custom function $f : X \mapsto Y$ can be applied to map preference attributes (or combinations thereof) X to the set of preferred rest areas Y. $\mathcal{P}$ denotes the power set, i.e., the set of all subsets. For this thesis, uniform preferences for all truck drivers are assumed. The literature showed that typical preferences are the availability of showers, food, fuel, and good lighting. Consequently, the preference set $Y_t \ \forall t \in T$ consists of the rest areas *Fürholzen*, *Köschinger Forst*, *Greding*, and *Feucht*. All metrics are time-dependent and a snapshot of the current situation. The total number of simulated trucks is $|T_{total}| = 806$.

5.2 Different Recommendation Strategies

This first analysis section, also called the first scenario, aims at validating the general working principle of the proposed Truck Optimization Parking System (TOPTIPS). It should be verified whether the recommendations lead to results that are in line with what is expected from the mathematical theory. To make this concrete with an example, this means that optimizing exclusively for improved productivity (without considering other

objectives) should result in the best values regarding the unused HOS metric. Other recommendation strategies should not achieve better results because they consider additional objectives or optimize for non-productivity related objectives. Different recommendation strategies are compared with each other by applying different weighting combinations with respect to the following four objectives:

- Minimize relative occupancy differences (system objective) $\mapsto$ Even Filling, abbreviated with EvenFil

- Minimize unused HOS (individual objective) $\mapsto$ Maximize Productivity, abbreviated with MaxProd

- Minimize overcrowding (system objective) $\mapsto$ Avoid Overcrowding, abbreviated with AvoidCrowd

- Maximize individual preference satisfaction (individual objective) $\mapsto$ Preference Matching, abbreviated with PrefMatch

The details concerning the objectives were explained earlier. Regarding the derivation of the objectives from the literature, it is referred to Section 2.3 Derived User and System Objectives from the Literature. The mathematical objectives are mapped to the underlying goals, which facilitates the interpretation of the results. It should be noted that the missing objective *Maximize average velocity*, abbreviated with MaxAvgVel, is relevant in case of traffic congestion and researched separately in Section 5.5 Large Traffic Jam.

5.2.1 Simulation Approach and Assumptions

By applying different weighting combinations to the objectives, different recommendation strategies can be investigated. Due to a large number of possible weighting combinations, a subset has to be selected. A variety of possible recommendation strategies, considering both system and user objectives, should be covered. Therefore, the subset is focused on strategies that maximize the productivity of the truck drivers (user objective) and also consider the system objectives of even filling or avoiding overcrowding. Moreover, upper bound strategies are included for which single objectives are optimized without considering the remaining objectives. This spans the solution space and allows for analysis of how much single objectives deteriorate by considering another competing objective. Finally, the status quo is included for comparison.

Concerning the TOPTIPS equipped trucks, this scenario assumes penetration rates of 100 % and almost perfect Estimated Travel Times (ETTs). The term almost perfect refers to the fact that even lane-based predicted travel times, as explained in Section 4.5.2 Travel Time Estimation, exhibit small inaccuracies. The distribution of travel time errors is

shown in Appendix E: Results in Figure A.11. It can be seen that the majority of the errors lie within ±50 s centered around 0. The high prediction accuracy results in a Root Mean Square Error (RMSE) of 28 s. In order to achieve this high level of prediction accuracy, the randomness due to speed deviations (parameter *speedDev*) and driver imperfection (parameter *sigma* of the Krauß car-following model) of the TOPTIPS trucks is eliminated for this scenario. Moreover, each recommendation strategy is simulated with the same random seed. This approach intends to compare different recommendation strategies without the noise of random behavior. This allows attributing differences in the metrics to the chosen recommendation strategy in an easier way. The optimization frequency is the last aspect of this scenario to be described. TOPTIPS is run every 15 min. This is also true for the other scenarios unless otherwise stated.

5.2.2 Results: Recommendation Strategies

Figure 5.1 shows the MAROD metric over time for the selected recommendation strategies. The study period is extended by one hour because some strategies recommend rest areas that cannot be reached before midnight. The lower the metric, the more even filling is achieved. It can be observed that the MAROD metric varies between 2.1 % and 23.8 % at the end of the study period. As expected, the two recommendation strategies 1.0EvenFil and 0.2MaxProd0.8EvenFil exhibit the lowest figures. Optimizing for even filling alone results in the best possible MAROD value. The latter shows a slightly higher value with 2.5 %, which is according to the theory since there is an additional conflicting objective weighted with 20 %. Moreover, it can be seen that the MAROD metric starts at approximately 10 % and that the two strategies actively work to reduce the uneven filling down to about 5 %. From 6 p.m. until 11:30 p.m., the two curves fluctuate. The fluctuation happens due to multiple reasons: In general, trucks have limited remaining driving time and are only considered one hour in advance, which limits the system's degrees of freedom to make recommendations. Moreover, there are also leaving trucks which constantly create imbalances. After 11:30 p.m., less trucks leave the rest areas and TOP-TIPS can further reduce uneven filling. The dark green (0.3MaxProd0.7EvenFil) and red (0.5MaxProd0.5EvenFil) curves show the third and fourth lowest MAROD values with 5.9 % and 9.7 %, respectively. This is due to further reduced even filling weightings and is in line with what is expected.

At the upper end, there are three recommendation strategies which lead to relatively high MAROD values: 1.0MaxProd (23.8 %), 0.5MaxProd0.5PrefMatch (22.3 %), and 1.0Pref-Match (21.1 %). TOPTIPS proposes rest areas that lead to imbalances because the recommendation strategies only consist of user objectives or a combination thereof. In contrast, the first four recommendation strategies are based entirely or partly upon the system ob-
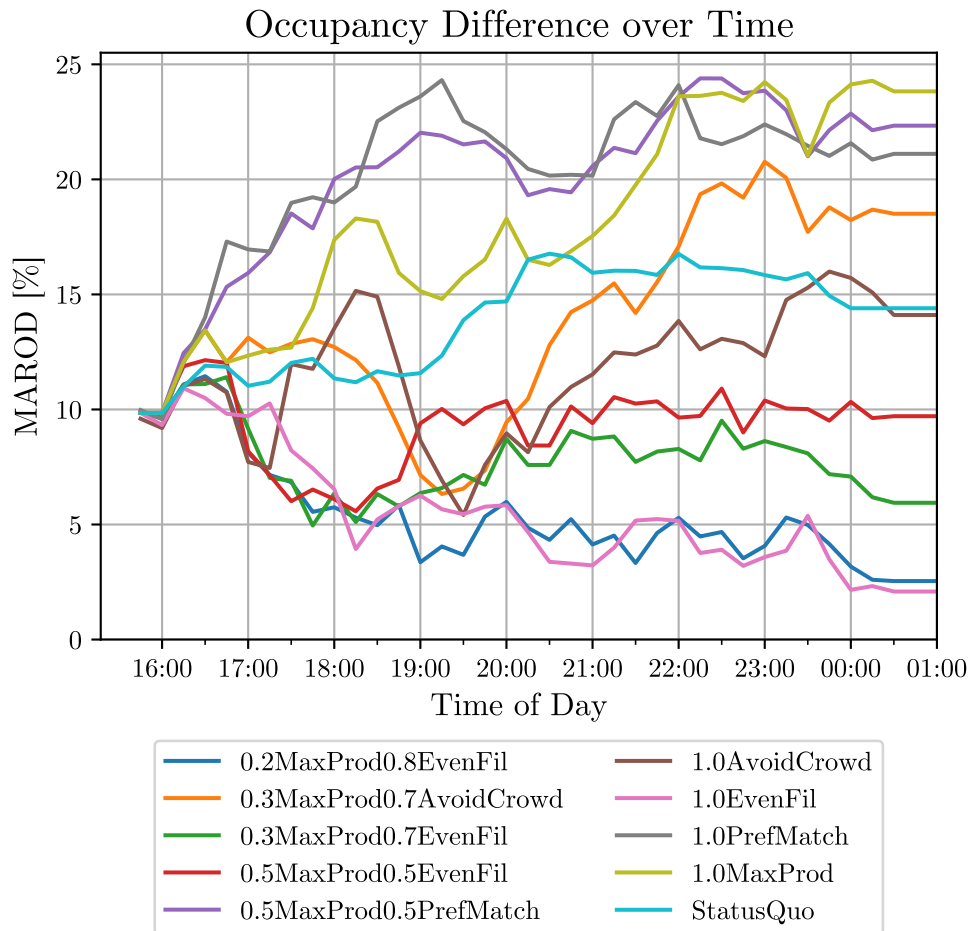
Figure 5.1: Even filling evaluation using the MAROD metric

jective even filling. For comparison, the status quo is shown in turquoise, exhibiting a final MAROD value of 14.4 %, which is close to the 1.0AvoidCrowd strategy (14.1 %). This result is remarkable in that the difference is almost negligible. More explanation is needed regarding the similarity of the two recommendation strategies. The 1.0AvoidCrowd strategy is included because it is most similar to the state-of-the-art parking guidance systems (it can be considered an idealized parking guidance system as drivers avoid overcrowding whenever possible). Current parking guidance systems indicate available parking spaces until the official maximum capacity is reached. After this point, only the information "full" is provided. The results clearly show that this limits the potential with respect to even filling because after reaching the maximal official capacity no more guidance can take place. It should be noted that the similarities between the status quo and the 1.0AvoidCrowd strategy run like a common thread through the remaining evaluations.

The productivity evaluation analyzes the lost driving time due to early parking by comparing the total unused HOS_{sum} metric. Figure 5.2 shows the unused HOS over time. The recommendation strategies StatusQuo (395.45 h) and 1.0AvoidCrowd (394.57 h) lead
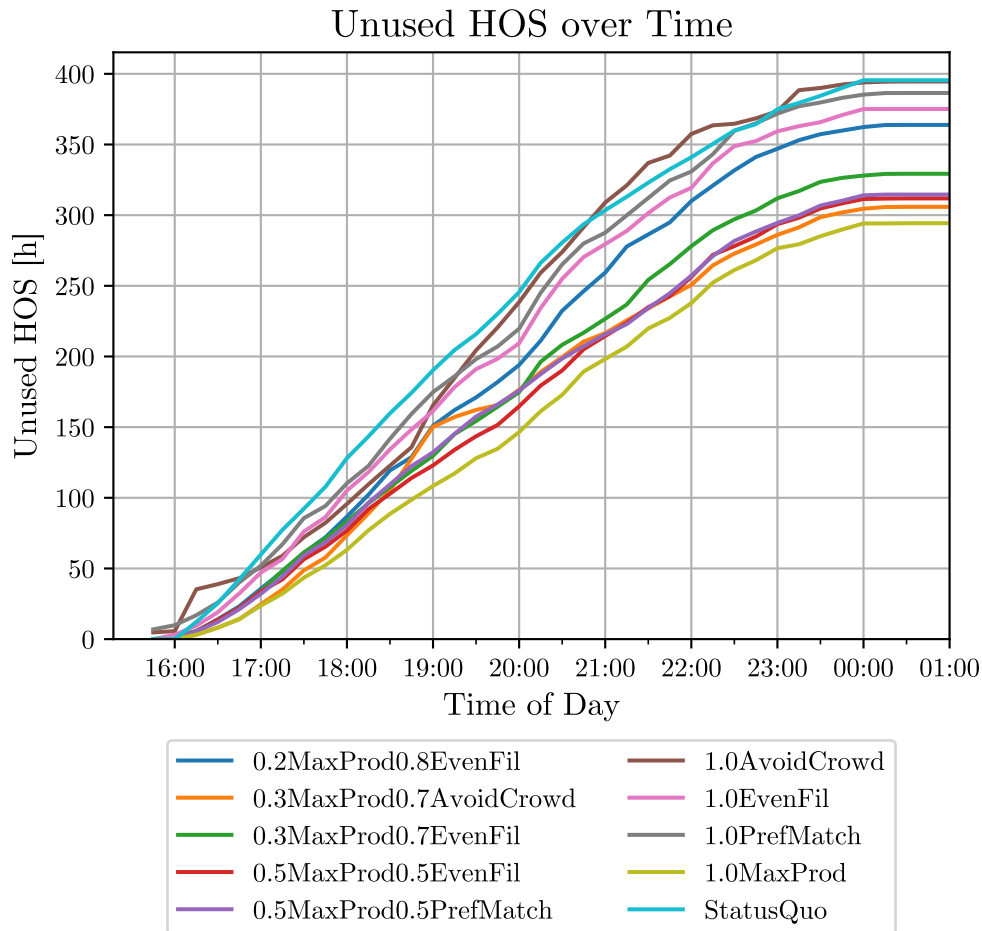
Figure 5.2: Productivity evaluation using the HOS metric

to the highest HOS losses. As described in Section 4.3.2 Truck Parking Demand, the unused driving time per truck in status quo is derived from the literature and conservatively assumed to be 30 min. The results show a good match of this assumption and the actual realized losses. The unused HOS of status quo translates to 1766 s, which is close to the theoretical value of 1800 s. The next highest losses are indicated for 1.0PrefMatch (386.45 h), 1.0EvenFil (375.11 h), and 0.2MaxProd0.8EvenFil (363.85 h). The recommendation strategy with the highest productivity is 1.0MaxProd (294.32 h), which is in line with what is expected. TOPTIPS recommends rest areas that minimize the unused HOS of each truck; however, this leads to uneven filling (MAROD: 23.8 %), as shown in Figure 5.1. This situation nicely illustrates the conflicts between individual and state objectives in truck parking and is one of the reasons for the multi-criteria optimization approach. By weighting, different extents of objective achievement can be selected. The stategy 0.3MaxProd0.7EvenFil, for example, seems to be a good trade-off in terms of even filling and maximizing productivity. It results in 329.28 h of unused HOS, which is a reduction of 16.7 % compared to status quo. At the same time, the uneven filling is

reduced by 59.0 % (from 14.4 % to 5.9 %).

In Figure 5.3, the results with respect to the overcrowding metric are shown. The overcrowding figure underscores a phenomenon that has already been observed: individual objectives lead to uneven filling and are thus related to the total number of overcrowding trucks. The two recommendation strategies 1.0MaxProd and 1.0PrefMatch both result in
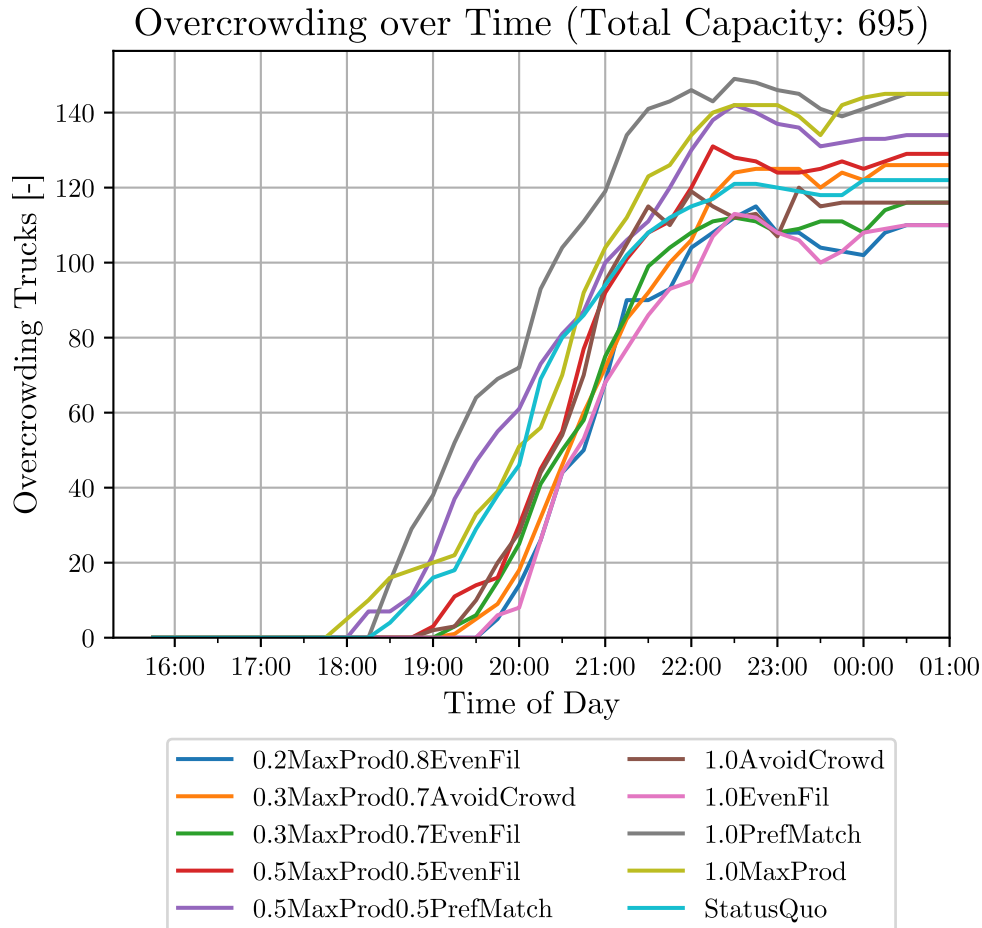
Figure 5.3: Overcrowding evaluation

145 trucks that park at rest areas beyond the maximum official capacity. For all rest areas, it is assumed that 140 % of the maximum official capacity is the capacity at which the rest area cannot accommodate any more vehicles. It is also called closing capacity. As previously explained, this assumption is derived from real-world parking data and an example is presented in Figure 4.2 in Section 4.1.2 Parking Data. The lowest number of overcrowding trucks (110) is achieved with the strategies 1.0EvenFil and 0.2MaxProd0.8EvenFil. Interestingly, the dedicated strategy 1.0AvoidCrowd can only achieve the second-lowest number of overcrowding trucks (116). The reason for this is assumed to be the leaving trucks. Once all rest areas are in overcrowded state, the 1.0AvoidCrowd strategy is indifferent in terms of rest area recommendation as no other weighting is present. This, in

turn, can lead to uneven filling, as shown in Figure 5.1, with some rest areas just exceeding the maximum official capacity. When trucks leave these rest areas in the late evening, not all vacated spaces can be refilled by the remaining trucks on the trunk. However, the strategy performs better than the StatusQuo (122 overcrowding trucks), albeit by a small margin. In summary, this again underscores the similarity of the two strategies.

In Figure 5.4, a subset of the strategies is evaluated regarding the preference matching metric. The excluded recommendation strategies do not consider maximizing individual preference satisfaction and, thus, are not relevant for this evaluation. In general, there are some subtleties with respect to preference matching, which need to be explained. Hence, some further analyses are presented on these subtleties in Figure 5.5. But first it begins with the preference matching metric in Figure 5.4. The highest percentage of matched trucks is shown for the strategy 1.0PrefMatch (57.6 %, 464 trucks), which is expected according to the working principle of TOPTIPS. The individual preference satisfaction is increased by 14.1 % compared to the StatusQuo100%, which will be explained further shortly. The second-best strategy is 0.5MaxProd0.5PrefMatch (51.9 %, 418 trucks). For the status quo, it is not known what share of the drivers actually park at the well-equipped rest areas due to having a preference for them. Therefore, the share has to be estimated. The reported figures for StatusQuo100% are a very cautious, upper bound approach. It assumes that any truck that parks on any of the well-equipped rest areas had a preference for it. This is a very strong assumption and results in a relatively high preference matching value of 50.5 %. On the one hand, this can be considered as support for the findings from the literature that truck drivers pay attention to amenities when staying overnight. On the other hand, it needs to be noted that the well-equipped rest areas have the largest capacities. Consequently, high matched preference values can happen coincidentally to some extent. Additionally, the curves StatusQuo80% and StatusQuo60% are shown to illustrate the situation when the strong assumption is relaxed. StatusQuo80% indicates that only 80 % of the trucks that park at one of the well-equipped rest areas actually had a preference for it.

However, the question remains why no greater improvements can be observed. The modeling approach of TOPTIPS is predestined to consider individual preferences. The reason is the underlying preference assumption. Drivers are assumed to have uniform preferences: availability of food, fuel, bathrooms, and good lighting. It is shown in the literature section that these types of amenities make rest areas more attractive for a night's rest. The uniform preference assumption leads to the same rest area preference set for all trucks, i.e., $\forall t \in T$: $Y_t = \{$*Fürholzen, Köschinger Forst, Greding, Feucht*$\}$. The matching of trucks works as expected, but, at some point, the preferred rest areas reach their closing capacity, and no more matching can take place (apart from leaving trucks). The assumption of uniform preferences somewhat limits the application range of TOPTIPS. However, it is ar-
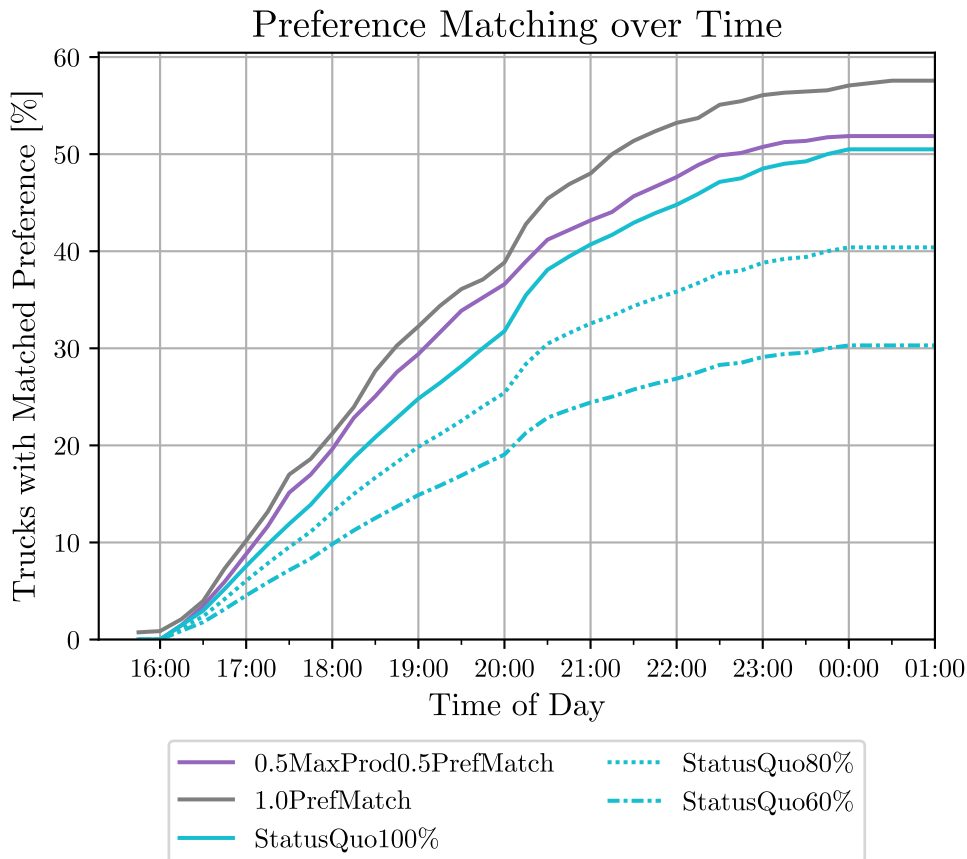
Figure 5.4: Preference matching evaluation

gued that these assumptions are supported by the literature. Therefore, they are the most sound ones. Of course, other preference assumptions would be conceivable: befriended drivers may like to rest at the same parking facility, some drivers may have specific preferences for some rest areas (e.g. wifi access, special food), or some drivers/carriers may have agreements with specific gas station operators. However, further research is needed to derive sound assumptions, which can then be considered by TOPTIPS. No vaguely substantiated assumptions are to be tested here.

Nonetheless, there remains one research direction where the literature-backed preference assumptions do not need to be altered and matching capabilities can still be further investigated. Instead of assuming that all truck drivers have preferences, only a proportion of the drivers may have them. This proportion is varied from 0 % to 100 % with step size 10 %. Additionally, a different recommendation strategy is required where the closing capacities do not impact the application range of TOPTIPS. The strategy 0.5EvenFil0.5PrefMatch is chosen because the strategy compares well with the status quo. In Figure 5.5, the results with respect to the matched preference and the MAROD metrics are shown.

The blue curve indicates that up to a share of 50 %, the preferences of all trucks can

PrefRate Analysis: 0.5EvenFil0.5PrefMatch
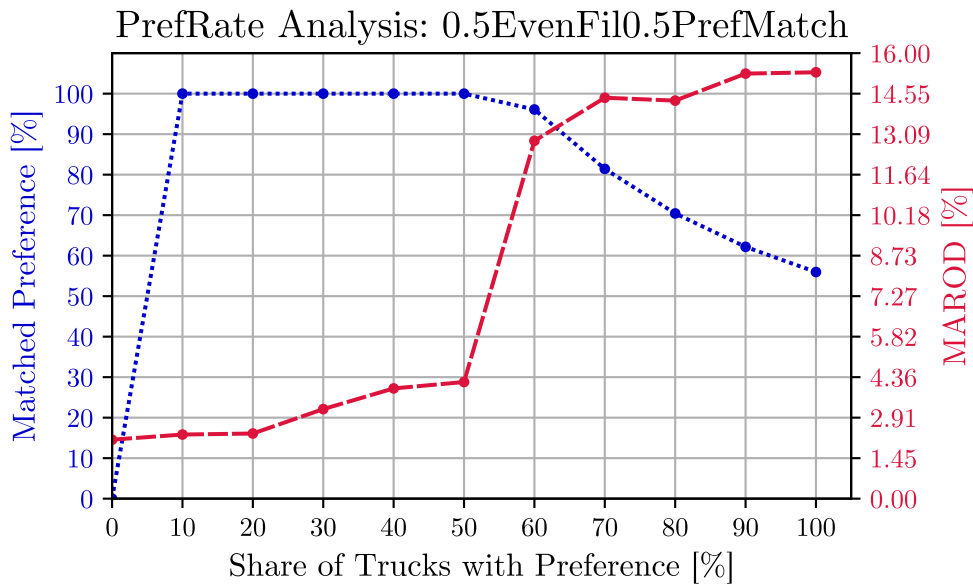
Figure 5.5: Detailed analysis of preference matching

be met. At the same time, the even filling metric (red curve) only worsens slightly from 2.1 % to 4.2 %. For comparison, the status quo shows a MAROD value of 14.4 %. These results demonstrate the capability of TOPTIPS to recommend rest areas that are within the preference set of the truck drivers. Compared with the strongest preference assumption (StatusQuo100%), in both cases about half the trucks can park at a preferred rest area. However, TOPTIPS can reduce uneven filling by 70.8 % at the same time. However, increased shares of trucks with preferences decrease the matching metric to 56.0 % and increase the MAROD metric to 15.3 %. This is due to the saturation of the system. Concretely, not all trucks can park at the same preferred rest areas if, at the same time, no significant imbalances should happen. The multi-criteria approach balances the conflicting objectives optimally according to the chosen weights. Lastly, as a side note, the MAROD metric (2.1 %) when no trucks have preferences is the same as for the recommendation strategy 1.0EvenFil, shown in Figure 5.1. This is not surprising, as in this case, the two recommendation strategies are equivalent.

In summary, the preference matching functionality seems to be an important aspect of providing individual parking recommendations. Therefore, it is integrated generically into the TOPTIPS system. However, more research is required to understand the individual preferences of truck drivers better. Consequently, the presented preference matching evaluation can only be a first step. Yet, the results already demonstrate that TOPTIPS can improve the situation compared to the status quo. Even with the most conservative assumption on current preference matching, an increase of 14.1 % is achieved.

5.2.3 Research Question Assessment

The original research question to be answered is:

Q1: What impact can truck-specific parking recommendations have for drivers and road authorities?

The results show that truck-specific parking recommendations can well serve the goals of truck drivers and road authorities. With respect to the drivers, TOPTIPS facilitates truck parking by providing parking recommendations which comply with HOS regulations, increase productivity, and are able to account for individual preferences. With respect to road authorities, parking recommendations can avoid overcrowding and lead to even filling. Unfortunately, road authority and driver objectives conflict. To overcome this issue, TOPTIPS allows weighting different objectives arbitrarily. By doing so, composite recommendation strategies can be applied. These strategies optimize the objectives according to the a priori chosen weights. The results show that the weighting approach works as expected and provides great flexibility. No evaluation is to be made as to which recommendation strategy is the best because it depends on the goals that should be achieved. However, the status quo can be improved because unnecessary driving time is lost and maximal capacities of the rest areas are not optimally used. It is also shown that the system objective to avoid overcrowding is more complex than commonly assumed in the literature. On motorways where the demand surpasses the official supply, this strategy partially loses effectiveness. The strategy of even filling seems to be more promising. However, for lower demand situations (e.g., weekends) or recommendation strategies which require temporary imbalances (see Section 5.5 Large Traffic Jam), the avoid overcrowding objective proves to be useful.

From the literature, it is known that truck drivers' individual preferences for certain types of amenities are important for the parking choice. Because TOPTIPS provides truck-specific parking recommendations, it is well suited for considering individual preferences. The mathematical modeling is shown and ready to be applied. However, only limited results could be provided because more research is needed with respect to truck drivers' preferences. Current knowledge leads to more or less uniform preference assumptions for all drivers. This, in turn, limits the application range as soon as the well-equipped rest areas reach their closing capacity. As a consequence, the impact of truck-specific parking recommendations with respect to individual parking preferences could only be partially answered. However, this shifts the focus to an under-researched field. First, it is important to understand whether a uniform preference assumption is a good approximation of the underlying distribution. If the uniform distribution turns out to be suitable, the supply characteristics should be studied in more detail. Efforts could be undertaken to make

certain rest areas more attractive. If the distribution turns out to be more complex, further in-depth TOPTIPS assessments can be carried out based on it.

5.3 Penetration Rate Variation

The previous evaluation of truck-fine parking recommendations was based on the assumption of full equipment levels. Even though Floating Truck Data (FTD) is becoming increasingly available, it has to be assumed that TOPTIPS cannot start with penetration rates of 100 %. In general, there are system and individual objectives which are impacted by different penetration rates. The literature review showed that road authorities have a strong interest in improving parking conditions through increased use of data. Therefore, this scenario should reflect the perspective of road authorities, which would most likely try to achieve as much even filling as possible with as few equipped trucks as needed. However, the authorities cannot entirely neglect the truck drivers' perspective. This results in a recommendation strategy with a primary system objective (higher weight) and a secondary user objective (lower weight).

5.3.1 Simulation Approach and Assumptions

To study the penetration rate effects, the recommendation strategy 0.2MaxProd0.8EvenFil is selected as it weights the global objective of even filling relatively high with 80 %. At the same time, it also considers the productivity of the truck drivers with 20 %. By and large, it is a very likely recommendation strategy to be applied in practice. In reality, traffic exhibits randomness and it must be considered in two ways. The first way deals with the randomness of the simulation behavior itself. Randomness due to speed deviations and driver imperfection are reset for the TOPTIPS trucks to the SUMO default values (*speedDev=0.05* and *sigma=0.5*). This, in turn, reduces the accuracy of the travel time prediction to a RMSE of 160 s compared to 28 s in the first scenario. However, the ETTs can still be considered quasi-perfect. Besides the SUMO internal randomness, the trucks that are equipped with TOPTIPS also have to be chosen at random. To distinguish the trucks, some naming convention is introduced. All trucks that park at one of the rest areas are called parking trucks which consist of TOPTIPS and non-TOPTIPS trucks. The parking trucks are defined in a separate route file, which is connected to the random seed of the simulation. The random seed is changed for every simulation run and also decides which trucks are TOPTIPS and non-TOPTIPS trucks. For the evaluation, the metrics MAROD and mean unused HOS, both applied at the end of the study period, are used.

As randomness is considered, the question arises how many simulation runs are required

to detect differences. Potentially identified differences should be statistically valid at a confidence level of 95 %. To determine the required sample size, the approach suggested in the recommendations for microscopic traffic simulation ("Hinweise zur mikroskopischen Verkehrsflusssimulation") of the FGSV [2006] is followed. The number of simulation runs has to be computed iteratively and is given as follows:

$$n \geq \frac{t(\alpha, n-1)^2 \; s^2}{C^2} \tag{5.6}$$

n	Number of required simulation runs
$t(\alpha, n-1)^2$	Critical value from the Student's t-distribution
s	Sample standard deviation of the metric of interest
C	Differences that should just be recognized as significant

Pre-tests with the main metric of interest MAROD resulted in a sample standard deviation of $s = 0.9$. The detectable difference is set to $C = 1$ and the critical value for the 95 % confidence interval for $n - 1 = 5$ degrees of freedom is 2.57. Applying the formula, there should be $n = 6$ simulation runs. The penetration rates are simulated from 0 % to 100 % with step size 10 %. Overall, this requires 66 simulation runs with different random seeds, which is computationally expensive. On the given hardware (i7-8700 CPU @ 3.20GHz, 6 cores, 128GB RAM), this scenario takes about 2 days.

5.3.2 Results: Penetration Rates

In Figure 5.6, the even filling performance with respect to the different penetration rates is shown. On the far left, the current situation is depicted with a MAROD of 14.4 %. In general, it can be observed that the MAROD metric improves with more equipped trucks. At a penetration rate of 30 %, the MAROD is already at 3.0 %. After this point, the situation stays more or less the same with respect to the even filling metric. To test the observations more rigorously, the Kruskal–Wallis H test is conducted, which is the non-parametric equivalent of the one-way Analysis of Variance (ANOVA). The non-parametric test is used as the prerequisites for an ANOVA (the samples need to be independent, the standard deviation of the groups need to be equal, and samples need to be from a normal distribution) [FGSV, 2006] are difficult to test reliably with the small sample sizes. The Kruskal–Wallis H test allows rejecting the null hypothesis that the medians of the different penetration rates are equal ($\chi^2(10) = 46.81$, $p \leq 0.001$). It should be noted that non-parametric tests with small sample sizes tend to have less power (i.e., correctly rejecting a false null hypothesis) [LANE, 2018], and still the null hypothesis can be rejected. The Dunn's post-hoc test (equivalent of the Tukey's honestly
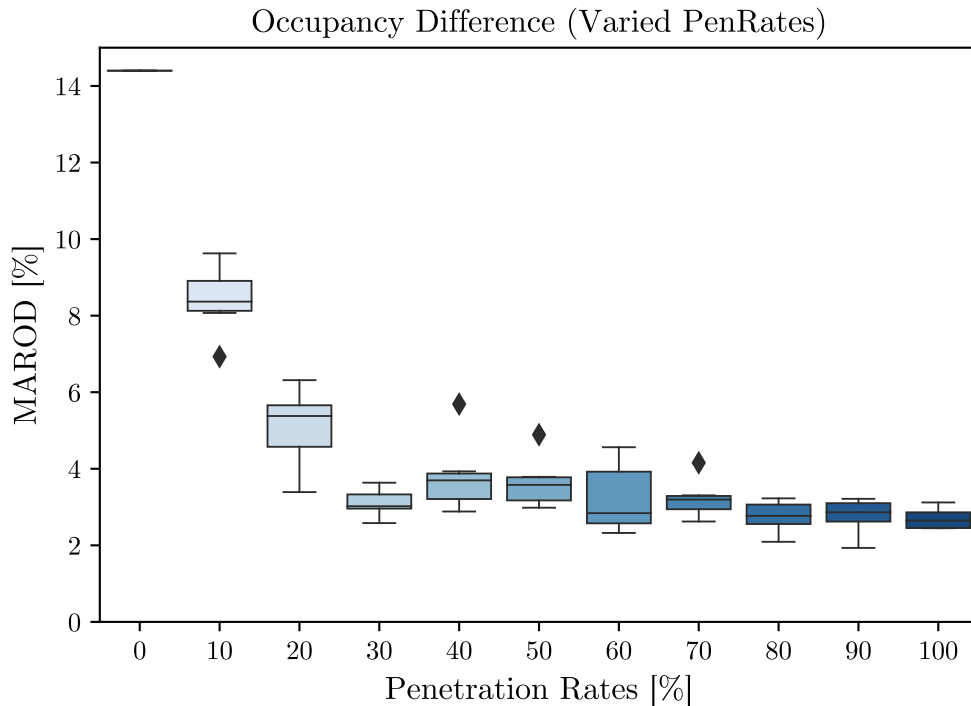
Figure 5.6: Even filling performance for different penetration rates

significant difference test) is required to find out which groups differ. The p-values for all pairwise comparisons of penetration rates up to 50% are shown in Appendix E: Results in Table A.3. The family-wise error rate is controlled at $\alpha = 0.05$ with the Benjamini-Hochberg method [BENJAMINI and HOCHBERG, 1995]. The results indicate that there is a significant difference in MAROD values as of 20%. This supports the visual boxplot analysis. The greatest MAROD reduction (79.2%) compared to the status quo is observed for a penetration rate of 30%.

To further study the results, the unused HOS_{mean} metric is evaluated and differentiated by TOPTIPS and non-TOPTIPS trucks. The HOS_{mean} instead of the HOS_{sum} metric is used to make different equipment levels comparable. Figure 5.7 shows the mean unused HOS per truck for different penetration rates. It can be observed that the values for the non-TOPTIPS trucks stay at $1695.83\,s$ regardless of the penetration rate. This is expected as these trucks do not get recommendations and have approximately $30\,min$ unused HOS when they arrive. With regard to the TOPTIPS trucks, there is a minimum at 20% penetration rate (Mdn=$1087.74\,s$). Increasing the equipment levels also increases the unused HOS per truck reaching $1553.98\,s$ at 100% equipment level. Even though the small difference of $141.85\,s$ may seem negligible, it has to be considered that this is a mean value. Therefore, this adds up to more than $30\,h$ of total productivity difference each weekday.
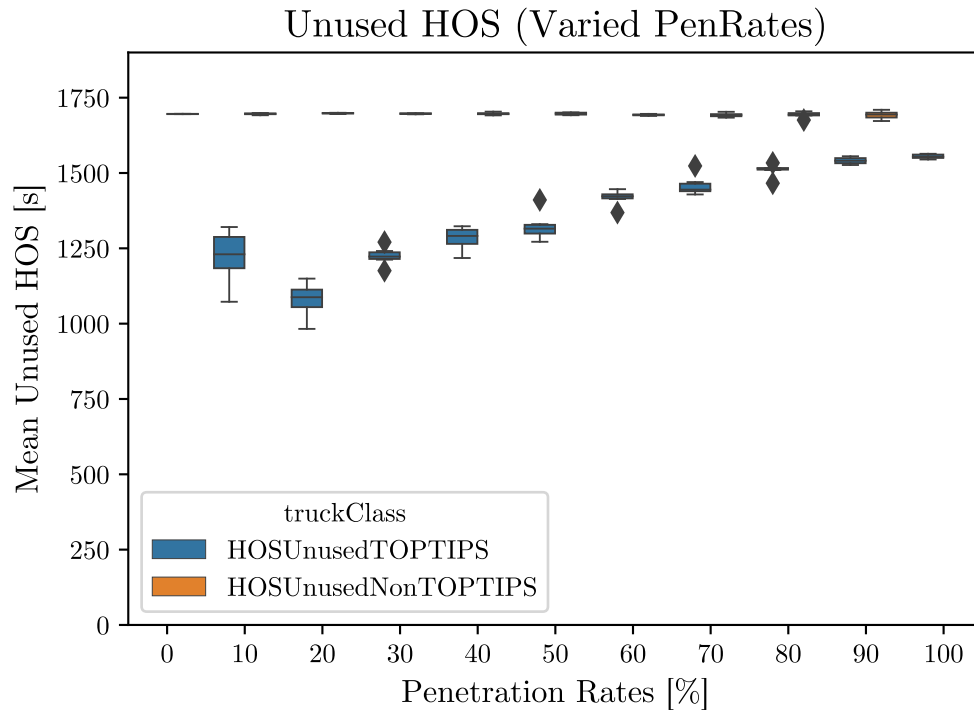
Figure 5.7: Unused HOS performance for different penetration rates

The trend of first decreasing and then increasing HOS values can be explained by taking into account the MAROD metric and the recommendation strategy (0.2MaxProd-0.8EvenFil). In Figure 5.6, it is shown that low penetration rates ($\leq 30\,\%$) have a significant impact on reducing uneven filling. TOPTIPS recommends parking that primarily results in more even filling (weighted $80\,\%$), and at the same time productivity (weighted $20\,\%$) is also considered. Apparently, penetration rates between $20\,\%$ to $30\,\%$ are ideal for fulfilling both objectives with the given weighting. Figuratively speaking, TOPTIPS can fill the holes by sending the "right" trucks up to a $30\,\%$ penetration rate. Once even filling is achieved and penetration rates are further increased, TOPTIPS recommends rest areas that maintain even filling at the expense of increased unused HOS because of the relative importance of the even filling objective.

5.3.3 Research Question Assessment

The original research question to be answered is:

Q2: What are the effects of different penetration rates?

The intended benefits of TOPTIPS are reduced stress and increased convenience without the mental load to consider HOS regulations. These advantages are available to any truck driver who participates, regardless of the penetration rate. In addition, there are system and individual objectives, which are impacted by different penetration rates. As an example, the recommendation strategy 0.2MaxProd0.8EvenFil is studied. The results show that small penetration rates of 30 % can already significantly improve even filling by 79.2 % and at the same time still improve the productivity per truck by 27.9 %. However, with further increased penetration rates, even filling can only be maintained at the expense of some of the productivity gains. The fact that small penetration rates can have a large effect predestines TOPTIPS for practical application by road authorities.

In general, there are many more recommendation strategies that can be applied using any combination of system and user objectives. However, the required computational resources do not allow testing them all. Investigating recommendation strategies that include individual preferences could be a promising next step. However, first a better understanding of the uniform preference assumption is required. Additionally, new research directions are opening up concerning the truck drivers' willingness to accept system weights in recommendation strategies. Ultimately, the question boils down to how much individual productivity/amenity convenience truck drivers are willing to give up to improve global safety for all traffic participants by avoiding unorganized parking. There is also a need to explore what incentives could be given to encourage more social behavior.

5.4 Noisy Travel Time Predictions

Reliable travel time predictions are necessary for many applications and also play an important role for TOPTIPS. As previously mentioned, the TOPTIPS design assumes ETTs to be provided by any specialized Real-Time Traffic Information (RTTI) provider. However, these ETTs are necessarily inaccurate to some extent. Therefore, the aim of this scenario is to evaluate the impact of typical prediction errors on TOPTIPS. Inaccurate travel time predictions are considered particularly serious when the recommendation strategy aims to maximize productivity. Hence, the strategy 1.0MaxProd is studied in-depth. If the ETTs are underestimated, truck drivers risk violating HOS regulations. If the ETTs are overestimated, the objective achievement is worsened.

5.4.1 Simulation Approach and Assumptions

The overall idea to model real-world travel time predictions is to add artificial noise to the quasi-perfect travel time predictions. The noise is added randomly and is drawn from a distribution that is yet to be defined. Implementation-wise, the random noise generation is connected to the random seed of the SUMO simulation. At this point, the question arises as to how accurate travel time predictions are on motorways, also considering evening peak hours. Typical prediction accuracy levels on motorways were already described in Section 3.1.2 System Boundaries and Assumptions' Assessment. However, the main findings are repeated here briefly. ZHANG and HAGHANI [2015] studied freeway travel time predictions in Maryland using a Gradient Boosting Model (GBM), which is a state-of-the-art machine-learning technique, and compared it to a random forest model. A classical Autoregressive Integrated Moving Average (ARIMA) model served as a benchmark. The Mean Absolute Percentage Error (MAPE) was used as the evaluation metric. The results show that 30 min ahead predictions of all three models for non-peak hours are between 5.30 % and 18.96 % and for peak hours between 22.95 % and 30.01 %. From these figures, it is derived that travel time prediction accuracy can be assumed to be somewhere between 20 % to 30 %. To account for prediction uncertainty, noise is modeled with a continuous random variable $X \sim \mathcal{U}(a, b)$. The probability density function f_X is given as follows:

$$f_X(x) = \begin{cases} \frac{1}{b-a} & a < x < b \\ 0 & x < a \text{ or } x > b \end{cases} \tag{5.7}$$

Let the values for a and b be given by $(a, b) \in \{(-0.1, 0.1), \ldots, (-0.5, 0.5)\}$. The calculation of the expected value of X, given that either $X < 0$ or $X \geq 0$, is shown below for the case where $a = -0.5$ and $b = 0.5$:

$$\mathbb{E}[X|X < 0] = \int_{-\infty}^{\infty} x \, f_{X|X<0}(x) \, dx \tag{5.8}$$

$$= \frac{1}{\mathbb{P}(X < 0)} \int_{-0.5}^{0} x \, f_X(x) \, dx = -0.25 \tag{5.9}$$

$$\mathbb{E}[X|X \geq 0] = \int_{-\infty}^{\infty} x \, f_{X|X\geq0}(x) \, dx \tag{5.10}$$

$$= \frac{1}{\mathbb{P}(X \geq 0)} \int_{0}^{0.5} x \, f_X(x) \, dx = 0.25 \tag{5.11}$$

This reflects the findings from the literature and ensures that over- and underestimates are incorrect by 25 % on average. Furthermore, over- and underestimates happen with the same probability, i.e., $\int_a^0 f_X(x) \, dx = \int_0^b f_X(x) \, dx$. Besides the variation of the noise values, two different optimization frequencies (every 15 min and 30 min) are tested.

5.4.2 Results: Noisy Predictions

Figure 5.8 shows the mean unused HOS per truck for different expected noise levels. First,
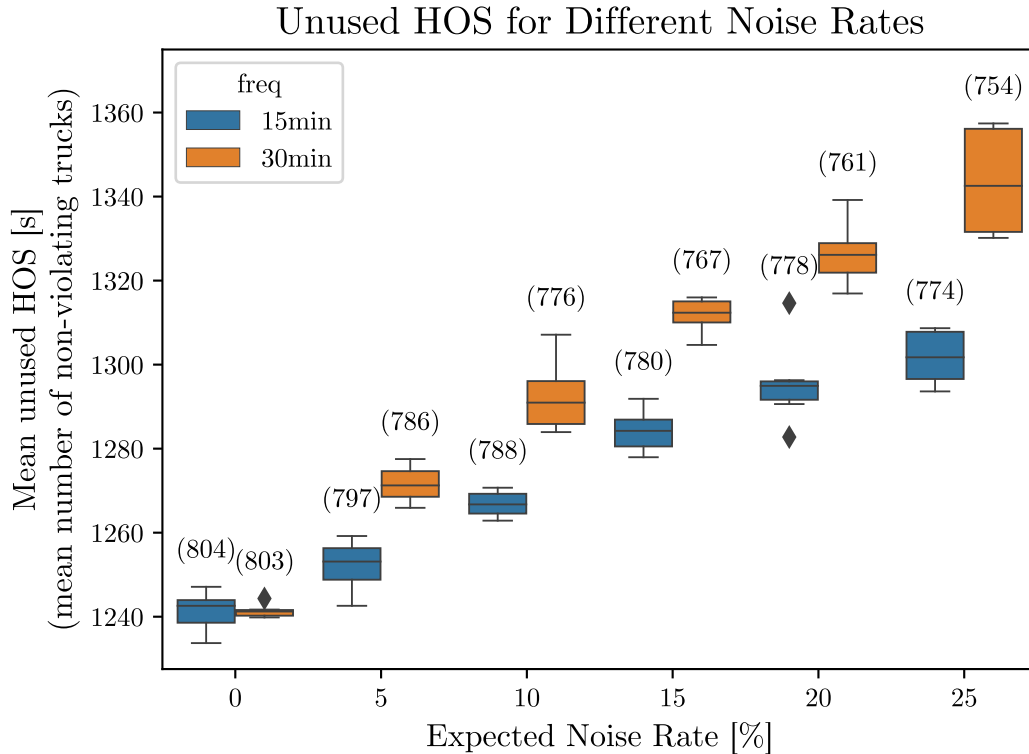
Figure 5.8: Unused HOS for different expected noise rates

it can be observed that higher noise rates lead to increased unused HOS per truck. Second, a lower optimization frequency results in higher unused HOS values. Third, the figures inside the brackets, which indicate the mean number of non-violating trucks, reduce with higher noise rates. These figures require some more explanation. For each boxplot, there are mean unused HOS results from six simulation runs. In each simulation run, only the trucks that do not violate HOS regulations are considered for the mean unused HOS metric. The number in brackets indicates how many non-violating trucks contribute on average. In total, there are 806 trucks. In the case of 0 % noise, almost all trucks comply with the HOS regulations. In contrast, given an optimization frequency of 30 min and a noise level of 25 %, "only" 754 trucks do not exceed their driving time.

This leads to the evaluation of the trucks that exceed their driving time, which can be seen in Figure 5.9. This figure can be understood as the inverse of Figure 5.8. Higher noise rates and a lower optimization frequency both increase the mean HOS violation. Analogous to the previous figure, the numbers in brackets show the average number of trucks contributing to the metric. An interesting observation can be made with respect to the rate of increase of the mean HOS violation. For a frequency of 15 min, the boxplots
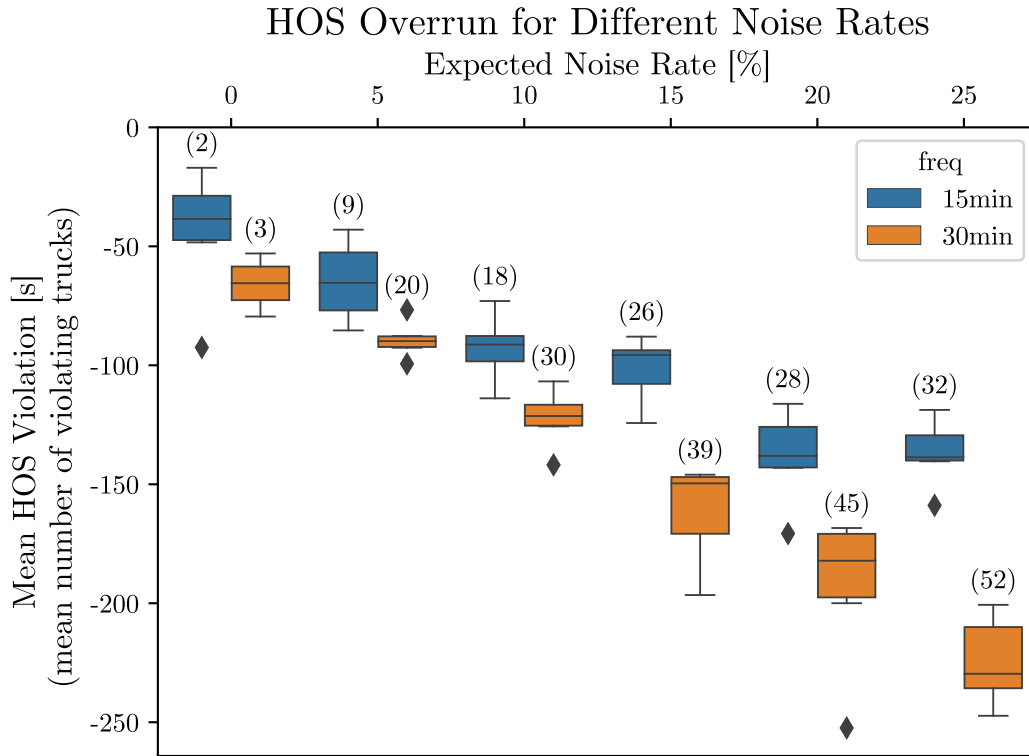
Figure 5.9: HOS overrun for different expected noise rates

seem to level off for higher noise rates. Apparently, this is not the case for a frequency of 30 min.

All visual observations of the boxplots can also be tested more rigorously using statistics. However, the small sample sizes require special caution in interpreting the results. The Kruskal-Wallis H test is applied for the mean unused HOS metric ($\chi^2(11) = 68.34$, $p < 0.001$) and the mean HOS violation metric ($\chi^2(11) = 65.77$, $p < 0.001$). The p-values allow rejecting the null hypothesis of equal sample medians for both analyses. As post-hoc test, Dunn's test is applied again. The family-wise error is controlled at $\alpha = 0.05$ with the Benjamini-Hochberg method. The two post-hoc test results support the findings of the visual boxplot analysis. For the pairwise comparisons with a larger noise spread, there is a significant difference ($p_{adj} < 0.05$). However, there are also cases where non-significance supports the visual analysis. For example, comparing the mean HOS violation for a frequency of 15 min between 20 % and 25 % does not indicate a significant difference ($p_{adj} = 0.49$). This underscores the observation that the mean HOS violation seems to level off for higher optimization frequencies. In summary, the statistical analyses are performed to provide additional insight, but the small sample sizes and assumed similar distribution shapes must be taken into account when interpreting the results.

5.4.3 Research Question Assessment

The original research question to be answered is:

Q3: What are the effects of different levels of travel time prediction accuracy?

To evaluate TOPTIPS with different levels of travel time prediction accuracy, an "upper" bound approach is pursued. Inaccurate predictions can lead to a violation of HOS regulations. Therefore, the recommendation strategy 1.0MaxProd was studied as it exposes the truck drivers to the greatest risk of exceeding legal driving times. The results show that increased noise in the predictions causes more truck drivers to overrun their HOS by a greater amount. However, in the worst case, the average number of trucks that experience an overrun is still relatively small with 4.0 % for a frequency of 15 min and 6.5 % for a frequency of 30 min. Another interesting observation is made with respect to the higher optimization frequency as the mean HOS violation seems to level off. This is a promising outlook and could be tested further with larger sample sizes and higher noise rates. Lastly, it is shown that the mean unused HOS only increases by 4.8 % and 8.2 % for the 15 min and 30 min optimization frequency, respectively. In summary, the results confirm the hypothesis that noisy travel time predictions make it more difficult for TOPTIPS to recommend appropriate rest areas.

Besides the visual boxplot analysis, a series of statistical non-parametric tests were carried out to gain more insight. However, these results are subject to small sample sizes. Therefore, it has to be stated that the statistical analysis can only be considered as a first step and is only partially completed. If a specific scenario should be studied in more detail, it is recommended to perform more simulation runs. Another option is to use the bootstrapping technique. Furthermore, many more recommendation scenarios can be evaluated. For example, it would be interesting to see how the even filling performance is impacted by noisy travel time predictions. Besides the single-objective recommendation strategies, combined multi-objective strategies can be tested. In summary, the basis for modeling multi-destination real-world travel time predictions is laid by adding noise to quasi-perfect predictions. The underlying idea is to model the noise as a random variable drawn from a uniform distribution so that the expected value matches the findings from the literature. This opens up the possibility to investigate other recommendation strategies in the future.

5.5 Large Traffic Jam

Traffic congestion seems to be almost an inevitable side effect of traffic. In particular, large jams (definition follows later) lead to substantial travel time increases and delayed arrivals for all affected drivers. However, for truck drivers there is another undesirable effect: reduced remaining driving time with only a few revenue kilometers driven [FHA, 2015]. If it is impossible or disadvantageous to reroute, it can be beneficial to stop temporarily at the next suitable rest area and wait until the jam dissolves. Truck-specific recommendations seem to be predestined to handle this kind of situation. Therefore, the goal of this scenario is to study whether TOPTIPS can support drivers in avoiding congestion.

5.5.1 Simulation Approach and Assumptions

The term congestion needs to be defined in more detail. In congestion research, different classification schemes have been proposed, for example, by KERNER [2009], HELBING et al. [2009], and TRANSVER [2010] and further studied in KARL et al. [2019]. This work uses the latter classification scheme where four different congestion types are defined:

- Jam wave (single speed break-down)
- Stop-and-go waves
- Wide jam
- Mega jam

The goal is to study TOPTIPS during large jams; therefore, the category mega jam is used as the basis for this work. KESSLER et al. [2020] conducted a hot spot analysis for the A9 between Munich and Nuremberg (southbound) using the four congestion types. Data for the northbound direction is provided by KESSLER et al. [2020] for eight months in 2019. In total, ten mega jams are registered with a mean length of 18.1 km and a mean root location at kilometer 479.1 of the A9, which is approximately at the interchange *AD Holledau*. The congestion sizes range from 903.25 km · min to 9049.75 km · min. The mean length and root location are used to model an artificial jam at the lower end of the congestion size range. The lower end is chosen because TOPTIPS should already provide benefits for "smaller" traffic jams. Further, the "more" congestion is simulated, the more computational resources are required that are already scarce due to the spatio-temporal extent of the simulation. The congestion is modeled by reducing the allowed edge speed (on three edges, total length 378 m) to 10 km/h upstream of the *AD Holledau*.

In Figure 5.10, the Adaptive Smoothing Method (ASM)-smoothed contour plot of the

artificial large jam, based on real data, is shown with contour lines for different critical speed values.
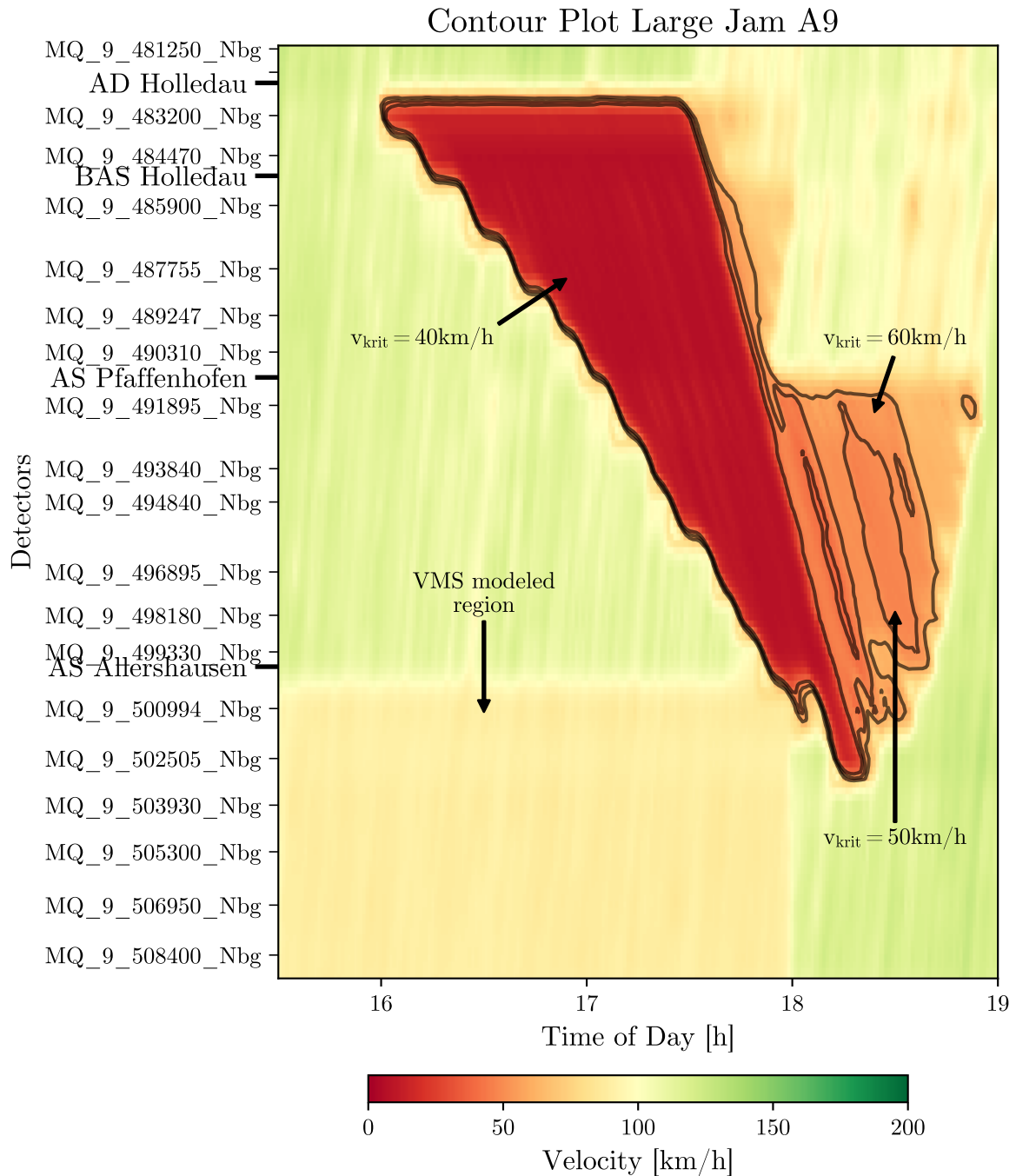
Figure 5.10: Artificial large jam based on real mega jam data

The critical value $v_{krit} = 40\,\text{km/h}$ results in a congestion length of $20\,\text{km}$, which is $10.5\,\%$ longer than the mean mega jam length from real data. More importantly, the congested area ($864.2\,\text{km} * \text{min}$) matches the real data quite well ($95.7\,\%$). The spatial extent of the contour plot can be inferred from the detector names. The respective location of the

detectors in meters along the A9 is part of the detector name (six digits separated by leading and trailing underscores). In this figure, the focus is on the full detector names (not abbreviated) so that they can be easily distinguished. In order to leave enough space for the actual plot area, explicit kilometrage is omitted. It is interesting to note that when the jam dissolves, the bottleneck due to the ramp *AS Pfaffenhofen* remains clearly visible. To a lesser extent, this is also true for the provisional ramp *BAS Holledau*.

A large traffic jam is a special circumstance which requires that all available capacities can be used. Therefore, the two recommendation strategies 0.5MaxProd0.5AvoidCrowd, abbreviated *NonAvoidJam*, and 0.1MaxProd0.1AvoidCrowd0.8MaxAvgVel, abbreviated *AvoidJam*, are compared. The two strategies have in common that maximizing productivity and avoiding overcrowding have the same relative weight. Yet, the second strategy additionally aims to maximize the average velocity. The average velocity can be increased by preventing trucks to enter the jam. Instead, a temporary stop recommendation for any of the upstream rest areas is issued. The trucks then continue their journey after the jam has resolved. Trucks for which it makes sense to continue their journey are called restartable trucks. The prerequisite to be labeled as a restartable truck is that the unused HOS is greater or equal than the parameter $t_{restart}$, which is set to 45 min in this scenario.

5.5.2 Results: Traffic Jam

The results of the large jam scenario are depicted in Figure 5.11. For both recommendation strategies, 30 simulation runs are performed. In the upper left part, the number of slow trucks per run is shown. Slow trucks are defined as trucks with an average velocity $v_{avg} \leq 60$ km/h. The Shapiro-Wilk test indicates that the NonAvoidJam group ($W = 0.885$, $p = 0.004$) is not normally distributed, whereas the AvoidJam group ($W = 0.952$, $p = 0.191$) seems to be normally distributed. To be on the safe side, the non-parametric Mann-Whitney U test is carried out. However, first the assumption of similar distribution shapes is checked. The Kolmogorov–Smirnov test (NonAvoidJam distribution shifted by the median difference) indicates similarity of the two distribution shapes ($D = 0.3$, $p = 0.135$), which allows making a statement about the medians. Finally, the Mann-Whitney U test shows a significant difference ($U = 900$, $p < 0.001$) between the NonAvoidJam ($Mdn = 101$, $SD = 2.66$) and the AvoidJam ($Mdn = 55.5$, $SD = 2.54$) recommendation strategies. Even though the number of slow trucks is roughly halved, the AvoidJam strategy cannot entirely prevent reduced speeds. The reason for this is twofold: First, the capacities of the upstream rest areas eventually reach their closing capacity so that pull-over recommendations can no longer be issued. Second, trucks get inserted into the congested stretch. This is due to the design of the simulation, explained in Section 4.3.2 Truck Parking Demand.
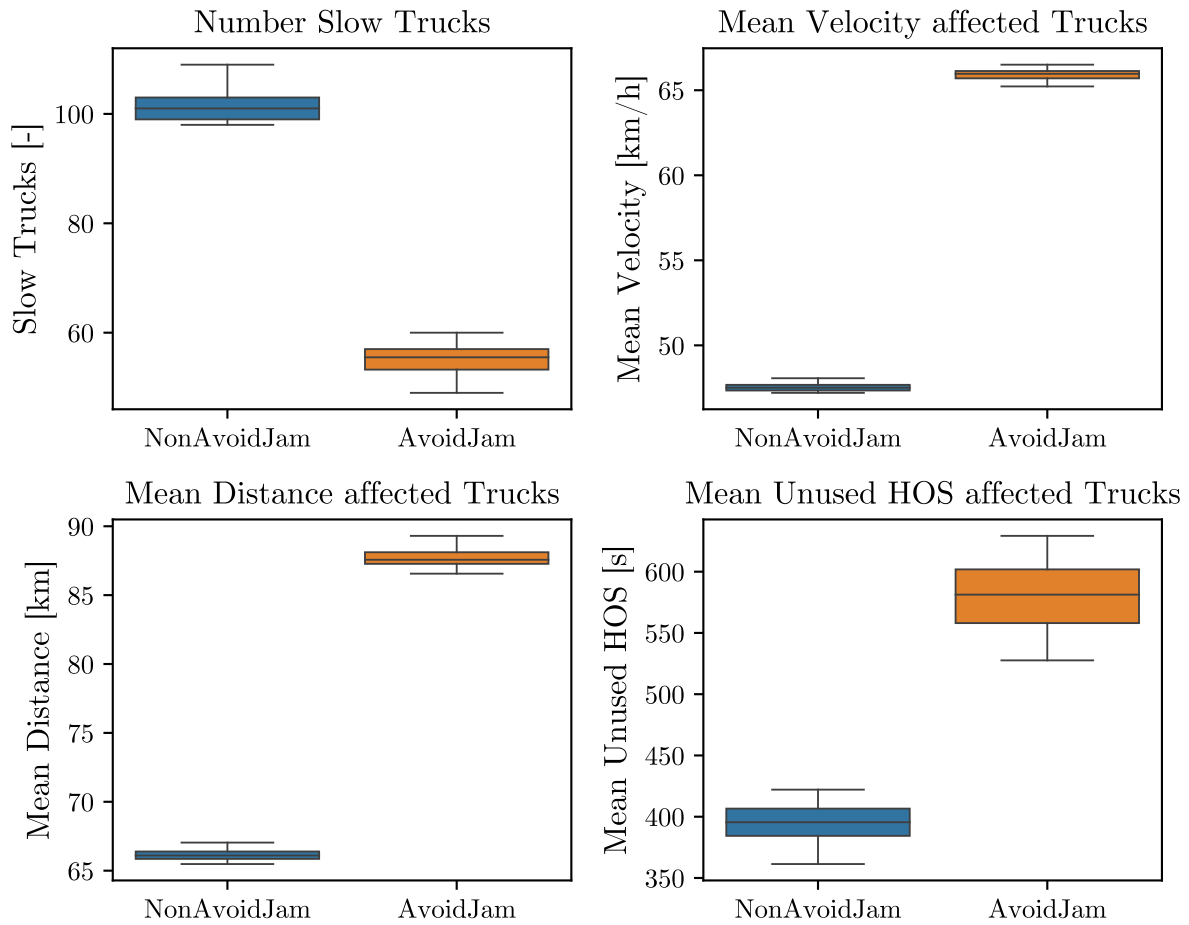
Figure 5.11: Multi-metric evaluation of large jam scenario

For the remaining three metrics, mean velocity, mean distance driven, and mean unused HOS, the Shapiro-Wilk tests indicate normally distributed samples ($W = [0.948, 0.979]$, $p = [0.150, 0.801]$). However, Levene's test for homogeneity of variances for mean distance ($F(1, 58) = 5.177$, $p = 0.027$) and mean unused HOS ($F(1, 58) = 19.181$, $p < 0.001$) suggest unequal variances between the recommendation strategies. Therefore, Welch's t-test is applied, which is similar to the Student's t-test but accounts for unequal variances.

In the upper right part of the figure, the mean velocity of the affected trucks is depicted. To compare the two strategies, the set of slow trucks is extended by the trucks that get a pull-over recommendation to avoid the jam. The union of the two sets is called the set of affected trucks. It can be seen that the mean average velocity for the strategy NonAvoidJam ($M = 47.5$, $SD = 0.24$) is slower than for AvoidJam ($M = 65.9$, $SD = 0.33$). The Welch's t-test shows that the difference is significant ($t(52.5) = 246.702$, $p < 0.001$). To conclude, the average velocity is increased by $38.7\,\%$.

In the lower-left part, the mean distance of the affected trucks is plotted. The Welch's t-test indicates a significant difference ($t(47.21) = 147.675$, $p < 0.001$) between NonAvoid-

Jam ($M = 66.1$, $SD = 0.41$) and AvoidJam ($M = 87.7$, $SD = 0.69$). The results suggest that the driven distance can be increased by 32.7 % when TOPTIPS instructs the truck drivers to avoid the congestion.

In the lower right part of the figure, the mean unused HOS of the affected trucks is shown. At first glance, the results seem counterintuitive as there is a significant difference ($t(44.38) = 30.68$, $p < 0.001$) between NonAvoidJam ($M = 394.89$, $SD = 15.55$) and AvoidJam ($M = 579.36$, $SD = 29.03$). Concretely, this means that the truck drivers have more unused HOS when they avoid the congestion. Further in-depth research reveals a blocking effect. The capacities of the rest areas upstream of the traffic jam (e.g., *Fürholzen*) are large and completely exploited to store trucks temporarily. After the congestion has dissolved, the restartable trucks continue their journey. However, if they use up all their remaining driving time, they reach smaller rest areas (e.g. *Greding*, *Gelbelsee*). As a consequence, the capacities of these rest areas are exhausted quickly, and the next larger rest area upstream *Köschinger Forst* is recommended by TOPTIPS. This results in higher unused HOS than necessary. On the other hand, trucks that are stuck in congestion arrive with little unused HOS.

5.5.3 Research Question Assessment

The original research question to be answered is:

Q4: In case of large traffic jams, can the productivity be increased?

The results show that truck-specific parking recommendations are predestined to increase productivity in the case of large traffic jams. When large congestion builds up, TOPTIPS uses the upstream rest areas as temporary storage but only until the closing capacities are reached. After the jam has dissolved, the restartable trucks continue their journey. With this approach, the number of slow trucks can be reduced by 45.0 %, and the mean velocity and mean distance driven of the affected trucks are increased by 38.7 % and 32.7 %, respectively. However, the metric mean unused HOS deteriorates by 46.7 % due to a blocking effect. More research is required to understand the effect in full detail. It has to be noted that the study area has certain characteristics that may limit the transferability of the results regarding the blocking effect. Further, whether the metric mean unused HOS is at all suitable for congested scenarios needs to be studied. It may not be appropriate if the HOS is reduced primarily due to congestion with very few revenue kilometers driven. In the previous scenarios, the unused HOS was a good metric to measure productivity (as suggested by the literature). In congested scenarios, there are indications that it is not. Therefore, the mean distance and mean velocity are introduced as surrogate productivity metrics.

In summary, it can be stated that the average velocity and average driven distance are increased by the AvoidJam recommendation strategy. From this point of view, the research question is considered as answered. With respect to the metric mean unused HOS, the research question is considered partially answered. Moreover, new questions have arisen. For example, insight is missing on what strategies truck drivers currently pursue in case of large traffic jams. If this was known, the TOPTIPS results could be compared to those strategies. Furthermore, the scenario was studied with quasi-perfect travel time predictions. This setup was used because in the case of large traffic jams the exact delay may not be of the greatest importance. However, accounting for noise would provide further valuable insight and should be one of the next steps. Lastly, if more knowledge of the blocking effect was available, alternative strategies could be devised. Some countries have HOS regulation exceptions in place which could be considered to mitigate the effect. For example, in Germany the driving time can be extended by 1 h two times a week. Integrating these exceptions could further improve the TOPTIPS performance in situations with large traffic jams.

5.6 Summary, Discussion, and Transferability of the Results

TOPTIPS was evaluated with respect to the four research questions. In Figure 5.12, an overview of the evaluations is shown. In summary, the proposed recommendation

Result Summary

Different Recommendation Strategies

Q1: What impact can truck-specific parking recommendations have for drivers and road authorities?

Aim:
- Compare TOPTIPS with status quo
- Study different weighting combinations

Approach and Assumptions:
- Keep random seed fixed
- Almost perfect travel time predictions

Results:
- TOPTIPS outperformes status quo
- Productivity increases by 16.7%
- Reduction of uneven filling by 59.0%

Penetration Rate Variation

Q2: What are the effects of different penetration rates?

Aim:
- Study different penetration rates (PR)
- Main focus on system objective

Approach and Assumptions:
- Different random seeds
- Random TOPTIPS truck selection

Results:
- Small PRs reduce uneven filling significantly by 79.2%
- PRs ($\geq 30\%$) gradually reduce the productivity (second objective)

Noisy Travel Time Predictions

Q3: What are the effects of different levels of travel time prediction accuracy

Aim:
- Study productivity impacts
- Study HOS regulation violations

Approach and Assumptions:
- Different random seeds
- Random noise up to E[X]=25%

Results:
- Noisy predictions reduce productivity by 4.8% to 8.2%
- 4.0% to 6.5% of trucks exeed their driving time

Large Traffic Jam

Q4: In case of large traffic jams, can the productivity be increased?

Aim:
- Study number of slow trucks, mean velocity, and mean distance

Approach and Assumptions:
- Different random seeds
- Large jam (based on real mega jams)

Results:
- Reduction of slow trucks by 45%
- Increase of mean velocity by 39%
- Increase in driven distance by 33%
- Blocking effect discovered

Figure 5.12: Result summary

system can organize truck parking efficiently. As a result, this transforms today's largely unorganized truck parking situation into a controlled environment. By using FTD and multi-criteria optimization, truck-specific parking recommendations are issued. These recommendations can consider conflicting objectives of truck drivers and road authorities. The main two advantages of TOPTIPS are (I) a greatly simplified search process for the drivers and (II) optimal use of existing parking infrastructure. However, the evaluation of TOPTIPS also has some limitations, which are explained in the following.

Limited Route Information

The evaluation of TOPTIPS was carried out for the motorway A9 between Munich and Nuremberg (study area). The trucks that park in this region are considered 1 h in advance (model area). From the available data, it is not known where the trucks are located 1 h in advance. For this thesis, it is assumed that the trucks follow the Trans-European Transport Network (TEN-T) [van Weenen et al., 2016], concretely the Scandinavian–Mediterranean Corridor. This assumption allows for multi-destination travel time estimation using virtual trajectories. However, it is a simplification. Further improvements with respect to the simulation are conceivable. Probe FTD could be used to estimate routes more accurately. If data on routes is difficult to obtain, the estimated travel times could be modeled in more detail. Different routes may have different travel time prediction accuracy. Consequently, the noise-adding procedure could be modified to reflect different routes. Another improvement concerns the assumed objective of maximizing productivity. There may be truck drivers for whom the maximizing productivity objective on a specific leg is not valid (e.g., scheduled unloading the next day and already close to the destination). These trucks could provide TOPTIPS with additional degrees of freedom.

Spatial Extension Considerations

Another important aspect is the spatial end of the model area. *Feucht* is the last modeled rest area, which is a limitation. In the simulation, all trucks that park at this rest area in the status quo cannot receive a recommendation for a rest area further downstream but only upstream. This restriction implies that the remaining HOS for these trucks cannot be reduced. In other words, the maximizing productivity objective is considered in a conservative way. A less conservative approach would assume that a rest area further downstream can be recommended. However, the question arises of how this should work. One idea is to work with hand-over procedures, similar to air traffic control. The downstream TOPTIPS could get a hand-over notification and consider the trucks from the upstream TOPTIPS. Having dedicated TOPTIPSs for specific stretches connected by hand-over procedures is called a decentralized approach. On the other hand, a centralized approach which covers all rest areas is also conceivable. One advantage could be simplification because no hand-over procedures are required. Further, more complex routing

capabilities could be integrated. However, centralized systems are generally considered to be more challenging in terms of data privacy.

Data Privacy and Incentives

TOPTIPS is data-driven. Therefore, it is important to address privacy issues. Personal data such as location and HOS data is required. Moreover, not only personal data but also business secrets, such as routes and (un-)loading locations, could be exposed. Therefore, it is necessary to operate TOPTIPS in a protected environment by a trusted party. In addition, efforts must be made to guarantee appropriate anonymization of the data. One option could be to operate TOPTIPS by a state-owned company. For example, in Germany it could be the same company that is responsible to manage truck tolling (Toll Collect). One of the advantages would be that the trust for handling sensitive data is already in place. Further, the toll collection entity already processes some of the same FTD that is required for TOPTIPS (e.g., Global Positioning System (GPS) location data). Additionally, monetary incentives could be provided. A state-owned company could incentivize social behavior (i.e., less individual objective achievement) by reducing the tolls for the affected trucks. As the results show, even filling can be achieved with relatively small penetration rates of 30 %. However, in the end, the question boils down to how much individual productivity/amenity convenience truck drivers are willing to give up to improve global safety for all traffic participants. Incentives may play an important role in achieving the objectives of road authorities.

Environmental Impacts

The focus of this thesis is on the most pressing issues of truck parking derived from the literature. However, the environmental impacts of transportation systems are becoming increasingly important. In general, there are two research areas that should be studied further: First, the environmental impacts of TOPTIPS with regard to different recommendation strategies, penetration rates, and travel time prediction accuracy are potential domains for further research. Second, potentially induced road freight traffic could be investigated. This aspect requires some more explanation. The results showed that productivity is increased with TOPTIPS and at the same time overcrowding is mitigated. These effects could lead to even more road freight traffic because there are "new" capacities. In transport research, this phenomenon is referred to as induced traffic (known since the late 1930s). GOODWIN [1996] provides empirical evidence that road improvements can lead to increased traffic of 10 % in the short term and 20 % in the long term. It is commonly agreed upon in the literature that the shortage of truck parking became worse over time (and will in the future) due to increased economic activities. Therefore, precautions should be taken not to aggravate the already worsening problem.

Building Cost Savings

SMITH et al. [2005] state that all currently known solutions for the truck parking issue fall into two categories: (I) better matching of supply and demand, (II) building more supply. TOPTIPS uses FTD to match supply and demand optimally according to the chosen recommendation strategy. However, due to increasing road freight traffic, even with TOPTIPS in place, rest areas must be extended and new parking spaces need to be built. TOPTIPS can only improve the situation within the physical limits. The situation is similar to motorways that operate at the critical density. To some extent, Variable Message Signs (VMSs) can homogenize flows and prevent a breakdown. However, at some point more lanes or hard shoulder running need to be applied in parallel. In order to estimate potential cost savings from the use of TOPTIPS, figures from Germany are considered. In the past ten years, the German Federal Government spent about €100 million per year for expanding truck parking capacities along the motorway network [GERMAN FEDERAL GOVERNMENT, 2019; GERMAN FEDERAL GOVERNMENT, 2021]. The same amount per year is projected for the future. Under the assumption that 10 % of the spending can be saved with TOPTIPS, there are potential cost savings of €10 million each year. Even if the initial development and the operation costs for TOPTIPS are considered, there is still great saving potential.

Key Takeaways: Results

- Parking recommendations are beneficial for drivers and road authorities at the same time.

- The multi-criteria optimization approach can accommodate a variety of recommendation strategies and has great potential to improve the current truck parking situation.

- Small penetration rates of 30 % can already have a significant impact.

- Even with noisy travel time predictions, only a small fraction of drivers exceed their driving time.

- In case of large traffic jams, the productivity of drivers can be significantly improved by recommending temporary stops.

- The Truck Optimization Parking System can save a significant amount of construction cost.

Chapter 6

Conclusion

6.1 Summary and Contributions

The goal of this thesis is to advance truck parking through individual parking recommendations. Currently, trucks are the most important mode of freight transport and represent the backbone of our economy. However, parking along major freight corridors is becoming an ever-growing problem and was ranked the most important issue among truck drivers in 2020 [AMERICAN TRANSPORTATION RESEARCH INSTITUTE, 2020]. Population growth, falling trade barriers, reduced transport costs, increased consumption, customized products, and better transport infrastructure are going to make the situation worse [KOUROUNIOTI et al., 2020].

Increased availability of Floating Truck Data (FTD) offers new opportunities to better match parking supply and demand. This thesis developed an optimization framework, called Truck Optimization Parking System (TOPTIPS), which provides truck-specific parking recommendations. This relieves drivers from the search process. Recommending truck parking spaces requires accounting for various constraints. One of the most important constraints is the legally allowed remaining driving time of each driver that must not be exceeded. Moreover, truck drivers and road authorities have conflicting objectives. Whereas the drivers often face pressure to generate revenue miles and prefer to have some amenities (shower, food, fuel, bathroom) at the end of a working day, road authorities are mostly concerned with overcrowding and maintaining safety for all traffic participants. In order to balance the conflicting interests, TOPTIPS is based on multi-criteria optimization.

The central idea of the thesis is to model truck parking mathematically and to solve the resulting MIP optimization problem. In order to evaluate the proposed model, a large-scale microscopic traffic simulation was set up. The simulation was calibrated and validated with real data. The truck parking demand was derived from minute-by-minute field occupancy data. The results showed a well-calibrated model that exhibits an RMSE of 181 veh/h. Besides the traffic flows, two velocity-centric metrics, originally developed for RTTI quality assessment, were applied. The SIMPE metric indicated small spatio-temporal speed deviations ($f \approx 0.89$) and the TTD index underscored well-matching

travel times ($f \approx 0.96$). The last step to complete the evaluation framework was the connection of the simulation with the MIP solver environment and a multi-destination travel time estimation module based on virtual trajectories.

In total, there were four evaluation clusters, each to answer a particular research question. In the first cluster, different recommendation strategies were studied to quantify what impact truck-specific parking recommendations have. The results showed that TOPTIPS can serve both truck drivers and road authorities in achieving their goals. The uneven filling of the rest areas was reduced by 59.0 %, and, at the same time, the productivity of the drivers was increased by 16.7 % compared to the status quo. Individual preferences, such as the availability of food, fuel, shower, and bathroom, could also be accounted for. In summary, it was demonstrated that the multi-criteria optimization approach can accommodate a variety of recommendation strategies and has a great potential to improve the current truck parking situation.

In the second cluster, what happens if not all trucks are equipped with TOPTIPS was studied. The results showed an interesting picture. Small penetration rates of 30 % could significantly reduce uneven filling by 79.2 %. At the same time, the secondary objective of reducing unused HOS was improved by 27.9 %. However, increased penetration rates worsened the results with respect to the secondary objective. Figuratively speaking, TOPTIPS could fill the holes by sending the "right" trucks in situations with up to 30 % penetration (critical mass). Once even filling was achieved and penetration rates were further increased, TOPTIPS recommended rest areas that maintain even filling at the expense of increased unused HOS. This result demonstrated the immediate effects of truck-specific recommendations at low penetration rates.

An important prerequisite for TOPTIPS is multi-destination travel time predictions. The third cluster evaluated the effects of inaccurate predictions. In order to simulate realistic travel time predictions, noise was added to quasi-perfect travel times. The noise was modeled by the conditional expectation of a random variable that corresponds to values found in the literature. Noisy predictions reduced the productivity by 4.8 % to 8.2 % depending on the optimization frequency. However, only a small fraction (4.0 % to 6.5 %) of the trucks exceeded their driving time. The results demonstrated that TOPTIPS can cope with noisy predictions. An optimization frequency of 15 min leads to good results and could readily be applied in practice.

In the fourth cluster, whether truck drivers can benefit from TOPTIPS when a large traffic jam happens was researched. Congestion means reduced remaining driving time with only a few driven revenue miles and is particularly undesirable. A large traffic jam was simulated based on real mega jam data on the A9. The results showed that truck-specific recommendations are predestined to handle congested situations. Two recommendation

strategies (NonAvoidJam and AvoidJam) were compared. It was shown that the number of slow trucks is reduced by 45 %. Moreover, the mean velocity and the mean driven distance of the jam-affected trucks could be increased by 39 % and 33 %, respectively. At the same time, excessive overcrowding of rest areas was prevented, which is important for traffic safety.

In conclusion, TOPTIPS serves both drivers and road authorities. However, both stakeholders have conflicting objectives. The weighting of the objective functions determines the degree of each objective achievement. Truck drivers are assisted by simplifying the parking search process, resulting in less stress, better HOS compliance, higher productivity, and fulfilled parking preferences. Road authorities benefit from better-matched parking demand and supply, resulting in improved traffic safety and reduced building costs. It is estimated that in Germany alone about €10 million in building costs could be saved each year. In conclusion, FTD offers new opportunities to transform today's largely unorganized truck parking situation into a controlled environment. The developed TOPTIPS is the first step in this direction and hopefully inspires more researchers to advance knowledge in this field. Assuring efficient and reliable freight traffic is more important than ever for our economy.

6.2 Outlook

The results of TOPTIPS are promising; however, there are limitations that need to be addressed in future research. The statistical analyses had relatively small sample sizes due to the high computational resources required for each simulation run. This made it difficult to test statistical assumptions. This also applies to the non-parametric tests (e.g., Kruskal-Wallis H test) for which it was assumed that the distributions have a similar shape. Moreover, TOPTIPS was "only" evaluated with a simulation. As a first step, more simulation runs could be performed to improve the statistical power and to gain further insight. Additionally, other study areas could be simulated. This would be a critical step in demonstrating the transferability of the results to other motorway sections. The present results refer to the specific study area of the A9. As a next step, a field test could be conducted to study the behavior of the system under real-world conditions. The simulation results showed that even small penetration rates can have a significant impact, which is a good prerequisite for a field test.

TOPTIPS requires personal data such as the GPS location. Therefore, privacy issues need to be addressed to keep personal information safe and anonymized. A related question is who should operate TOPTIPS? As there is not only sensitive personal data involved but also business secrets, a well-trusted and neutral entity seems appropriate. A state-owned

company that already partially processes the required data (e.g., for toll collection) could be such an entity. This would have another advantage because the objectives of road authorities could be incentivized easier. For example, reduced individual productivity for the purpose of less excessive overcrowding could result in a toll bonus.

Another major aspect to be studied is potentially induced truck traffic because parking is improved. Improved traffic conditions have been known to lead to increased demand since the late 1930s. However, the environmental impact of transportation systems is becoming more and more important. TOPTIPS will likely lead to more road freight traffic if no precautions are taken. On the other hand, advances in FTD could lead to more efficient scheduling, environmentally friendly routing, and more efficient bundling of Less-Than-Truckload shipping. As always, opportunities and risks have to be balanced.

The trend for cars is to become battery-electrified. With respect to heavy-duty vehicles, renewable fuels, battery-electric, and fuel-cell powered alternatives are conceivable among others. As a consequence, preferences regarding specific recharging options or hydrogen gas stations could be incorporated into TOPTIPS in the future. Moreover, it may be beneficial to align longer recharging times with mandatory rest breaks. Further research is required on whether the recharging problem type can be reduced to the temporary stop problem during traffic congestion.

In summary, important research questions have been answered during this work, but new questions have also arisen. However, the most important issue that needs to be addressed is the popularization of FTD-based research in freight transportation. FCD attracts much research attention, but FTD seems partially overlooked. This is a problem because FTD has a great potential to improve the status quo. After all, friction-less road freight transport is urgently needed for the exchange of goods, has a significant environmental impact, and affects the safety of all traffic participants.

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List of Abbreviations

ABS   Agent-Based Simulation 33, 34

ANOVA Analysis of Variance 113

API   Application Programming Interface 45, 65, 95

ARIMA   Autoregressive Integrated Moving Average 117

ASM   Adaptive Smoothing Method 85, 90, 96, 99, 121

BASt   German Federal Highway Research Institute ("Bundesanstalt für Straßenwesen") 76

BIC   Bayesian information criterion 27

DE   Data Device ("Daten-Endgerät") 76

DZ   Permanent Counting Location ("Dauerzählstelle") 73, 74, 76, 87

ETT   Estimated Travel Time 83, 84, 92, 95–97, 103, 112, 116

EU   European Union 1, 2

FCD   Floating Car Data 43, 46, 134

FD   Fundamental Diagram 75

FTD   Floating Truck Data v, 5–7, 25, 28, 42–44, 46, 47, 64, 112, 128–131, 133, 134

GBM   Gradient Boosting Model 117

GPS   Global Positioning System 21, 22, 24, 27, 28, 34, 43, 46, 47, 73, 74, 77, 129, 133

HOS   Hours of Service v, 3–5, 7, 18, 20, 21, 23, 24, 33, 35, 36, 42–44, 46, 47, 49–51, 53–55, 60–62, 83, 101, 103, 105, 106, 111, 112, 114–116, 118–120, 123–126, 128, 129, 132, 133, 135, 136

TOPTIPS   Truck Optimization Parking System v, 9, 40, 43–48, 50, 51, 53, 54, 56, 58, 62–65, 68, 70, 75, 79–84, 87–89, 91, 92, 94–99, 102–104, 106, 108–112, 114–116, 120, 121, 125–134

TPIMS   Truck Parking Information Management System 29, 31

TPP   Truck Parking Prediction 32

TTD   Travel Time Difference v, 84, 92, 93, 99, 131

TUM   Technical University of Munich 83

VMS   Variable Message Sign 29, 30, 70, 73, 89, 95, 130, 135

XGB   Extreme Gradient Boosting 32

XML   Extensible Markup Language 68, 74

ZVM   Competence Centre for Traffic Management ("Zentralstelle für Verkehrsmanagement") 83

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Appendices

Appendix A: Raw Data

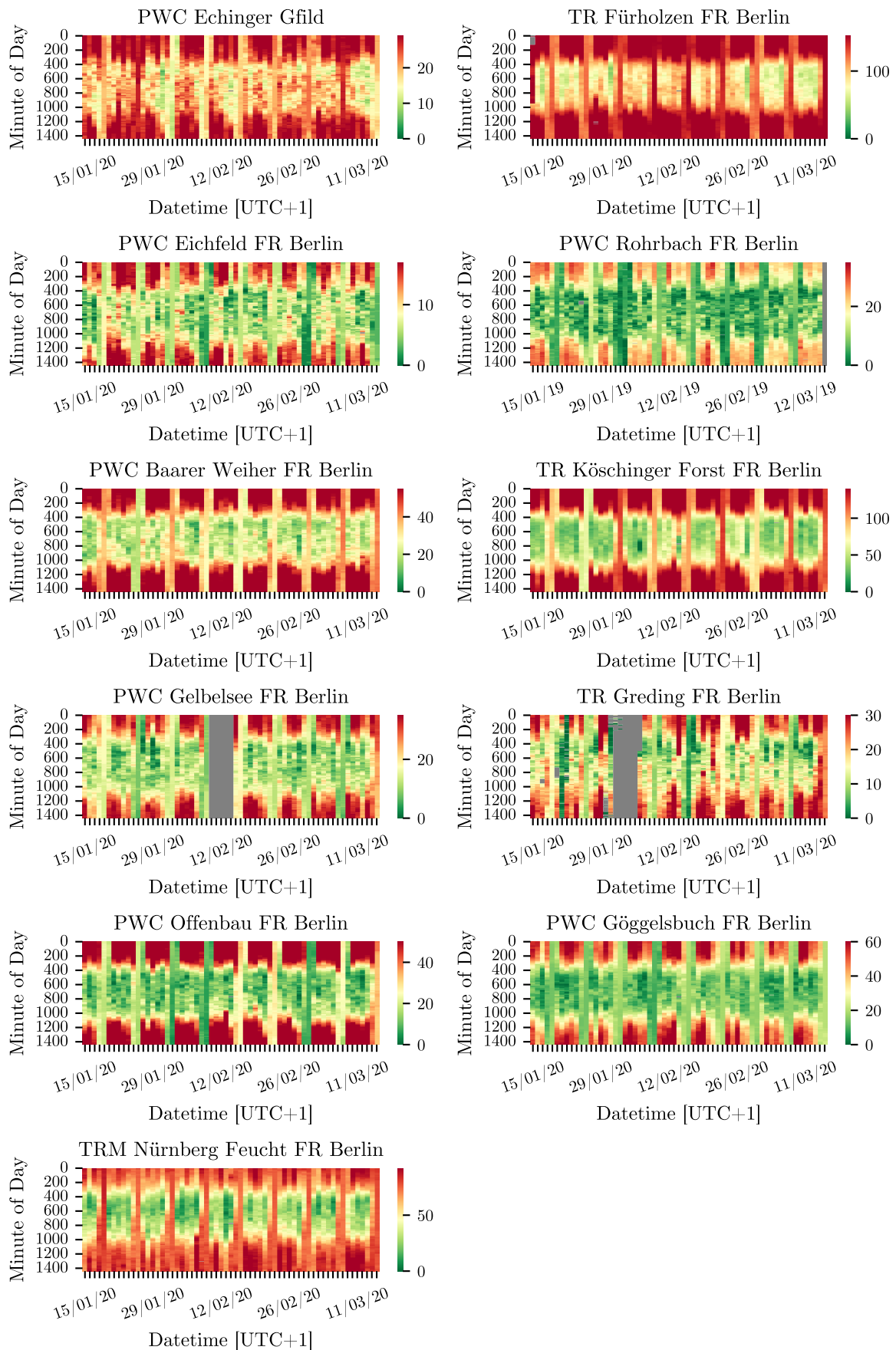# Occupancy Raw Data for all Rest Areas

Figure A.1: Occupancy raw data of all rest areas between January 15, 2020 and March 16, 2020. Substitute data for PWC Rohrbach from 2019 due to road works.

Appendix B: Modeling Supply

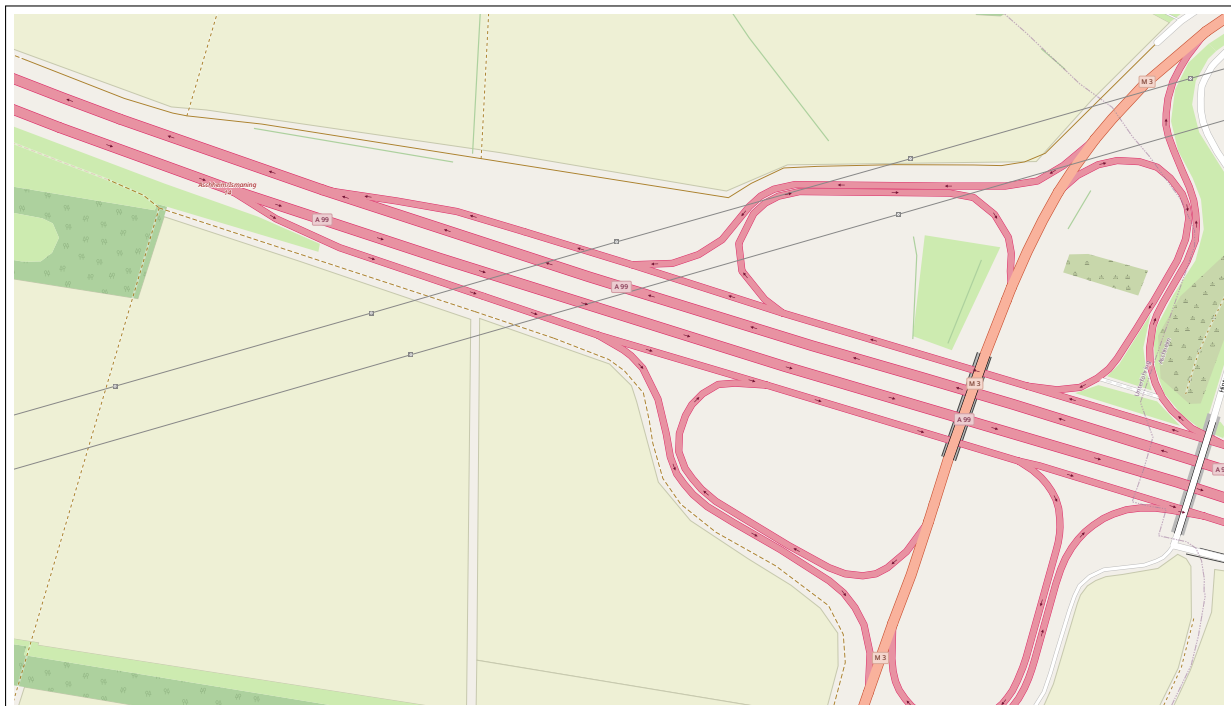Figure A.2: Motorway access Aschheim satellite view - source: BayernAtlas

Figure A.3: Motorway access Aschheim OSM view. The on-ramp to the A99 is missing and modeled as a simple junction. The same is true for the feeder road leading to the A99 on-ramp. The two locations can be seen in Figure A.2.
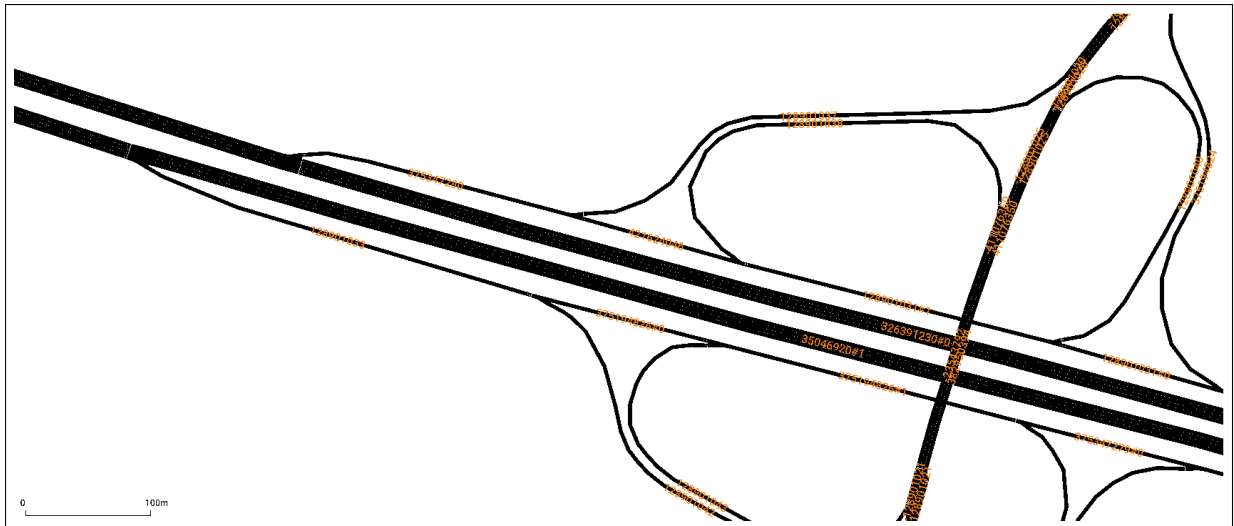
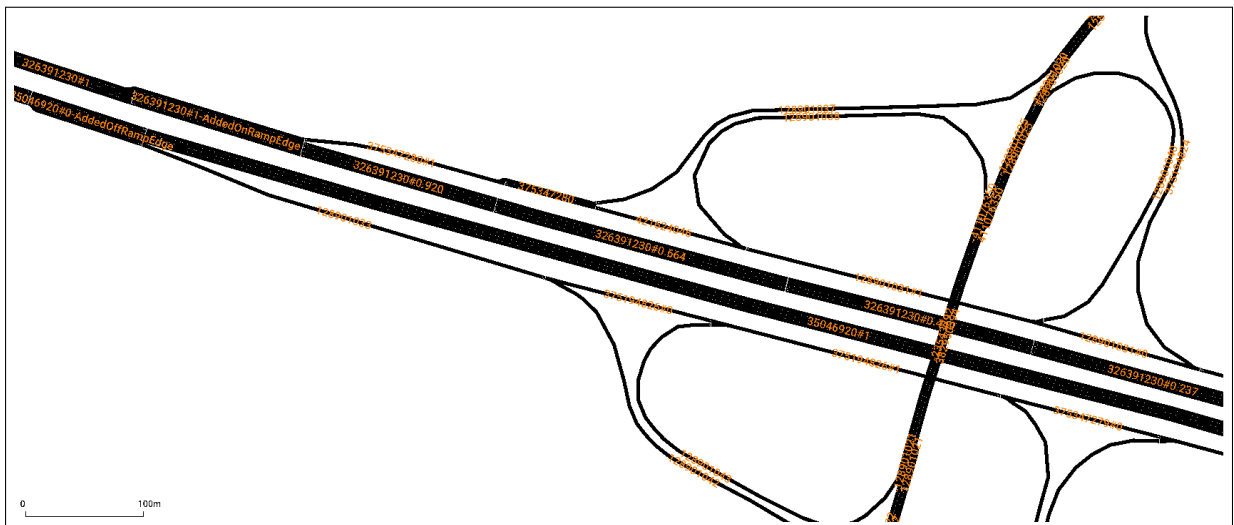Figure A.4: Motorway access Aschheim converted from OSM raw data.

Figure A.5: Motorway access Aschheim converted from OSM raw data with ramp guessing and manual corrections

Appendix C: Modeling Demand

| Parameter	Value
Car Following Model	Extended Krauß (SUMO Default)
Lane Change Model	LC2013 (SUMO Default)
Speed Restriction Trucks Motorway	$80\,\mathrm{km/h}$
Passenger Cars	vClass: passenger
Max Acceleration (a_{max})	$2.6\,\mathrm{m/s^2}$
Max Deceleration (b_{decel})	$4.5\,\mathrm{m/s^2}$
Emergency Deceleration (b_{decel})	$9.0\,\mathrm{m/s^2}$
Max Speed (v_{max})	$200\,\mathrm{km/h}$
Speed Deviation ($speedDev$)	0.1
Driver Imperfection (σ)	0.5
Minimum Time Headway (τ)	$1\,\mathrm{s}$
Gap Acceptance (lc_{ass})	1.5
Trucks	vClass: truck
Max Acceleration (a_{max})	$1.3\,\mathrm{m/s^2}$
Max Deceleration (b_{decel})	$4.0\,\mathrm{m/s^2}$
Emergency Deceleration (b_{decel})	$7.0\,\mathrm{m/s^2}$
Max Speed (v_{max})	$85\,\mathrm{km/h}$
Speed Deviation ($speedDev$)	0.05
Driver Imperfection (σ)	0.5
Minimum Time Headway (τ)	$1\,\mathrm{s}$
Gap Acceptance (lc_{ass})	1.0

Table A.1: SUMO parameters
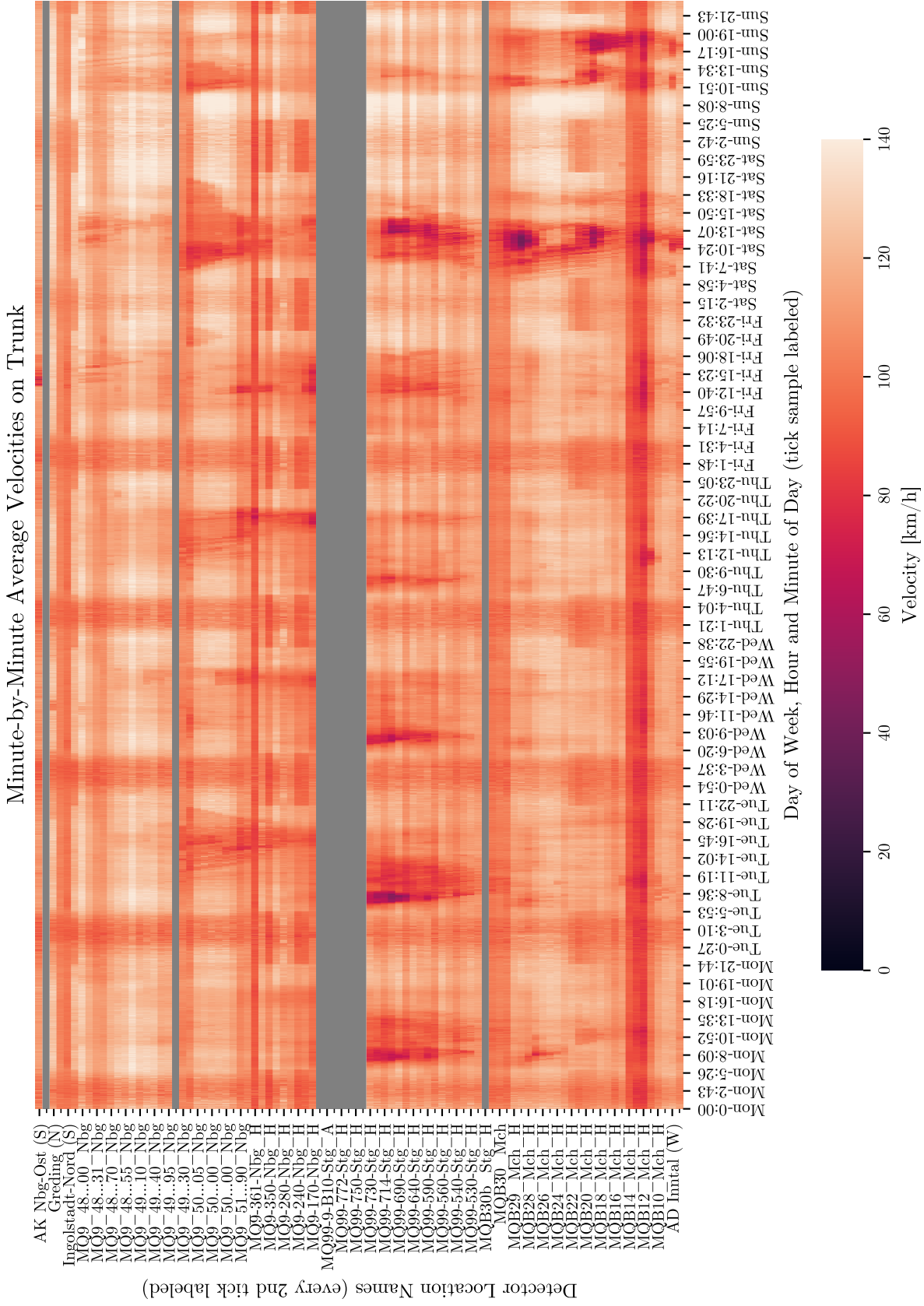
Figure A.6: Minute-by-minute velocities (10080 values) for trunk including defective detector locations
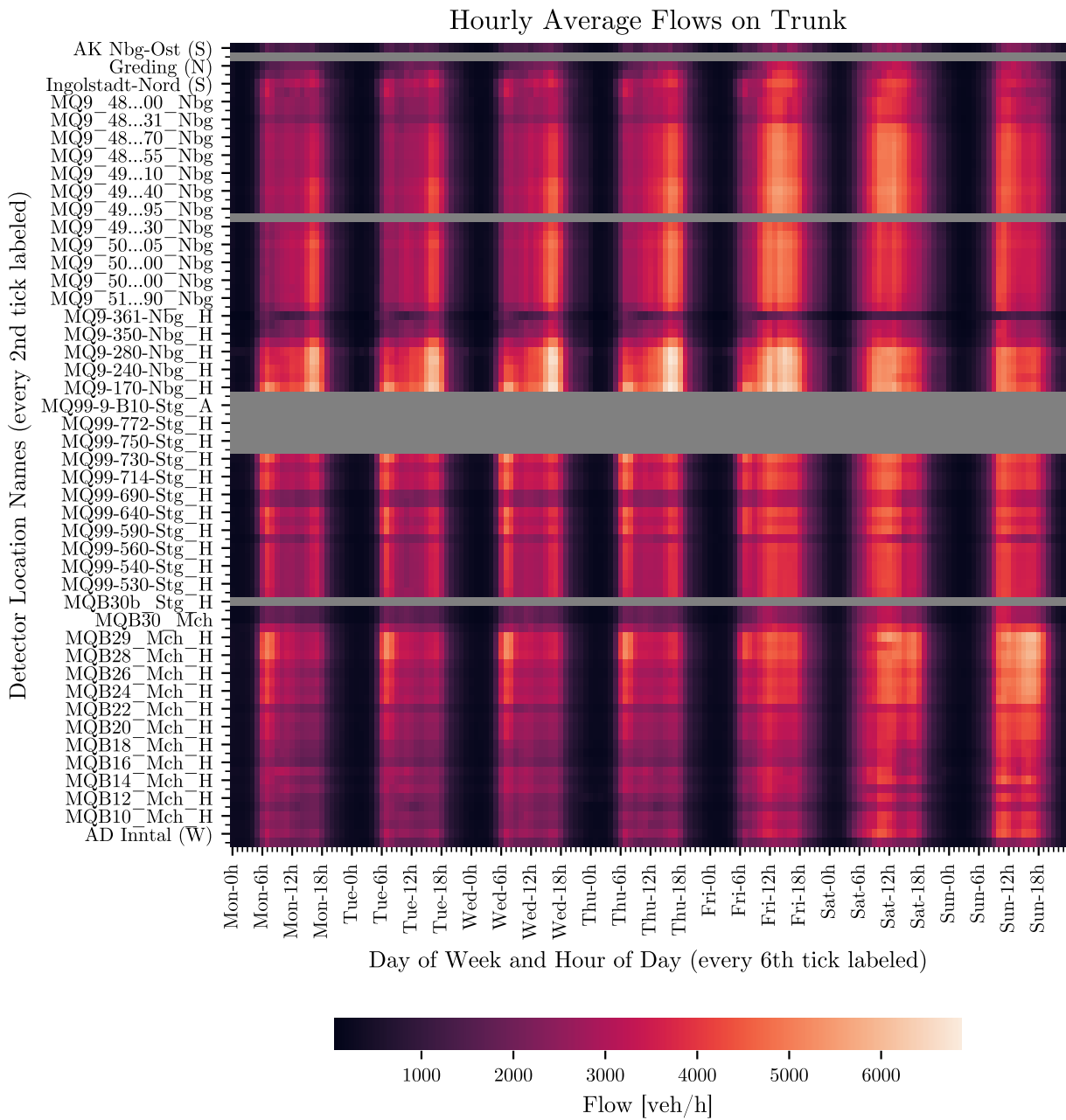
Figure A.7: Hourly averaged flows on trunk including defective detector locations

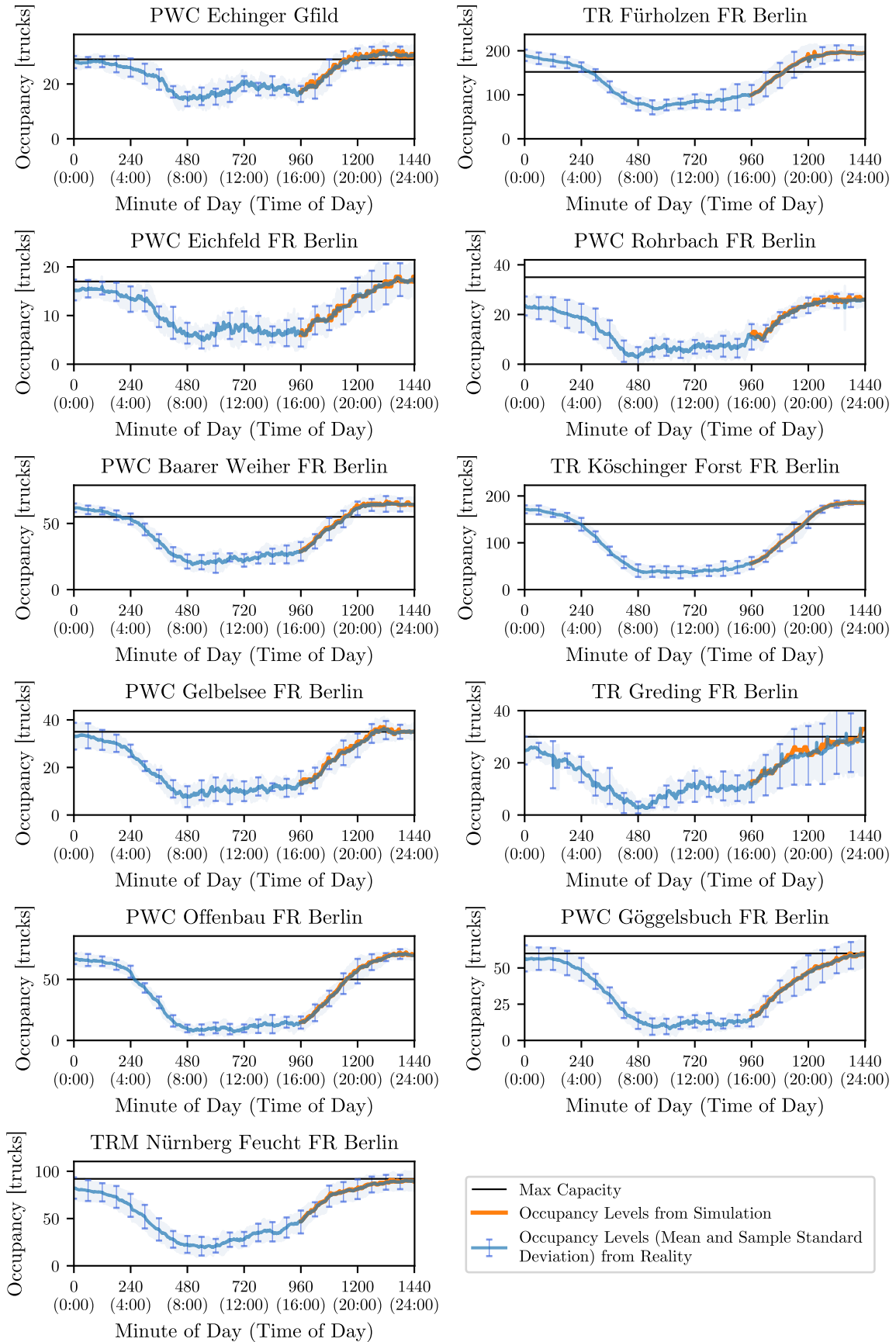## Truck Parking Demand Typical Tuesday

Figure A.8: Truck parking demand reality vs. simulation from 4 p.m. to 12 a.m. 169
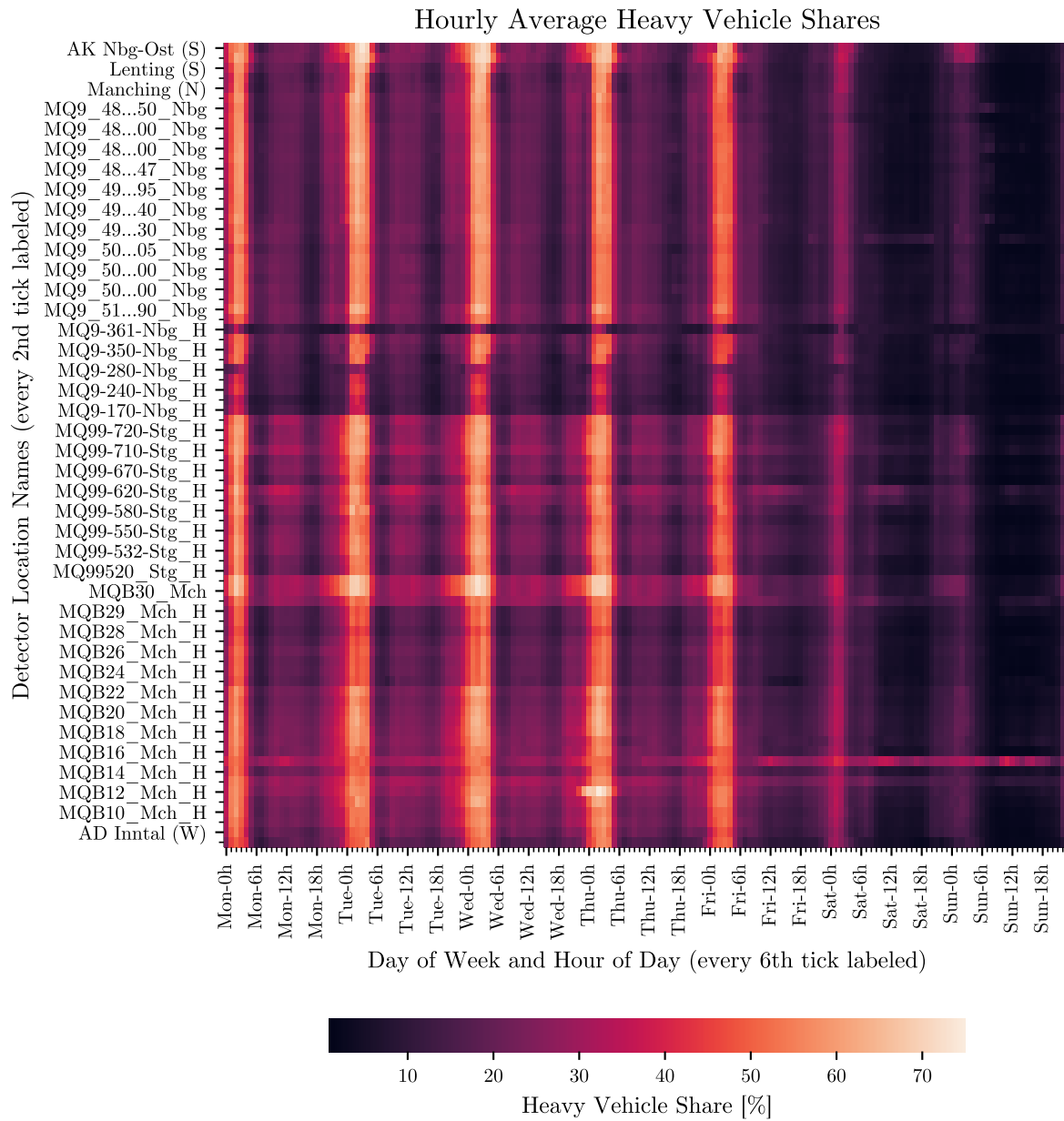
Appendix D: Calibration and Validation
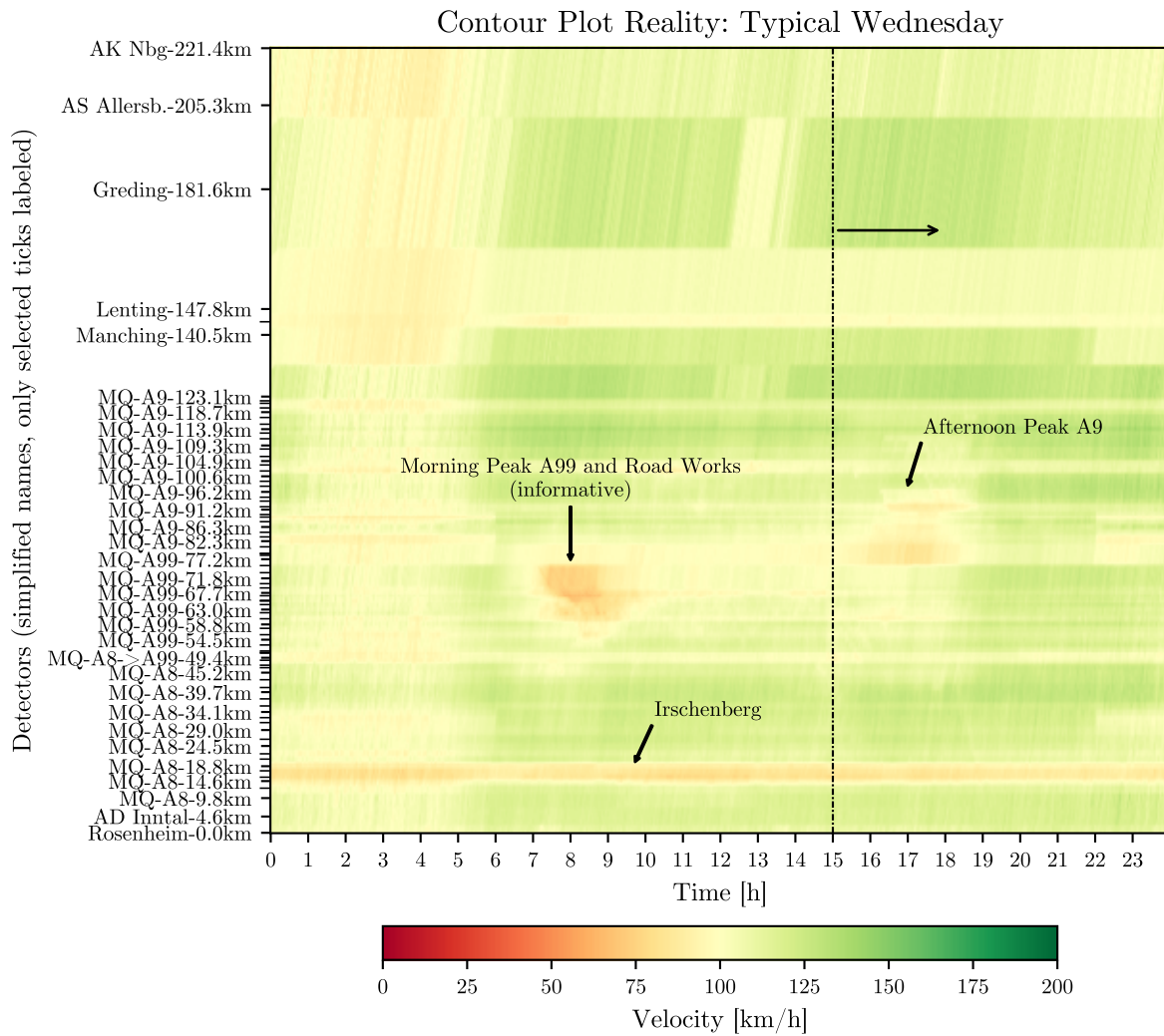

Figure A.9: Hourly heavy vehicle shares

Figure A.10: ASM smoothed contour plot reality of a typical Wednesday

Software/Library(selected only)	Version
Gurobi	9.1.1
SUMO	1.12.0
R	4.1.3
RStudio	2022.02.1 Build 461
Python	3.7.9
Spyder IDE	5.2.2
Conda	4.9.2
PostgreSQL	12.8
QGIS	3.10.9
Docker Engine	20.10.6
Octave	6.2.0
MiKTeX	21.8
TeXstudio	4.1.1
JabRef	5.3
lxml	4.6.1
matplotlib	3.3.4
multiprocess	0.70.12.2
numpy	1.19.5
oct2py	5.2.0
pandas	1.3.5
pathos	0.2.7
psycopg2	2.9.1
regex	2022.1.18
scikit-learn	0.24.1
scipy	1.6.0
seaborn	0.11.1
sqlalchemy	1.4.23
statsmodels	0.13.2

Table A.2: Software and key libraries used
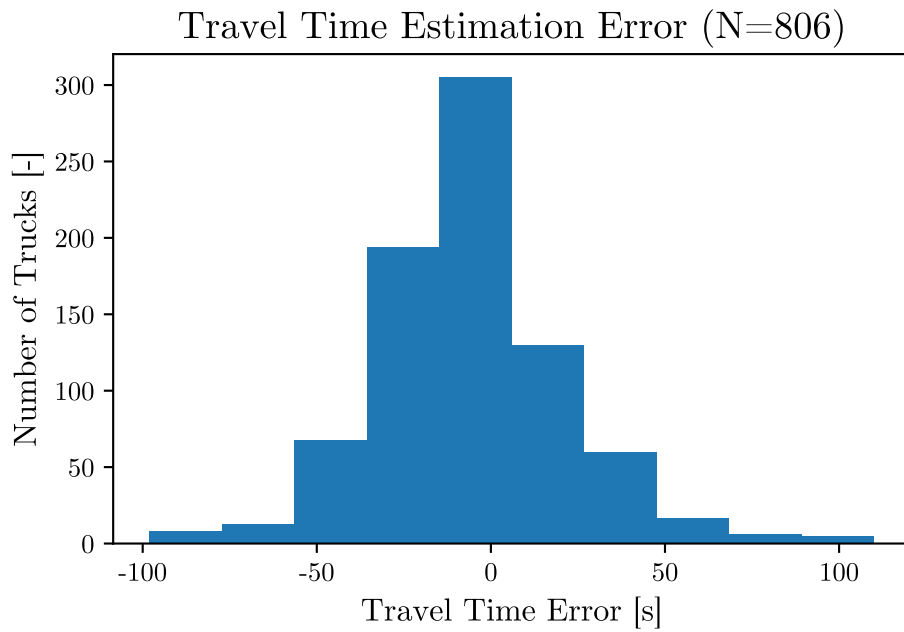
Appendix E: Results

Figure A.11: Error distribution of estimated travel times (based on virtual trajectories). Travel time prediction conducted at the beginning of each trucks' journey. The error is calculated as realized minus predicted travel time. RMSE is 28 s.

Chi2	Z	P	P.adjusted	Comparisons
28.92609	0.9886231	0.1614238	0.1862582	0 - 10
28.92609	2.3617107	0.0090954	0.0194902	0 - 20
28.92609	1.3730876	0.0848626	0.1414376	10 - 20
28.92609	4.4762655	0.0000038	0.0000570	0 - 30
28.92609	3.4876425	0.0002436	0.0012182	10 - 30
28.92609	2.1145549	0.0172340	0.0323137	20 - 30
28.92609	3.4601807	0.0002699	0.0010121	0 - 40
28.92609	2.4715577	0.0067263	0.0168157	10 - 40
28.92609	1.0984701	0.1359996	0.1854541	20 - 40
28.92609	-1.0160848	0.1547945	0.1934931	30 - 40
28.92609	3.5425660	0.0001981	0.0014860	0 - 50
28.92609	2.5539429	0.0053255	0.0159766	10 - 50
28.92609	1.1808553	0.1188301	0.1782452	20 - 50
28.92609	-0.9336996	0.1752294	0.1877458	30 - 50
28.92609	0.0823853	0.4671702	0.4671702	40 - 50

Table A.3: Dunn's post hoc test MAROD metric adjusted for family-wise errors with the Benjamini-Hochberg method ($\alpha = 0.05$)