Road Network Performance Measurements

Incorporating Location Intelligence into Decision Support Systems for Logistics

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List of Abbreviations

API Application Programming Interface

BI Business Intelligence

DERNP Database for Estimation of Road Network Performance
DFF Digital Freight Forwarder
DSS Decision Support Systems

FCD Floating Car Data

GIS Geographic Information System
GPS Global Positioning System

LI Location Intelligence
LSP Logistics Service Provider

OD Origin-Destination
OSM OpenStreetMap

RNP Road Network Performance
RS Remote Sensing

TSP Transportation Service Provider
TTR Travel Time Reliability

UBD Urban Big Data
UESS Urban Environment, Society, and Sustainability

WLTP Worldwide Harmonized Light Vehicles Test Procedure

Part I

Thesis Overview

CHAPTER 1

An introduction to Road Network Performance Measurements - or the apparent lack thereof

The performance and state of a road network is of primary concern when evaluating the attractiveness of any given region [1–5]. How long does it take to arrive at work every morning? How long will I take to get back home? How fast can I arrive at the nearest grocery store? How easy is it for my kids to get to school? How much noise of passing-by vehicles will I subject myself to? How will my loved ones be affected by road pollution?

Any and all of these questions are in some way related to the underlying road infrastructure and the usage patterns of its road traffic participants. Building a home in a rural area can be considered advantageous and beneficial in terms of child-welfare, potential for relaxation and available space of living but might coincide with negative impacts in terms of accessibility of labor opportunities, educational institutions or past-time activities. In contrast, urban conglomeration allows for many opportunities within a short distance, but achieves these conglomerations by exchanging decreasing lengths of travel for increasing travel times due to traffic congestions whenever large accumulations of people within a small geographical area claim concurrent usage to the same finite infrastructure [6–8].

All of the above holds true for commercial considerations as well, in some ways increasingly more so. Where private citizens can, at least to some degree, consider and decide between rural live and urban conglomeration, Transportation Service Providers (TSPs), be it freight forwarders or the public transport sector, have no choice but to adapt their mode of operation to include congested metropolitan areas - after all, where else would large amounts of goods or services be required if not at points of accumulation of the populace?

Today, more than ever, many long-term decisions as well as daily activities heavily depend on the availability and general freedom of movement throughout urban networks [9, 10]. These characteristics can be summed up as the general performance of any given road network - in short, the Road Network Performance (RNP). It appears that a topic of such concern to everyday-life, be it private or commercial [11–13], should be well-researched and readily available for reference outside academic literature. Why, then, do we not know of a single source of information available to the general public to compare RNP across geographical regions? Similar to the way in which, for example, housing and property prices are made transparent for any geographic area? Why do transportation service providers still struggle to correctly and arithmetically determine why the same service is significantly more lucrative in one service area compared to another? Why do we still fail to account for differences in economic, ecological and social impact of road transportation between regions?

In essence - why do we still not recognize that the cost of traveling a distance of 1 kilometer is not equal to the same cost of 1 kilometer for every region?

It is astonishing, that in a time when every single trip, no matter how long or short, no matter the means of transport, is planned via Google Maps [14] or comparable services in a matter of seconds - that we still rely mostly on assumptions and gut-feeling when comparing economical or ecological impacts of region-specific road transport decisions [15].

It is this discrepancy - the discrepancy between near unimaginable amounts of information readily available within seconds and their non-appliance to critical decisions in logistics - that this research endeavor sets out to alleviate.

1.1 Concerning Location Intelligence

While the aforementioned statements generally hold true and achieve their desired effect of highlighting the importance of regional specificity in urban transport evaluation and its impact on most aspects of everyday life, it is of course sensational to proclaim a complete lack of research concerning RNP.

A multitude of fields of study have acknowledged and derived partial solutions to the problem of RNP measurements, either in reference to or independent of each other. Many of these attempts can be summarized and linked to the umbrella terms of Location Intelligence (LI) and Urban Big Data (UBD) - the science of deriving relevant (business) information from geographically referenced data [16–19].

In our highly digitized world, nearly every movement and all activities, be it related to goods or people, generate digital geographic markers [20–22]. Cellphones and wearable devices connect to a comprehensive set of cellular network towers [23]. Global Positioning System (GPS) trackers record a list of coordinates for every step taken [24, 25]. Navigational devices leverage third-party services such as Google Maps [14] - seemingly at no expense - in exchange for submitting the data that is generated by that very application to a remote server. Aggregation of such data provides insight into urban movements of the entire populace - a representative study of a scope and quality that has never been achievable before [26].

It is this well of data that inspired Clive Humby's term "data is the new oil" [27]. And it is this "new oil" that LI tries to mine, refine and convert to palpable business insights.

1.1.1 Applications of Location Intelligence

The concepts of LI are predominantly, but not exclusively, found in fields of study related to Geography, esp. Geographic Information System (GIS), Computer Science and Network Science, Urban Planning as well as Business Administration. While each discipline applies comparable means of analyzing geographically referenced data, they do so for a selective subset of problems relevant to their domain. LI within the context of Geography and Urban Planning tends to focus on environmental impacts on specific road links (or edges) to identify vulnerabilities and critical components within a transportation network [28–30]. Computer Science and Network Science mainly focuses on graph theoretical analyses of network nodes, i.e. centrality measures, to algorithmically identify important network components [31]. While graph theory is not inherently concerned with geographically referenced networks, increasing digitization has led to a broadened focus of applications, i.e. leveraging GPS or cellular signals to track, analyze and derive urban movement patterns [32, 33]. Business Administration and its subdivisions apply tools of so-called Business Intelligence (BI) and Data Mining to extract valuable information on potential customer clusters and consumer behavior in order to better adjust supplied services and goods to observed demands [34–36].

While Chapter 2 presents detailed applications of LI, this general overview demonstrates that the relevance of leveraging available location data to generate insight into domain-specific problems is no revolutionary insight. Recorded applications of what is nowadays referred to as GIS [37, 38] date back to 1854 and John Snow's Cholera Map in London [39] - long before the days of computers, automation and Artificial Intelligence. Going back even further in human history, during the days of tribalism, it was common sense to set up camps near hunting grounds where game has been successfully tracked on previous incursions but far away from other tribes as to not provoke territorial wars. All of the above decisions are made and improved upon by prior experience - data in its most simple form.

Why, then, is it, that one of the most important sectors of service providers, the logistics and freight hauling sector [40], in large parts has yet to incorporate this "new oil" into their business operations?

1.1.2 Location Intelligence in Logistics

Logistics as a field within the domain of Business Administration is concerned with the efficient movement of peoples and goods throughout transportation networks [41, 42]. These networks come in different forms. Aerial and maritime networks, road transportation networks and even private assembly lines and warehouse transportation systems can be considered relevant networks within the context of logistics. While each of these network types, in their essence, follows the same basic structure of a set of nodes connected by (directed) edges [32, 43], they differ significantly in function and relevance to the proposed research goal.

This thesis focuses on logistics operations concerned with the distribution of finished goods from point of origin, either a commercial company or private consignor, through public road networks to their specified point of destination, commercial or private recipients. In a more abstract form, this dissertation is concerned with so-called truck-based Last-Mile Deliveries [44, 45] in Business-To-Business (B2B) and Business-To-Customer (B2C) transactions.

This subset of logistics operations, generally considered as distribution logistics, is the main enabler of modern commerce [46]. In 2020, the German modal split depicts that 71% of all freight transport is conducted via the road network [47]. Distribution logistics, even though essential to all aspects of modern trade networks, is considered a commodity [44]. Its requirements are fast and efficient deliveries at minimal costs [48]. TSPs, also known as shipping or freight hauling companies, face ever-increasing transportation requirements. Differentiation strategies tend to be hard to pursue - a typical characteristic within commodity markets.

"May the best one win" is no longer of relevance. "May the cheapest one win" is the new status quo [49]. But how can TSPs become the "cheapest one" without going out of business? The keyword is efficiency. And in recent years, efficiency has gotten a face to it - Amazon [50]. The market entry of Amazon into the freight hauling sector impressively demonstrated one thing: "May the best data win".

In recent years, Digital Freight Forwarders (DFFs) have successfully identified these discrepancies between operational inefficiencies and data-driven availability of opportunities [51]. By leveraging highly digitized platform-based business models [52], DFFs are transforming the logistics sector, causing an increasing amount of disruption in the road freight market - by using data [53, 54]. The entire transit procedure along the shipment life cycle has been digitalized, which sets them apart from conventional freight forwarders [55]. To remain competitive, conventional freight forwarders have to adjust their processes to leverage data themselves [56, 57].

Within this thesis, six common issues in distribution logistics that should be supported by precise RNP information are identified:

1. **Location analysis** is a topic of major concern for every TSP [58] as last mile distribution necessarily starts at a logistics facility, either run by a shipper or by a logistics service provider [46]. Where to locate this facility is an important, long-term decision. This decision is primarily driven by the trade-off between location cost (rent) and delivery cost or delivery speed. Proximity to market significantly increases rent but might result in decreasing delivery times and therefore reduced total delivery costs. Assume, for example, being tasked with identifying a good location to serve the market “Munich” with last mile logistics. Almost all inbound cargo is distributed from the north, so any location north of Munich will be interesting. A major provider for cold chain last mile logistics located a terminal in Schweitenkirchen. This certainly allowes for a comparatively low rent but produces long daily travel times to serve the majority of customers in the Munich area. A proper RNP analysis would allow to calculate the additional cost of having decided for such a remote location.

2. **Freight Quotation** is concerned with correct a priori evaluation of charges involved in the movement of potential cargo from origin to destination [49]. In contrast to open rate or spot market prices [59], the process of freight tendering selects an appropriate carrier amongst a list of all submitted quotations. While it is common, as pointed out earlier, to select the cheapest available option based on the commodity market of logistics operations, it is nonetheless important for TSPs to validate and ensure economic feasibility [60]. In order to automatically assess feasibility, regional specificity of road networks needs to be incorporated to correctly account for varying local efficiency and expected performance based on current information [61, 62]. RNP measurements can deliver these insights based on a topological evaluation of the OSM road network in combination with historic and real-time traffic information from aggregate Floating Car Data (FCD).

3. **Fleet Productivity Benchmarking** is a matter of concern to all TSPs [63, 64]. A correct assessment of regional specificity in terms of achievable productivity is mandatory in order to better adjust capacity held between regions and avoid customer dissatisfaction due to operational inefficiencies [42, 65]. While productivity is impacted by internal as well as external factors, TSPs are historically concerned with internal procedures as they are subject to and can be adjusted by organizational control [66–68]. While this generally holds true today, it has become a predicament in correctly assessing and comparing fleet productivity between geographic regions. Even when

accounting for identically optimized internal processes, significant deviations in measured performance arise based on external regional characteristics [69, 70]. Achievable speeds as well as traffic congestion patterns vary significantly between day times and regions [71, 72]. While facility A might profit from a high accessibility of efficient road networks, i.e. highway links in close proximity to the facility, facility B might suffer from an opposite external situation. Even when comparing performance between two well-located facilities, both with short-range access to the highway network, significant differences might arise in operational efficiency due to individual spatio-temporal characteristics of specific road sections [73, 74]. It was mentioned earlier, that a distance of 1 kilometer is not necessarily comparable to a distance of 1 kilometer in every geographic area. RNP measurements can serve to shed light on these hidden characteristics of road freight transportation by quantitative evaluation of relevant road section attributes.

4. **Operational routing** is the bread and butter of last mile logistics [75, 76]. Since daily distribution runs tend to call for multi-stop tours, what is known as the so-called vehicle routing problem [77] has to be solved in order to determine the number of locations to be serviced within the tour as well as their ideal sequence. Whereas this problem was historically delegated to and solved by the driver, more recent approaches try to create optimal routes on a daily basis using a computer and attempt possible rerouting during the day in response to updated traffic situations [78, 79]. This will only produce acceptable results if the performance of each road within the network is known. RNP measurements can provide the necessary information (i.e., congestion, detours, speed limits, travel times) on a per-edge basis to allow for efficient and responsive rerouting.

5. **Tariff Calculation**, while closely related to fleet productivity, is a topic of significant interest, especially to road freight shipping alliances [80, 81]. Correct reverse calculation in order to adequately distribute shared profits often requires reliable and representative road freight tariffs. Such tariffs, in their most basic form, are comprised of two-dimensional matrices based on distance and shipment weight classes [42, 82, 83]. For each distance-weight pair, the tariff contains approximate costs of shipping, generally based on analyses of historic shipment structures or experiences [84]. While tariffs, at least in their historical external function as "shipping price" lists [85], focus on a generalizable representation of approximate shipping costs, internal tariffs have to be concerned with regional specificity if profits and costs should be a function of operationally feasible performance [62]. While RNP measurements are not concerned with shipment weight, they provide a reasonable approach to incorporate underlying road network attributes in order to correctly and more appropriately determine distance-based costs in distribution tariffs with regard to regional specificity.

6. **Carbon Offset** and the underlying ability to correctly determine the ecological impact of road transport services will most likely become a topic of great concern for future LSPs [4, 86, 87]. Literature on allocating CO_2 emissions to specific shipments is generally concerned with distance and weight-based attributes contributed to the overall delivery run by individual consignors [88–90]. Nonetheless, while existing literature proposes several methodologies to allocate CO_2 emissions to shipments, few methodologies focus on the correct assessment of total CO_2 emission produced by a specific delivery run [91] as well as the concrete and billable amount attributed to each specific shipment based on its geographic fit to the shipment structure. Digital road network graphs in combination with traffic information derived via Application Programming Interfaces (APIs) can alleviate this issue by precisely tracking and evaluating achievable real-world driving cycles. While the analysis of in-vehicle trajectory data would provide optimal measures of CO_2 emission [92], aggregate FCD in digital road network simulations can serve as a second-best approach as long as vehicle fleets lack the required sensoric equipment.

1.2 Research Gap

The concepts of LI and UBD presented across a multitude of distinct fields of study provide solutions to many of the same data-driven problems TSPs face within distribution networks. Distribution networks, in their essence, have to be concerned with RNP [62]. It is their primary modus operandi to transport goods by vehicle across a finite set of interconnected roads. Therefore, intelligent transportation systems should incorporate and evaluate specific attributes of these road networks [93]. However, as a historic result of simpler times, the corpus of relevant literature concerning itself with the efficient use of external data sources within distribution logistics to adequately measure RNP is sparse.

In general, RNP directly impacts not only economic, but ecological and social sustainability, both during commercial and private activities. Nonetheless, models for road transport cost estimation often fail to account for regional specificity of RNP, instead relying on general assumptions derived from often outdated selective studies. While availability of suitable tools, data sources and computational capacities to measure concrete RNP on a wide scale has steadily increased across a multitude of academic fields, it remains unclear why researchers and practitioners alike do not leverage and integrate it more heavily to improve estimations of transportation impact on all dimensions of sustainability.

This research therefore aims to integrate the fields of Geography, esp. GIS, Computer Science and Network Science, esp. Graph Theory, as well as Urban Planning and Business Administration and their respective achievements on the topic of LI to develop and present efficient methodologies of incorporating diverse data sources to allow for better estimation of RNP and its impact on the economic and ecological dimensions of sustainability.

It does so by cumulatively answering the following research question:

Which data sources and data processing routines associated with Location Intelligence should be employed to measure Road Network Performance?

1.3 Research Structure

Chapter 2 presents the current state of the literature on the topic of RNP and LI within Decision Support Systems (DSS). To achieve a thorough overview of each concept, the literature review outlines the most important contributions per field of study in chronological order.

Chapter 3 concludes Part I of this thesis by outlining the methodologies to be presented within Part II and their individual contribution to answering the research question based on the most import insights generated through the literature review.

Part II contains the three manuscripts constituting the core of this cumulative dissertation in their originally published version.

Finally, Part III summarizes the key takeaways from each methodology and puts them into context within the academic discussion. Relevant aspects for further research as well as limitations are presented.

CHAPTER 2

Literature Review

As this dissertation follows a methodological approach to propose new ways of integrating RNP into DSS, so does the upcoming literature review. Each of the three main topics to this thesis, DSS in logistics, LI and UBD as well as RNP, will be investigated and unraveled into their most relevant sub topics. Each sub topic will be presented by means of current and historic methodologies applied within them. Based on these existing approaches, shortcomings and implications for this research are derived. A graphical representation of these main topics and their relationship with regard to last mile decision making is depicted in Figure 2.1 in order to better understand the underlying coherences relevant to this dissertation.

2.1 Decision Support Systems, Location Intelligence and Urban Big Data

DSS can be classified as either model-based or data-driven. Model-based systems rely on a set of rules or assumptions about how the world works while data-driven systems use information about what has happened in the past or is currently happening to make predictions about how events will affect the business [94]. While model-based approaches tend to be implemented in business analytics systems, data-driven approaches are commonly found in Business Intelligence systems [95]. BI is generally defined as a collection of information systems to transform data into information and information into knowledge to support decision-makers [96–98].

A subfield within BI focusing on geo-spatial and temporal data is LI, also referred to as the study of UBD. Both Wang and Hess [16] as well as Kong et al. [5] studied developments in the field of Urban Environment, Society, and Sustainability (UESS) and examine a large increase in recent publications related to applications of UBD. Across all publications, the most commonly used Big Data in UESS research is human behavior data. In general, UBD can provide insights into what people do and how they move throughout urban areas. While UBD is a comparatively new concept directly related to the exponential increase in data availability and computational capabilities generally referred to as Big Data, it is no more than a modern name for an existing concept: GPS traces.

2.1.1 GPS: General idea and early approaches

GPS data and its potential for data mining is well-researched. As early as 1999, Rogers et al. [99] propose the usage of GPS position traces in combination with differential corrections to augment road models in road traffic safety applications. In 2000, He et al. [100] presented one of the earliest mobile mapping systems using GPS, inertial navigation systems, and stereo cameras to capture road infrastructures and accurately measure road performance. In 2002, Schäfer et al. [101] present a procedure that leads to a nearly complete data coverage of all major roads in Berlin, Nuremberg and Vienna by utilizing GPS position data of several hundred vehicles of a taxi company. Two years later, in their 2004 article "Transit buses as traffic probes: Use of geolocation data for empirical evaluation" [102], Bertini and

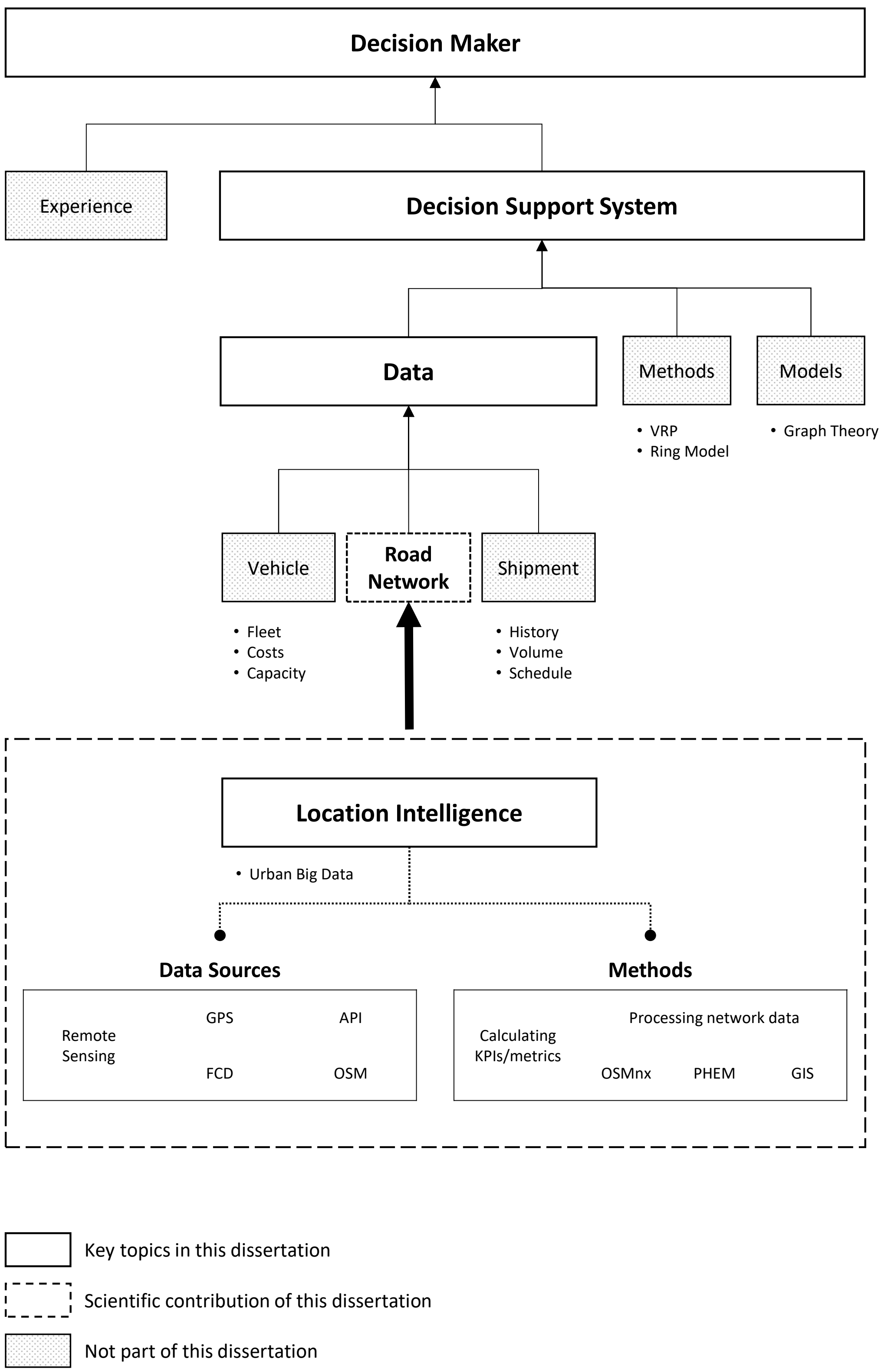


Figure 2.1: Graphical overview of relevant concepts in last mile logistics decision making and their importance to this dissertation.

Tantiyanugulchai [102] discuss the same concept to study arterial road performance in Portland, Oregon. These studies form the first attempts at leveraging what is nowadays widely known as Floating Car Data. Applications of FCD range from real time data for traffic management to the compilation of very accurate Origin-Destination (OD) matrices [103].

In 2005, Civilis et al. [104] adopted the idea of FCD by proposing a new methodology to track moving objects more accurately throughout road networks by means of GIS while Pan et al. [105] propose a new approach to project GPS data onto an existing arterial road network in order to collect travel time and intersection delay information. In 2007, Brockfeld et al. [106] offer the first critical assessment of benefits and disadvantages of recent FCD technology. The study analyzes performance of the earlier system developed by Schäfer et al. [101] in Nuremburg, Germany. One of the main problems identified during this evaluation is a low penetration rate of FCD derived via commercial probe vehicles. A few hundred to a few thousand vehicles in urban street networks attempt to digest information across several thousands, up to hundreds of thousand road kilometers. In an attempt to solve this problem, de Fabritiis et al. [107] present the first study that leverages a large fleet of 600,000 privately owned vehicles generating GPS traces on a 3-minute interval. Testing results based on an artificial neural network showed that the proposed approaches for short-term predictions based on private vehicle FCD are effective. In 2009, Tong et al. [108] present one of the most cohesive studies to date on the topic of integrating GPS and GIS to support highway performance studies. At the same time, Berkow et al. [109] demonstrate that combining data from traffic signal systems and buses acting as probe vehicles can improve arterial performance measures.

A key takeaway of all early studies is the notion that data acquisition is the most expensive part of establishing a road network database. Acquisition of sufficiently large sets of GPS data on a per-vehicle basis has been a major limitation. Kumar et al. [110] summize this limitation by stating that in order to accurately predict traffic in an intelligent transportation system, data needs to be collected either from fixed-location sensors (like traffic lights) measuring all traffic within a selected area or from individual cars themselves (FCD). While the former technology, generally referred to as vehicle trajectory data, has been used extensively throughout developed countries, the acquired data has historically been mostly unavailable due to size constraints of data publication and privacy concerns; with the latter being private property of commercial navigation service providers [111]. The usage of commercial probe vehicles presented an early means to circumvent the restrictions of data availability, but, as Bachmann et al. [112] point out in a critique to Berkow et al. [109], there are limitations to using fleet vehicle data (including buses or taxis) because the operational characteristics of commercial vehicle fleets differ significantly from regular traffic.

In 2012, Hofleitner [113] proclaims that a paradigm-shift towards intelligent transportation systems can be observed with the emergence of internet services and location-based services on mobile devices. Where, historically, specific vehicle fleets had to be equipped with sensory equipment in an attempt to record relevant data on urban movements, the advent of smartphones and large-scale 3G networks led to an exponential increase in representative navigational data generated by daily activities of network participants.

2.1.2 APIs: Easy access to FCD

A side-effect to the introduction of location-based services on mobile devices is the requirement of publicly available navigational data. Studies from this point onwards tend to focus on incorporating and integrating different and continuously increasing public repositories of FCD, generally referred to as Application Programming Interfaces, to measure urban movement.

In a 2013 study led by Qiulei Guo from the Chinese Academy of Sciences [114], researchers looked into a data-driven approach for predicting convergence of traffic volumes in transportation systems. By using large sets of location data through GPS, they demonstrate the possibility to predict traffic events with great accuracy. At the same time, Arellana et al. [115] developed a freely available web-based geographic software which can be used to process API information and display level-of-service results for public transport based on FCD. Tostes et al. [116] present a methodology based on Bing Maps information in order to acquire, aggregate, analyze, visualize, and predict traffic jam in Chicago. In 2014, Fancello et al. [117] propose the first integrated performance indicator which takes into account different factors that affect road performance, laying the foundation for integrated approaches to RNP based on publicly available traffic data. In 2015, Yuan et al. [118] present a methodology to discover and segment city networks into functional zones based on latent activity trajectories. Zheng [119] presents the first systematic survey on major research into trajectory data mining. In addition to the survey, methods of transforming trajectories into other data formats such as graphs, matrices, and tensors are introduced, enabling more effective data mining and machine learning techniques. In 2016, Kong et al. [120] propose a novel approach to estimate and predict urban traffic congestion by efficiently combining large amounts of FCD to enable a unified performance assessment that satisfies the aspects of accuracy, instantaneity and stability. This research is followed up by a solution to automated long-term traffic anomaly detection based on crowd-sourced bus trajectory data in Hangzhou, China [121]. In 2018, Xia et al. [122] propose an integrated computing method to rescale heterogeneous traffic trajectory data in order to combine traffic data from subway card transactions and taxi GPS trajectories to derive human mobility patterns in Shanghai, China. In 2019, Gao et al. [123] present the first approach to the integration of static household data and dynamic FCD derived from APIs in order to improve travel behavior analysis. Wang et al. [124] build upon this insight by investigating the applicability of additional location traces in order to support or substitute expensive household traffic surveys. Their results implicate that, while official homogeneous survey data remains the most accurate source of information, heterogeneous crowd-sourced data from map APIs can serve as a cost-efficient proxy for traffic evaluation indicators.

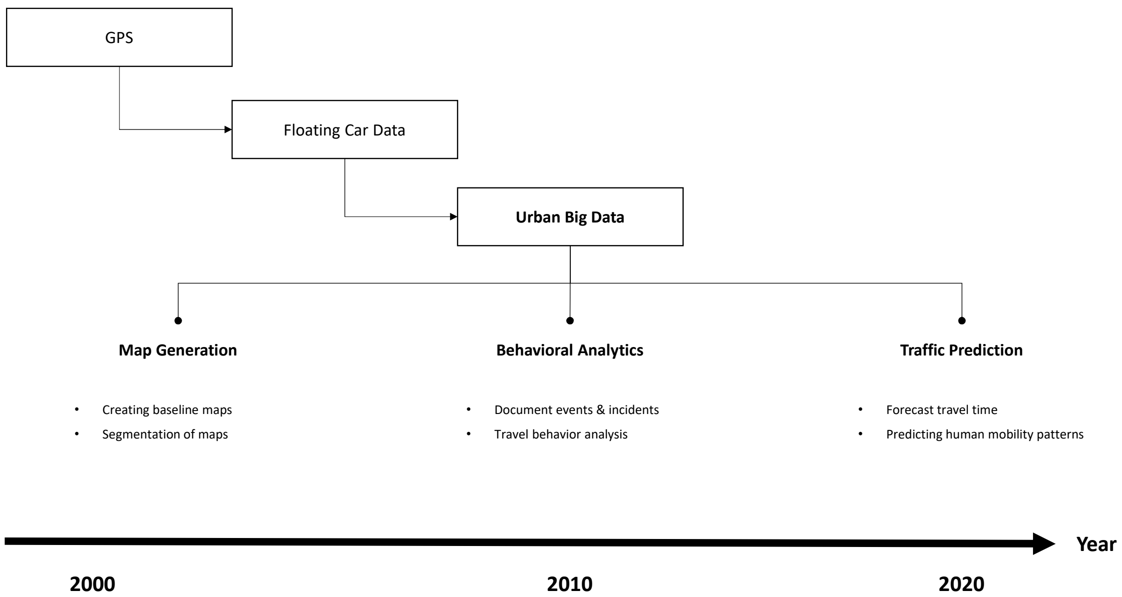


Figure 2.2: Graphical overview of the evolution of GPS into Urban Big Data and its most common applications found in literature.

The aforementioned studies present the most cited research on the topic of FCD and API approaches, accurately depicting the evolution of traffic measurements and behavioral studies within the field of UBD as depicted in Figure 2.2. Nonetheless, many smaller studies have been conducted within the same field. Across all relevant studies, two general tendencies can be derived. Extensive research is focusing on either (1) novel methodologies to incorporate heterogeneous Big Data sources or (2) novel methodologies to achieve better insights from existing sets of homogeneous trajectory data. While western reserach tends to focus on the former, research in Asia-Pacific focuses predominantly on the latter. This effect is most likely caused by the availability or absence of open data sets and APIs within different research communities. The result is an increased methodological focus on efficient means of data extraction and preprocessing of Big Data in the western community while eastern research mainly focuses on applications of statistical machine learning and artificial intelligence to derive improved insights from limited sets of data.

2.1.3 Current challenges concerning Urban Big Data

According to Wang and Hess [16], researchers need to shift their focus from acquiring data to acquiring data science knowledge and programming skills to analyse continuously increasing amounts of UBD. Referring back to the cohesive study by Kong et al. [5], there are several challenges that need to be addressed in order to use Big Data in research concerning (1) the quality of the data; (2) how it is acquired; (3) where it is stored; (4) how it is managed; (5) how it is protected; and (6) how it is cleaned and preprocessed. This research relates to the raison d'être of RNP studies, which is to propose the integration of multiple Big Data sources in an attempt to efficiently measure and evaluate everyday movements of goods and peoples throughout road networks.

2.2 On the nature of road networks

Before investigating the current state of RNP measurements in literature, it is essential to define what is meant by the term "road network". Every city is, in its essence, a large collection of networks that lets people connect with each other. Each network is characterized by the sum of its nodes connected via directed edges. A graphical representation of such networks is generally considered a pairwise graph depicted via a set of points (nodes) connected by lines (edges) [33]. A network is therefore a specific kind of graph where edges are marked with a certain direction [125].

In terms of city networks, each node depicts a certain type of location, ranging from private residences to commercial activities, while edges depict individual sections of transportation infrastructure, ranging from sidewalks and bicycle lanes to car and railway roads, serving as traversable paths to overcome geographical distances. Each node can serve as origin or destination of a so-called OD-path [126].

Adhering to this graph theoretical definition, it is possible to model all transportation networks, be it intermodal or specific to a certain mode of transport. Within the context of this thesis, a distribution network is a specific type of road network that is primarily concerned with the activity of freight or personnel distribution and can generally be defined as the set of nodes and edges that is traversable by passenger car and heavy-duty vehicles. Nodes represent geographically referenced settlements and crossroads [127]. Edges represent public streets [128] and are typically assigned weights or capacities. Weights are generally comprised of attributes such as section length, travel time, applicable speed limit or information on traffic congestion [129].

While logical evaluations of road network characteristics can be determined by visual inspection of graphs, algorithmic evaluation, which is necessary for inclusion in automated DSS, requires a digital representation of road networks as dynamic and programmatically accessible network graphs. Methodologies for generation of such representations are included and discussed in the upcoming section.

2.2.1 Remote Sensing: The ideal way to create maps?

The earliest and most widely used method to generate digital representations of geographic road networks is referred to as the field of Remote Sensing (RS). It is also the most cost-intensive approach to road network generation as RS is performed by specially equipped aerial vehicles, i.e. planes and drones, as well as by satellite imagery. Results from such RS technologies are optical as well as radar data.

In 2003, Lacoste et al. [130] propose an unsupervised approach to road network extraction from optical and radar images which relies on the theory of marked point processes within Markow chains. In 2004, Coifman and Yang [131] conducted a systematic performance comparison between ground-based sensory data and high-resolution[1] satellite imagery. They found that high-resolution imagery remotely sensed from satellite or airborne platforms is an attractive alternative to ground-based sensors and can be used to supplement temporally rich ground-based optical data by large spatial coverage of radar data. In 2005, Zhu et al. [133] present a novel approach to road network extraction from high-resolution satellite imagery based on a three-step process including evaluation of binary and greyscale mathematical morphological characteristics of image sections followed by line segment matching. In 2007, Peteri and Ranchin [132] develop a different approach to high-resolution road extraction. Their methodology relies on a representation of roads that uses both linear and surface models. This is done in order to reduce the effects of local artifacts in satellite imagery. Map accuracy is further improved by preliminary application of advanced image processing tools. In 2009, Kavzoglu et al. [134] leverage highly detailed IKONOS satellite imagery to not only extract but evaluate asphalt conditions of road networks in Turkey. A

[1]High-resolution satellite imagery generally refers to a spatial resolution better than five meters in the panchromatic channel [132]

similar study by Yun et al. [135] in 2010 analyzes spectral imagery from ASTER and IKONOS satellites to evaluate road surface information and remotely identify areas susceptible to road deterioration in Korea. In 2013, Nagne et al. [136] demonstrate the applicability of GIS to assess, identify, collect, store, retrieve, manage, analyze, communicate and visually present satellite imagery for transportation network analysis. In 2014, Singh and Garg [137] conducted a review of existing methodologies and case studies related to road network extraction. They found that the presence of varying and various noises requires continous and region-speficic tuning of heuristic parameters across extraction models, signficantly complicating the task of automatic road network extraction. In 2015, Schnebele et al. [138] investigate the applicability of current remote sensing methodologies with regard to their suitability for pavement management and assessment. The study found that remote sensing techniques offer nondestructive methods for road condition assessment with large spatial coverage by providing an opportunity for frequent, comprehensive, and quantitative surveys of transportation infrastructure. In 2021, Jia et al. [139] present a comprehensive overview of active and passive remote sensing techniques for road extraction. They investigate extraction methods based on various remote sensing data sources, including high-resolution images, hyperspectral images, synthetic aperture radar images, and light detection and ranging (LiDAR) data. The main result is a quantitative insight that different data acquisition techniques have unique advantages, and the combination of multiple sources can significantly improve the accuracy of road extraction procedures. Pan et al. [140] present a generic approach for extraction of road networks from very high-resolution (less than or equal to 1 meter) remote sensing images using OSM as a benchmark. Tan et al. [141] developed and published the first remote sensing methodology achieving state-of-the-art performance of 98.25% accuracy on the DeepGlobe dataset based on deep neural networks in a U-Net-like architecture. This performance is achieved by enhancing the context and stripping irrelevant features using image segmentation. The signficant performance boost achievable by deep learning approaches is investigated and confirmed by a systematic review performed by Khan and Singh [142] in July 2021.

While RS has been the default approach to highly accurate road network extraction and generation, modern data sources are becoming increasingly more common due to significantly reduced costs and significantly increased availability of large public data sets. Nonetheless, RS will most likely remain relevant, independent of technological advances in other areas, as spectral imagery provides insights into environmental land-use that are irreplacable by optical or trajectory data.

2.2.2 Estimating road networks from vehicle trajectories

Since prior research on trajectory generators were concerned with objects moving over Euclidean space, limiting their applicability to studies concerning the road network, in 2007, Baek et al. [143] presented one of the earliest methodological approaches to transform vehicle trajectory data into approximate OD paths to better resemble driving preferences in real network environments. In 2012, first attempts at algorithmic generation of road network graphs from vehicle trajectory data are presented by Karagiorgou and Pfoser [144]. Applicability is demonstrated by generating a small subset of the road network in Athens, Greece by referencing trajectory data from a school bus fleet. Since trajectory data for larger geographical areas can be considered Big Data as it contains both highly detailed spatial and temporal information for many individual vehicles, Jiang et al. [145] propose a thinning-algorithm in order to efficiently construct road network graphs from large volumes of trajectory data. In 2015, Wang et al. [146] published a novel approach for generating routable road maps from vehicle GPS traces using circular boundaries to separate road intersections and road segments. This research focuses on the insight that most inaccuracies in existing approaches to road network generation from vehicle traces are caused by an inability to correctly assert the geometrical topologies at intersections. Applicability of the proposed solution is demonstrated by comparison with human-interpreted results of trajectory data, indicating a high quality of the generated routable road network, even accounting for correct movements at intersection, during interchanges and U-turns. In 2016, Miao et al. [147] provide a three-step solution to the issues that low sampling rates of user-generated mobile trajectory data bring to road network generation. Within this study, sets of intersections are produced by grid and quad tree methods, which are then clustered based on the Density-Based Spatial Clustering (DBSCAN) algorithm and connected via triangulated edges. This procedures enables efficient generation of road networks from sporadic location traces, greatly reducing the requirements in terms of high-quality, i.e. highly detailed and continuous, trajectory data. Applicability is demonstrated by comparison to road networks extracted from Google Maps. Deviating from contemporary research on FCD, Ulbrich et al. [148] demonstrate that the reconstructed trajectories of vehicles detected by LiDAR and radar sensors can be used to reliably generate high-quality road network graphs to support research on autonomous driving. In 2017, Karagiorgou et al. [149] improve on their previous iteration of algorithmic generation of road network graphs [144] by proposing an enhanced map construction algorithm that is based on segmenting the original tracking data according to different types of movement and hierarchical construction of the road network topology. In 2018, Ni et al. [150] propose a so-called incremental learning approach to generate road network representations from scratch by evaluating vehicle trajectories. Comparable to Miao et al. [147], scattered trajectory positions are clustered and geographically referenced based on the original trajectory data and connected via edges deduced from Delaunay triangulation. Similarly, the CellNet method developed by Mariescu-Istodor and Fränti [151] as well as the intersection-first approach by Zhang et al. [152] attempt to solve the previously mentioned issue of low-frequency crowd-sourced trajectory data by first detecting intersections using a clustering-based technique and then creating road segments in-between. In 2019, Li et al. [153] propose the use of a lane structure-aware filter that clusters vehicle trajectories based on noise and outliers in combination with a road tracing operator to segment the road network geometry. Experimental results show that the proposed method is more accurate than existing methods in dense urban contexts and offers increased robustness to noise and differences in sampling rates. In reference to the topic of algorithmic robustness to differences in vehicle trajectory data, Fu et al. [154] present a thorough examination of existing road mapping approaches. They find that large degrees of parameter optimization are required as most algorithms presented in literature are currently not robust to high variances in trajectory datasets.

Based on the aformentioned studies, existing methods for constructing a road network using vehicle trajectory data can be roughly divided into three categories:

(1) Point clustering is a way of grouping together points based on similarities between them. Different clustering methods can be used to create a road network map.

(2) Incremental track insertion is a way of gradually adding new tracks to an existing network graph. It uses the idea of map matching to figure out where the new tracks should go, incrementally growing the road network graph.

(3) Intersection linking connects separate intersections by estimating the motion characteristics (speed and direction) or point density of traversing vehicles, and then connecting the intersections via interpolation.

2.2.3 OSMnx and crowd-sourced topology data

In comparison to the previous sections on road network graph generation from vehicle trajectory data or remotely sensed satellite imagery, crowd-sourced topology data forgoes algorithmic evaluation of noisy data at the cost of labor-intensive manual work to achieve high-quality geographical representations of road network graphs. Where applicable, open-data platforms such as OpenStreetMap (OSM) provide researchers and practitioners with highly optimized and granular sets of topology data in a preprocessed and detail-rich format. Open topology data is accessible either via API or via nightly full dumps containing the entire worldwide geographic database. Earliest research citing OSM can be found from 2010 onwords as the platform achieved critical mass of independent and voluntary contributors.

In one of the earliest studies on OSM accuracy, Haklay [155] conducts a comparative analysis between OSM data and governmental geo-spatial data in London, England. The analysis shows that OSM information, even in its early stages, has been fairly accurate: on average within about 6 m of the position recorded by the governmental data, and with approximately 80% overlap of motorway objects between the two datasets. In 2011, Zilske et al. [156] first establish the relevance of OSM as a valuable data source for accurate microscopic traffic simulation models. In 2014, Chen et al. [157] propose an integrated approach of image-based characterization of road network sections from satellite imagery in combination with OSM topology data. The inclusion of OSM road vectors significantly improved image recognition and allowed for automatic completion of missing network sections from optical and radar data. Li et al. [158] found that while OSM provides large amounts of complex road network data, it contains many duplicate and wrong entries, decreasing its practical applicability. A comparative case study revealed that roads extracted based on OSM road type attributes differ, in some cases significantly, from those extracted using a polygon-based method depending on the examined geographic region. In 2015, Funke et al. [159] attempt to solve the problem of missing road network data by means of automatic gap detection and extrapolation of missing street names by analyzing topological and semantic characteristics of road networks. In 2016, Fan et al. [160] develop a polygon-based approach to match and map transit authority data to OSM road networks. The study revealed that computational cost can be substantially reduced by matching on the basis of polygons instead of individual road lines. Case studies on Heidelberg and Shanghai datasets show that the proposed methodology achieves a precision higher than 96% and an F1-score better than 90%. Karduni et al. [161] present an ArcGIS based tool to convert OSM data to a workable network format. As a result of their study, a dataset of 80 urban areas has been released for further studies. In 2017, Brovelli et al. [162] develop a new method for comparing the geometry of OSM and authorative road datasets. Quantitative measures for the completeness and spatial accuracy of OSM within a specific geographic area are computed, allowing for an objective and automated assessment of OSM applicability to regional research endeavors. Within the same year, Geoff Boeing [163] published the most important contribution to the field of crowd-sourced topology data yet: OSMnx. According to Boeing [163], OSMnx is a new tool to make the collection of data and creation and analysis of street networks simple, consistent, automatable and sound from the perspectives of graph theory, transportation, and urban design. Most applications of OSM data from this point onwards rely either on OSMnx for extraction and generation of routable road networks or on the public dataset provided by Karduni et al. [164–169].

Besides applications based on OSMnx, additional studies have focused on efficient means to enrich, store and validate OSM road network data. In 2018, Steinmetz et al. [170] present a conceptual model to transform extracted OSM road networks into a graph database in an attempt to improve ease-of-use and computational efficiency. In 2019, Szwoch [171], similar to Fan et al. [160], developed a method to efficiently combine OSM with an authoritative database to create highly detailed computer models of road networks to enable microscopic traffic simulations.

2.2.4 Automatic road network generation for Road Network Performance research

Based on the previous section, a multitude of possibilities exist to automatically generate digital representations of road networks. Most relevant to this thesis is the observation that OSM provides highly detailed and accurate topological data that allows for automatic, region-specific extraction of road networks for most developed countries. The ease-of-use of OSMnx is unrivaled in terms of efficiency and alleviates many issues with regards to data processing and cost-intensive data collection of prior approaches based on vehicle trajectories or RS. It allows researchers and practitioners alike to generate routable road network graphs that adhere to graph-theoretical and urban planning requirements and thereby enables the enrichtment of such digital representations with extensive feature-sets to provide an efficient groundwork for effective RNP measurements described within the next section.

2.3 State of the science in Road Network Performance

In general, RNP research is concerned with assessing the strengths and weaknesses of road networks. This is done by measuring concepts like connectivity, resilience, and vulnerability. While the term itself appears simple in nature, its field of study is characterized by ambiguity and confusion as to what should be considered relevant criteria to assess the performance of road networks. In a systematic literature analysis, Rivera-Royero et al. [172] identify 11 central concepts related to RNP. The upcoming sections will inspect each concept in more detail, outlining its history, main theories as well as existing methodologies and potential overlap.

2.3.1 Connectivity

Connectivity is frequently described as the existence of at least one path which connects each pair of vertices [173, 174]. If a network fails to connect a given origin to a given destination via uninterrupted paths, it is said to be disconnected [175]. According to Scott et al. [176], the network's connectedness is exclusively based on its structure and unaffected by its dynamic properties (e.g.traffic demand, capacity, or congestion). When evaluating a network's connectivity, the only relevant aspect is its topological structure consisting of a collection of edges (road segments) connected to a collection of vertices (intersections, journey origins, and destinations) [177, 178]. First studies concerning network connectivity date back to 1964 and Garrison and Marble's [179] factor-analytic study of the Venezuelan local service air transport network. The study developed an automatic approach to identify and assess disconnected as well as important network nodes by means of a connection matrix. A connection matrix describes the existence or non-existence of direct links between nodes or vertices in a transportation network. As matrices tend to become increasingly complex in real-world applications, a preliminary factor analysis is proposed to identify critical structural relationships within the transportation system. A follow-up study in 1965 [174] is concerned with connectivity-based forecasting of transportation developments for railway connections in Northern Ireland. More recently, a new technique is presented by Bell et al. [180] to allow transport planners and network designers to locate possible bottlenecks in the transport network in the absence of origin-destination paths. In 2017, Wang et al. [181] construct a new measure to characterize an urban road network by incorporating lane properties into topology-based connectivity measures to examine urban road features more thoroughly with regard to operational performance bottlenecks. In 2019, Zhou et al. [182] introduce the concepts of "global" and "local" connectivity to post-earthquake disaster analysis. Local connectivity evaluates the distances between each node and its neighbors, whereas global connectivity assesses how well the entire network is connected. While topology-based connectivity measures present an efficient tool to identify critical bottlenecks in infrastructural design, they fail to account for operational characteristics.

2.3.2 Redundancy

Redundancy is the capacitiy of a network to tolerate disruptive occurrences [183, 184]. According to Jenelius and Mattsson [185], redundancy is related to the availability of other paths or modes of transport to connect network nodes. Within the context of road transport, redundancy is the extra capacity that can be used in case of recurring or non-recurring delays on the most popular routes [186–188]. Poor redundancy, when used as an indicator, denotes a lack of or absence of alternate routes to be employed in the event of disruptions. In 2010, Jenelius [189] introduces the concept of redundancy importance. The proposed flow-based measure considers the net traffic flow that is redirected to a specific link when other links are closed while the impact-based measure considers how much worse the next-best backup alternative would be in case the specific link itself is unavailable. In 2015, Jenelius and Cats [190] propose a method for evaluating the importance of new links for the robustness of the public transportation system while taking into account disruptions to existing lines and links as well as the new links themselves. Results prove that it is posible to evaluate new links in terms of passenger welfare under disruptions in comparison to traditional welfare benefits and investment costs. A study by Khademi et al. [191] suggests a method to determine which areas of the city are most vulnerable to disruptions in the transportation system as a result of a major earthquake by developing redundancy-based isolation strategies. A common element to each study is the identification of road link bottlenecks both in terms of topography as well as available flow capacity.

2.3.3 Accessibility

Taylor et al. [192] and Chen et al. [11] define accessibility as the opportunity or ease provided by the transportation system for individuals to access a specific activity or service from other physical locations. In other words, accessibility is the ability to reach spatially distributed opportunities, such as services and facilities, from a given location using a road network [193–195]. From an RNP standpoint, accessibility is a conditional concept, which means that once the facilities are established at certain nodes, network accessibility determines the ability to reach such facilities. Accessibility is commonly defined as the cost of moving across the network as well as the quality and quantity of opportunities [29, 193, 196, 197]. This cost can be measured in terms of money, time, or distance. As a result, RNP indicators should not be solely determined by the number of opportunities available in a given area but should preferably be a function of the relative distribution of nodes (opportunities) and the presence of paths that allow users to move between them within a given budget, such as a time threshold. In 2001, Chang and Nojima [198] present research which develops and applies post-disaster system performance measures to the urban rail and highway transportation systems in the Kobe, Japan, region devastated by the 1995 Hyogoken-Nanbu earthquake. According to the paper, explicitly measuring transportation system performance based on accessibility can greatly aid in both understanding the effects of past disasters and planning for future hazard events. In 2006, Sohn [199] conducts an analysis to determine the importance of highway network links in Maryland, USA that are possible subjects to flood damage. The distance-decay effect and the volume of traffic influence on the transportation network are incorporated into an accessibility index. The results show that critical links identified using the distance-only and distance-traffic volume criteria appear to be different and that the percentage loss of accessibility due to a link disruption is generally higher in the latter, underlining the importance of correctly assessing traffic conditions in accessibility measurements. In 2007, Chen et al. [11] present network-based accessibility measures for assessing the vulnerability of degradable transportation networks. Measures take into account the impact of one or more link failures in terms of network travel time or generalized travel cost increase, as well as user behavioral responses as a result of the network failure. Findings prove that accessibility measures can represent the impacts of various travel choice dimensions on the network vulnerability and are capable of quantifying the effects of changes in supply and demand on the network. In 2012, Taylor and Susilawati [195] extend the earlier work on accessibility-based vulnerability analysis, which was limited to assessment of impacts on selected nodes in a network, by suggesting a region-based accessibility index. With this approach, effects on both specific places (which are not required to be represented as network nodes) and the area as a whole may be studied, greatly increasing the applicability and generalizability of accessibility measures. In 2018, Yücel et al. [200] propose a network improvement methodology that aims to idenfity most effective link investments by means of artificial path generation. By introducing a dependency model for random link failures to predict the post-disaster status of the network, the probability of any network realization can be computed using a Bayesian network representation. Results prove that artificial and weighted random path generation can serve to evaluate accessibility in large road transport networks.

2.3.4 Reliability

Reliability is the capability of a network to allow for constant performance in the event of recurring or non-recurring disruptions. It is measured as the probability that the service level of the road network remains above a user-defined threshold when the transport system is subject to variations in travel times and demand [172]. Because it affects both the network infrastructure and user behavior, reliability is a more complex performance indicator compared to topology-based approaches [175, 201, 202]. Studies on road network reliability can be further divided into three main indicators, each assessing different aspects relevant to road transportation.

Connectivity reliability

Connectivity reliability, also referred to as structural integrity, was introduced in 1982 by Mine and Kawai [203]. It is widely defined as the probability that network nodes and connecting paths remain intact in the event of natural disasters. Due to its origin, the main as well as most criticized characteristic of connectivity reliability is that it asusumes only two possible states for each link: (1) operative, or (2) failed [172]. This assumption severly limits its applicability outside the scope of catastropic events such as natural distasters. While attempts have been made to soften the restriction by introduction of fixed thresholds of acceptable deterioration, connectivity reliability remains less relevant to recurring RNP measurements than its siblings.

Travel time reliability

Travel Time Reliability (TTR), developed by Asakura and Kashiwadani [71] in 1991 and also referred to as dynamic reliability, aims to incorporate the impact of fluctuations in OD demand on travel time. It measures the probability that a journey between certain OD pairs can be successfully completed within a given amount of time [29, 40, 71, 204–207]. In the presence of travel time unreliability, travellers typically allow more time for their trips in order to limit the possibility of arriving late [208]. Additional definitions of TTR exist as (1) the probability that travel times on the network remain below acceptable levels [209]; (2) the probability that the ratio between the travel time before and after an event exceeds an acceptable level [210]; as well as (3) the probability of the network total travel time to be less than a threshold [211]. Travel time reliability is one of the most researched topics in recent RNP literature. Rivera-Royero et al. [172] found a total of 39 studies related to TTR in RNP indicators between 1999 and 2019. A selection of the most important contributions in terms of novel methodologies is included below. In 2014, Uchida [212] suggests two network models based on the route-choice behavior of the risk-averse driver that simultaneously measure the value of trip time and travel time reliability. Using GPS information from mobile phones, in 2017, Woodart et al. [213] forecast the probability distribution of journey time on any route in a road network at an arbitray time. Torrisi et al. [208] propose a methodology for estimating TTR of an extended road network through the calibration of empirical relations and GIS. Primary factors impacting the accuracy of TTR estimations are journey times for each network link, which are calculated using a traffic model that combines dynamic assignment, rolling horizon techniques, and real-time traffic data from radar sensors. Zheng et al. [214] develop a linear model to predict TTR based on automated number plate recognition (ANPR) data while Chen et al. [215] derive a probability distribution of the travel time rate from the largest on-demand ride service platform in China. Studies found that the road network is more unreliable during morning and evening peak hours than during other times, and the most reliable time period is early morning. Additionally, road networks tend to be more unreliable in terms of travel time in close proximity to the central region of the city in comparison to outer boundaries.

Capacity reliability

Chen et al. [204] established capacity reliability, which they defined as the likelihood that the network's capacity can support a specific amount of demand. More specifically, capacity reliability can be defined as the likelihood that the network's capacity can support a specified traffic demand at the desired service level [40, 205, 207, 209]. By including service level in the definition, it is implied that demand must not only be satisfied but that operational conditions must also be adequate to adhere to a specified threshold, such as a maximum travel time [207]. Coverage of capacity reliability in recent literature is limited. A total of seven methodological approaches can be found, none of which delivers relevant insights to this thesis.

2.3.5 Flexibility

The ability of a transportation system to adapt to changes in a variety of parameters, including route choice behavior, infrastructure, prices and policies, while maintaining a sufficient level of service is known as flexibility [216–219]. According to Chen and Kasikitwiwat [220], each of those factors should be taken into account when evaluating the overall effectiveness and adaptability of a transportation network. Capacity flexibility, a specific kind of flexibility, evaluates capacity responses to variations in demand levels. It has been described as a transportation system's capacity to adapt to variations in demand while maintaining a reasonable degree of performance [216, 218, 220]. Besides these insights, no additional methodologies are presented in contemporary RNP literature.

2.3.6 Robustness

A network's robustness is typically thought of as its capacity to handle unexpected events [29]. The degree of severity is the key distinction between all available definitions. Nonetheless, most studies exclusively refer to robustness within the context of disastrous events such as floodings, earthquakes and terrorist attacks. While of significant importance to urban planning and emergency response evaluation, robustness remains irrelevant to this thesis and should be substituted by the closely related and more generally applicable concept of network resilience.

2.3.7 Resilience

Resilience describes the ability of a transportation network to absorb disruptive events with low decrements on its regular performance [172] and evaluates its ability to return to regular operational performance within a reasonable timeframe [218, 221]. A resilient network should also be able to deliver an acceptable performance by redistributing flow across the remaining functional components. Resilience assessments make it possible to pinpoint crucial variables and weak points that are important for the network to recover quickly from disruptive incidents. Additionally, it displays which OD pairs are most impacted by a particular disturbance, successfully identifying critical network links. In 2009, Ip and Wang [222] use an undirected graph to describe transportation networks, with cities acting as the nodes and highways as the edges. Their study shows that the weighted average of the number of reliable independent paths that a city node has with all the other city nodes in the network can be used to assess a city node's resilience because the number of independent paths that connect two cities determines their ability to survive as transportation hubs in the event of traffic disruptions. Following up on their approach, Ip and Wang [223] propose the concept of friability to identify critical road lines or hub cities in networks. Friability is defined as the reduction in total resilience upon removing an edge or hub city. Following the resilience and friability evaluation, a structure optimization model with a computational algorithm for transportation network design is recommended. In 2011, Omer et al. [224] present a study in which the road system connecting Manhattan in New York City to the other regions is evaluated using the Networked Infrastructure Resiliency framework (NIRA). The concept suggests modeling the system as a network onto which fictitious disturbances can be inserted, and measuring resiliency as the effect of disruptions on the system's performance metrics. The base resiliency of the system is calculated as the ratio of the travel time prior to an interruption to the travel time subsequent to a disturbance. In 2015, Zhang et al. [196] systematically compare 17 digital representations of network structures to algorithmically confirm the impact of network topology on the expected level of resilience. In 2017, Aydin et al. [225] integrate graph theory with a randomized stress testing methodology to evaluate the transport network in Kathmandu, Nepal in terms of resilience to natural disasters. A comparison with historic earthquake data from 2015 validates the accuracy and efficiency of the proposed methodology. Similarly, the Link Performance Index for Resilience (LPIR), developed by Calvert and Snelder [226] in 2018, measures the resilience of individual road segments in respect to a larger road network. The indicator can be used to identify road segments that are not resilient to traffic disruptions and to investigate the underlying road and traffic features that are responsible for this non-resilience. Finally, in their 2019 research, Zhang and Alipour propose a comprehensive methodology to integrate flooding threats with topologic risk analysis, flow-based risk assessment, and vulnerability analysis of transportation road infrastructures to assess the resilience to natural hazards throughout the Iowa state primary road system.

2.3.8 Vulnerability

Vulnerability describes the inability of a road network to maintain its functionality and normal performance under disruptive circumstances [227]. According to Berdica [29], vulnerability is the network's susceptibility to incidents that can result in considerable reductions of its serviceability; or inversed, as described by Jenelius et al. [228], the ability of a transport network to maintain its intended function[2]. The primary goal of vulnerability evaluations is to determine which individual network components would cause the most damage to the overall system in the event of a disruption. Similarly to network robustness, its main applications belong to non-recurring and disastrous incidents. Due to this, vulnerability measurements have to be concerned not only with the consequences of potential threats but with the probability of occurence of a disruptive event. When focusing on vulnerability to unlikely disruptions without historic data, vulnerability can be extended to conditional vulnerability, also referred to as exposure.

Similar to the fields of study related to LI outlined in Section 1, 58% of all investigated articles belong to literature on Operations Research, Management Sciences, Transportation Science as well as Mechanical Engineering; 25% to Computer Networks and Information Systems as well as 17% to Urban Planning and Development, Environmental and Social Sciences [172]. The increasing interest on RNP studies is most likely influenced by increasingly occuring natural disasters [194, 229] and the important role of a public road network in disaster relief. This hypothesis is further supported by the geographical distribution of RNP case studies documented in literature. Statistical analysis implies a strong correlation between RNP case study settings and population density as well as total road network length [172]. Unsurprisingly, highly developed and commercialized geographic regions heavily rely on efficient road transportation for daily socio-economic activities, warranting increasing efforts to correctly assess critial links and RNP in order to guarantee a resilient critical infrastructure. Nonetheless, contemporary research concerning German RNP measurements is non-existent, most likely due to the relative safety of Central European countries in terms of susceptability to natural disasters and comparable non-recurring incidents.

2.3.9 Road Network Performance in Distribution Logistics

While a multitude of methodologies and individual concepts related to RNP have been highlighted within the previous section, only a small subset of these concepts holds significance for evaluation of operational RNP regarding recurring traffic patterns. Table 2.1 summizes these concepts of interest as well as their relevance to RNP in distribution logistics.

At its core, last mile logistics is content with a simplified list of criteria that constitute an efficient transportation network: (1) Short routes between customer nodes which are connected by (2) a large set of alternative paths that provide (3) reliable and fast movement of goods on a daily basis.

Based on these criteria, a total of three common RNP concepts are required in order to measure the recurring performance of a transportation network: (1) Connectivity in order to evaluate the regional detour factor, (2) Redundancy in order to quantify the number of relevant available network paths as well as (3) Reliability to analyze and measure historic traffic flows and their region-specific characteristics.

In addition to these operationally relevant concepts, accessibility can provide additional essential information concerning mid- to long-term evaluations and decisions within the context of distribution

[2] While all concepts of RNP discussed in this chapter exist in literature, it can be argued that many concepts overlap significantly. Especially Flexibility, Robustness, Resilience and Vulnerability are basically different words for an identical concept. Nonetheless, each term is included to cover every aspect of RNP literature. Section 2.3.9 discerns the most applicable concepts to RNP in distribution logistics.

logistics. While accessibility can be subdivided into inbound and outgoing performance, i.e., measuring the availability of performant paths towards a location or the availability of efficient paths and reachable activities from a point of origin, the latter is predominantly significant for logistics decision making.

By combining and integrating these four RNP concepts into decision support systems, each of the six main issues within distribution logistics outlined in Section 1.1.2 can be algorithmically supported and partly or completely alleviated:

1. The **facility location problem** should be supported by accessibility metrics as well as by a thorough evaluation of the surrounding road network and its performance in relation to the incumbent shipment structure in order to quantify the cost of a remote versus a centralized location in a long-term planning horizon. Although considerably large amounts of economic studies on accessibility exist [172], surprisingly little is still known about the location patterns of logistics firms, and more specifically about the role of accessibility in their location decisions [230]. Results of a 2018 study by Holl and Mariotti [58] reveal that LSPs are situated nearer to highways and other transportation facilities than those in other industries, and that the logistics industry is highly urbanized. Nonetheless, the apparent lack of accessibility-based studies should be reconciled by enrichment of road networks with historic traffic data to enable improved location-based decisions with regard to logistics facility location problems.

2. The issue of **freight quotation** requires region-specific performance measurements based on geographic distances (i.e., connectivity, structural reliability and redundancy) as well as dynamic traffic patterns (i.e., travel time reliability). So far in literature, little attention has been paid to the explanation of the detour factor, its determination, and the investigation of its influencing factors regarding network connectivity. Nonetheless, the detour factor heavily influences all costs related to travel distance as well as driver costs since less connected networks inflict a high distance as well as time penalty. In a systematic review, Neilson et al. [231] point out that UBD and analytics can garner insights and improve transportation systems, including road transport, based on a better understanding of GPS traces and fleet-wide trajectory data to derive fine-grained insights into day-to-day operations. These insights can receive further support by systematically evaluating the network topology of OSM road networks with regard to connectivity, redundancy and accessibility. Therefore, a problematic region with a high general level of congestion and a low connectivity should incur a higher quote since driver and vehicle must be reserved for a longer duration (time-based cost component) and potentially require longer trip lengths in order to cover a set air distance (distance-based cost component), significantly decreasing overall tour performance.

3. Akin to freight quotation, general **fleet productivity benchmarks** must be concerned with both distance and time-based cost components which are significantly influenced by RNP. In order to reliably compare fleet performance between geographic regions, both the structural and dynamic attributes, i.e., human behavior and its impact on traffic patterns, must be integrated.

4. **Operational routing** and its underlying algorithms currently tend to rely exclusively on structural characteristics of road networks, i.e., connectivity and redundancy and the shortest distance to connect a set of customer nodes within a given time constraint. Incorporating traffic patterns into the fulfillment of such delivery trips is delegated to the human driver as he can rely on experience in order to transpose the shortest possible distance into the most efficient and fastest route based on characteristics and circumstances specific to his distribution district. Nonetheless, due to the bounded rationality of a human entity and its inherent personal reflection, algorithmic evaluation of network reliability can overcome limited experiences of individual drivers by thoroughly evaluating a complete set of historic traffic patterns. Of all concepts depicted within Table 2.1, most contemporary logistics research is focused on network reliability, especially travel time reliability [65, 232] as the most important factor that helps optimize routes is predicting how long it will take to travel between places. Recent examplary studies by Spoel et al. [233], Gayialis et al. [79], Alvarez et al. [234] and do C. Martins et al. [78], while in essence concerned with travel time reliability, do not apply any network-theoretical approaches but instead rely mostly on historic data to estimate future travel time performance. Due to this, fundamental characteristics to the underlying road network remain hidden to TSPs, complicating the understanding of regional variances.

5. **Tariff calculations** can be improved and adjusted to regional specificity by accounting for dynamic traffic characteristics in the form of travel time and capacity reliability in order to adjust distance-based metrics by time-based attributes. In addition, accessibility metrics can provide the basis for

dynamic customer pricing by incorporating a specific node's reachability (inbound and outbound) into the equation. If a customer provides a good fit for the incumbent shipment structure, the margin for available price discounts increases.

6. **Carbon offset** calculations and evaluations are currently not included in most decision support systems for logistics. The relevance of congestion and its impact on logistics operations and resulting CO_2 emission is undisputed and has been researched extensively [64, 235–238]. A multitude of approaches to CO_2 emission allocation can be found in logistics research [88, 89]. Allthewhile, most modeling techniques within existing studies rely on generalized CO_2 factors based on fuel consumption [236, 239] but disregard the impact of network topology on achievable driving cycles [240]. While the relationship between increased travel distance and increased fuel consumption directly correlates to increased CO_2 emission, a distance-based assessment ignores the variability that individual driving cycles and traffic patterns introduce into CO_2 estimation. By combining connectivity, reliability and redundancy, more specific driving cycles can be generated in order to realistically estimate fleet-wide CO_2 emission in an attempt to provide accurate carbon offset payments.

In addition to these use cases specific to distribution logistics, RNP measurements derived by combining FCD and OSM may help identify pertinent network weaknesses such as a lack of essential facilities, i.e. hospitals, schools and supermarkets, as well as significant OD pairs with abnormally high travel times or frequencies. Based on these findings, specific geographic areas or network sections can be weighted according to their spatial relevance instead of relying on the common approach of average global thresholds independent of individual geographic characteristics, allowing for a more applicable representation of reality [172].

Resulting from the aforementioned insights, RNP within this dissertation is defined as the network driven economic costs of moving a vehicle from a specified point of origin (O) to a specified destination (D) on a daily basis using the public road network wherein the recurrent performance of this network is evaluated via a combination of structural (i.e., connectivity, structural reliability and redundancy, esp. detour factor) as well as dynamic (i.e., travel time reliability and accessibility, esp. travel time and travel speed) attributes.

Table 2.1: Relevant concepts to recurrent operational RNP measurements.

Concept	General Objective in Literature	RNP Measurement	RNP Indicator
Accessibility	Analysis of reachable nodes within a threshold	Distance Time	—
Connectivity	Design/Redesign of networks	Distance	Detour Factor
Redundancy	Analysis of alternative paths	Distance Time	Detour Factor Travel Time Speed Profile
Reliability	Analysis of traffic flows, density and speed	Time Air Pollution	Congestion Factor Travel Time Speed Profile CO_2 Emission

2.4 Summary

Poor RNP results in (1) decreased economical performance represented by increasing transportation costs [45, 65, 241, 242], (2) negative ecological effects in terms of higher greenhouse gas emissions [75, 243, 244], and (3) a decrease in social sustainability via a combination of the aforementioned factors in addition to traffic induced health issues [245–249]. Despite its importance for most aspects of everyday life [9, 10] and its impact on productivity and costs of constantly increasing [21] short-distance freight operations [45, 65, 237, 250, 251], the literature review reveales a lack of practical RNP research for logistics services in Germany. Existing RNP studies mainly focus on hard-to-grasp theoretical concepts and mathematical models within the context of non-recurring, extraordinary traffic incidents such as natural desasters or terrorist attacks [172]. What is required is an easy-to-understand and easy-to-access RNP index that can be incorporated into academic endeavors and practical day-to-day operations. RNP measurements for operational evaluation should focus on recurring traffic and general usage patterns to better estimate the regional and temporal impact of varying amounts of traffic congestion.

The availability of aggregate FCD in combination with crowd-sourced topology data is an underresearched field of study that provides great potential for reliable and representative RNP measurements. While FCD repeatedly proved a reliable source for evaluation of traffic congestion patterns [26, 252–254], difficulties exist mostly in the integration of different sources of UBD, esp. topology data, and their efficient programmatical evaluation.

This thesis aspires to overcome these difficulties and to close the existing gap of lacking RNP measurements for German road networks by discovering and developing new and efficient methodologies to combine publicly available Big Data sources.

CHAPTER 3

Research Outline

Chapter 2 indicates a lack of generalizable solutions to automatically assess recurring RNP on a wide geographic scale. Most previous attempts instead focus on deriving relevant general insights on the basis of selective individual studies. To alleviate this issue, the upcoming chapters depict three specific attempts at leveraging available public data sources to generate reliable RNP measurements.

Each article included within this cumulative thesis is published as an independent and peer-reviewed manuscript and focuses on one specific question subordinate to the overarching research question proposed in Section 1.2. All manuscripts adhere to Open Access publishing in a scientifically recognized journal.

Manuscripts are included in chronological order, not only due to their publishing date but due to their impact and contribution to the overall research goal. Each manuscript builds upon insights gained from its predecessor, incrementally improving upon the path to a generalizable methodology to estimate RNP.

3.1 Focus of manuscript 1

Table 3.1: Overview of manuscript 1.

Title	**Towards Sustainable Cities: Utilizing Floating Car Data to Support Location-Based Road Network Performance Measurements [255]**
Research Question	How can relevant data be collected programmatically to measure road network performance?
Authors	Maximilian Braun, Jan Kunkler, Florian Kellner
Journal	Sustainability (VHB-Ranking: C, Impact Factor: 3.889) Special Issue: Sustainable Operations and Logistics
Author Share	25%
Date	02.10.2020
DOI	https://doi.org/10.3390/su12198145

Manuscript 1 (see Table 3.1 and Chapter 4) constitutes the first attempt to leverage an isochrone-based API to estimate regional differences in RNP. By referencing the TomTom Reachable Range API, it deviates from common practices of measuring RNP based on pre-existing selective studies and datasets, instead focusing on aggregate data collected and made available by navigation service providers. Reachable range requests deliver information on travel times, travel speeds and traffic conditions based upon a specified node of origin. By selecting comparable points of origin for different geographical regions, generalizable RNP measurements are enabled.

In accordance with the first research question of this dissertation, the manuscript answers the question:

How can relevant data be collected programmatically to measure Road Network Performance?

As a result, this publication develops and presents a novel data collection approach to enable location-based RNP analysis using publicly available traffic information. Operational capability is demonstrated by a case study comparing four of the largest German cities in terms of network characteristics, esp. detour factor, infrastructure and traffic congestion. The main takeaway for subsequent research is the applicability and ease of access to relevant and important traffic information by means of navigational service providers and their APIs.

3.2 Focus of manuscript 2

Table 3.2: Overview of manuscript 2.

Title	**Speed Limit Induced CO2 Reduction on Motorways: Enhancing Discussion Transparency through Data Enrichment of Road Networks** [256]
Research Question	How can road networks be enriched by publicly available real-world data to enable CO2 emission calculations?
Authors	Jan Kunkler, Maximilian Braun, Florian Kellner
Journal	Sustainability (VHB-Ranking: C, Impact Factor: 3.889) Special Issue: Sustainable Operations and Logistics
Author Share	50%
Date	04.01.2021
DOI	https://doi.org/10.3390/su13010395

Based upon the key takeaway from manuscript 1 (see Table 3.1 and Chapter 4), publication 2 (see Table 3.2 and Chapter 5) aims to examine and discover potential use cases of API traffic data in combination with publicly available OSM road networks. In an attempt to enhance transparency of ongoing discussion on the topic of motorway speed restrictions and the impact of such measures on CO_2 emission savings within German political debates, manuscript 2 (see Table 3.2 and Chapter 5) constitutes a direct response to a research article published by the German Environment Agency.

Since the amount of emission directly correlates to the velocity of a vehicle via energy consumption factors, a general speed limit of 120 kilometers per hour is proposed within the original study. This article presents a methodology to combine openly available topology data of road networks from OSM with pay-per-use API traffic data from TomTom to evaluate such measures transparently by analyzing historical real-world circumstances.

The following research question is answered:

How can road networks be enriched by publicly available real-world data to enable CO_2 emission calculations?

The exemplary case study for the German motorway network discovers that most parts of the motorway network on average do not reach their maximum allowed speed throughout the day due to traffic, construction sites and general road utilization by network participants. Based upon this finding and in case of the proposed speed limit of 120 kilometers per hour, 50.74% of network flow kilometers would require restrictions for a CO_2 reduction of 7.43% compared to the current, unrestricted network state.

Within the context of this doctoral thesis, more importantly than the calculated results is the essential learning that OSM topology data and its programmatic evaluation in combination with aggregate historic traffic data can serve as a significant contributor to enable representative and generalizable RNP measurements.

3.3 Focus of manuscript 3

Table 3.3: Overview of manuscript 3.

Title	**Sustainable City Evaluation using the Database for Estimation of Road Network Performance [257]**
Research Question	How can representative routes be generated and evaluated to reliably measure Road Network Performance and overcome limitations of contemporary RNP estimation?
Authors	Jan Kunkler, Florian Kellner
Journal	Sustainability (VHB-Ranking: C, Impact Factor: 3.889) Special Issue: Sustainable Logistics and Environmental Protection
Author Share	90%
Date	31.12.2022
DOI	https://doi.org/10.3390/su15010733

The applicability of OSM topology data revealed as a result of manuscript 2 (see Table 3.2 and Chapter 5) provided the foundation for the final endeavor of this doctoral thesis: the generation of a realistic and representative reference database for RNP applicable and relevant both to researchers and practitioners.

While manuscript 1 (see Table 3.1 and Chapter 4) provided insight into the efficient extraction of aggregate traffic data via navigation service provider API and manuscript 2 (see Table 3.2 and Chapter 5) developed a scalable solution to working with effective representations of real-world road networks, the missing piece to enable generalizable RNP measurements is a solution to comprehensive network evaluation for large geographic areas.

Previous attempts, as outlined during the literature review, have been focused on selective areas and exemplary studies. In some cases, existing shipment data for a specific TSP has been investigated for regional comparisons. What both of these approaches fail to achieve is an acceptable level of generalization.

Manuscript 3 (see Table 3.3 and Chapter 6) aims to overcome the shortcoming of previous studies by answering the following research question:

How can representative routes be generated and evaluated to reliably measure Road Network Performance and overcome limitations of contemporary RNP estimation?

As a result, the Database for Estimation of Road Network Performance (DERNP) is generated as the cumulation of all research endeavors within this thesis by integrating and combining all previous insights and methodologies.

The DERNP is based on a randomized route sampling procedure that utilizes the Worldwide Harmonized Light Vehicles Test Procedure (WLTP) in combination with the tile-based HERE Maps Traffic API v7 and a digital elevation model provided by the European Union's Earth Observation Programme Copernicus to generate a large set of independent and realistic routes throughout OSM road networks. The artificially generated routes are evaluated using the PHEMLight5 framework to provide a comprehensive list of RNP parameters for all German metropolitan areas.

Part II

Publications

CHAPTER 4

Towards Sustainable Cities: Utilizing Floating Car Data to Support Location-Based Road Network Performance Measurements

4.1 Introduction

Rising urbanization around the globe leads to high requirements in terms of urban sustainability [258]. Therefore, indicators to measure urban sustainability are an extensively discussed topic in literature [244, 259–261]. These indicators often contain terms such as "mobility" [262], "efficient transportation", or "transportation and roads" [263]. When dealing with the sustainability of transportation and the efficient movement of people and goods, in addition to topics such as railways [264] and public transportation [265–269], the urban road network is a major research area [2, 10, 250, 270–273]. This stems from the fact that road network performance (RNP) can lead to significant negative impacts on all three dimensions of urban sustainability:

Economic sustainability can suffer in several ways. Many authors found that poor RNP, in terms of traffic congestion, is a reason for higher costs and reduces efficiency significantly [7, 45, 235, 274–276]. In addition to that, traffic congestion intensified in the past [64, 277], causing as much as 23 percent of all truck transportation delays [237].

Environmental sustainability is mainly focused on pollution and greenhouse gas emissions. A lot of literature proves the relation between traffic congestion and air pollution [238, 278–281]. Longer travel distances and congestion lead to more pollution and a lower level of sustainability.

Social sustainability focuses on the well-being of the population. Poor RNP can lead to several health issues. Traffic congestion implies a higher number of vehicles polluting engine noises on road. The generated noise has a significant health impact [246, 282] such as sleep disturbance and anxiety [283]. In addition to that, the number of accidents happening can depend on the road network [284–286].

RNP in general has been studied extensively over the years, employing different methods and geared towards different purposes [40, 117, 185, 287, 288]. Especially the relation between the three-dimensional urban sustainability (economy, environment, and society) and the road network has been addressed.

An extensive body of literature discusses the reduction in traffic congestion [289–291]. Russo and Comi [292] analyze the effects of logistics measures on the economy of the city, Baghestani et al., Armah et al., Borza et al. and Zhang et al. [280, 293–295] deal with on-road emissions and Kleizienė et al., Ohiduzzaman et al. and Sirin [282, 283, 296] discuss vehicle noise reduction and the development of quieter pavements.

To carry out these analyses, all stakeholders who are dealing with road networks and urban sustainability must gather a real-world data base to work with. Therefore, the research hypothesis of this paper can be formulated as follows:

How can relevant data be collected programmatically to measure road network performance?

The long-term trend towards digitizing the environment, including the logistical infrastructure such as road networks and vehicles, fundamentally eases the programmatical assessment of information and gives way to study new data collection methods [5, 297–299]. Due to this, the purpose of this paper is to develop a new methodological approach to gather relevant RNP data on an area-wide scale. An exemplary application of the gathered data on the economic dimension is demonstrated on four selected cities in Germany to prove the usability of the proposed methodology. Thus, the paper deals with what Sun et al. [252] call the physical issues of RNP, i.e., we are concerned with the determination of travel times, travel speed, and traffic conditions.

The paper is organized as follows: Section 2 provides theoretical information on RNP measurement and the underlying data collection procedure. In Section 3, a data collection method for measuring RNP is presented by providing an exemplary use case. In Section 4, this methodology is applied to four German cities and a comparison of these cities is carried out. In Section 5, theoretical and practical implications are discussed. An outlook for further research is provided in Section 6, followed by a short conclusion highlighting the main takeaways of this paper.

4.2 Literature Review

4.2.1 Fundamentals on Road Network Performance Measurements

The assessment of RNP has been widely researched. We start by introducing our definition and will then give reference to the extant body of research. We suggest defining RNP generally as the network driven impact on sustainability. In the context of this paper, we particularly focus on the economic dimension, which leads to the refined definition of RNP as being the network driven economical costs of moving a vehicle from a specified origin to a specified destination using the road network. Although the definition is open, we confine our analysis to urban transportation, i.e., short distance traffic, sometimes called the last mile or urban cargo traffic [44, 300]. The road network is defined as the set of roads that can be used by vehicles. Thus, our definition of RNP is geared towards the structural properties of the network that shapes the flows within the network and affects operational performance [301, 302]. The definition acknowledges but excludes the analysis of further notions or indicators of network performance, such as levels of service, capacity, safety, smoothness of flow, reliability, vulnerability, accessibility, resource constraints, or travel time reliability [303], that, respectively, represent the functionality of the network for particular research goals. As our analysis is restricted to network driven costs only, it is confined to a share of the total cost only. The cost of moving a vehicle is determined by many factors such as vehicle type [304], toll [305] or fuel [306]. We restrict the analysis to those factors that are related to the road network. The definition of RNP borrows in part from Santosa and Joewono [307] who measure RNP by speed and vehicle cost.

We suggest measuring RNP by detour and travel speed. Detour is defined as "road distance from origin to destination" over "aerial distance from origin to destination" [308]. Thus, detour represents widely discussed network attributes such as density [302] or connectivity [14]. Travel speed is defined as the average speed that can be driven from origin to destination considering vehicle and road constraints. Thus, travel speed summarizes road network attributes such as speed limits, traffic lights, or the level of congestion within the network [26, 309, 310]. Travel speed can be easily converted into travel time [311]. Thoen et al. [312] demonstrate that longer travel times lead to higher transportation costs, emphasizing the importance of determining travel times objectively.

Road distance is defined as the distance of a tour. A tour is defined as the network path a rational decision maker would choose to minimize the travel time from origin to destination. Thus, we assume an efficient use of existing road infrastructure and available traffic status information [313]. We suggest measuring RNP with reference to two factors only and thus depart from earlier approaches that suggest multi-criteria measurements such as Fancello et al. [117].

RNP results vary by tour since characteristics of the road network vary across space. Ciscal-Terry et al. [25] called this the origin-destination-distribution problem. Thus, a meaningful RNP statement must be specific on how to select the locations that enter the analysis.

Fundamentally, RNP can be measured via three origin-destination settings. One is to measure across the complete network, i.e., from anywhere to anywhere. A second setting measures from defined origins to defined destinations [65], i.e., from somewhere to somewhere. We suggest following a third setting, given an origin, we do not specify a destination and then measure detour and travel speed for the origin-destination pair but specify the origin only and list all destinations that can be reached within a given range or time frame.

Since we focus on studying RNP for general cargo moving purposes, typical logistics service providers' locations such as freight transport centers, logistic zones or urban consolidation centers represent meaningful origins. For a case-specific analysis, Alho A.R. et al. [314] find that declared data regarding bases might not be as accurate as inferred data, suggesting the identification of central network nodes via algorithms instead of relying on survey data to determine meaningful points of origin. Referring to Saedi et al. [303] our approach does not report RNP across the complete road network but well-defined partitions.

4.2.2 Road Network Data Collection: Developing A New Method

Data sources to compute RNP have been mentioned in recent literature but have never been an explicit focus of the research community. Some papers model the variability of RNP via a stochastic framework and compute journey time estimators [315]. Figliozzi [274] uses tour data reported in the literature to perform a sensitivity analysis on changes in travel time and tour characteristics. The problem with this procedure is the availability of data as the current literature does not provide suitable or publicly available tour data for most areas around the world. Another way to gather road data is the usage of equipped single cars [316, 317]. These cars are equipped with a range of sensors to record road data while driving. The extensive manpower and machinery required for this solution is multiplied as global coverage is attempted. Urban areas could be analyzed under consideration of induction loops, cameras, and sensors measuring current road traffic [318, 319]. Data accessibility as well as processing data from a lot of different sources drive complexity of this data collection method. Mondschein and Taylor [7] interviewed people about personal trip data and corresponding travel times. Two major concerns arise when we take a closer look at this procedure. Global coverage is very weak as a lot of interviews must be conducted to gather enough data for one specific area. An additional problem are people's privacy concerns when sharing their driving data [274]. A "digital version" of interviewing people is the usage of navigation service providers' application programming interfaces (APIs) as these providers gather and compress anonymized data from all their users [320]. The anonymization of data also overcomes the privacy concerns mentioned before. Kellner et al. [65] used navigation service providers' data to build distance matrices with customers' locations and requested travel times at different times throughout the day. To generalize the approach by Kellner et al. [65] and bypass any problems related to subjective trip generation, as for example experienced by Sun et al. [321], we use real-world floating car data (FCD) with compressed information collected over time.

The use of FCD to evaluate traffic status has been studied intensively [20, 120, 232, 253, 254, 322, 323]. However, there is no research that exploits FCD, especially FCD processed into reachable ranges, to assess RNP. That is what we suggest doing.

Processing FCD to measure RNP is challenging as traffic data can be considered big data due to its complexity and heterogeneity [314, 324, 325]. However, navigation service providers can produce the needed data efficiently [320]. Due to this, we suggest using navigation service providers' APIs, especially retrieving so-called "reachable ranges".

A "reachable range" is defined as an area that can be reached by a specific vehicle under certain constraints such as maximum travel time or maximum travel distance starting at a specified location. The use of reachable ranges to assess networks has gained only limited attention so far. Hirako et al. [326] analyze reachable areas to understand the travel behavior of elderly citizens to medical facilities. Referring to Phan et al. [327], calculating a reachable range is one part of the algorithm for maximizing range sum queries turned inside out.

In our case, we retrieve a reachable set K^c that consists of 50 nodes that can be reached from origin node v_0 by the end of constraint c [31]. As a result, we obtain a subgraph showing only one origin and 50 reachable destinations. Assuming a completely paved environment, the reachable range would resemble a circle. In a real-world scenario, it will be a snowflake-shaped object with some locations being closer to the origin (areas with poor RPN) and some locations further from the origin (areas with good RNP).

By combining this information with the need for multi-time measurements, we obtain time-dependent graphs. By varying the defined timeframe, the RNP measurement can be suited to different goals of the analysis.

Our approach is considered efficient as wide areas can be analyzed by a few API calls. This allows measuring RNP on a large scale for defined origins without the need for second best solutions such as regional aggregation as suggested by Casadei et al. [328] for instance.

4.3 Methodology

4.3.1 Basic Idea

To measure RNP and make regional comparisons using speed information, the following data are required: free flow and congested speeds, which can be derived from travel times and travel distances as well as air distances, which in relation to previously determined actual road travel distances enable a detour calculation. To investigate the relation between the time of day and congestion-induced delays, exemplary trips are simulated leading from the city center outwards (to the east, west, north and south) for every city considered in the comparison below (Section 4.4). The results generated via the TomTom routing API are shown in Figure 4.1. From 03:40 to 21:50 delays are occurring in every city. Two rush hours can be identified, the first one can be classified as the morning rush hour where large numbers of employees commute to work and more than 75 percent of commercial distribution tours depart from their origin as observed by Nuzzolo et al. [329]. It peaks at about 08:00, in accordance with the observations made in Italy. The second rush hour peaks at 17:00, when most people are heading home from work. In between these rush hours the congestion-induced delays settle in Hamburg, Munich and Stuttgart whereas Berlin shows a rise in level of delay until peak rush hour is reached. The interval from 22:00 to 03:30 the next day can be considered as free flow state as there are no congestion-induced delays measured.

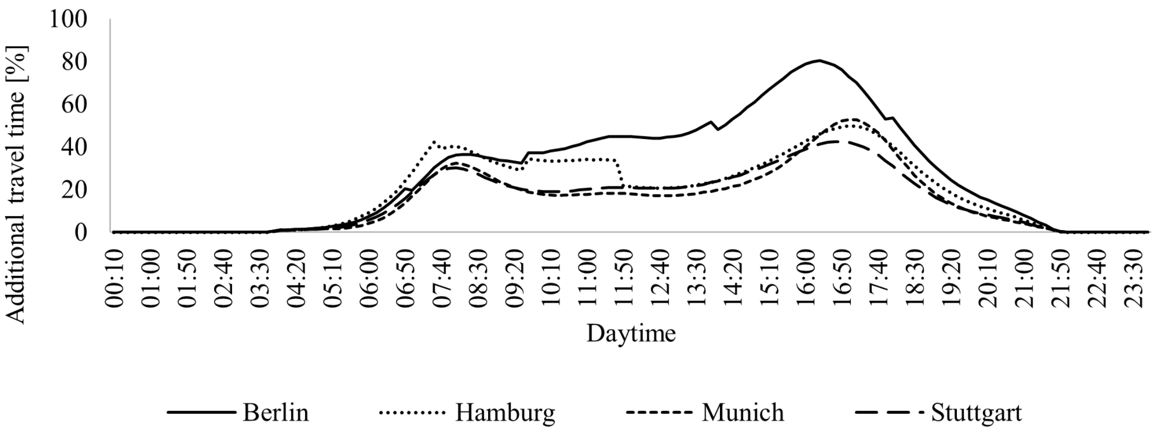


Figure 4.1: Time-delay dependency.

The data collection process uses the TomTom reachable range API. It returns the reachable area in the form of reachable destinations from a certain starting point in the form of a polygon. The restrictions for the reachability analysis can be as follows: maximum travel distance = “distance budget”, maximum travel time = “time budget”, or maximum fuel consumption = “fuel budget”.

This API has become more and more interesting, especially during the electrification of vehicles because it is possible to determine which locations can be reached with a given battery capacity and a corresponding consumption. In the context presented in this paper, the API is used to determine all locations that can be reached within a time or distance restriction. Many parameters can be specified as input variables. The most important parameters in this context are shown in Table 1 below:

Table 4.1: TomTom reachable range application programming interface (API) parameters.

Parameter	Unit/Format	Description
Origin	Latitude, Longitude	Origin describes the starting point of the request.
Time Budget	Seconds	Time restriction that limits the maximum travel time.
Distance Budget	Meters	Distance restriction that restricts the maximum travel distance.
Route Type	Fastest; Shortest; Eco	Describes the routing mode. Fastest optimizes travel times, shortest travel distance, eco finds a compromise.
Depart At	Date in the RFC 3339 Format	Start time of all fictitious routes. Must be in the future.
Travel Mode	Van/Truck/Car	Historical speed profiles that are used depending on the vehicle type.

As a result, the API always provides a polygon with a maximum of 50 corner points (see Figure 4.2), regardless of the selected input parameters. The area described by the polygon includes all geolocations that can be reached considering the specified restrictions. For each corner point of the polygon, the corresponding air distance can be estimated using the great circle distance formula [330]. Consequently, the air distance can be used as a common base to compare queries for different restriction parameters.

The data collection methodology to determine the attributes detour factor, infrastructure and traffic congestion is explained below. The parameters Origin, Travel Mode and Route Type are identical for all queries. In case of the following example, the starting point “Schäftlarnstraße 10, 81371 Munich, Germany” with the coordinates of 48.116431 degrees latitude and 11.556811 degrees longitude is selected. The parameter Travel Mode is set to “truck”, the Route Type requested is “fastest”.

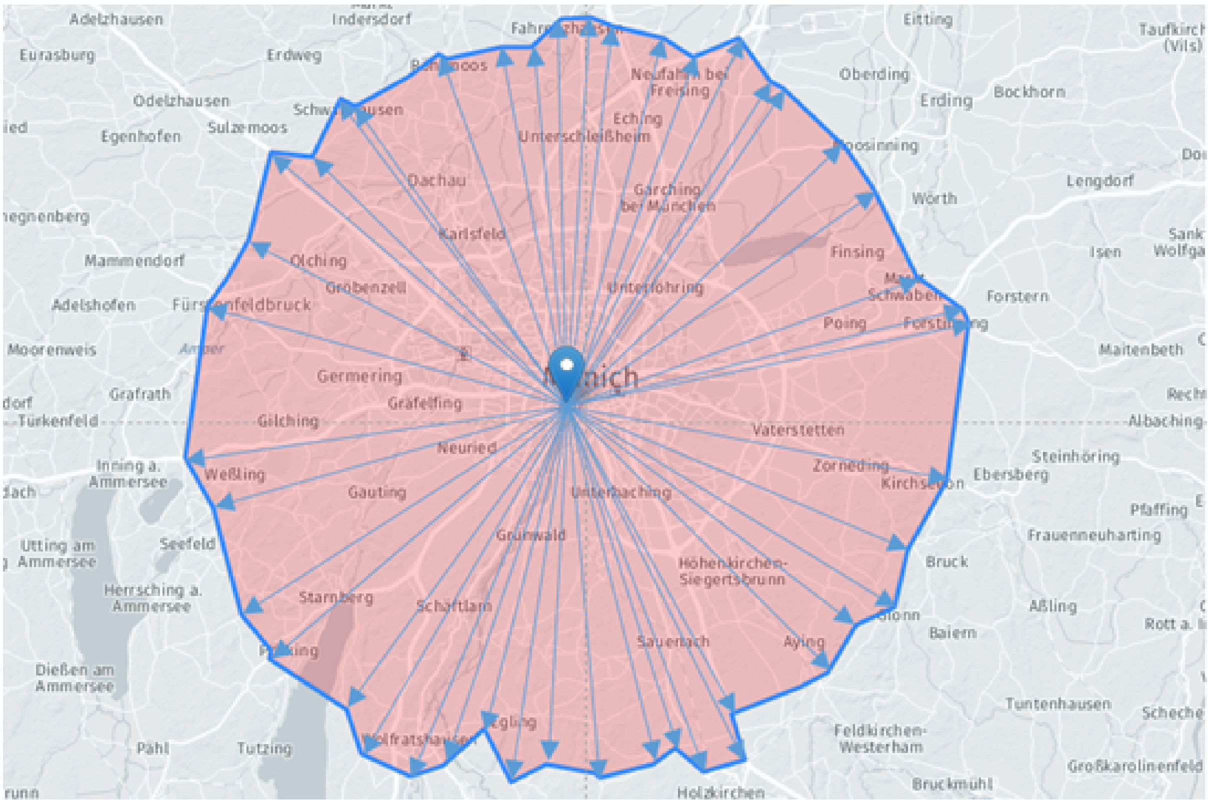


Figure 4.2: Result of a TomTom reachable range request with a 30 km travel distance restriction.

To summarize the data collection methodology, necessary variables are defined in Table 2. All three calculation steps are presented in Table 3 and explained in depth in the following sections.

Table 4.2: Variables and descriptions.

Variable	**Description**	**Explanation**
d_t	Travel distance	The road distance from a start point to an end point
d_a	Air Distance	Air distance with $d_a = \frac{1}{n}\sum_{i=1}^{n} d_i$ where d_i is the air distance between the polygon’s corner point i and the request’s origin and n is the number of polygon corner points (in our case 50).
t_t	Travel time	The time needed to travel from a start point to an end point
$df(d_a)$	Detour Factor Regression	Continuous Detour Factor regression based on discrete measures
$v_f(d_a)$	Free flow velocity regression	Continuous free flow velocity regression based on discrete measures
$v_c(d_a)$	Congested velocity regression	Continuous congested velocity regression based on discrete measures

The next subsections focus on an in-depth explanation of the collection methodology to understand the requirements and results of every step. In addition, the generated data are visualized by individual charts. Connections between marks within one chart indicate that the gradients are results of continuous regressions based on discrete measures.

Table 4.3: Data collection overview.

Calculation Step	1: Detour Factor	2: Infrastructure/Free Flow	3: Traffic Congestion
API Restriction	d_t	t_t	t_t
API Result		Polygon to estimate average reachable d_a	
Deduced information	$\frac{d_t}{d_a} = df(d_a)$ Polynomial Regression $df(d_a)$	$d_a \cdot d_f(d_a) = d_t$ $\frac{d_t}{t_t} = v_f(d_a)$ Power Regression $v_f(d_a)$	$d_a \cdot df(d_a) = d_t$ $\frac{d_t}{t_t} = v_c(d_a)$ Power Regression $v_c(d_a)$

4.3.2 Detour

Detour in general is defined as the difference between travel distance via road and the corresponding air distance. The detour factor is defined as the quotient of travel distance and calculated air distance between two points. It will always be greater-than or equal to 1.0, because the shortest travel distance is always a straight line and thus equals the air distance. The detour factor changes with the length of the travel distance/air distance (with increasing air distance, straight routes such as highways can be used, which reduces the detour factor). However, the API query only accepts one maximum travel distance value as a restriction at a time.

Consequently, one query for each value between 1 km and 30 km travel distance (= distance budget) with a step size of 1 km is requested and the returned polygons analyzed. The parameter Depart At is not relevant here as the polygon is calculated via a traffic-independent shortest path algorithm.

In the last step, the query's restriction (= travel distance) can be related to the average value of the calculated air distances. Thus, for each travel distance a corresponding air distance and a detour factor is calculated. The relationship between air distance and detour factor can be displayed using a polynomial regression. In our example, this results in the chart shown in Figure 4.3:

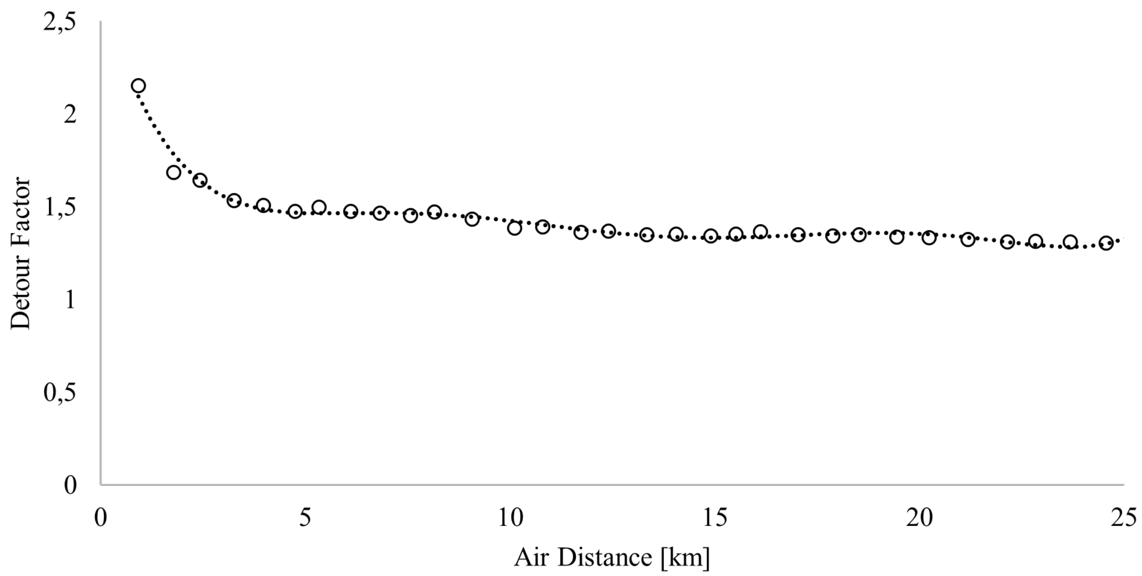


Figure 4.3: Detour factor for Munich, Germany.

One can clearly see that the detour factor decreases with increasing air distance, which is due to the possibility of using relatively straight routes (e.g., access to inner-city highways or the German motorway network), until it reaches a nearly stable value (in this case about 1.5).

4.3.3 Infrastructure

After determining the detour factor regression, the API can be used to determine the average speed during free-flow state. The free-flow state describes the traffic flow without congestion exceeding an agreed upon norm [331]. This means that delays due to infrastructural influences such as speed limits or traffic light changes are considered part of the free flow. Consequently, the average free-flow speed provides a quantification of the existing infrastructure. In order to determine this average speed, queries are formulated sequentially to retrieve points that can be reached for a certain journey duration. For this purpose, the queries are restricted by applying a time budget restriction. To ensure free-flow conditions, the parameter Depart At is set to 00:00:00. This time is derived from Figure 4.1 as there is no delay measured in any of the investigated regions. Using the returned polygon, the average air distance between all polygon corners and the starting point can be calculated per iteration step. The time steps and their corresponding free flow distances are shown in Figure 4.4. However, the magnitude of the travel distance is dependent on the air distance and implicitly manipulated via the detour factor. For this reason, a travel distance is estimated using air distance averages and the corresponding detour factor, as is shown by the formula in Table 4.3. The ratio of travel distance to travel time returns the average free flow travel speed.

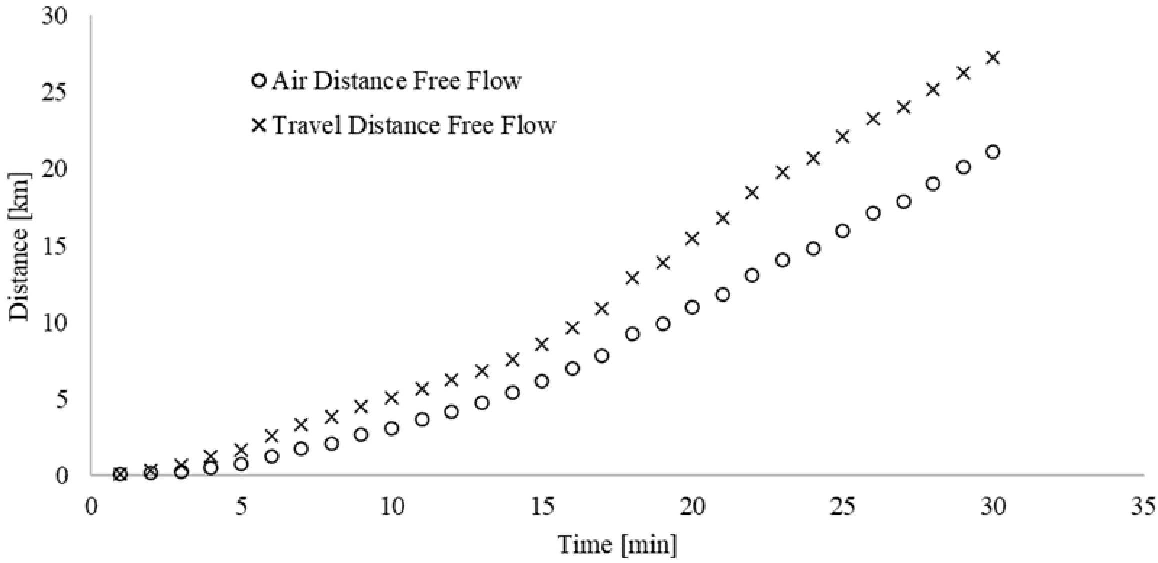


Figure 4.4: Distance covered during free flow for Munich, Germany.

4.3.4 Traffic Congestion

With the given definition of free-flow state in mind, the effect of traffic congestion can be measured by the difference between free-flow speed and congested speed. The travel speed in congested state can be determined by repeating the procedure for calculating the free-flow speed, setting the Depart At parameter at a time suitable for the analyzed scenario. In the context of this research, we set the Depart At parameter of the API query to 07:00:00. The results are shown in Figure 4.5. The ratio of travel distance (estimated by using the detour factor regression) to travel time again gives the average travel speed.

4.3.5 Speed Comparison

To compare free flow and congested states more clearly, Figure 4.6 shows the average travel speed as a function of the travel distance for both states of the road network. By using a power regression model of the free flow and congested speeds, the speed difference can be determined continuously throughout the analyzed travel distance interval.

Both speed profile curves displayed in Figure 4.6 clearly show a degressive course. When reaching beyond the localized, urban space, both slopes approach a common value. The convergence of these curves can be explained as follows: as the travel distance increases, the traffic density usually decreases outside the inner-city boundaries and traffic volume considered with the API-calls corresponds more and more to the free flow state. The actual value that both graphs converge towards can be explained by referring to the route type, which is defined as fastest for all calls. This means that roads with the highest possible travel speed (usually motorways) are favored for the analysis. Consequently, the asymptote of

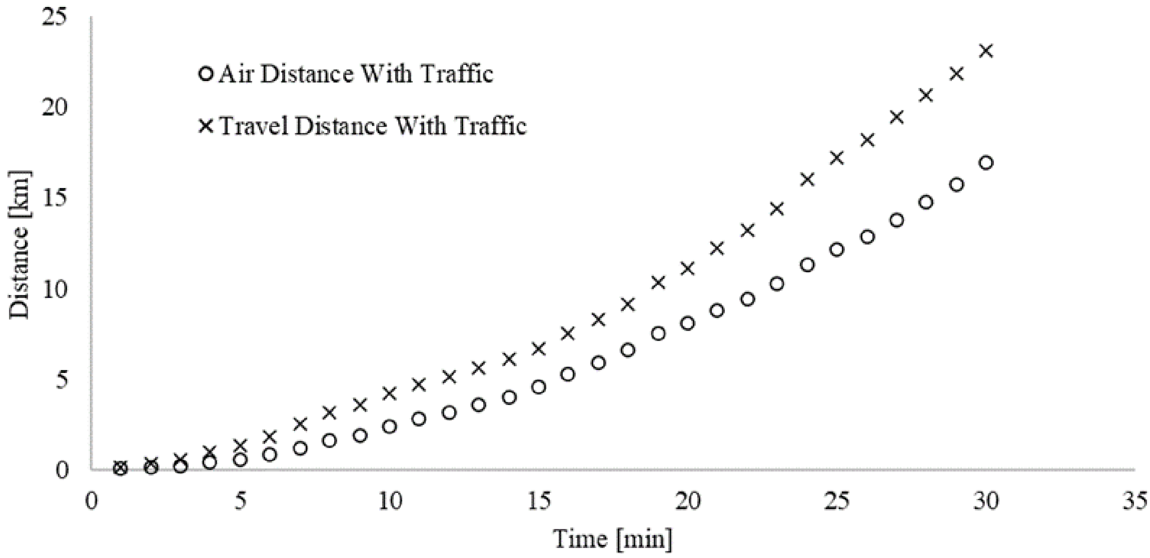


Figure 4.5: Distance covered including traffic for Munich, Germany.

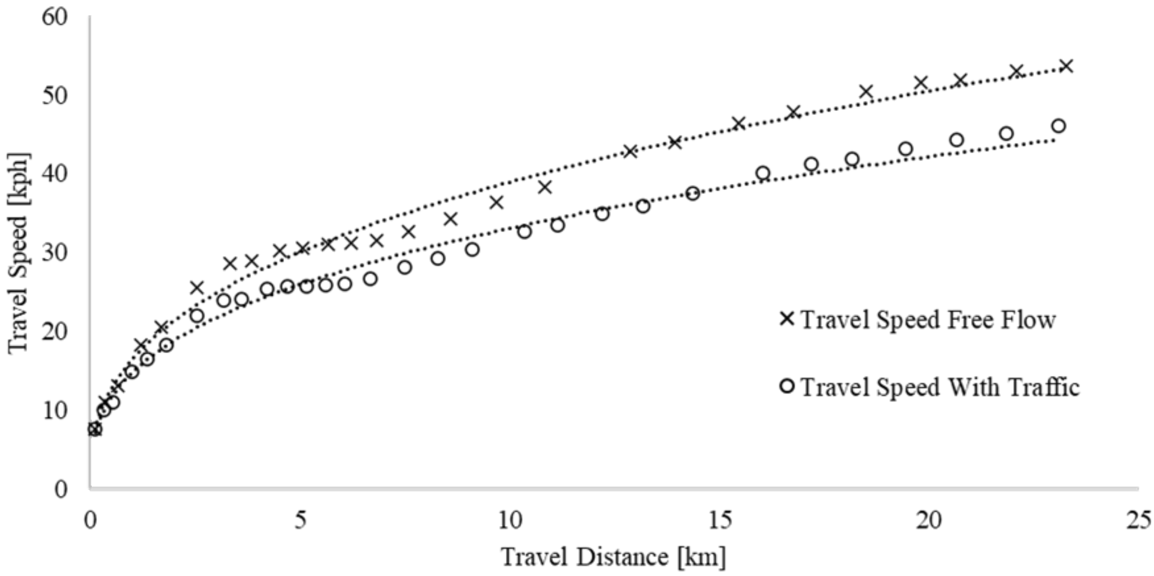


Figure 4.6: Speed profile comparison for Munich, Germany.

the two speed graphs corresponds to the average speed at which the vehicle type defined in travel mode moves on motorways.

4.3.6 Area Comparison

Travel times needed to reach an end point from a start point are the result of travel distance and travel speed of the specific route. To compare different areas, a combination of detour based on the street layout and delays based on traffic influences must be considered. This means that both the detour and traffic factor for different areas must be calculated based on a comparable variable. Since in practice, the determination of air distances with the help of the great circle formula is easy to implement and free of location-specific influences, the air distance is chosen as the comparable variable. The goal of this area comparison is to derive a travel distance and travel time for free and congested states depending on the covered air distance. The travel distance on the one hand can already be determined by the air distance multiplied with the detour factor: $d_t = d_a \cdot df(d_a)$. On the other hand, the travel time is calculated as follows: $t_t = d_a \cdot df(d_a) \cdot v(d_a)$. The travel time comparison is shown in Figure 4.7.

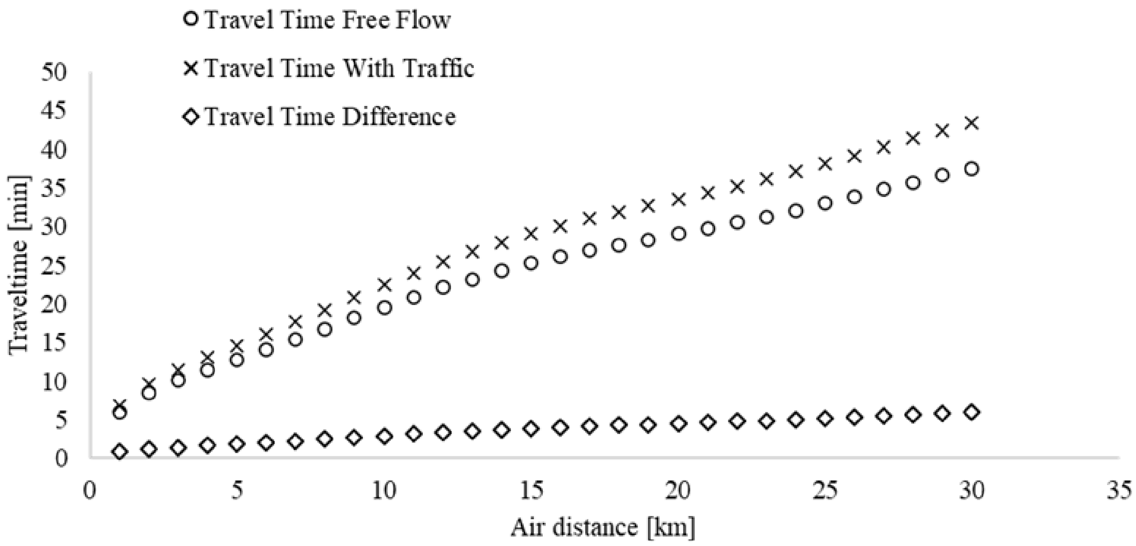


Figure 4.7: Travel time comparison for Munich, Germany.

The combination of travel distance per air distance and travel time per air distance allows us to assess the considered area based on sustainability aspects. To show the applicability of our measures in the context of sustainability we focus on analyzing one specific sustainability dimension: the economical sustainability is measured by costs per air distance. Therefore, we assume EUR 0.7 per kilometer driving costs, an hourly wage of EUR 20.5 as driver costs and EUR 7.5 per hour of vehicle occupation costs, which is in line with other literature [332]. Continuing, the costs per air distance kilometer for Munich are shown individually and in total in Figure 4.8.

All curves are degressive. The costs during free flow (dashed lines) are always slightly below the congested graphs, although they become more and more similar over time due to the aforementioned reason of motorway access when the air distance increases. The relationship between driving costs and the combination of driver plus vehicle occupation costs is particularly noteworthy. With increasing distance, the driver and vehicle occupation costs are dominated by the driving costs. In this example, the driving costs exceed the driver and vehicle occupation costs in free flow/in the congested state from 8/12 air kilometers. On average, the congested mode results in higher costs of about 12 cents per air distance kilometer compared to free flow, which corresponds to additional costs of about 6.7%.

4.4 Case Study

Comparison of Four German Cities by Detour, Infrastructure and Traffic Congestion Indices and Their Impact on Road Network Performance

In order to compare four different cities, data on detour factor, travel speed, and costs are determined in free flow and congested states for each city using the previously described methodology. The four selected cities are Berlin, Hamburg, Munich, and Stuttgart as they are ranked among the top six German cities within the 2019 TomTom traffic index ranking. The central starting locations shown in Table 4.4, mainly based on existing depots by local transportation service providers, were used in this case study:

In the following paragraphs, all results are plotted and interpreted. In the descriptions of the diagrams, the keyword “collected” indicates that the data shown are displayed as it has been retrieved and has not been smoothed or modified in any way. “Calculated” means that the data were estimated by regression and therefore smoothing can occur. The curves of the different cities are always marked identically to allow for easy comparison as shown in Figure 4.9:

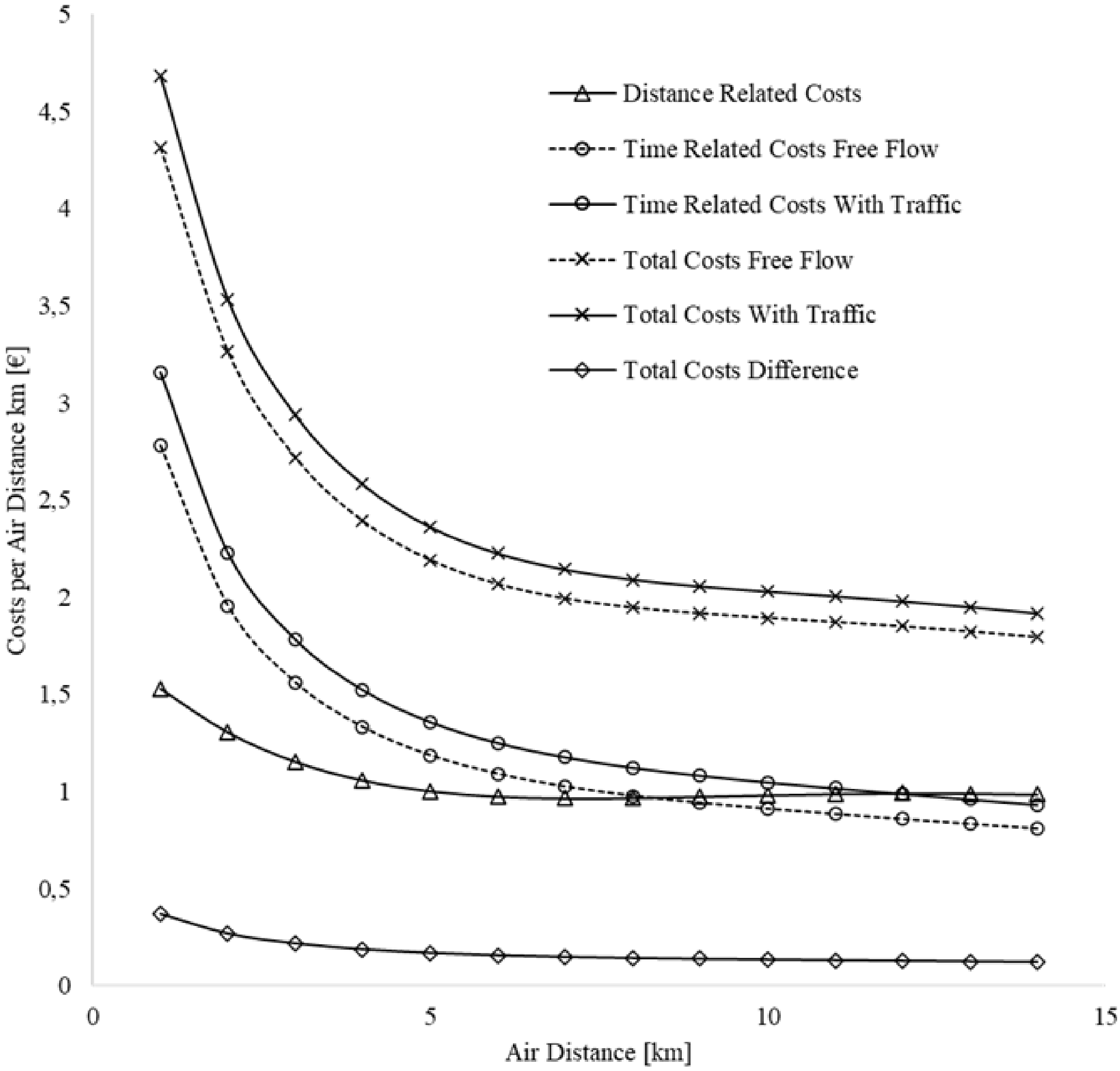


Figure 4.8: Costs per air distance for Munich, Germany.

Table 4.4: Selected cities' starting locations.

City	Latitude	Longitude	Street-Level Address
Berlin	52.519051	13.408583	Berliner Innenstadt, 10,178 Berlin
Hamburg	53.551181	9.992416	Alter Wall, 20,095 Hamburg
Munich	48.116363	11.556560	Schäftlarnstraße, 81,371 Munich
Stuttgart	48.776248	9.180116	Dorotheenstraße, 70,173 Stuttgart

Figure 4.9: General graph legend.

4.4.1 Detour Factor

The detour factors in Figure 4.10 describe the interaction between air distance, street network density, and straightforwardness of existing connections. By taking a closer look at the curves of the detour factors, it is noticeable that the detour factors of the three cities Hamburg, Munich, and Stuttgart develop nearly identically, starting at about 11 km air distance and approach a value of 1.4. In addition, the course of the curve for Hamburg is noteworthy, as it is rather constant at the beginning in contrast to the other curves. This indicates a strong deviation from a road network made up of straight connections around the centralized starting point, which is the case in Hamburg due to the river Elbe and its many waterways inside the inner-city area. Only after exiting the inner-city area and gaining motorway access, the detour factor decreases as more direct connections become available. Lastly, Berlin's detour factor is consistently lower than all other detour factors, which indicates a well-developed road network.

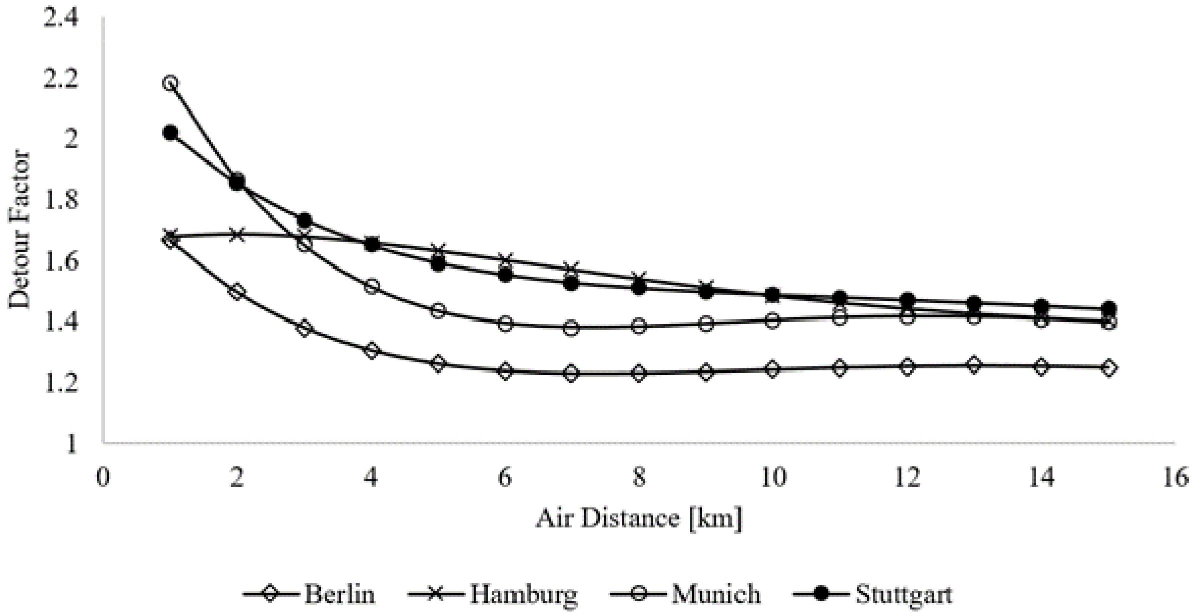


Figure 4.10: City comparison: detour factors (collected).

4.4.2 Travel Times

The travel time curves provide information on how cities position in terms of infrastructure and congestion measurement. Four different charts are generated. The two charts in Figure 4.11 show the travel distance in relation to the travel time both in free flow and congested states. The next two charts in Figure 4.12 focus on travel distance loss. The left chart in Figure 4.12 shows the absolute difference between these curves. The right chart shows the relative loss of travel distance from free flow to congested status. It is apparent that Stuttgart has the highest travel distances compared to the given travel times in both free flow and congested states. When looking at the relative loss curve for Stuttgart, we notice that it is relatively low compared to the other curves. This means that Stuttgart does not have a major congestion problem and the city has a very good infrastructure.

The counterexample to this is Hamburg. The speed of movement tends to be lowest in Hamburg in free flow and congested states. The relative loss curve for Hamburg is above average. This suggests a poor infrastructure, as the possible travel distances without traffic are already relatively low. The congested state in Hamburg can be classified as slightly above average in comparison.

The most congested cities are Munich and Berlin, with Berlin showing a relatively constant relative loss of around 16 percent (0.16) compared to free flow. Munich, on the other hand, is characterized by an increasing level of relative loss, which is approaching 17 percent (0.17).

Depending on the observation interval, Berlin (up to 10 min of travel time) or Munich (from 10 min of travel time) can be classified as the most congested city in the comparison at 07:00:00 departure time.

4.4.3 Transportation Costs

The economical sustainability of infrastructure, congestion and detour factor is reflected in total costs of transport. The cost rates from section 4.3.6 were used for this calculation. The first two curves from left to right shown in Figure 4.13 represent costs per air distance kilometer for free flow and congested conditions. The right curve in Figure 4.13 shows the cost difference between congested and free flow.

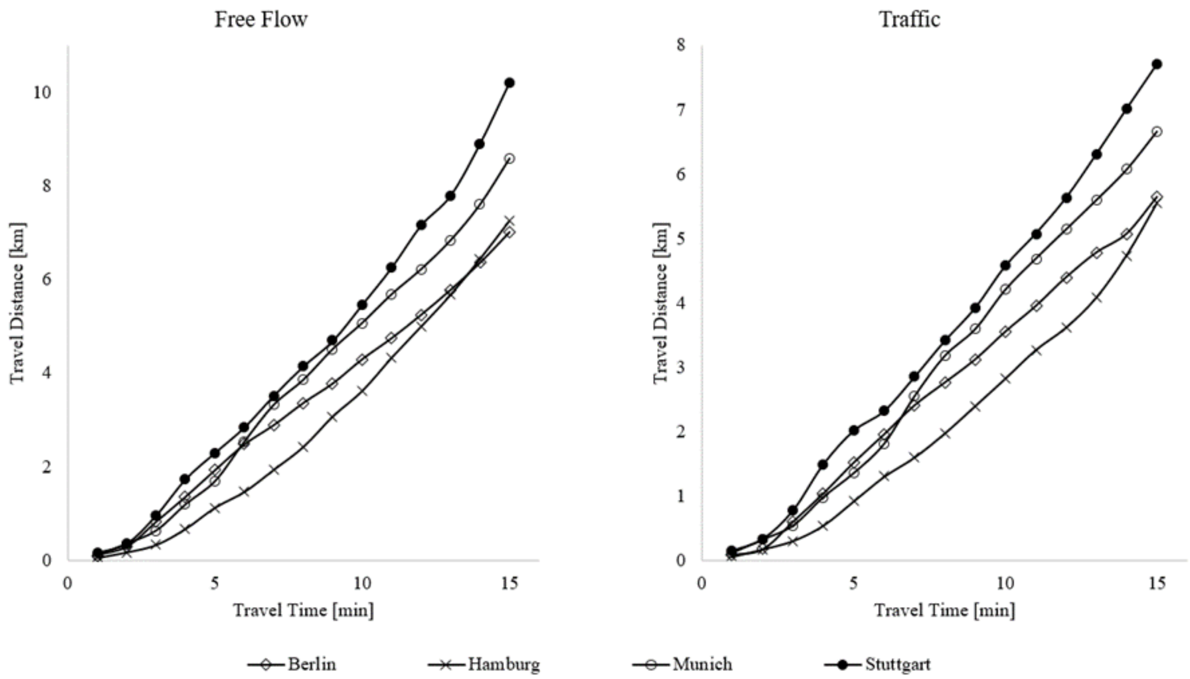


Figure 4.11: City comparison: travel distances (collected).

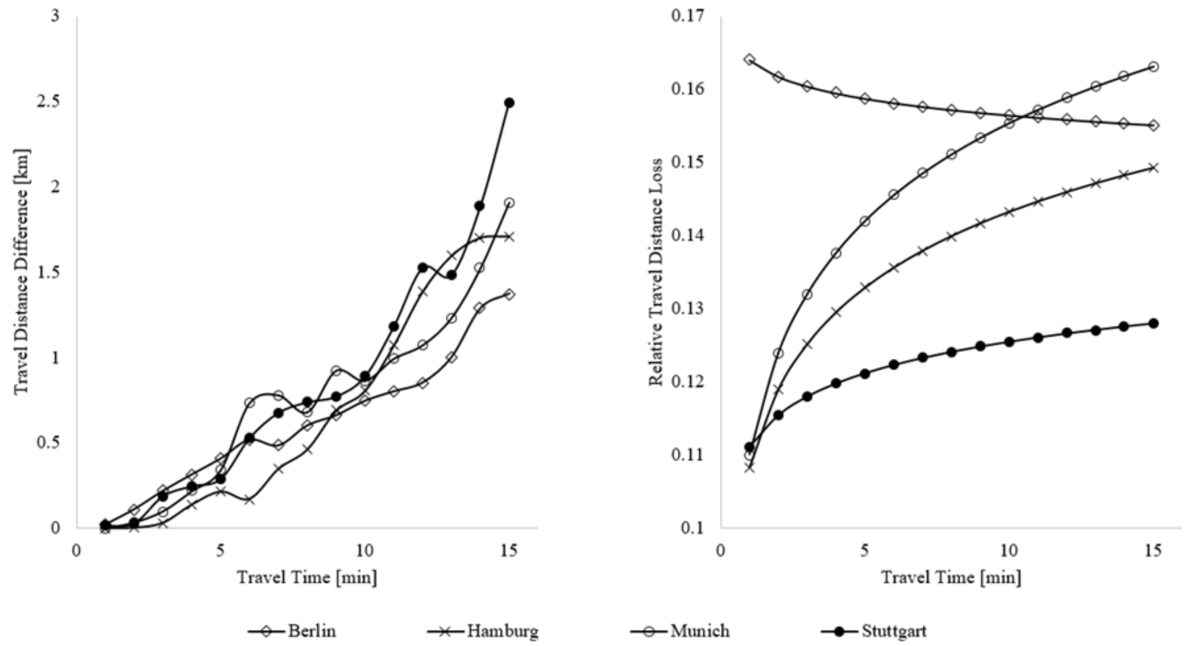


Figure 4.12: City comparison: absolute travel distance difference (collected) and relative travel distance loss (calculated).

The costs per kilometer are highest in both free flow and congested conditions in Hamburg. This can be explained by the fact that Hamburg has an average detour factor, a poor infrastructure, and a moderate traffic congestion level. Due to the average detour factor, the driving costs per air distance are also average, whereas the driver and vehicle occupation costs are far above average due to the low absolute speeds.

The graphs for Stuttgart in free flow and congested states are slightly above the curves of Munich and Berlin, which describe a comparable course. The absolute speeds are highest in Stuttgart, which means that the higher costs can only be explained by the higher detour factor of Stuttgart. Stuttgart's detour curve is always above average and to a large extent the highest amongst all cities.

Munich and Berlin share the lowest costs per air distance kilometer. In Munich, the absolute speed is higher than in Berlin, both in free flow and congested states, with Berlin having a significantly lower detour factor. These two facts cancel each other out, resulting in both cities having an almost identical level of transport cost.

The cost difference curves allow conclusions to be drawn as to how much additional cost per air distance kilometer is incurred depending on the choice of departure time. In Berlin, different departure times cause the highest difference, Stuttgart the least and Hamburg and Munich show almost identical cost difference curves. In addition, the costs induced by congestion can vary between EUR 0.07 and EUR 0.5 per air distance kilometer, depending on the distance and city, which results in a considerable total cost difference for a high number of kilometers travelled.

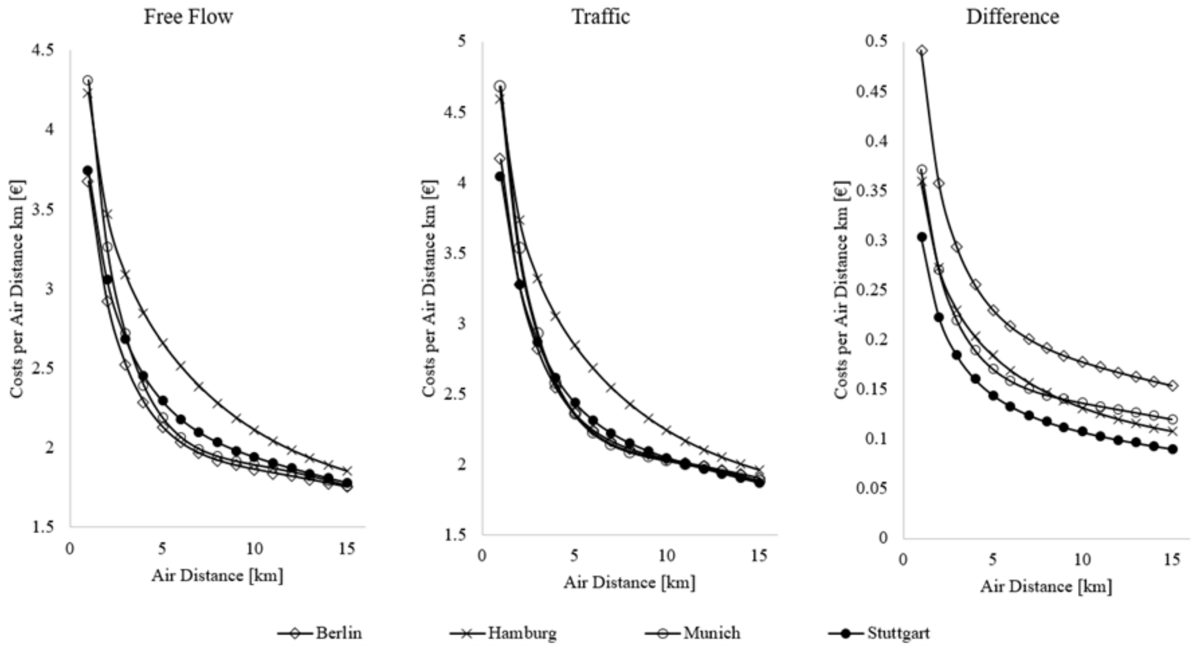


Figure 4.13: City comparison: costs per air distance km (calculated).

4.4.4 City Comparison

When approaching a comparison of two or more regions from a RNP standpoint it is essential to define the scope of comparison. As we can derive from the subsections above it is not enough to know detour/travel speeds to conclude a transport cost related order of different regions. To order regions within the context of RNP, a clear perspective to interpret the data must be set. This perspective consists of the following three characteristics: (1) performance indicator; (2) daytime; and (3) air distance. To begin analyzing our four regions, one of the suggested (1) performance indicators must be chosen. This stems from the fact that analyzing only one regional performance indicator indicates high costs per kilometer but at the same time another performance indicator value compensates the first one and leads to lower costs per kilometer as we would have expected. For example, Stuttgart has a high detour factor, which—considered isolated—would lead to the expectation of high costs per kilometer. Stuttgart's high travel speeds in contrast lead to low travel times and therefore result in transportation costs per kilometer being only slightly above average. Due to this, the interpretation of the level of different performance indicators must not be mixed up. Following that, a (2) daytime to compare regions must be set. This is of course necessary due to the fact that the level of traffic congestion and thus congested speeds/costs in congested state are highly time dependent as shown in Figure 1. As the peak congestion times are slightly different for specific regions the decision must be made whether different regions are analyzed at different times or whether one daytime for all regions is set. Individual daytimes for every region would allow comparison of peak congestion states whereas an identical starting time for every region increases comparability in cases where departure times are fixed (e.g., due to business and delivery hours/time windows). The last aspect to take care of is the air distance (3). Performance indicator values are dependent on the travelled air distance. Therefore, specific air distance intervals or fixed air distance values should be set to ensure context-specific analysis. To remotely compare regions without any knowledge about locations to be approached from the starting point, an average air distance of potential trips should be estimated. If precise information about locations to be approached is available, the distances between these locations and the starting point should be calculated and used for further analysis.

4.5 Discussion

The collection method presented in this paper assumes that the free flow condition in a traffic area occurs at midnight. This means that the time of departure influences the volume of traffic and thus the transportation costs incurred. To minimize these costs, the additional costs caused by the traffic volume must be included in scheduling algorithms. These are often offset by penalty costs for delayed deliveries. Scheduling algorithms should therefore not solely minimize the penalty costs but consider the addition of congestion costs and penalty costs.

As previously described in literature [318, 331], free flow is characterized by an accepted delay. This means that even in free flow, the maximum speeds allowed will mostly not be reached. On the one hand, this is due to a certain number of road users that are considered acceptable, on the other hand, parts of the infrastructure such as road conditions, traffic lights and traffic routing considerably influence the maximum speed any road user can be expected to reach. Traffic congestion therefore is not defined by a speed lower than the maximum speed, but as the excessive delay above an agreed upon norm. So far in literature, little attention has been paid to the explanation of the detour factor, its determination, and the investigation of its influencing factors. It has a direct influence on the cost per air distance kilometer. Driving costs are influenced because travel distance is dependent on the air distance and the detour factor. In addition, driver and vehicle occupation costs are influenced, since longer travel distances also increase travel times. As shown in section 3, the cost factors detour factor, infrastructure, and traffic change with increasing air distance. This means that describing regions by using only a single value for detour, infrastructure, and traffic would be very imprecise. Therefore, when considering the individual performance indicators, a progressive function should be modelled to ensure accuracy. In addition, when comparing different regions, observation intervals must always be defined (here 15 min travel distance or 15 km air distance) and kept constant across all observations, since the arrangement of the curves can change relative to one another for increasing distances.

The detour factor decreases with increasing air distance in urban areas. This means that the greater the air distance to be covered, the less detour is required. As previously explained, this stems mainly from the fact that motorways or inner-city highways, which usually follow a comparably straight or direct course, can be accessed as air distances increase. Consequently, when calculating costs, transportation companies must take a closer look at short distances, as the costs per kilometer can be many times higher than for longer distances. These short distances occur mainly in distribution between customer locations.

The conducted studies show that the arrangement of the curves can differ considerably from detour, travel speed, and cost per kilometer. The transportation costs per kilometer are always the product of the factors detour, free flow speed, and delay by congestion. A consideration of individual cost drivers such as detour or traffic makes sense from certain interpretation points of view, but to estimate or even compare the transportation costs, an isolated consideration is not enough.

Section 4.4 shows that significant cost differences can arise between different geographical regions. As transport companies mostly charge prices for distribution regardless of the region, the contribution margin of a single shipment will vary between regions. It is therefore advantageous to carry out the analysis presented prior to choosing a location for a terminal or depot. This will allow managers to compare all available locations and make a final choice dependent on future transportation costs. In addition, single customer locations could be evaluated by selecting a customer's delivery address as the starting point for the analysis. The results obtained can be used to model or adjust customer-specific tariffs.

4.6 Limitations and Further Research

The results of our analysis are directly dependent on the choice of starting locations. This means that when comparing regions, care should be taken to ensure that the characteristics of the different starting locations are comparable. During the exemplary case study presented in this paper we have decided on terminals or depots of local transportation service providers. For a comparison that is not dependent on the distribution context, we recommend that the centrality of the location should be considered. Consequently, the most accessible and central point within the region to be investigated should be chosen. However, this is only a rule of thumb. Future research could focus even more intensively on the correct choice of starting location. Large areas where no passable infrastructure is available can influence the result of the analyses. All corner points of the retrieved polygons necessarily form accessible points and are therefore located directly on existing roads. In case of areas without (accessible) roads, the polygon points directly at the edge of the area and remains constant until a road can be reached. This distorts the result of the detour factor. In most cases, this leads to a higher detour factor since the points bordering the road-free area produce small air distances in relation to the increasing API query's restriction. After overcoming the road-free area by sufficiently large travel distances (= API restriction), the air distances, which have been constant before, increase dramatically and the error of the detour factor is corrected.

Currently, all polygon corner points are included in equal parts in the air distance's mean value calculation. However, if there are areas within the region to be investigated that are irrelevant for the analysis or that should not be considered, certain corner points could be excluded from the air distance calculation. The key points could also be weighted in relation to the customer locations. The modification of the point weights to individual business cases offers more room for further research.

The TomTom API always returns a polygon with a maximum of 50 corner points. This means that regardless of the size of the accessible area, a maximum of 50 accessible points relates to straight lines and this polygon is used for further evaluation. However, depending on the restrictions of the query, this number of points may be too low. Fifty points are too few if the result of a query with high restrictions (e.g., 120 min of travel time) is retrieved. In this case, many roads could be accessible, i.e., the polygon would have to show many more corner points. TomTom reduces this large number of accessible points to exactly 50 polygon points and thus distorts the average air distance. The methodology on when and especially how this reduction occurs is a black box as TomTom is not providing any details on the algorithm in use. A remedy could be the usage of the HERE maps API, because the maximum number of corner points is unlimited for this service and grows with the number of reachable points. However, the quality of the traffic data currently does not allow the use of HERE's API. In the future, researchers could try to combine the two APIs, i.e., the accuracy of HERE's presentation and the accuracy of TomTom's traffic data.

To estimate the environmental impact of RNP, our presented method can help to estimate pollution per air distance based on speed and detour. Therefore, we must combine our results with vehicle data such as power and fuel type. This information combined with speed values can be used as input variables to calculate energy consumption per kilometer via COPERT regression functions [236, 333]. With the information derived by Deutsches Institut für Normung e.V. (DIN) [334], the energy consumption can easily be converted into pollution per driven kilometer. Based on aerial distance and the offset with detour factors travel distances can be derived. The combination of vehicle data, COPERT regressions, travel distance and speed leads to overall emissions produced by certain road users [335, 336]. Following that, our method can be used to analyze the impact of the RNP on emissions of specific user groups and areas.

One impact of RNP on social urban sustainability can be expressed by road noise emissions. A widely used calculation model for road noise is Calculation of Road Noise Emission (CoRTN) [337], which was originally designed by the Great Britain Department of Transport [338] and adapted by different researchers for several regions such as Tehran and the whole of the European Union [339, 340]. In addition to the travel speed measurements, this model processes information such as traffic flow and road characteristics, which must be gathered from other resources. Combining all of the needed information to implement the CoRTN model, our method can help to quantify the impact of RNP on urban social sustainability.

4.7 Conclusion

The contribution of this paper is an efficient methodology of programmatical data retrieval, supplementation and analysis for RNP Measurements utilizing publicly available traffic information.

We base our methodology on the scarcely researched reachable range concept. Reachable range APIs allow for time and resource-efficient retrieval of area-wide results by outsourcing data processing. Due to this, the problem of defining the sum of all relevant destinations can be overcome by defining a centralized starting location and analyzing the retrieved polygons encompassing all possible, by definition reachable, destinations within a road network. We have quantified and shown that when examining the impact of road network performance on the economic dimension of sustainability, it is mandatory to consider two types of costs in tandem: distance-based as well as time-based costs. These cost factors are driven by the specific network performance characteristics of detour and travel speed as presented in this paper. Evaluating any of these two factors in isolation, for example by referencing the publicly available TomTom Traffic Index Ranking [341], does therefore not allow for reliable inference of total costs and might lead to wrong business decisions.

Future studies could head in different directions. Considering our methodology, the accuracy can be increased by combining technology from different navigation service providers. Considering the three dimensions of sustainability, our methodology can be used to evaluate the RNP's environmental and social impacts on urban sustainability with the combination of the retrieved data and a framework such as COPERT or CoRTN.

CHAPTER 5

Speed Limit Induced CO_2 Reduction on Motorways: Enhancing Discussion Transparency through Data Enrichment of Road Networks

5.1 Introduction

Greenhouse gas emissions, especially carbon dioxide emissions, are a significant driver of climate change [342]. Therefore, political discussions and ecological debates have focused on reducing CO_2 emissions to slow down the impact of man-made climate change for more than 25 years [343].

According to the European Environment Agency (EEA), the energy supply and transport sectors are main contributors to this problem by producing the largest amounts of CO_2 emissions. More specifically, one major factor is road transport, which accounted for 18% of European CO_2 emissions in 2018. Road transportation can generally be divided into the commercial and private transportation sectors. The European Commission stated that commercial road transportation accounts for about 38% of all CO_2 emissions produced via road transportation, whereas private road transportation represented by passenger vehicles contributes the remaining 62% of CO_2 emissions. Extensive literature can be found on the topic of dealing with the connection between the public road transport sector and greenhouse gas emission as well as potential actions to achieve certain reductions [236, 344–350]. While examining the literature, two major proposals to reduce greenhouse gas emissions within the private road transport sector are identified: (1) a global change of fleet to electric vehicles powered by renewable energy sources instead of fossil fuels, as well as (2) the introduction of general speed limits to reduce higher amounts of emission produced at increased velocities.

The proposal of switching to electric vehicles has one significant disadvantage: It is considered a long-term strategy and therefore has no significant instant impact on CO_2 emissions [351]. Research on electric vehicle sales forecasting provides evidence that the first country to achieve a targeted market penetration of electric vehicles of 50% will be Norway by the year 2026. Germany is considered to reach the 50% mark of electric vehicle market penetration by 2032 [352]. This slow diffusion stems from two sub-problems: The first and rather obvious problem lies in the fact that people are required to swap their combustion engine vehicles for electric vehicles. In most cases, this means buying a new car. Buying a new car leads to an additional financial burden, which results in people not daring to take the step without need or necessity [353]. The financial burden can be lowered by governmental support in the form of subsidies or tax discounts [354]. In addition to that, the willingness to adopt this new technology is highly dependent on the available charging infrastructure, which must be improved to make using an electric vehicle over long distances a viable alternative [355, 356]. Therefore, the problem of conversion time from conventional vehicles to electric vehicles is dependent on the life cycle of current conventional fleets, the financial support provided by the government and the willingness of consumers to adopt and accept this new technology. Secondly, a more severe problem inhibiting a short-term change of fleet is the required power supply to support large fleets of battery-powered vehicles. Electric vehicles do not rely on fossil fuels during operation, which results in reduced operating CO_2 emissions. Nonetheless, one key fact that is easily forgotten is the heavily increased CO_2 emission as a result of generating large amounts of electric energy via conventional means of power generation. Therefore, electric vehicles can realistically only help reduce road-transport-induced CO_2 emissions under the assumption that electricity output is generated in a decarbonized way [357, 358]. Inspecting the G20 states, Brazil and Canada lead the comparison with shares over 70% of renewable power generation capacities. Indonesia, Republic of Korea, and South Africa are considered negative examples with shares of renewable power generation capacities under 20%. Trailing far behind in terms of renewable power generation is Saudi Arabia with zero renewable power generation capacity [359]. Generating most of the electricity demand via renewable resources like wind and sunlight is part of most governmental and ecological plans but certainly is not the main contributor to power generation in many countries yet. Implementing and realizing these plans cannot be achieved overnight and therefore still impede a fleet-wide electrification [360]. Consequently, politicians and researchers are looking for actions to reduce CO_2 emissions quickly. An action that is meant to instantly reduce CO_2 emissions is the introduction of speed limits on public streets.

To allow for a better understanding of the political debate in general, we take a closer look at the following question: How do speed limits affect CO_2 emissions? Speed limits directly influence and, in most cases, reduce the average velocity of motorized vehicles [361, 362], even if not every driver can be expected to obey the restrictions [363]. Since the amount of energy required to move a conventional vehicle at a specific speed directly results in liters of fossil fuel burned, which in turn leads to carbon dioxide emissions, the total amount of pollution created by a vehicle is heavily correlated to the velocity it is moving at [335, 364, 365]. Therefore, in theory a restriction in maximum allowed speed significantly reduces the maximum amount of CO_2 produced on a per-kilometer basis. This correlation between speed limits and CO_2 reductions has been researched extensively [363, 366–370].

Furthermore, a general speed limit can smooth out the velocity across network participants, leading, theoretically, to a smoothed traffic flow, which requires less braking and accelerating [371]. Since the amount of fuel burned during acceleration is much higher than during cruising speeds, this in turn results in less air pollution by CO_2 emissions [368, 370] while also decreasing the likelihood of accidents caused by speeding within the traffic network as well as noise emissions [246, 284, 296].

As a result, one key argument that is heavily controversial within the German parliament and public opinion alike is the introduction of a general speed limit on the German autobahn. This stems from the fact that carbon dioxide emissions generally increase disproportionally above 120 kph and the German autobahn is one of the last motorway networks worldwide where it is legally allowed to drive at unrestricted speeds throughout large parts of the network. Studies cited in favor of speed reductions on urban streets as well as highways presented substantial savings in CO_2 emissions in the range of 5 to 30%, depending on the intensity of traffic congestion [369, 370]. Additionally, the German Environment Agency (GEA) recently published a study to evaluate the consequences of a general speed limit on German motorways. According to this official study, the proposed reduction to a maximum velocity of 120 kph should result in yearly total CO_2 savings of 2.6 million tons. These savings assume that 55.5% of the entire motorway network flow is unrestricted and driving speeds along these unrestricted edges average at about 124.7 kph [372]. Critics question the validity of the proposed savings in terms of the assumptions made and the methodology used, since the official study partly relied on old data from 2010 as well as non-public information. When reading the referenced study [373], three suggestions for improvement regarding the estimation of vehicle velocities stand out that should be considered and improved upon:

1. The study references data from nearly one decade ago to estimate an underlying distribution of vehicle velocities throughout the network. According to the study, additional data were gathered from 2010 to 2014 to measure velocity but this information has never received an update and could be outdated, since road conditions and construction sites have a significant impact on network velocity and could very well change within the span of 10 years. Therefore, more recent data should be included.

2. The aforementioned information was gathered via measuring points directly installed on individual motorway edges. However, the number of measuring points was very limited. In sequence for the years 2010 to 2014, the number of measuring points that were working as intended and generating data was 80, 102, 108, 114 and 116 points, respectively. Comparing the number of measuring stations to the total motorway network length of 25,665 km, one measuring point had to cover approximately 221 km. Due to this small coverage, relevance of the provided velocity estimations on a large scale is questionable and requires validation.

3. The last argument for an in-depth review of these velocity estimations is one concerning data transparency. The raw data basis as well as the presented estimations have never been published in detail, which inflicts doubts on the credibility of the used methodology and implementation.

Due to the shortcomings of the previously published study by the GEA as well as the general necessity to regularly update such assessments in a perpetually changing field of research [374], the following article aims to validate or disprove political and ecological statements transparently by using publicly available up-to-date data from providers such as OpenStreetMap (OSM) and TomTom. Within our context, publicly available means the source of the information allows access to the information by anyone upon request. We aim to evaluate whether the actual driving speeds as measured by navigation devices throughout the entirety of the road network are as high as presented during previous selected studies based on historical averages. Based on this evaluation, we compute possible savings via the introduction of a speed limit into the network by referencing general emission curves for motorized passenger vehicles. The general research question to be answered via this methodology can therefore be formulated as follows:

How can road networks be enriched by publicly available real-world data to enable CO_2 emission calculations?

The remainder of this article is structured as follows: Section 2 describes and applies our methodology to generate representative and routable (road) networks from publicly available data. We begin by retrieving geographical street data via OpenStreetMap to build the network and continue by supplementing the network by means of static, official traffic count and traffic distribution data provided by the GEA. In addition to this static information, we reference and map historically averaged traffic flow information from the TomTom API onto our network to approximate network usage on a per-edge basis throughout any given day. Section 3 continues by outlining the calculations applied to this enhanced network to derive results in terms of CO_2 emission reductions achievable by introducing speed limits into the traffic network. Finally, Section 4 discusses the results of our calculations in comparison to the previously published study by the GEA, while Section 5 discusses our findings in relation to previous studies on dynamic traffic speed limits and road participant acceptance in different countries.

5.2 Generating Routable Networks from Publicly Available Data

5.2.1 Extracting Data from OSM

At its core, the methodology to be presented is based on a programmatic analysis of traffic networks. Within this context, a traffic network is defined as a combination of nodes and edges, while edges are defined as a direct link between a set of exactly two nodes. One key component of mapping traffic information onto network data structures is the assumption of directed connections. Therefore, two-way streets are defined by different nodes and edges for each individual direction. This fact plays a crucial role in our need to develop auxiliary functions to correctly map external data onto the right nodes and edges within our network.

Building such networks from scratch would require mapping any relevant street within the network as a connection of nodes and edges while also adding geospatial information to each data point. Due to the sheer size of a country-wide motorway network, this would require hours upon hours of manual and labor-intensive work. This is where open-data platforms like OpenStreetMap come into play. These platforms use crowdsourcing to keep information up to date and openly accessible. Especially for primary road networks, this approach results in a high coverage and accuracy [155, 375].

Unsurprisingly, these data pools are used regularly by researchers and practitioners alike to extract detailed topological information. One such framework to create spatial networks from OSM data is the Python package OSMnx by Geoff Boeing [163]. By using this package, we extracted the relevant motorway network, in the example defined via bounding box, and saved the network to disk as a GraphML file. This GraphML file not only contained information about nodes and edges, which, in their sum, define the network, but also included additional information from OSM such as, for example, speed limits as enforced by traffic signs as well as the length in meters for any given edge throughout the network. Note, however, that this information is entirely crowdsourced and might therefore include errors or missing details if no OSM user has added a specific parameter to the platform yet. Nonetheless, this first step left us with a fully connected and routable road network that already contained most basic information. In our context, fully connected and routable describes the fact that the network topology enables the construction of routes from a source to a destination both defined by separate nodes via an uninterrupted path containing several edges. Since every node at least contains information about its geospatial location in the form of latitude–longitude coordinate pairs, we can already visualize the retrieved network as depicted in Figure 5.1.

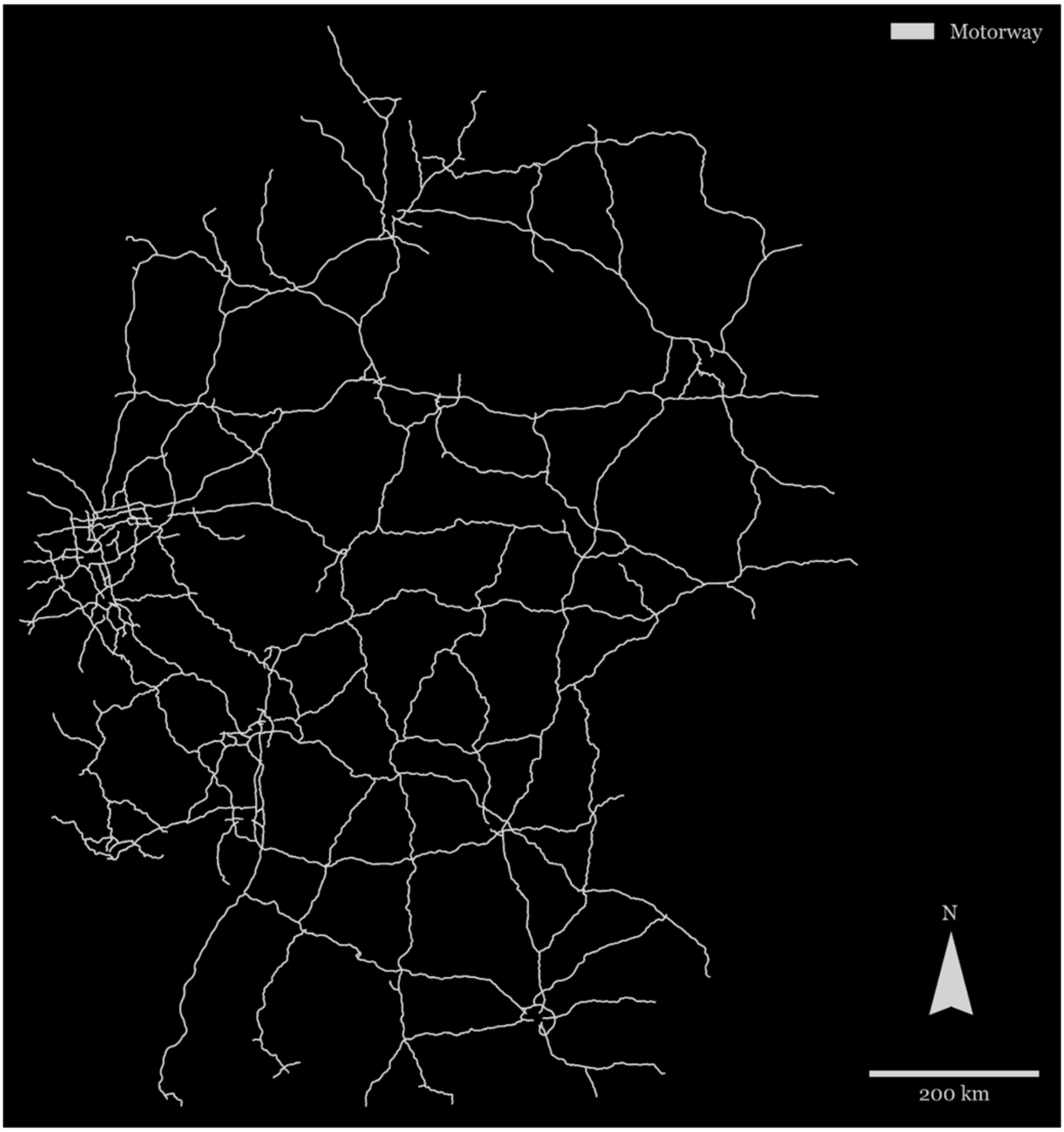


Figure 5.1: German motorway network defined by nodes and edges as retrieved from OpenStreetMap (OSM) using OSMnx.

5.2.2 Adding Official Traffic Count Data

We began enhancing the information density of the network by adding traffic count data to identify estimated total quantities of cars on a per-edge basis for any average day. In case of the German motorway network, the “Bundesanstalt für Straßenwesen” (BASt), a governmental institution, regularly measures traffic counts on German primary and secondary roads via a total of 1913 counting points. For application in different countries or regions, corresponding local data sources must be identified accordingly. Of these 1913 counting points throughout Germany, 1125 are located on motorways.

The most recent data available at the time of this writing were from the year 2018. Data was exported as a comma-separated values (.csv) file. It was then imported into the Python workspace where the network resides. By using a getNearestNode function from the OSMnx package with a maximum cutoff radius of 5 km, we mapped the traffic count data (which include latitude/longitude coordinate pairs for every counting point) onto their respective nodes in the network. The contextually relevant information included in this data was comprised of

- the average daily quantity of cars measured by the counting point,
- as well as the average daily quantity of trucks measured by the counting point.

After successful mapping, these data were incorporated into the network and could be referenced as a data dictionary for every node's unique ID. Figure 5.2 depicts all nodes that now contained traffic data information in yellow.

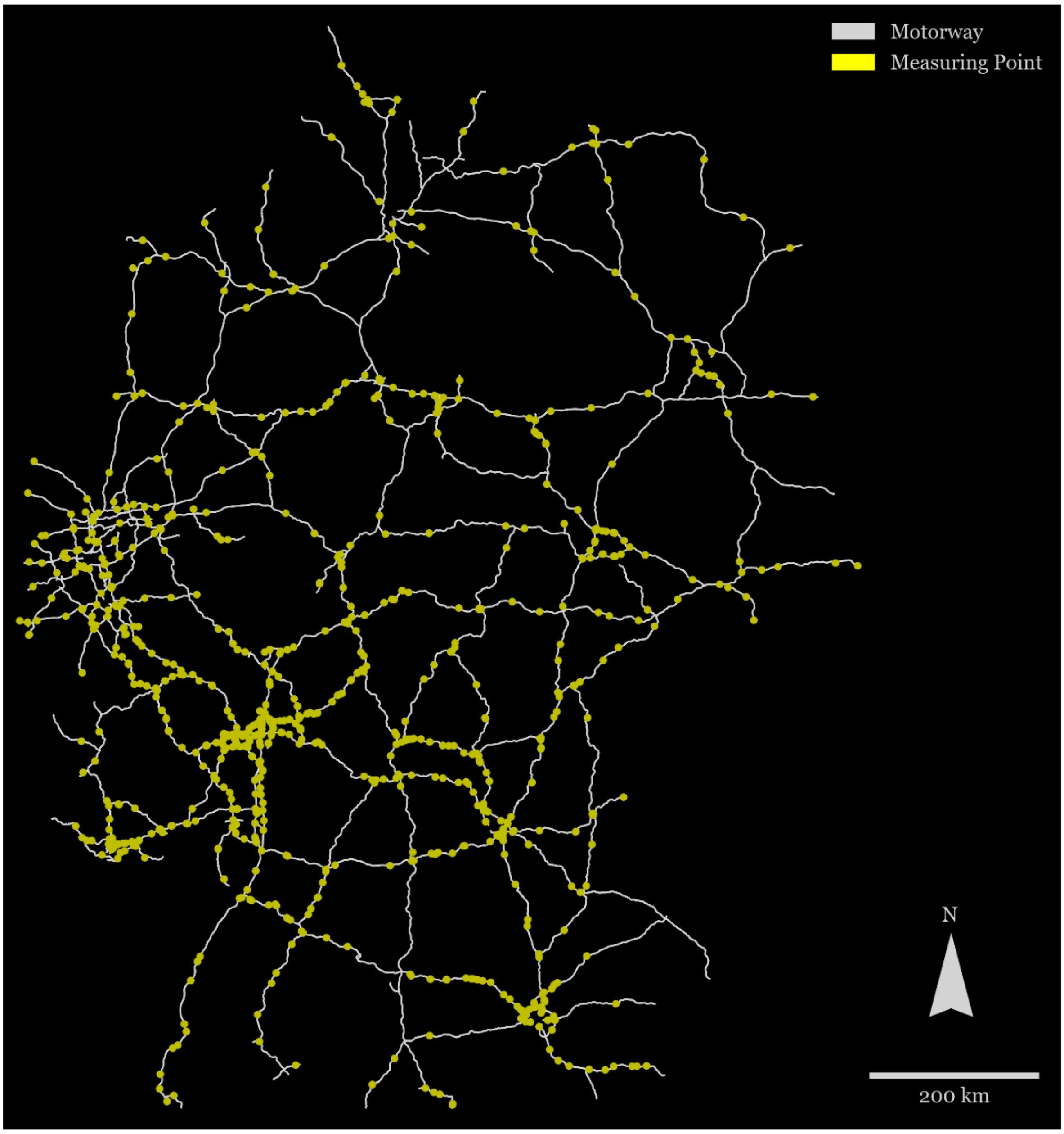


Figure 5.2: Depiction of traffic count data mapped onto the network. Yellow nodes contain traffic count data.

Since we only mapped data onto the individual closest node identified via getNearestNode, as can be seen in Figure 5.2, we needed to enrich all remaining nodes throughout our network as well. We achieved this by iterating over all nodes without data and identifying the closest node that contained traffic count data via great-circle distance. Therefore, all nodes around the individual nodes we mapped traffic count data onto were supplied with the same traffic count information. Since our analysis was mostly concerned with actual road sections instead of selective points, we needed to derive a methodology to approximate the traffic count for every edge between two nodes. Throughout multiple iterations of this process, we found that a simple average calculation led to satisfactory and sensible results. Therefore, the formula to estimate the traffic count (TC) for any given edge E defined by one start- and endnode (n1, n2) inside the network is the simple average of both its adjacent nodes. By applying this logic to every edge in the network, we arrived at the first intermediate result of our methodology: A road network enriched by daily traffic count data.

$$TC_{E(n1,n2)} = \frac{1}{2}(TC_{n1} + TC_{n2}) \tag{5.1}$$

As can be seen in Figure 5.3, throughout Germany, certain areas showed a specifically high traffic count. The western area, mainly the state of North Rhine–Westphalia, as well as the areas around Frankfurt, Stuttgart, Berlin and Munich, depicted a higher-than-average traffic count, which was to be expected since these geographical areas are known socioeconomic conurbations and therefore are central traffic turnstiles throughout the German traffic landscape. Note, however, that by now, the network only contained averaged daily traffic count information for every edge. To perform a thorough and time-specific case study, region-specific car distribution data on an hourly or even a 30-min interval basis needed to be added. Otherwise, all calculations performed within the network would need to be averaged for an entire day. This would require the assumption that traffic was evenly distributed throughout any given day, ignoring the existence of rush hours.

5.2.3 Adding Additional Traffic Distribution Information throughout the Day

To be able to divide the daily total traffic count per edge into 30-min intervals, a distribution function was derived using another set of officially published BASt data. This second data set is a more detailed version of the previously used traffic count data set and includes hourly data points for the same traffic counting points. We grouped this data by hour and extracted bidirectional traffic counts, derived the average hourly traffic count, and used linear interpolation to approximate data for every half-hour mark. This results in the distribution shown in Figure 5.4.

As expected, two major peaks were identified, corresponding to the daily commuting rush hours across the German motorway network. At 8:00 a.m., on average, 3% of the total daily number of vehicles were traveling along any given edge. Between 9:00 a.m. and 7:00 p.m., the average percentage of daily vehicles on edge varied between 2.5 and 4%, peaking in between 5:00 p.m. and 6:30 p.m. Between 11 p.m. and 4:00 a.m., only a marginal amount of daily traffic occurred on German motorways. This distribution later allowed for a more precise calculation of flow kilometers across edges for any given timestamp within the network. The total quantity of daily cars per edge (see Section 5.2.2 and Figure 5.3) was therefore multiplied by the average percentage from Figure 5.4. By applying this transformation, specific travel speeds could be weighted by the total sum of applicable flow kilometers. A detailed description of the flow kilometer calculation is given in Section 3.1.

In case no suitable, region-specific data set to estimate a daily traffic distribution is available, the distribution provided in Figure 4 can be used as a reference for countries with comparable size and similar official working hours.

5.2.4 Adding Real-World Traffic Flow Information to the Network

Continuing, the next part of our methodology was concerned with adding external real-world traffic flow information, in this case using the TomTom Routing Application Programming Interface (API) into the network. Real-world information refers to historical data gathered under practical circumstances, in this case via navigation devices. In comparison, the official (in this case mostly governmental) data sources used in previous studies by the GEA were mostly estimations from small-scale data samples or simulation-based. Therefore, the accuracy of real-world data was considered significantly higher on a wide scale. Data that adhered to this definition could be retrieved programmatically by sending HTTP-compliant GET-requests to a remote API endpoint provided by TomTom. The endpoint allowed access to a database of navigation information supplemented by historical data gathered via personal and commercial navigation devices. Every route request, excluding free quotas provided to experiment with the API, required authentication and incurred a cost. To request and incorporate this data efficiently, we first needed to generate routes such that, at best, every edge included in the network was also included in at least one or more TomTom routing calls while minimizing the total number of routes required.

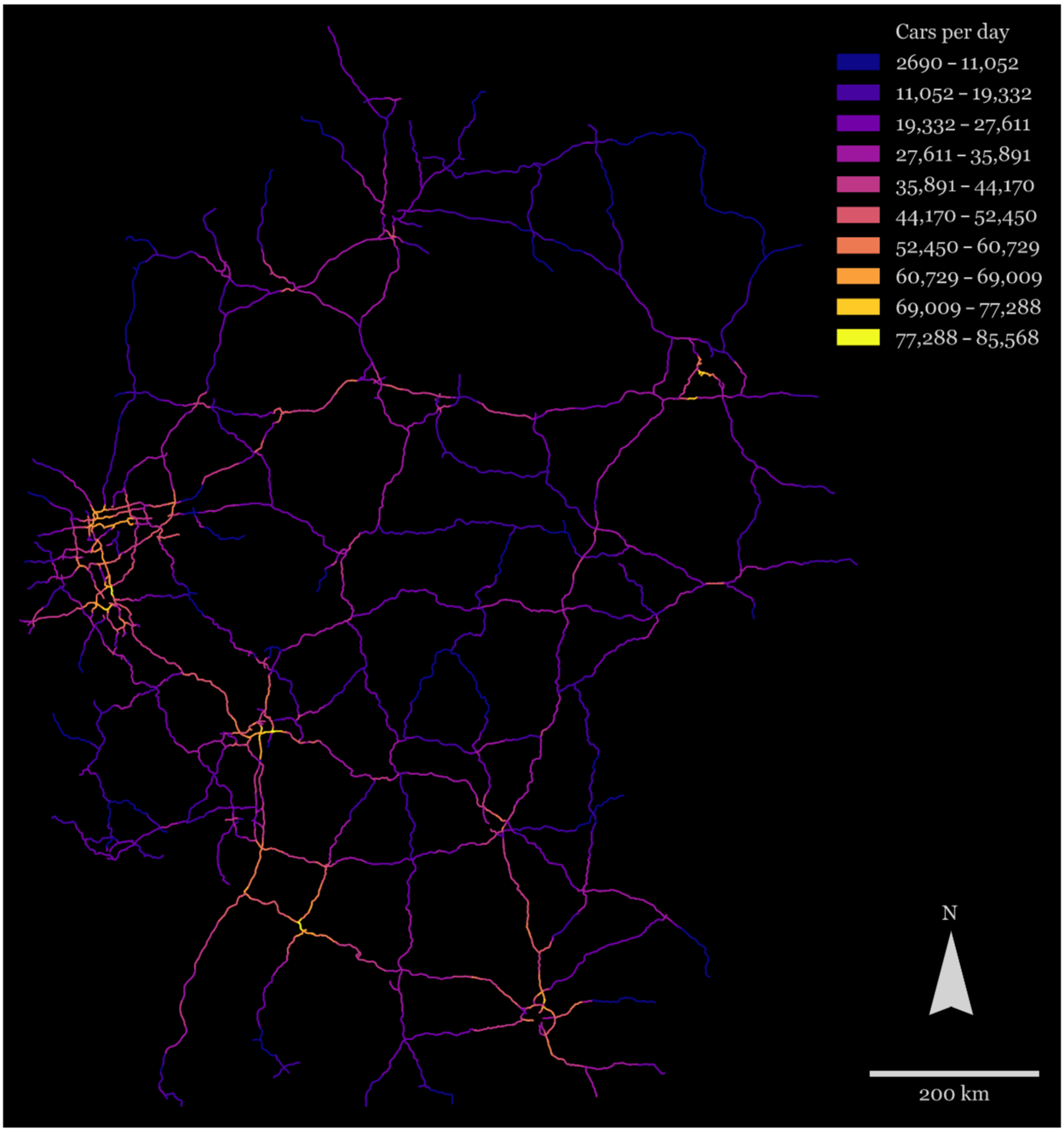


Figure 5.3: Visualization of traffic count within the network. Network edges are colored based on their daily quantity of cars. Brighter color corresponds to higher traffic count.

Generating Network Routes Requestable via TomTom Routing API

A TomTom route is defined by a single source and destination coordinate pair. In between these two points, up to 148 points along the route can be inserted. By trial and error, we devised a five-step process to generate a list of 958 routes in total, which resulted in a network coverage of 98.79% of all relevant motorway nodes. These five steps can be summarized as follows:

1. Identify all motorway endpoints by filtering for network nodes with only one adjacent motorway edge.

2. For every node identified in such a way (destination), apply the Dijkstra algorithm to calculate the shortest path from the network's central node (source) identified via degree centrality. The result is a sequence of nodes comprising the shortest path.

3. Since the network is defined as a directed graph, Step 1 only handled one direction. Therefore,

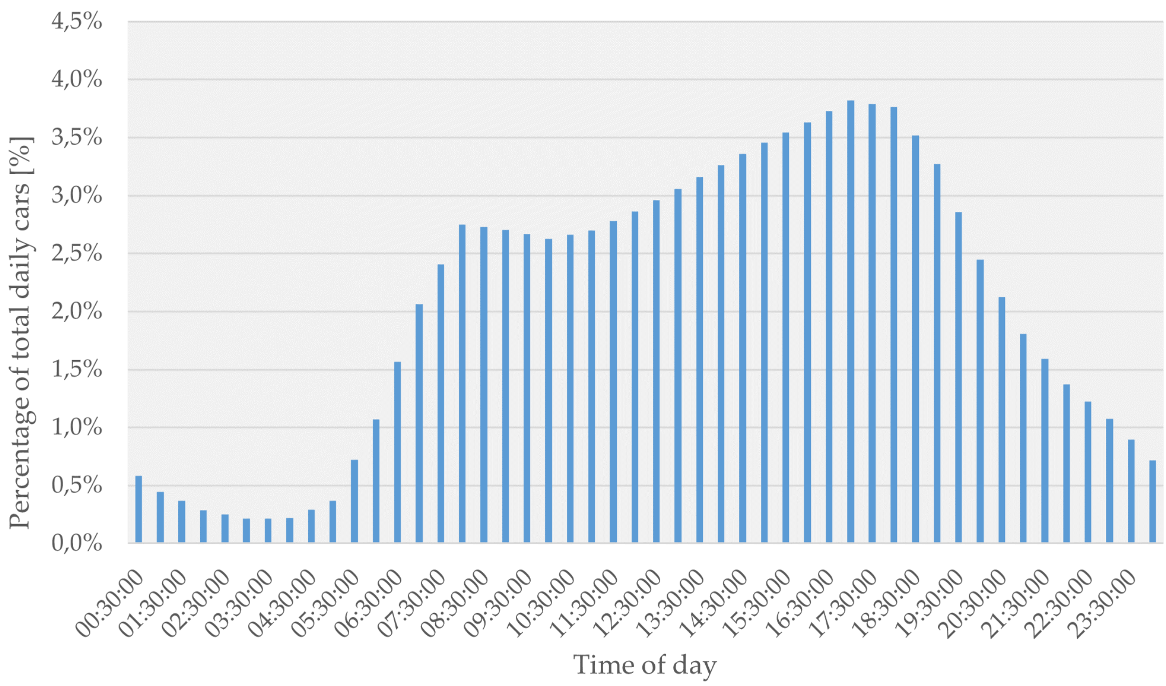


Figure 5.4: German motorway traffic distribution throughout the day. Two peaks can be identified, corresponding to daily commuting rush hours.

apply the same logic from Step 1 in reverse to all endpoints that have not yet been found in any route from Step 1.

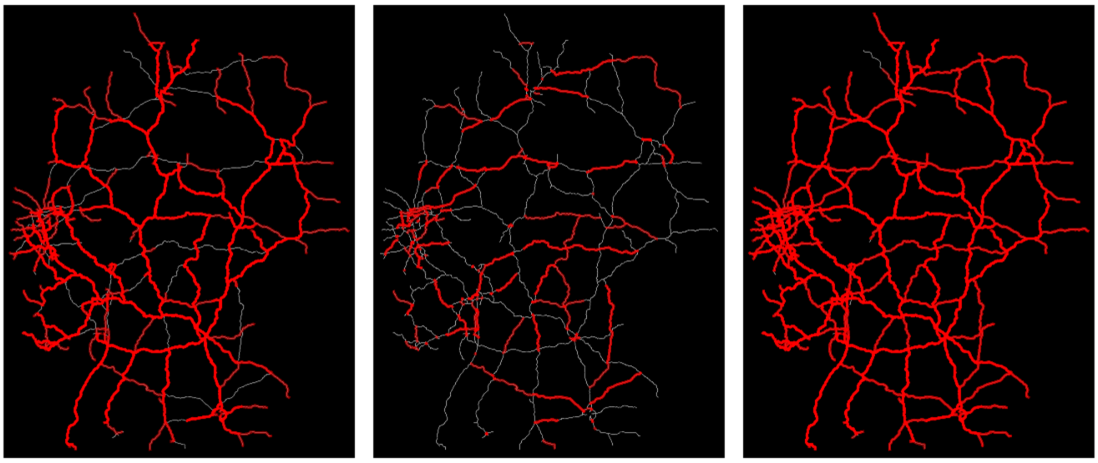
4. For every remaining endnode, calculate the shortest path from the endnode (source) to the central node (destination).

5. After applying Steps 1 and 2, a total of 3630 nodes (out of 13,763 network nodes) were still not included in any path, since these nodes did not lie on any shortest path to or from the previously identified network endpoints in combination with the central node. To handle these nodes as well, we derived the following logic: Select new start- and endpoints within all remaining nodes by identifying nodes that border on exactly one node already included in paths from Steps 1 and 2. For every start- and endnode pairing identified this way, once again create the shortest paths using the Dijkstra algorithm. Figure 5.5 depicts the different stages of route coverage described above.

As a next step, all 958 routes needed to be converted to a suitable format to use with the TomTom Routing API. In its most basic form, the API requires a route as a colon-delimited list of successive coordinate pairs. We therefore retrieved the latitude and longitude attribute for every node along a route and added them together as a text string in the format.

$$routeString_{1ton} = lat_1 : lon_1; lat_2 : lon_2; ...; lat_n : lon_n \tag{5.2}$$

Since the maximum number of points contained within any given TomTom route is restricted to 150, we only added one coordinate pair for every motorway exit along the route, since these exit nodes were the only possible change in direction on a motorway. In case a route contained more than 150 individual points, we divided the full route into individual slices, resulting in multiple API calls for full route coverage. An additional restriction was added in the form of a minimum aerial distance of 100 m between consecutive coordinate pairs. This was incorporated to compensate for slight discrepancies between our network coordinates and TomTom's routing network, which in the case of high-granularity routing led to mismatches and unwanted detours. The resulting list of routes comprised of coordinate pairings as specified and required for use with the TomTom Routing API was then saved to disk as a .csv file.



(a) (b) (c)

Figure 5.5: Different stages of network coverage after Steps 2 (a), 4 (b) and 5 (c). The rightmost image depicts the final network coverage. Road sections highlighted in red are traversed by at least one route request.

Mapping TomTom Routing API Data onto the Network

Using the comma-separated values file created during the previous paragraph, a total of 45,984 API requests were necessary to retrieve all relevant data via the Routing API. The total amount was comprised of 958 requests per individual pass. One pass equaled the request of all routes throughout the network for a single timestamp on any future date, in this case, a future Monday. Requesting a future date led to the calculation of historical averages by TomTom. We observed a timeframe from 0:00 a.m. to 11:30 p.m. in 30-min intervals, leading to 48 separate API passes. One important parameter that must be set is the $sectionType = motorway$ parameter. Using this optional parameter, the TomTom response included additional information describing which of the return legs, corresponding to network edges, lay on the motorway network. This was necessary because, as previously mentioned, the TomTom routing network marginally deviates from the underlying OSM network data. In some cases, this led to TomTom mapping the provided coordinate pairs slightly off to the side of any actual motorway, resulting in high deviations of route length caused by significant detours to navigate to the next freeway ramp and get back on route. Since we did not want to map any of these detours onto our network, we eliminated this problem by using the sectionType parameter.

The result for any individual API call was saved to disk as a JSON file. Every JSON response file contained multiple trip legs. Every leg contained multiple successive coordinate points. Additionally, every leg contained information such as length of the leg in meters, travel time in seconds required to fully traverse the leg, the associated travel speed in kilometers per hour as well as historically averaged counterparts and information about traffic-induced delays. All of these details remained to be incorporated into the local OSM network. To do this, we derived the following logic, which was applied to every response file:

1. Iterate through all legs within the response file;
2. Check if the entirety of points inside a leg are included in a motorway section (meaning the leg is entirely located on a motorway and therefore relevant);
3. If true, calculate the shortest paths from start- to endpoint of the leg within the OSM network, resulting in a list of network nodes along the TomTom leg;
4. If leg length and corresponding OSM network path length deviate by less than 10%, a correct mapping is found;
5. Therefore, iterate across all edges of this path and update the edge attributes with TomTom leg traffic flow information.

By running this logic, we created a data dictionary for every edge contained in the OSM network with a single index for every timestamp during which the edge was traversed by the API response data.

This allowed for indexing by specific timestamps and retrieving the average travel speed for any given edge for a specific time of the day. In total, this methodology reached a traffic flow information coverage across the OSM network of 81.5% of all edges.

5.2.5 Translating Average Speed into Estimated Actual Speed

Up to this point, all calculations were based on a single average travel speed for any given edge at a specified time t. Gathering reliable data on travel speed distributions for motorway networks is a laborious task and is, to the best of our knowledge, only undertaken by governmental organizations in small sample sizes. To adjust our calculations, we therefore needed to rely on individually published excerpts of a non-public data set by the GEA. Depicted in Figure 5.6 is an averaged version of the original speed distribution according to the GEA. By applying this speed distribution to the historically averaged travel speeds returned by TomTom, a more realistic indication of network speeds on any given edge was estimated.

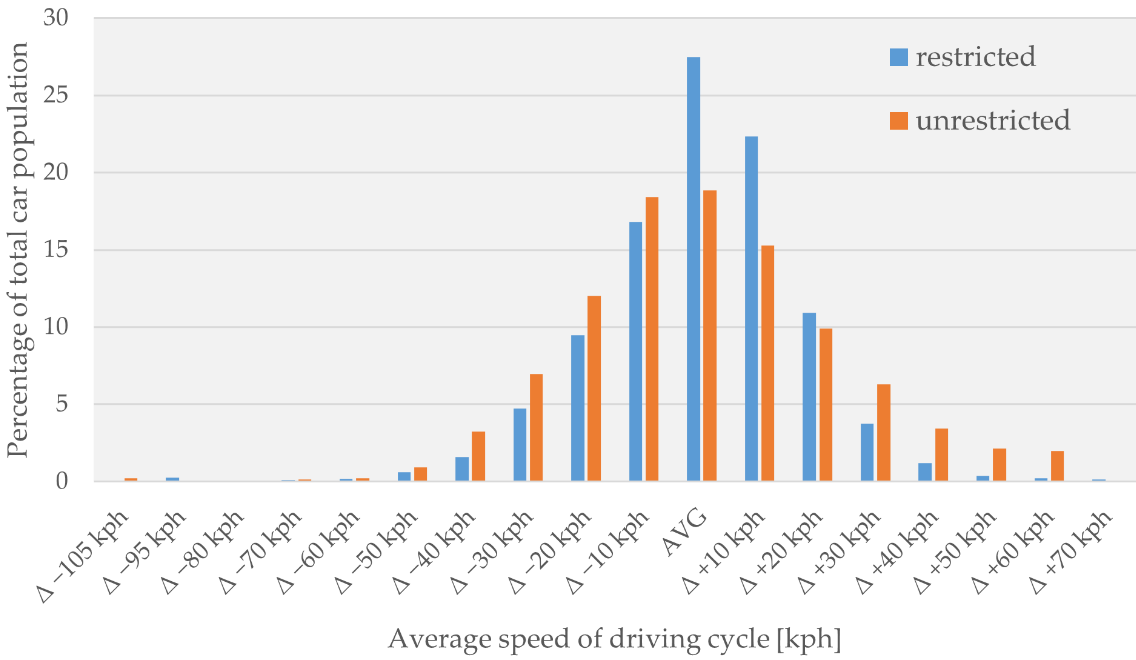


Figure 5.6: Averaged speed distribution for restricted (as in derived from sections with a legally allowed maximum speed of 130 kph) and unrestricted network state, according to the German Environment Agency.

5.3 Case Study: Calculating CO_2 Emissions

The methodology provided in the previous section can be applied to any region that can be defined either via a geographical bounding box or a unique literal identifier like "Bavaria, Germany" to create a programmatically analyzable traffic network as long as general traffic information, OSM and TomTom data are available. The types of analyses possible are predefined solely by the type of additional data that can be gathered. For this case study, we focused on CO_2 emission calculations, but the necessary steps can easily be modified to include traffic-induced noise emissions or similar data as well.

5.3.1 Establishing General Key Parameters for CO_2 Calculations

According to the DIN EN 16258:2013-03 norm, every Megajoule of petroleum burned produces 75.2 g of CO_2 equivalents (CO_2e), while one Megajoule of diesel leads to 71.0 g of CO_2e emissions [334]. According to the European Automobile Manufacturers Association, one liter of diesel fuel has an energy density of 36.9 Megajoule, while one liter of petroleum has an energy density of 33.7 Megajoule. Therefore, both engine types produce roughly the same amount of CO_2e emission on a per-kilometer basis, depending on the exact composition of the fuel and drivetrain efficiency. Due to this fact, the different fuel types were not analyzed separately.

To quantify the total amount of possible CO_2 savings resulting from the introduction of a speed limit, it was necessary to compute the total emissions by any given vehicle in relation to its velocity. As a basis for this calculation, we concurred with the recommendation of the German Environment Agency by referencing adjusted driving cycles provided by the Handbook Emission Factors for Road Transport (HBEFA). For all driving cycles, CO_2 emissions on a per-kilometer basis were calculated using the Passenger Car and Heavy-Duty Emission Model (PHEM). For this model, modern Euro-6 passenger vehicles were used as a baseline. Euro-6 vehicles have a nearly identical fleet average of CO_2 emissions in day-to-day usage compared to older vehicles adhering to previous Euro-3 to Euro-5 norms [372]. Since more than 90% of registered vehicles in Germany adhered to at least Euro-3 standard and newer, we considered PHEM as representative and generally applicable for this analysis. Since most emission models, PHEM included, are only defined for velocities up to 130 kph, the GEA provides unpublished "further driving cycles" up to 190 kph inside their study, which we could neither validate nor disprove but adhered to for comparability between both studies. Figure 5.7 depicts the final regression model used to estimate CO_2 emissions by means of averaged travel speeds.

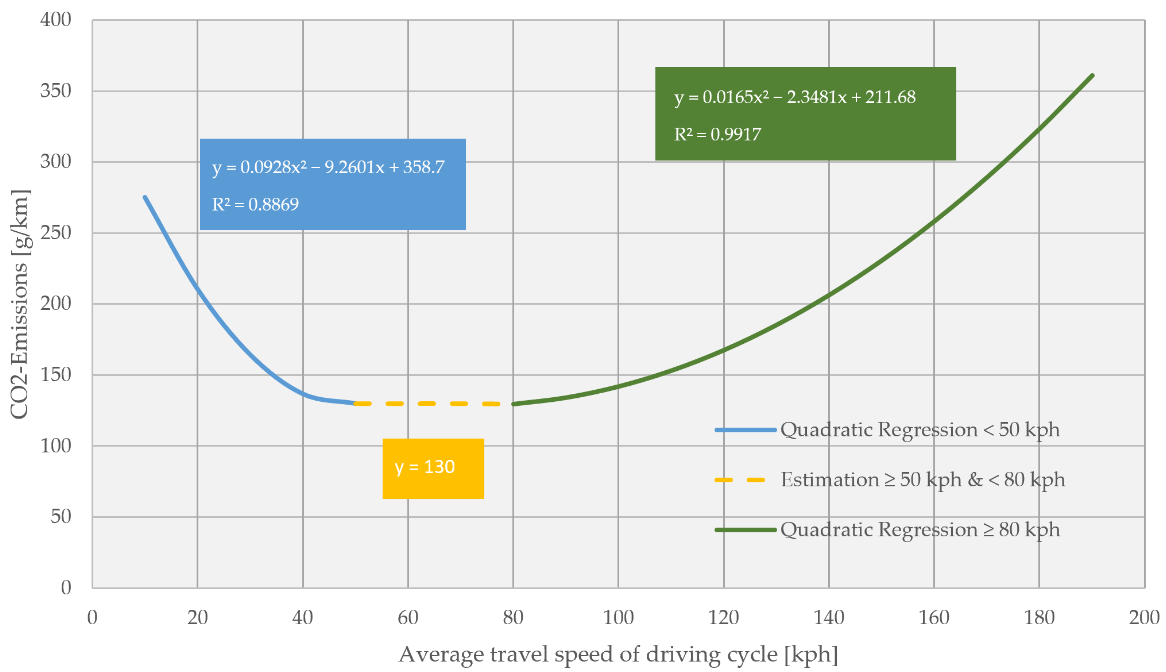


Figure 5.7: Threefold regression model based on Handbook Emission Factors for Road Transport (HBEFA) and Passenger Car and Heavy-Duty Emission Model (PHEM), according to the German Environment Agency.

Applying this regression to all edges within the network resulted in the total amount of CO_2 g emitted on any average Monday throughout the German motorway network. Unfortunately, this result only held true under the previous assumption that all traffic is evenly distributed across the day. It was therefore prone to error because travel speeds as well as traffic delays vary throughout the day, as can be measured by inspecting the specific attributes across edges throughout the day. Given the fact that during a possible morning rush hour, the travel speed on a specific edge is much lower than during the rest of the day, this should be weighted accordingly by also including the percentage of daily cars that need to traverse the edge at this specific time of the day into the calculation (see Section 5.2.3).

The measurement of kilometers traveled along an edge multiplied by the number of total applicable cars at any specific time t was therefore defined as the edge flow kilometers of any edge at time t. Due to this, the total edge flow kilometers (TEFK) of any edge can be calculated via the formula

$$TEFK = \sum_{t=1}^{48} \frac{\text{edge length}[m]}{1000} \cdot (\text{Percentage of daily cars}(t) \cdot TC_E) \tag{5.3}$$

which enables weighting of time-specific edge calculations based on their proportion of total edge flow kilometers. All following calculations and results depicted were based on these weighted flow kilometers.

5.3.2 Applying Speed Limits to the Network

Introducing a speed limit into the network was as simple as defining a cut-off-threshold that was applied at time of calculation. During unrestricted state, every network edge contained several average travel speeds - one value per timestamp. By defining an exemplary threshold of 120 kph, we simply cut off any average travel speeds above 120 kph on a per-unrestricted-edge basis. Any edge with a speed below the threshold remained unchanged while sections above the threshold were limited to the threshold when included in any calculation. This simplified introduction of a speed limit could therefore be compared to the introduction of legally binding, static traffic signs on the motorway network. As depicted in Figure 5.6, not all network participants could be expected to implicitly comply with the legal restrictions. Therefore, we additionally applied the speed distribution in restricted state (see Figure 5.6, depicted in blue) to arrive at a more realistic speed distribution for any given edge at specified time t. A thorough discussion of the results achieved by introducing different speed thresholds into the network can be found in the upcoming section.

5.4 Results

In this section, we examine the results presented by the German Environment Agency within the official study and compare these results to calculations derived directly via the network.

5.4.1 Network Benchmark

We began by comparing basic statements concerning the general motorway infrastructure, its state of restriction and general usage-patterns to establish a baseline similarity between both the official study and our programmatical analysis. The results of this comparison are shown in Table 5.1.

Table 5.1: Benchmark between general motorway infrastructure according to the German Environment Agency (GEA) and proposed methodology for network analysis.

Speed Limit [kph]	**Ø Travel Speed GEA** [kph]	**Affected Flow GEA** [%]	**Ø Travel Speed Network Analysis** [kph]	**Affected Flow Network Analysis** [%]
100	103.3	10.95	102.9	8.38
120	115.6	17.17	114.24	25
130	118.3	7.4	118.82	8.8
Unrestricted	124.7	55.5	126.77	53.5
Network-wide	116.5	-	119.37	-

According to the GEA, 55.5% of the German motorway flow across the network currently has no permanent speed restriction (e.g., static traffic signs) in place. In cases of no speed restriction, hereby defined as “open” sections, the average travel speed across network participants is measured at 124.7 kph. A total of 10.95% of network flow is permanently restricted to 100 kph with a measured average travel speed of 103.3 kph. The largest part of the restricted network flow is statically restricted to 120 kph with an average travel speed slightly below the allowed maximum speed at 115.6 kph. Another 7.4% of network flow is presented as currently restricted to 130 kph with an average travel speed of 118.3 kph. The remaining 8.9% of network flow belongs to speed categories below 100 kph, as is the case with inner-city motorways or permanent construction sites. On average, travel speed across all network flow is 116.5 kph, according to the GEA.

By retrieving the same statistics programmatically via the motorway network, we arrived at comparable results for speed restrictions of 100 kph, 130 kph and for non-restricted traffic flow with 8.38% and 102.9 kph, 8.8% and 118.82 kph as well as 53.5% and 126.77 kph, respectively. In the case of network flow permanently restricted to 120 km, our results differed significantly from the official study. The network analysis resulted in 25% of flow kilometers that were currently restricted to 120 kph instead of the previously cited 17.2%. In terms of average speed on these sections, the results converged again with the network analysis, resulting in 114.24 kph compared to 115.6 kph. This difference was most likely caused by including versus omitting dynamic traffic signs during the analysis. While we have no specific information on how dynamic traffic signs were handled by the GEA, our network defaulted to assuming an average restriction of 120 kph. Across all flow kilometers, the network calculated an average travel speed of 119.37 kph.

5.4.2 Theoretical Versus Practical Speed Restrictions

By definition, a restriction only occurs if the historically averaged travel speed is higher than the threshold at which the speed limit would occur. This means that it is entirely possible that even though a particular section of the motorway network legally allows for a maximum speed of 130 kph, meaning that it would in theory be restricted by a speed threshold of 120 kph, in reality the historically achieved travel speed averages at about 118 kph. What this in turn means is that even though on first glance, a road previously limited to 130 kph might be restricted by a general speed limit, in reality most network participants on this road section are never able to reach travel speeds above the speed limit throughout most of the day, meaning the restriction would not affect them at all but would also not contribute to any CO_2 savings resulting from a general speed limit. While critics of general speed restrictions base their argumentation of heavy incursions on personal freedom on the first aspect of currently allowed maximum speed limits, the more relevant aspect in terms of CO_2 reductions is the analysis of practical, real-world facts as recorded by navigation devices.

Putting these claims to the test by adding the previously retrieved historical traffic details from TomTom into the equation, our network analysis revealed that only 7.19% of all flow kilometers allow for high-speed driving. High-speed driving is defined as the circumstance that a road section is currently not restricted by any traffic signs ("unrestricted" or "open") and has no traffic-induced delays, for example, caused by traffic jams or construction sites. Comparing this 7.19% of practically "unlimited" flow kilometers according to real-world TomTom data (where it is indeed possible to achieve high speeds in day-to-day driving) to the previously described 53.5% of theoretically unrestricted flow according to traffic signs, a major gap between theory and practice became obvious.

Additionally, a total of 65.61% of all flow kilometers on average do not reach their legally allowed travel speed (according to traffic signs) due to general traffic volume as well as traffic jams. To put it simply, most motorway sections operate at suboptimal performance due to traffic delays induced by too many network participants simultaneously claiming usage of the same finite infrastructure. Additionally, another 1.61% of all flow kilometers operate below their legally allowed speed limits without any traffic-induced delays at all. On the other hand, for 22.5% of flow kilometers, the average daily travel speed exceeds the legally allowed speed limit, leading to illegal speeding on certain motorway sections. It therefore appears that major reductions in CO_2 emissions can already be achieved by enforcing current speed limitations more strictly.

Referencing the speed limit of 120 kph as proposed by the GEA, the introduction of such a general speed limit across the entire network would restrict 50.74% of practical flow kilometers, leading to a decrease in average speed of 4.1 kph or 2.94% compared to the status quo.

5.4.3 Analysis of Possible CO_2 Reductions by Inducing Speed Limits

Now that we have established that a general speed limit of 120 kph across all German motorways would restrict 50.74% of total daily flow kilometers based on real-world traffic data, the question remains as to what proportions of CO_2 emission savings would result from such measures.

During the second major part of the analysis, we identified potential emission savings on a per-edge basis by calculating the total CO_2 emissions with and without a speed limit threshold in place. To achieve this, we calculated CO_2 emissions by inserting the historical travel speeds as measured by TomTom, adjusted by applying the travel speed distribution previously depicted in Figure 5.6 into the regression model and retrieved the respective CO_2 emissions. If the historic travel speed was higher than the introduced speed threshold, the value of the threshold was inserted instead. According to our traffic data network coverage of 81.5%, we scaled up the results of our calculations by dividing each absolute CO_2 value by .815, such that the remaining 18.5% of network edges not covered by any TomTom data were likewise included within the results to be presented. By applying this logic to the network, total daily CO_2 savings of 7.43% compared to the unrestricted network can be achieved, while the aforementioned 50.74% of flow kilometers throughout the German motorway network would practically be restricted. In absolute measures, this would save 9796.37 tons of CO_2 emission per day or 3,575,675.95 tons of CO_2 per year within the transport sector. To calculate yearly savings, we assumed a historically averaged

Monday is representative for any given weekday. Future research might focus on analyzing network characteristics depending on different days of the week, especially Monday to Friday versus the weekend. The same procedure was carried out for several different thresholds ranging from 60 kph to 130 kph, comparing potential CO_2 savings to network restrictions necessary to achieve these savings. The results are shown in Table 5.2.

Table 5.2: Sensitivity analysis of different speed limit thresholds and their impact on network speed compared to CO_2 savings. Highlighted in blue is the scenario of 120 kph referenced during most of this article.

Speed Threshold [kph]	**Restricted Flow Kilometers [%]**	**Ø Speed Restriction [kph]**	**Ø Speed Restriction [%]**	**CO_2 Savings [%]**	**CO_2 Savings [tons]**
60	96.91	57.52	46.73	28.04	36,965.63
70	96.91	47.83	38.37	27.45	36,184.47
80	92.06	38.26	30.54	25.98	34,251.81
90	87.92	28.77	22.66	23.16	30,536.46
100	80.68	19.51	15.1	18.94	24,963.77
110	69.23	10.95	8.27	13.49	17,777.05
120	50.74	4.10	2.94	7.43	9,796.37
130	35.23	-0.14	-0.26	2.39	3,144.28

One interesting result from Table 5.2 is the fact that a speed limit of 130 kph would result in a negative change of average speed (meaning an average speed increase) throughout the network. On first sight, this appears to be counterintuitive. Nonetheless, these results are a good indicator for the underlying assumption that the introduction of a speed limit would implicitly result in road participants adhering to these new regulations. Due to the previously described average speed throughout the network of 119.38 km an hour, adhering to the speed limit would require the general road user to increase their average driving speed. Since the current average network travel speed results not only from driver preference but also primarily from infrastructural performance of the network in general, it is highly unlikely that such a broad change could be realized.

To allow for a representative comparison between both studies it was important to keep in mind that while the GEA cited the total amount of CO_2 emitted by motorized vehicles as 44.5 million tons annually, a calculation within our network returned a total of 48.12 million tons, based on official and supplemented traffic count information as well as navigation service provider data. Therefore, percentage-wise comparison required normalization as provided within Table 3.

Table 5.3: Comparison between results presented by the German Environment Agency (GEA) versus results generated by programmatically analyzing the network.

Speed Threshold [kph]	**CO_2 Savings GEA [m tons]**	**CO_2 Savings GEA [%]**	**CO_2 Savings Network Analysis [m tons]**	**CO_2 Savings Network Anaalysis* [%]**
100	6.2	13.93	9.1	20.45
120	2.9	6.52	3.6	8.09
130	2.2	4.94	1.1	2.47

*Percentage-values normalized to 44.5 million tons according to the GEA

The estimated CO_2 savings for a targeted speed limit of 120 kph differed by 1.57 percentage points, based on the absolute difference of 700,000 tons annually between our analysis and the results presented by the GEA. This gap is a direct result of the different methodologies applied. While the GEA used a fixed set of measuring points to extrapolate traffic flow information across the network, the methodology presented in this article referenced real-world traffic data provided by navigation devices across 81% of the network. Results differed more significantly for the remaining two cases of 100 and 130 kph. These variations stemmed from the fact that Löhe [373], the major data source for the GEA analysis, only provides data from measuring points for restricted sections with a speed limit of 120 kph. Therefore, the GEA was only able to provide general estimations for scenarios of 100 and 130 kph, while our data-driven methodology could draw from broad navigation service provider data to estimate a more realistic speed distribution for these additional thresholds.

5.4.4 On the Way to Well-Chosen Speed Limits

While the goal of minimizing CO_2 emission is generally accepted as beneficial, discussions on the dimensions of restrictions necessary and acceptable to achieve these savings continue. To better compare the proportions of restrictions necessary for achievable CO_2 savings, the parallel coordinate plot in Figure 5.8 is used.

A completely parallel line in Figure 5.8 equates to a directly proportional relation between two parameters. An example for this is the left-hand side for a speed limit of 90 km (black line). To achieve percentage-based CO_2 savings of 23.16% compared to the unrestricted network state, the average speed across the network must be reduced by 22.66%. In contrast to that, a steeper line in any direction (upward or downward slope) indicates a non-proportional relation between two attributes. The steeper the line, the more disproportional the relation is. Coming back to the major example of this article, the blue line indicates a speed limit of 120 km per hour. While the left-hand side relation between the average speed to be restricted and the potential savings is a positive one (an average speed reduction of 2.94% results in average daily CO_2 savings of 7.43%), the right-hand side supports claims of disproportionate incisions as 50.74% of total flow kilometers would require restrictions to achieve this 7.43% of CO_2 savings. The same can be said for any of the other thresholds considered during this case study.

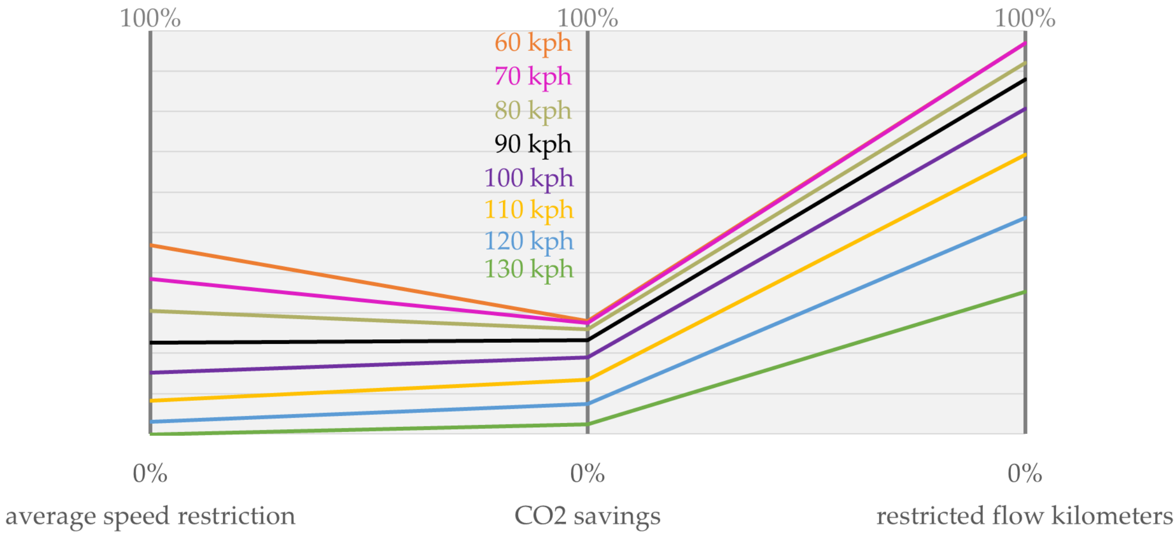


Figure 5.8: Parallel coordinate plot visualizing average network restrictions in comparison to potential CO2 savings.

To seek a mutually acceptable compromise for both parties - supporters and opponents of general speed restrictions - we took a closer look at the 120 kph restriction. In the case of 120 kph, 50.74% of traffic flow would practically be restricted. The total CO_2 emissions could be reduced by 7.43%, equaling 9,796.37 tons per day. Figure 5.9 indicates the consequences of partial restrictions. The street sections have been ordered by the corresponding percentage of reduced CO_2 emissions in the case of a 120 kph restriction. A restriction of the top 19% of street sections in terms of percentage of CO_2 savings would lead to absolute CO_2 savings of 5,000 tons daily, which equals about 50% of total possible savings considering a speed limit of 120 kph.

One fact worth mentioning while examining Figure 5.9 is the plateau value at approximately 72% of cumulated flow regulated by traffic signs, whereas our previous calculations showed a maximum restriction of 50.74% of flow kilometers. This stems from the fact that the conceptualized restrictions we applied to the network would be time-independent via the introduction of static and permanent speed signs on road sections, but the level of speed and therefore the classification of whether specific flow kilometers within the network will be restricted or not are highly time-dependent. In fact, a high amount of flow would theoretically be regulated by traffic signs, but in practice would not reach the threshold of 120 kph (i.e., originally unrestricted flow at rush hours). This suggests establishing dynamic traffic signs to adjust speed limits throughout different times of the day, based on actual traffic volume at specified time t. Therefore, the x-axis of Figure 5.9 indicates the flow that is driven on edges with potential speed signs, but its practical restriction depends on the daytime-specific actual driving speeds. As a result, the amount of flow kilometers that are theoretically restricted is higher than the amount

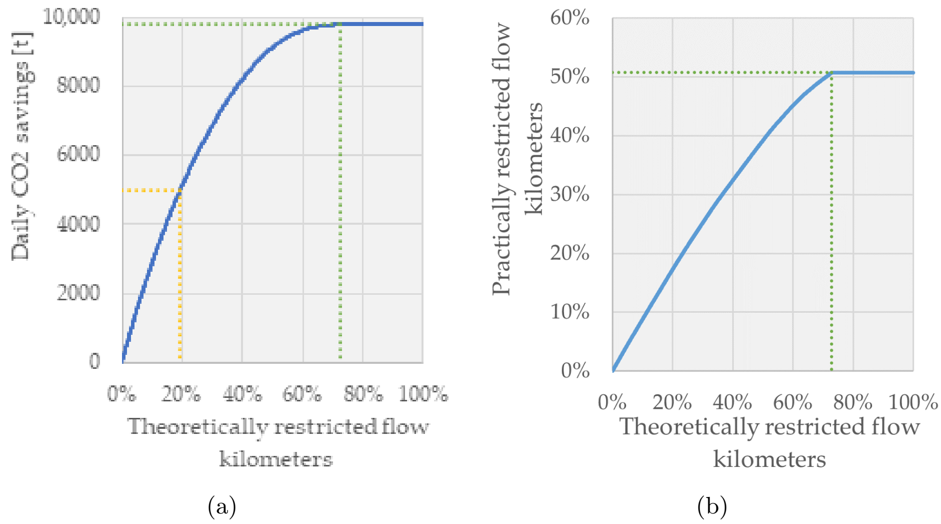


Figure 5.9: Depiction of the (a) direct relation between daily CO2 savings in tons and the necessary percentage-based restriction of network flow and the (b) ratio of theoretical (static) restriction versus practical (dynamic) restriction considering a 120 kph speed limit.

of flow kilometers that are practically restricted. This is worth mentioning since speed limit opponents will argue based on a 72% restriction extracted from Figure 5.9, which in fact distorts the proportion of restricted flow kilometers and ignores dynamic real-world conditions. A more in-depth analysis and discussion on the topic of dynamic traffic regulation can be found in the upcoming section.

Figure 5.10 depicts the result in terms of absolute CO_2 savings per network edge (with an average edge length of 1.8 km) throughout the German motorway network according to our network analysis. Unsurprisingly, the highest savings are to be found on motorway edges in between large cities. As proximity to city centers increases, only marginal savings, if any, exist, which is to be expected since most of the traffic converges at these network intersections before it splits into different directions. Therefore, these highly used parts of the network predominately suffer from traffic jams, decreasing the historically averaged travel speed. Due to this decrease in average travel speed, most motorways located in close proximity to major cities are not affected by a speed limit since their default travel speed is already below the maximum speed allowed via the introduction of a speed threshold, resulting in no noteworthy CO_2 savings on these network edges.

5.5 Discussion

Our results verify the assumption that a general speed limit throughout the German motorway network can help reduce the annual amount of CO_2 emission by reducing average travel speeds. The range of achievable savings calculated using our proposed methodology is in line with previous governmental studies by the German Environment Agency as well as the body of literature on this topic [364, 367, 369, 372]. The methodology presented in this paper delivers a coherent guide on how to programmatically leverage official governmental data, historical traffic information as well as open-data platforms to improve on many of the shortcomings of previous studies, mainly on the issue of non-published data sets as well as the lack of transparency and reproducibility caused by it.

As discussed in Section 5.4, it is not necessary to apply speed limits to the whole network. Instead of this, we suggest the usage of so-called Variable Speed Limits (VSL). In addition to reducing the obstacle of perceived justification, VSL contribute significant further side effects, mainly flow optimization, reduced travel times, a decrease in traffic shock waves as well as an increase in road safety in general [376–383]. Unfortunately, motorists generally do not adhere to speed limits [384]. Because of that, VSL still require enforcement to realize many of their implied benefits [385–387], which results in high upfront and maintenance costs. It is therefore necessary to precisely evaluate the benefits resulting from these investments. In our case, Sections 5.3 and 5.4 focused on environmental benefits in terms of CO_2 emission savings. The calculated savings of 3.6 million tons annually (by implementing a speed limit of 120 kph) would require 50.74% of daily flow kilometers to be restricted throughout the network. However, this

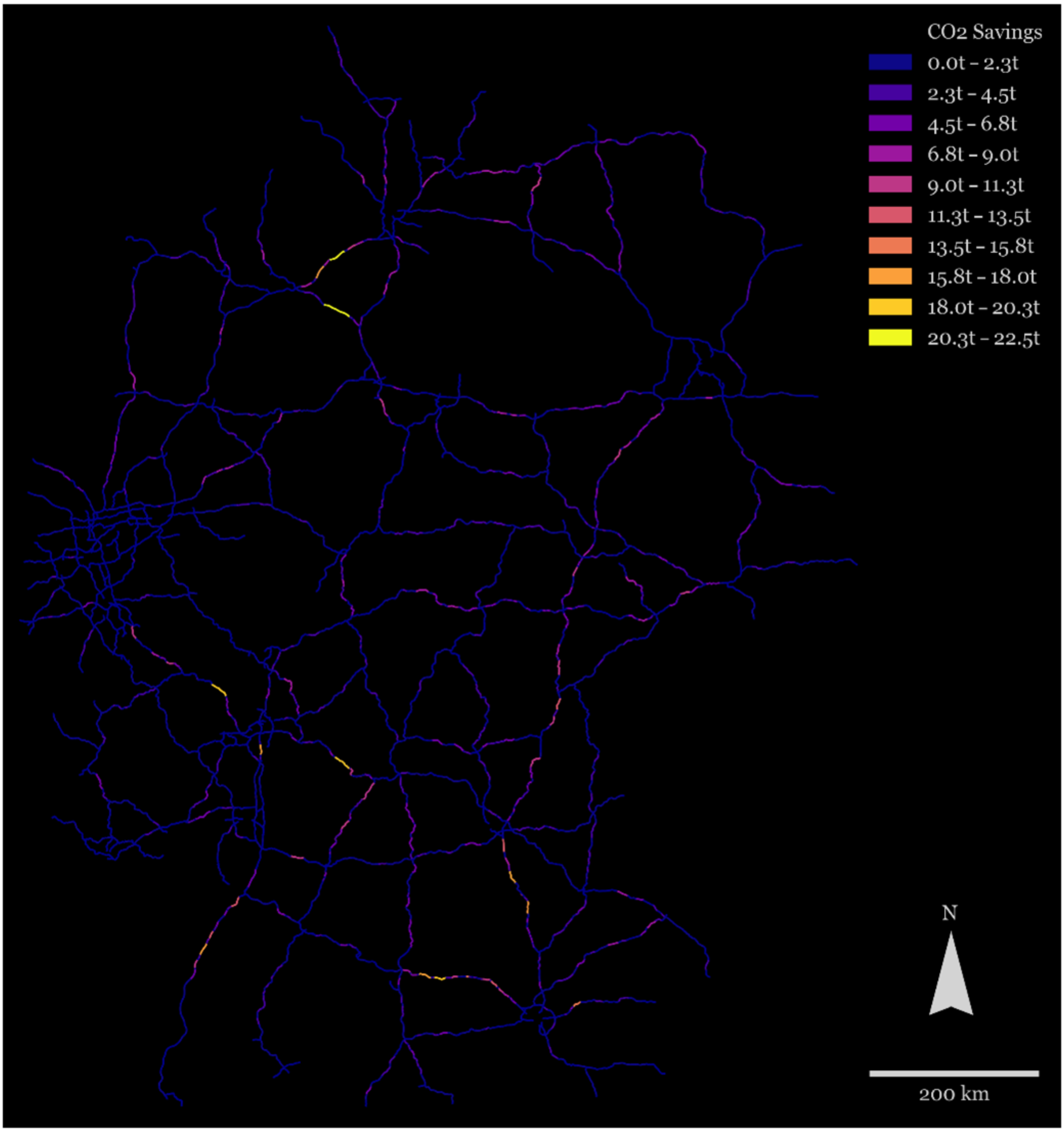


Figure 5.10: Network edges colored by the amount of daily CO2 savings per edge resulting from a general speed limit of 120 kph. Brighter areas correspond to higher savings.

estimation resides on the lower end of the spectrum since it currently neglects the positive impacts of VSL previously described. Due to this, a wide-scale implementation of Variable Speed Limits could lead to reduced road occupancy, resulting in a smoothed traffic flow, which transfers to better driving patterns that require less acceleration and braking throughout a journey, decreasing the fuel consumption of any given vehicle, which directly correlates to fewer fossil fuels burned and less CO_2 emitted throughout the network.

Unfortunately, the proposed introduction of VSL into the network highlights a major limitation of our methodology, since these effects cannot currently be determined because we adhered to simplifications and assumptions provided by the GEA for the sake of comparability. Due to this, future research might focus on improving on these assumptions and supplementing the network via more specific and scientifically verifiable calculations. Some key points to be approved upon can therefore be summarized as follows:

We adopted the average-based CO_2 emission functions derived by the GEA. Since data on how the underlying driving cycles have been calculated are non-public, we suggest building transparent CO_2

emission functions. To achieve this, vehicle registration data can be analyzed to extract the distribution of different vehicle types moving on German motorways. In addition to that, open access frameworks like COPERT could be utilized to differentiate CO_2 emission curves by vehicle and fuel type [336]. The biggest issue that needs addressing is the fact that CO_2 emission functions often have a limited definition range. COPERT functions are currently only defined up to velocities of 130 kph. Therefore, one crucial part is finding or developing emission functions that adhere to the following two requirements: (1) they should be detailed enough to differentiate between vehicle and fuel types, and (2) must be robust at higher speeds, which are driven on legally unrestricted motorways.

Additionally, the applicability and reliability of the traffic distribution functions provided by the GEA depicted in Figure 5.6 require further validation. Since the introduction of a general speed limit might significantly impact the driving patterns throughout the network, leading to increased travel times and longer lengths of stay within the network, future studies could focus on a simulation-based approach to validate the assumed distribution functions and their impact on network-wide CO_2 emission savings. Microscopic traffic simulation would also allow for the inclusion of VSL-based calculations [388–390], drastically improving on the applicability of our methodology to practical debates and potentially offsetting concerns on the topic of negative changes in driving patterns.

5.6 Conclusion

The contribution of this paper is a methodology to allow for transparent data analysis in road networks by enriching OpenStreetMap (OSM) data with publicly available traffic information on a dynamic scale.

We apply our methodology to contribute to the discussion of possible CO_2 emission savings via the introduction of a speed limit to the German motorway network by comparing our programmatical results to the official study by the German Environment Agency published in 2020. The comparison reveals that while the key facts and estimations in terms of network infrastructure as presented by the GEA hold true, major differences between the theoretical assumptions of network performance in terms of possible travel speeds and practical data gathered by navigation service providers can be identified.

We have quantified and shown that the introduction of a flat-rate speed limit of 120 kilometers per hour would result in a theoretical restriction of about 70% of total flow kilometers across the German motorway network, saving 3,575,675.95 tons of annual CO_2 emissions within the transport sector. More importantly, we quantify that nearly 100% of these savings could already be realized by restricting only 50.74% of all network sections dynamically throughout the day due to significant variations in time-dependent road utilization. Additional calculations for speed limits from 60 kph to 130 kph were provided as a means of sensitivity analysis to our findings.

Since we adopted multiple simplifying assumptions provided by the GEA for sake of comparability, future research might focus on speed distribution patterns in the context of 100 and 130 kph as well as on validating the presented driving cycles to calculate the speed-induced CO_2 emissions. In addition to that, the influence of Variable Speed Limits on traffic flow smoothness and its consequences, such as the level of CO_2 emissions and the probability of accidents, are currently not included and should be analyzed in detail.

CHAPTER 6

Sustainable City Evaluation using the Database for Estimation of Road Network Performance

6.1 Introduction

Road Network Performance (RNP) remains an integral part to the evaluation of urban sustainability [1–4]. According to Chen [40], the economy of a nation or geographic region depends heavily upon an efficient and reliable transportation system to provide accessibility and promote the safe and efficient movement of people and goods [11–13]. Poor RNP results in (1) decreased economical performance represented by increasing transportation costs [45, 65, 241, 242], (2) negative ecological effects in terms of higher greenhouse gas (GHG) emissions [75, 243, 244] and (3) a decrease in social sustainability via a combination of the aforementioned factors in addition to traffic induced health issues [245–249]. Despite its importance for most aspects of everyday life [9, 10] and its impact on productivity and costs of constantly increasing [21] short-distance freight operations [45, 65, 237, 250, 251], efforts on calculating RNP on a wide geographical scale remain scarce due to expensive equipment requirements for observational vehicles and so-called 'in situ' technologies [232, 391]. Measurements are often restricted to specific, predefined test tracks and restricted time intervals [20, 392] and often fail to account for infrastructural and temporal variances throughout large road networks [237, 249]. Furthermore, testing procedures may vary across cities and metropolitan areas, rendering them unreliable for systematic comparisons [393].

To solve several of these issues, analysts increasingly rely on digitization, specifically on open data platforms such as OpenStreetMap (OSM) and floating car data provided via Application Programming Interface (API) offered by navigation service providers such as HERE and TomTom, to estimate Road Network Performance on a wider scale by evaluating historical traffic data [20–22, 229]. These digital procedures alleviate many problems encountered in field-testing, i.e., expensive equipment, regulatory hurdles, low area coverage, and low external validity [238], by leveraging the aggregated historical data of a large fleet of private and commercial vehicles [394]. Unfortunately, most navigation service providers require a set of predefined routes to enable the retrieval of route-specific information, leaving analysts to figure out sensible ways to either obtain historical traffic patterns on an individual basis or generate or extract such vehicle-specific data from publicly available information.

In 2020, Braun et al. [255] presented a data collection methodology to overcome the obstacle of route generation by referencing the TomTom Reachable Range API. The API returns a polygon with exactly fifty corner points covering the geographical area reachable within a given distance or time budget. This polygon enables a one-directional analysis of traffic patterns from an outgoing centroid, delivering time-specific information on reachable distances and corresponding travel time requirements within a region. Based on these requests, researchers were able to estimate road network characteristics on a per air-distance kilometer basis in an efficient way. By choosing comparable starting locations for multiple regions, RNP became observable and comparable between the exemplary four German cities. Nonetheless, this methodology introduced its own limitations, mainly concerning the selection of comparable points of origin and the impact of a good or poorly chosen node of origin on the model's outcome. In addition to this major limitation, unidirectional routes ignore the fact that inbound traffic should be considered equally important for a generalizable RNP analysis.

To solve and remedy these shortcomings (i.e., unidirectional routes and subjective points of origin), a solution to algorithmically generate and evaluate a large set of representative network paths is required in order to establish a general road network performance measurement. To enable such a methodology, each path within a road network requires traffic information, but historically this has led to large amounts of API transactions [65, 236]. By utilizing a novel and previously unavailable feature of the HERE Traffic API [395], access to real-time traffic flow data is provided for large geographic areas within a predefined bounding box via a single request. Since each request delivers geographically referenced information on speed and jam factors for all road sections contained within the specified region, this new feature enables the efficient generation and enrichment of routable road network representations. Based on this finding, we set out to answer the following research question, deduced from the original publication by Braun et al. [255]:

> How can representative routes be generated and evaluated to reliably measure Road Network Performance and overcome limitations of contemporary RNP estimation?

The remainder of this article introduces and describes the methodology applied to generate the DERNP – the Database for Estimation of Road Network Performance in Germany. Section 2 examines the current state of RNP research and its lack of suitable, practical solutions. Section 3 presents the individual components utilized in generating and evaluating the underlying network routes of the proposed methodology. By aggregating all routes in a given region and distance class, DERNP includes polynomial regression coefficients to estimate factors such as detour, travel time and speed (with and without traffic), fuel consumption, and CO_2 emissions based on a set air distance in a specific region. Section 4 demonstrates the applicability of these models by comparing four major German cities in terms of their economic and ecological sustainability. In Section 5, theoretical and practical implications are discussed. Section 6 summarizes the main takeaways of this article and provides an outlook for further research.

6.2 Literature Review

6.2.1 Fundamentals on Road Network Performance

Literature on transport pricing is well aware of the fact that poor Road Network Performance, generally defined as the network driven impact on sustainability [255] and mainly referred to in the context of traffic congestion, significantly reduces efficiency and increases transportation costs [45, 65, 235, 274, 275]. Specific negative impacts of traffic congestion, i.e., delays due to decreasing achievable travel speeds [309, 396, 397], economic losses to drivers [289], degrading ambient air quality [238, 239, 279, 309] as well as general inconvenience and a reduction in quality of life [251] are well-researched topics in literature. While traffic congestion can be subdivided into recurring and non-recurring traffic delays [275, 398], i.e., regular and predictable road usage in comparison to road incidents such as collisions, medical emergencies, and vehicle breakdowns, studies on Road Network Performance, including the presented methodology, tend to focus on recurring or general congestion patterns. To account for non-recurring traffic patterns, several studies have been carried out to allow for an improved estimation [291, 315].

According to Mondschein and Taylor [7], geographic regions vary significantly in terms of adaption to traffic congestion. While congestion can constrain mobility and reduce accessibility, traffic is also associated with agglomerations of activity and is thus a byproduct of proximity-based accessibility. Whether agglomeration and congestion have net positive or negative impacts on activity participation thus varies substantially over space. In contrast to earlier studies of urban network performance focusing mainly on network reliability and resilience [28, 29, 40, 399–403], this new perspective on RNP aims to provide geographically comparable measurements of Road Network Performance to supply indicators on regional attractiveness and infrastructural relevance [30].

In line with prior research [65, 255] and supported by its predominant relevance for road freight transportation, we focus on the economic dimension of sustainability, which leads to a refined definition of RNP as the network driven economic costs of moving a vehicle from a specified point of origin (O) to a specified destination (D) using the public road network [255]. A public road network is characterized by the set of all roads within a geographical region that are accessible by all network participants and, therefore, excludes private road infrastructure. To narrow down the scope of analysis presented in this article, the methodology is predominantly concerned with urban transportation, i.e., short distance traffic up to 20 kilometers, also referred to as the last mile or urban cargo traffic [44, 300].

In line with existing literature on road network transportation [28, 45, 65, 275, 279, 309, 396, 397, 404, 405], we suggest measuring the geographically distinct Road Network Performance by answering the following general questions:

1. How efficient is the road infrastructure in terms of detour factor and achievable travel speed?
2. How utilized is the road infrastructure in terms of traffic congestion?
3. How resource-intensive is the utilization of the road infrastructure in terms of fuel consumption and CO_2 emissions?

Each of these questions is dependent on region-specific characteristics. Interestingly, as Bell [401] points out, network performance simultaneously depends on the state of the infrastructure and on the behaviour of network users, while user behavior is also governed by expectations about the general state of the network. Several studies have been carried out in support to this claim by examining and evaluating user behaviour in varying road networks. Milevitch et al. [287] apply agent-based traffic flow simulations to analyze the impact of planned road network development on the dynamics of the automobile transportation system during the departure of visitors after the semifinal match of the 2018 FIFA World Cup. Dia and Panwei [406] evaluate the impact of driving behaviour on emissions and RNP. Snelder and Calvert [404] propose the Macroscopic Dynamic Traffic Assignment and Marginal Model to evaluate the impact of weather conditions on driving behaviour and RNP.

In terms of infrastructure analysis, the detour factor, defined as the ratio of required road distance to cover a specific air distance, incorporates commonly used network attributes, such as density [302] or connectivity [14]. Travel speed is defined as the average speed achievable between origin and destination pairs considering vehicle and road constraints. Thus, travel speed implicitly accounts for road network attributes such as speed limits, traffic lights, or the level of congestion within the network [26, 309, 310] as well as user behaviour [400, 406]. By combining travel speeds and travel distances, travel times can be derived [311]. Thoen et al. [312] show that longer travel times result in significantly higher transportation costs, emphasizing the importance of determining travel times objectively.

6.2.2 Leveraging Floating Car Data

Recent studies increasingly rely on floating car data in order to appropriately measure RNP. Kellner [232] analyzes vehicle fleet data from German transportation service providers to measure and compare network performance and its impact on distribution costs between different service areas. Nuzollo et al. [329] provide distribution tour simulations based on extracted floating car data from logistics operations, while Waadt et al. [407] present a methodology to estimate traffic congestion based on GPS data extracted from cellular networks.

Due to no generally accepted standard in floating car data extraction, the handling of this data is considered difficult. The large size of datasets and the complexitiy and dynamics of traffic phenomena [253] in combination with reliability problems [26] lead to increasing requirements of data harmonization [393]. Additionally, vehicle fleet management data is usually constrained to specific areas and routes serviced by the originating company, enabling region-specific analyses but prohibiting general measurements of RNP.

In recent years, increasing availability of floating car data provided by navigation service providers via APIs delivers potential solutions to efforts on data harmonization and regional specificity [5]. According to Kellner [236], API data is considered a significant improvement in contrast to individual data from fleet vehicle management systems due to four primary reasons: (1) Reliability or ”completeness”, (2) area-wide coverage, (3) consistency, and (4) higher levels of representativeness. While APIs do not provide access to a complete set of individual routes due to privacy regulations, they record and deliver aggregated historic traffic information throughout many worldwide road networks in a structured query language. These databases enable researchers to ignore primary data acquisition, shifting focus to automated generation or extraction of origin-destination pairs. Kellner et al. [65] referenced navigation service providers' data to generate distance matrices for existing customers' locations and requested travel times at different times throughout the day. Wen et al. [408] propose a traffic congestion evaluation index system based upon Beijing floating car data. In the same vain, Sun et al. [319] calculate a congestion index for arterial roads in Changzhou, China. Li et al. [409] obtain real-time travel data from web services to measure urban tourism accessibility in Nanjing, China. Nuzzolo et al. [329] analyze freight delivery patterns

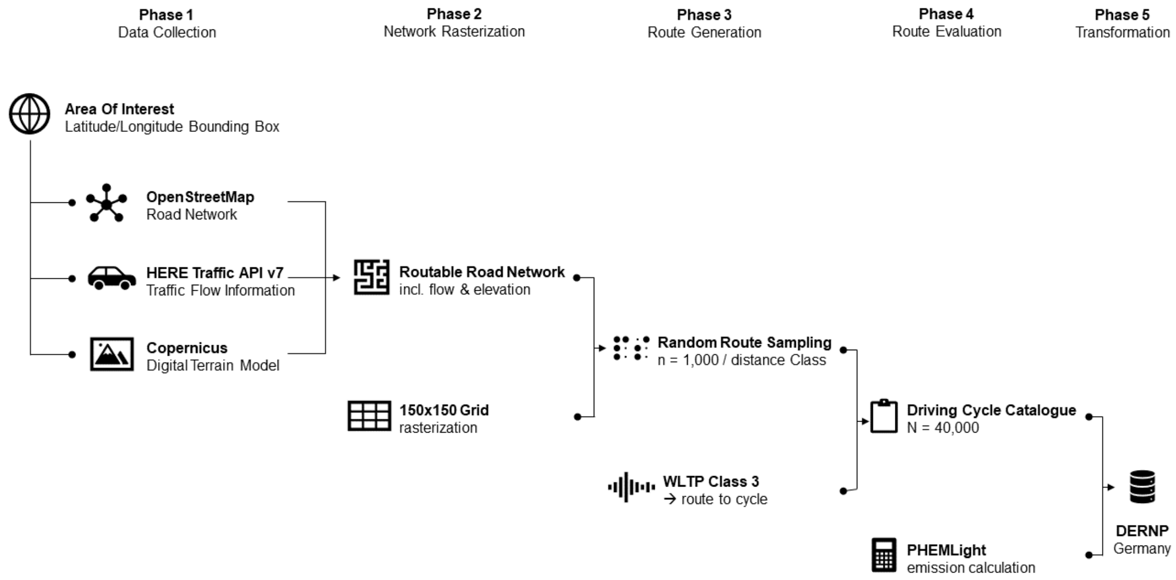


Figure 6.1: The five phases comprising the core methodology behind DERNP.

through floating car data in Italy while Waller et al. [410], comparable to Braun et al. [255], leverage data provided by TomTom, Google, and OSM to estimate RNP in Sydney through their Rapidex data exploration and visualization tool.

In an attempt to generalize methodologies presented in previous studies and alleviate many problems related to subjective trip generation, Braun et al. [255] suggest an improved approach to generalizable route generation based on real-world floating car data: for a given point of origin in the network, do not specify a destination and proceed to measure detour and travel speed for any origin-destination pair generated by a reachability approach using distance and time-based isochrones. While overcoming some limitations of previous research, especially concerning the availability of suitable or publicly available tour data, this methodology does not report RNP across the complete road network but manually selects well-defined partitions [303], constituting a lack of generalizability.

To the best of our knowledge, contemporary literature does not provide a suitable solution to the problem of limited individual route availability for wide-scale road network performance. By leveraging the HERE Maps API Version 7 [411] and its tile-based catalogue of historic traffic data in combination with publicly available OSM data on road network infrastructure [412], we propose a randomized route generation methodology which leverages floating car data and model-based traffic and emission simulation. The resulting Database for Estimation of Road Network Performance is inspired by the COPERT industry standard emissions calculator [413] and constitutes the first generalizable methodology for wide-scale RNP measurement for German metropolises. Our approach is considered efficient as the entirety of Germany can be analyzed by a total of 266 API calls per timestamp. Thus, DERNP allows measuring RNP on a large scale with no prior knowledge of origins and destinations and without a need to rely on second-best solutions, i.e., regional aggregation as suggested by Casadei et al. [328], alleviating a main concern of previous data collection methodologies.

6.3 Materials and Methods

The algorithmic measurement of RNP requires three main components: (1) a routable representation of the road network including all relevant public road sections in the area of interest, (2) traffic flow information for these sections, and (3) representative routes throughout the network along which the RNP is measured. The underlying methodology behind DERNP delivers solutions to acquire these components in combination with additional information to allow for an artificial generation of network traffic for any given area of interest. As depicted in Figure 6.1, the procedure consists of five phases.

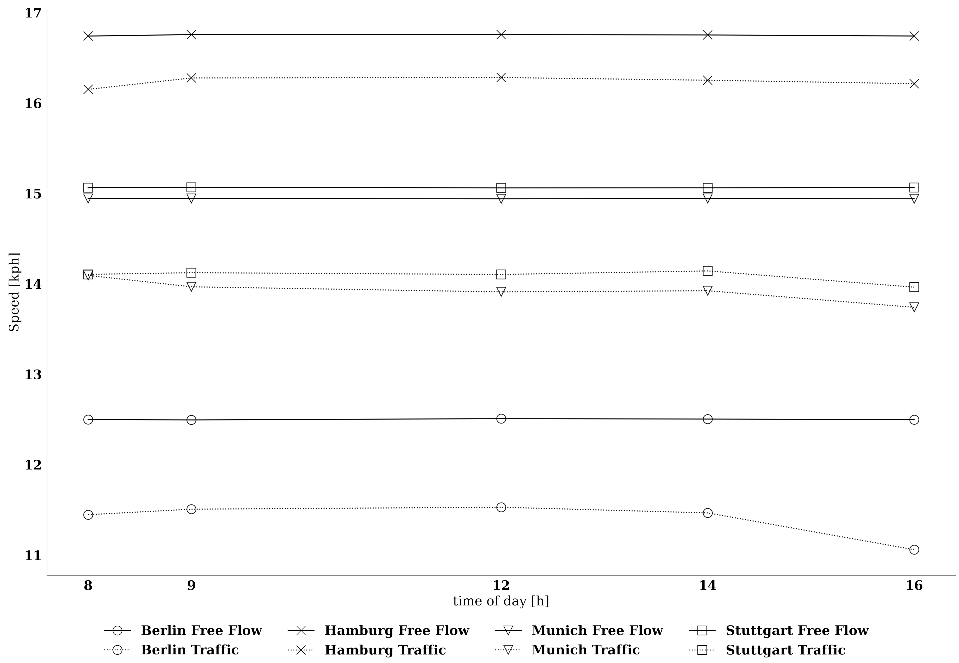


Figure 6.2: Comparison between average free flow and traffic speeds across four different timestamps for a period of seven weeks between July 25, 2022 and September 10, 2022.

6.3.1 Phase 1: Data Collection

The exemplary use cases in this article focus on German cities by defining the area of interest as the outermost rectangular boundary of any given city. To harmonize extraction procedures across data providers, DERNP relies on the commonly used, web-based Slippy Map Tile system [414]. Based on a list of required tiles per bounding box, a routable representation of the road network within the tiles is created using the OSMnx Python package [163]. This representation only includes user-generated data from the OSM community [412], which is prone to be incomplete, outdated, or incorrect. To alleviate this issue, the HERE Traffic API [411] is utilized to retrieve current traffic flow information on a per-tile basis. All tile references in this article rely on a set of HERE traffic data retrieved in between July 25, 2022 and September 10, 2022 at five different timestamps (08:00 a.m., 09:00 a.m., 12:00 p.m., 02:00 p.m., and 04:00 p.m.). Traffic data is held constant for purposes of reproducibility within this article but should be updated in regular intervals. The selected time frames are related to main working hours of German Transportation Service Providers. Additional time frames can be considered if relevant to the underlying business case. Figures 6.2 and 6.3 depict fluctuations of averaged flow speeds between the four exemplary German cities during this time frame. Exact results can only be guaranteed by referencing identical data at identical timestamps across all objects of comparison [400].

Concerning nomenclature, a network's free flow state describes the traffic flow without congestion exceeding an agreed upon norm [331] and corresponds to the average historic travel speed without extraordinary traffic incidents. Comparing free flow and traffic speeds at 08:00 a.m. on a specific date results in an indicator whether or not the inspected date is representative of average network usage or if higher-than-average traffic is occurring. Comparing free-flow speeds between different areas at the same timestamp provides a good indicator of average road network performance between geographies.

Using OSMnx [163], the network is initialized as a dynamic graph object [415] consisting of nodes and edges. Traffic flow data is mapped onto this graph based on latitude/longitude coordinate pairs. The mapping is validated by comparing the edge length attribute of both input sources.

The last information added onto the graph object is elevation data extracted from the digital elevation model provided by the European Union's Earth Observation Programme Copernicus [416]. To achieve compatibility with the given network structure, global elevation data provided in .tff format is converted into tile-based raster files.

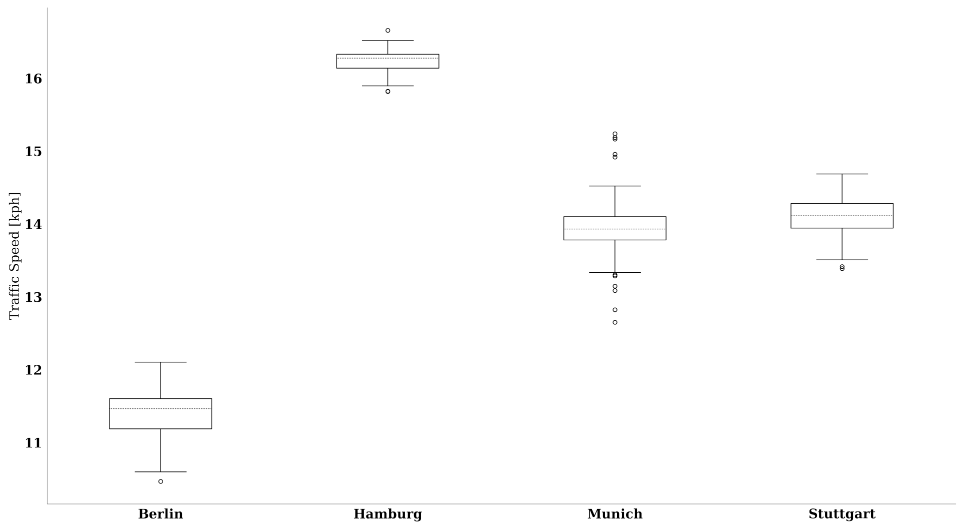


Figure 6.3: Variation in traffic speeds per city for a period of seven weeks between July 25, 2022 and September 10, 2022.

Successful application of Phase 1 results in a Routable Road Network (RRN).

6.3.2 Phase 2: Network Rasterization

During network rasterization, the RRN is subdivided into a grid of 150x150 equally-sized cells. Each cell is geographically referenced using the same coordinate reference system as the RRN. The centroid of each cell represents a point defined via latitude/longitude coordinate pairs.

Due to the high level of subdivision created by 150x150 grid cells, the smallest distance between two centroids is measured at 150 meters air distance for large cities like Munich. Based on this grid, a distance matrix between all centroids is calculated using the great-circle distance formula, resulting in a matrix of air distances c between all centroid pairs. Based on this distance matrix, randomized route sampling with a default sample size of $n = 1,000$ is applied to extract observations for each distance class. Distance classes for this study range from 500 meters to 20.5 kilometers air distance in increments of 500 meters, resulting in 40 distinct classes.

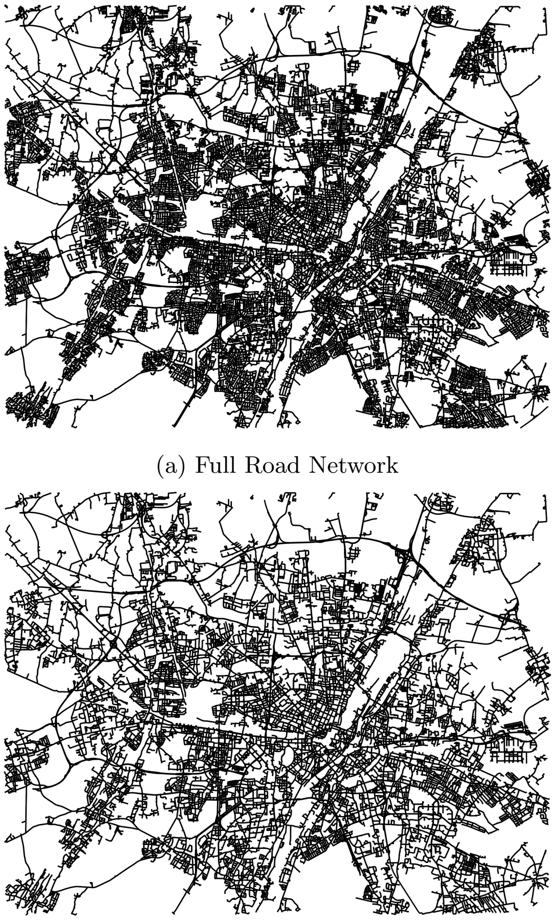
Random route sampling enables the independent selection of travel path connections across the entire network for each distance class. These travel paths need to be converted from direct air connections to actual vehicle routes utilizing the existing Routable Road Network. Non-routable connections are dropped.

Network rasterization returns a dictionary containing a key for each distance class and a list of artificial network paths as corresponding value. Figure 6.6 quantifies the achieved network coverage for all exemplary use cases.

Figure 6.4 depicts the complete graph for Munich in comparison to the graph that is traversed by all paths within the network rasterization dictionary generated using random route sampling. While smaller road segments are left out due to not being located on any fastest path between two nodes, the majority of arterial roads are covered and can therefore be utilized in calculating the RNP in the subsequent steps.

6.3.3 Phase 3: Route Generation

The network paths returned by the previous step correspond to the fastest path from origin to destination. While these paths are sufficient to calculate average travel speed under free flow and traffic conditions, realistic estimation of RNP in terms of economical and ecological sustainability requires representative driving cycles. To achieve realistic measurements without excessive field testing, the Worldwide Harmonized Light Vehicles Test Procedure (WLTP) [417] is the standardized testing scenario for new vehicles



(a) Full Road Network

(b) Traversed Road Network

Figure 6.4: Comparison between the full road network for Munich, Germany, and the network composed of edges that have been traversed at least once during Random Route Sampling. (b) indicates the network that is utilized for calculation of Road Network Performance.

since September 1, 2019. It includes a highly detailed set of representative driving cycles on a 1Hz (per-second) basis.

By referencing the WLTP, custom driving cycles are calculated for each network route. Although not perfectly accurate, especially on shorter road segments, these driving cycles do allow for a much more realistic representation of actual driving behaviour than mean speed calculations. A customized driving cycle for a 2.1 kilometer route in Munich is depicted in Figure 6.5.

By applying the customized driving cycle logic to all routes in the dictionary returned in Phase 2, a Driving Cycle Catalogue (DCC) comprised of up to 40,000 estimated driving cycles across all 40 distance classes is generated.

6.3.4 Phase 4: Route Evaluation

All driving cycles in the DCC simulate real-world network paths throughout the RRN, including acceleration and deceleration phases as well as stop times (speed = 0 kph) at intersections or traffic lights. This information is crucial since the number of existing intersections in a road network is heavily flow-regulating [240].

To achieve a realistic measurement of RNP, it is therefore mandatory to take specific driving behaviours and road characteristics into account instead of relying on averaged calculations. It is due to this that we dissuade from referencing COPERT emission curves [413] and instead focus on the cycle-based Passenger Car and Heavy Duty Emission Model (PHEM) [418]. An Open-Source version of PHEM tailored to Microscopic Traffic Simulation titled PHEMLight is available in the software package SUMO [419, 420]. For application in the DERNP methodology, PHEMLight Version 5 was transposed

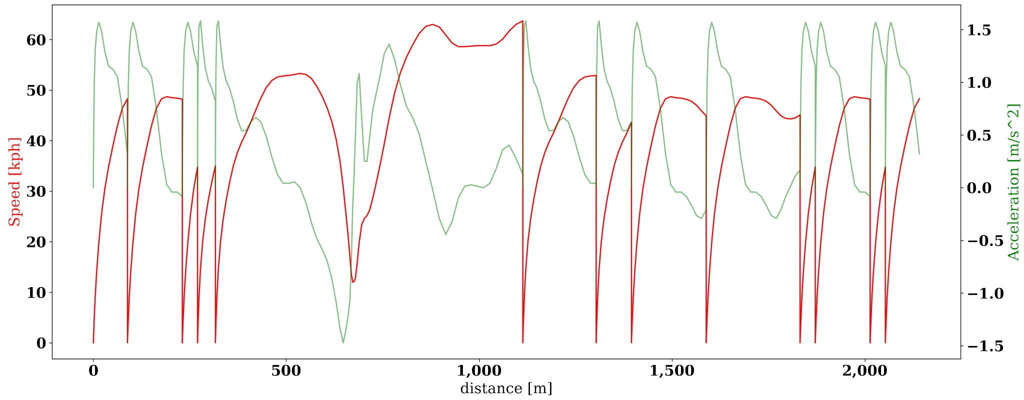


Figure 6.5: Customized Driving Cycle for a 2.1 kilometer route in Munich based on the WLTP Driving Cycle Class 3.

Table 6.1: Description of Network Performance Factors included in DERNP.

Variable	**Description**	**Explanation**
d_a	Air distance	The air distance from a start point to an end point
$d_f(d_a)$	Detour Factor regression	Detour Factor regression based on discrete measures
$v_f(d_a)$	Free flow velocity regression	Free flow velocity regression based on discrete measures
$v_t(d_a)$	Traffic velocity regression	Traffic velocity regression based on discrete measures
$t_f(d_a)$	Free flow travel time regression	Free flow travel time regression based on discrete measures
$t_t(d_a)$	Traffic travel time regression	Traffic travel time regression based on discrete measures
$fc(d_a)$	Fuel consumption regression	Free flow fuel consumption regression based on discrete measures
$FC(d_a)$	Avg. fuel consumption per 100 km regression	Fuel consumption regression based on discrete measures
$CO_2(d_a)$	CO_2 emission regression	CO_2 emission regression based on discrete measures
$CO_2^{avg}(d_a)$	Avg. CO_2 emission per 100 km regression	CO_2 emission regression based on discrete measures

to the Python programming environment. In its Creative Common License, PHEMLight only includes two vehicle types: light passenger vehicles rated EURO 4 for both gasoline and diesel engines. Due to this, all calculations presented in this article are based on a standardized EURO 4 Diesel Light Passenger Vehicle with a rated power of 74 kW, belonging to the WLTP Class 3.

6.3.5 Phase 5: Transformation

After evaluation of all 40,000 driving cycles using PHEMLight5, results are saved in a tabular structure. Individual data points are aggregated by their corresponding distance class using a median calculation, resulting in a table of 40 rows with one column per network performance factor as described in Table 6.1. Based on these aggregated results, 10th-degree polynomial regression curves are fitted for each factor to enable continuous approximation on the basis of air distance.

After successful transformation of all included factors, the DERNP reference database for the six largest German cities is depicted in Table 6.2. Additional cities or customized areas of interest can be calculated using the methodology described above. To calculate a specific factor F for a given air distance d_a in kilometers, coefficients from columns a to k need to be inserted into a 10th-degree polynomial function (Equation 6.1).

$$F(d_a) = d_a a^{10} + d_a b^9 + d_a c^8 + d_a d^7 + d_a e^6 + d_a f^5 + d_a g^4 + d_a h^3 + d_a i^2 + d_a j + k \quad (6.1)$$

Table 6.2: Excerpt of the DERNP reference database for the top six largest German cities.

city	vehicle	engine	category	factor	unit	d_{a_min}	d_{a_max}	a	b	c	d	e	f	g	h	i	j	k	RMSE
Berlin	PKW	Diesel	EUR 4	df	[-]	0.5	20.5	1.940×10^{-10}	-1.872×10^{-8}	7.288×10^{-7}	-1.408×10^{-5}	0.000	0.000	−0.015	0.124	−0.426	0.299	2.684	0.00
Berlin	PKW	Diesel	EUR 4	vf	[kph]	0.5	20.5	4.197×10^{-9}	-4.754×10^{-7}	2.285×10^{-5}	−0.001	0.010	−0.098	0.600	−2.076	3.068	2.615	33.630	0.03
Berlin	PKW	Diesel	EUR 4	vt	[kph]	0.5	20.5	4.708×10^{-9}	-5.335×10^{-7}	2.567×10^{-5}	−0.001	0.011	−0.111	0.686	−2.419	3.912	0.820	33.250	0.05
Berlin	PKW	Diesel	EUR 4	tf	[min]	0.5	20.5	1.980×10^{-9}	-2.118×10^{-7}	9.728×10^{-6}	0.000	0.004	−0.039	0.237	−0.812	1.187	2.019	0.644	0.02
Berlin	PKW	Diesel	EUR 4	tt	[min]	0.5	20.5	1.467×10^{-9}	-1.568×10^{-7}	7.214×10^{-6}	0.000	0.003	−0.030	0.180	−0.607	0.796	2.553	0.509	0.02
Berlin	PKW	Diesel	EUR 4	fc	[l]	0.5	20.5	1.174×10^{-10}	-1.272×10^{-8}	6.098×10^{-7}	-1.687×10^{-5}	0.000	−0.003	0.023	−0.092	0.176	0.200	0.084	0.00
Berlin	PKW	Diesel	EUR 4	FC	[l/100km]	0.5	20.5	4.292×10^{-10}	-5.421×10^{-8}	3.082×10^{-6}	0.000	0.002	−0.029	0.247	−1.333	4.251	−7.365	21.185	0.01
Berlin	PKW	Diesel	EUR 4	CO_2	[kg]	0.5	20.5	3.052×10^{-10}	-3.308×10^{-8}	1.586×10^{-6}	-4.386×10^{-5}	0.001	−0.008	0.059	−0.240	0.457	0.521	0.217	0.00
Berlin	PKW	Diesel	EUR 4	CO_2^{avg}	[kg/100km]	0.5	20.5	1.116×10^{-9}	-1.410×10^{-7}	8.014×10^{-6}	0.000	0.006	−0.074	0.642	−3.466	11.055	−19.151	55.090	0.04
Hamburg	PKW	Diesel	EUR 4	df	[-]	0.5	20.5	-1.792×10^{-10}	1.714×10^{-8}	-6.673×10^{-7}	1.310×10^{-5}	0.000	0.000	0.014	−0.143	0.719	−1.947	4.226	0.00
Hamburg	PKW	Diesel	EUR 4	vf	[kph]	0.5	20.5	1.712×10^{-9}	-1.816×10^{-7}	8.242×10^{-6}	0.000	0.003	−0.029	0.143	−0.252	−0.907	6.434	35.914	0.05
Hamburg	PKW	Diesel	EUR 4	vt	[kph]	0.5	20.5	1.130×10^{-9}	-1.214×10^{-7}	5.575×10^{-6}	0.000	0.002	−0.019	0.088	−0.071	−1.138	5.572	34.787	0.07
Hamburg	PKW	Diesel	EUR 4	tf	[min]	0.5	20.5	-2.701×10^{-10}	1.909×10^{-8}	-4.088×10^{-7}	-1.937×10^{-6}	0.000	−0.004	0.041	−0.202	0.414	1.655	1.387	0.01
Hamburg	PKW	Diesel	EUR 4	tt	[min]	0.5	20.5	-3.435×10^{-10}	2.495×10^{-8}	-5.875×10^{-7}	3.964×10^{-7}	0.000	−0.005	0.045	−0.222	0.479	1.780	1.411	0.01
Hamburg	PKW	Diesel	EUR 4	fc	[l]	0.5	20.5	-6.406×10^{-11}	5.459×10^{-9}	-1.846×10^{-7}	3.011×10^{-6}	-1.953×10^{-5}	-9.659×10^{-5}	0.003	−0.019	0.049	0.266	0.158	0.00
Hamburg	PKW	Diesel	EUR 4	FC	[l/100km]	0.5	20.5	-3.231×10^{-10}	3.153×10^{-8}	-1.271×10^{-6}	2.663×10^{-5}	0.000	0.001	0.018	−0.220	1.027	−2.384	19.251	0.01
Hamburg	PKW	Diesel	EUR 4	CO_2	[kg]	0.5	20.5	-1.666×10^{-10}	1.420×10^{-8}	-4.799×10^{-7}	7.830×10^{-6}	-5.079×10^{-5}	0.000	0.007	−0.049	0.127	0.692	0.410	0.00
Hamburg	PKW	Diesel	EUR 4	CO_2^{avg}	[kg/100km]	0.5	20.5	-8.403×10^{-10}	8.199×10^{-8}	-3.305×10^{-6}	6.925×10^{-5}	−0.001	0.002	0.048	−0.571	2.671	−6.199	50.061	0.06
München	PKW	Diesel	EUR 4	df	[-]	0.5	20.5	-3.203×10^{-10}	3.440×10^{-8}	-1.579×10^{-6}	4.032×10^{-5}	−0.001	0.006	−0.033	0.085	0.060	−0.929	3.302	0.00
München	PKW	Diesel	EUR 4	vf	[kph]	0.5	20.5	-2.995×10^{-9}	3.313×10^{-7}	-1.593×10^{-5}	0.000	−0.007	0.084	−0.610	2.840	−8.105	14.696	32.648	0.12
München	PKW	Diesel	EUR 4	vt	[kph]	0.5	20.5	-4.217×10^{-9}	4.607×10^{-7}	-2.185×10^{-5}	0.001	−0.010	0.109	−0.765	3.388	−8.926	13.501	31.246	0.12
München	PKW	Diesel	EUR 4	tf	[min]	0.5	20.5	1.201×10^{-9}	-1.266×10^{-7}	5.731×10^{-6}	0.000	0.002	−0.022	0.138	−0.494	0.818	1.393	1.013	0.00
München	PKW	Diesel	EUR 4	tt	[min]	0.5	20.5	1.424×10^{-9}	-1.503×10^{-7}	6.846×10^{-6}	0.000	0.003	−0.028	0.179	−0.668	1.237	1.237	1.159	0.01
München	PKW	Diesel	EUR 4	fc	[l]	0.5	20.5	1.262×10^{-10}	-1.505×10^{-8}	7.663×10^{-7}	-2.180×10^{-5}	0.000	−0.004	0.028	−0.114	0.233	0.079	0.160	0.00
München	PKW	Diesel	EUR 4	FC	[l/100km]	0.5	20.5	1.622×10^{-9}	-1.901×10^{-7}	9.611×10^{-6}	0.000	0.005	−0.055	0.401	−1.830	4.919	−7.311	21.459	0.02
München	PKW	Diesel	EUR 4	CO_2	[kg]	0.5	20.5	3.283×10^{-10}	-3.912×10^{-8}	1.993×10^{-6}	-5.668×10^{-5}	0.001	−0.011	0.073	−0.296	0.606	0.205	0.416	0.00
München	PKW	Diesel	EUR 4	CO_2^{avg}	[kg/100km]	0.5	20.5	4.219×10^{-9}	-4.944×10^{-7}	2.499×10^{-5}	−0.001	0.013	−0.143	1.043	−4.759	12.792	−19.013	55.801	0.13
Köln	PKW	Diesel	EUR 4	df	[-]	0.5	20.5	4.041×10^{-10}	-4.840×10^{-8}	2.513×10^{-6}	-7.405×10^{-5}	0.001	−0.016	0.126	−0.623	1.871	−3.212	4.473	0.00
Köln	PKW	Diesel	EUR 4	vf	[kph]	0.5	20.5	-4.075×10^{-9}	4.226×10^{-7}	-1.879×10^{-5}	0.000	−0.007	0.072	−0.466	1.997	−5.693	12.228	33.587	0.09
Köln	PKW	Diesel	EUR 4	vt	[kph]	0.5	20.5	-5.960×10^{-9}	6.259×10^{-7}	-2.827×10^{-5}	0.001	−0.011	0.114	−0.745	3.114	−8.138	14.139	32.156	0.11
Köln	PKW	Diesel	EUR 4	tf	[min]	0.5	20.5	-7.929×10^{-10}	7.798×10^{-8}	-3.219×10^{-6}	7.206×10^{-5}	−0.001	0.007	−0.028	0.038	−0.035	1.991	1.148	0.01
Köln	PKW	Diesel	EUR 4	tt	[min]	0.5	20.5	-6.828×10^{-10}	6.973×10^{-8}	-2.976×10^{-6}	6.854×10^{-5}	−0.001	0.007	−0.026	0.023	0.031	2.002	1.197	0.02
Köln	PKW	Diesel	EUR 4	fc	[l]	0.5	20.5	3.781×10^{-11}	-4.704×10^{-9}	2.545×10^{-7}	-7.801×10^{-6}	0.000	−0.002	0.014	−0.063	0.150	0.107	0.178	0.00
Köln	PKW	Diesel	EUR 4	FC	[l/100km]	0.5	20.5	3.692×10^{-9}	-4.036×10^{-7}	1.903×10^{-5}	−0.001	0.008	−0.089	0.615	−2.677	6.995	−10.279	21.893	0.01
Köln	PKW	Diesel	EUR 4	CO_2	[kg]	0.5	20.5	9.833×10^{-11}	-1.223×10^{-8}	6.617×10^{-7}	-2.029×10^{-5}	0.000	−0.005	0.036	−0.165	0.389	0.279	0.462	0.00
Köln	PKW	Diesel	EUR 4	CO_2^{avg}	[kg/100km]	0.5	20.5	9.600×10^{-9}	-1.050×10^{-6}	4.949×10^{-5}	−0.001	0.022	−0.232	1.599	−6.961	18.191	−26.730	56.931	0.07
Frankfurt am Main	PKW	Diesel	EUR 4	df	[-]	0.5	20.5	2.676×10^{-9}	-2.965×10^{-7}	1.419×10^{-5}	0.000	0.006	−0.070	0.489	−2.167	5.774	−8.516	7.485	0.00
Frankfurt am Main	PKW	Diesel	EUR 4	vf	[kph]	0.5	20.5	6.967×10^{-9}	-7.318×10^{-7}	3.299×10^{-5}	−0.001	0.013	−0.129	0.796	−2.904	5.212	0.590	39.073	0.09
Frankfurt am Main	PKW	Diesel	EUR 4	vt	[kph]	0.5	20.5	6.223×10^{-9}	-6.530×10^{-7}	2.944×10^{-5}	−0.001	0.012	−0.115	0.715	−2.594	4.583	0.373	37.502	0.15
Frankfurt am Main	PKW	Diesel	EUR 4	tf	[min]	0.5	20.5	-1.173×10^{-9}	1.201×10^{-7}	-5.301×10^{-6}	0.000	−0.002	0.021	−0.143	0.623	−1.716	4.126	0.440	0.01
Frankfurt am Main	PKW	Diesel	EUR 4	tt	[min]	0.5	20.5	-1.423×10^{-9}	1.447×10^{-7}	-6.337×10^{-6}	0.000	−0.002	0.024	−0.157	0.659	−1.721	4.217	0.552	0.01
Frankfurt am Main	PKW	Diesel	EUR 4	fc	[l]	0.5	20.5	-2.836×10^{-10}	2.938×10^{-8}	-1.306×10^{-6}	3.262×10^{-5}	−0.001	0.005	−0.032	0.125	−0.296	0.585	0.021	0.00
Frankfurt am Main	PKW	Diesel	EUR 4	FC	[l/100km]	0.5	20.5	-4.341×10^{-10}	4.092×10^{-8}	-1.584×10^{-6}	3.168×10^{-5}	0.000	0.001	0.021	−0.257	1.355	−3.991	18.952	0.01
Frankfurt am Main	PKW	Diesel	EUR 4	CO_2	[kg]	0.5	20.5	-7.374×10^{-10}	7.639×10^{-8}	-3.396×10^{-6}	8.483×10^{-5}	−0.001	0.013	−0.082	0.324	−0.770	1.521	0.053	0.00
Frankfurt am Main	PKW	Diesel	EUR 4	CO_2^{avg}	[kg/100km]	0.5	20.5	-1.129×10^{-9}	1.064×10^{-7}	-4.118×10^{-6}	8.239×10^{-5}	−0.001	0.002	0.055	−0.669	3.524	−10.379	49.282	0.05
Stuttgart	PKW	Diesel	EUR 4	df	[-]	0.5	20.5	-6.547×10^{-10}	7.186×10^{-8}	-3.378×10^{-6}	8.867×10^{-5}	−0.001	0.014	−0.087	0.291	−0.349	−0.666	3.596	0.00
Stuttgart	PKW	Diesel	EUR 4	vf	[kph]	0.5	20.5	1.109×10^{-9}	-8.093×10^{-8}	1.860×10^{-6}	4.439×10^{-6}	−0.001	0.022	−0.233	1.465	−5.433	12.278	33.859	0.06
Stuttgart	PKW	Diesel	EUR 4	vt	[kph]	0.5	20.5	1.706×10^{-9}	-1.436×10^{-7}	4.676×10^{-6}	-6.634×10^{-5}	7.573×10^{-5}	0.011	−0.168	1.208	−4.713	9.908	32.866	0.08
Stuttgart	PKW	Diesel	EUR 4	tf	[min]	0.5	20.5	5.500×10^{-10}	-5.351×10^{-8}	2.211×10^{-6}	-5.058×10^{-5}	0.001	−0.006	0.030	−0.068	−0.078	2.336	0.987	0.01
Stuttgart	PKW	Diesel	EUR 4	tt	[min]	0.5	20.5	2.543×10^{-10}	-2.566×10^{-8}	1.105×10^{-6}	-2.659×10^{-5}	0.000	−0.004	0.020	−0.050	−0.055	2.567	1.031	0.01
Stuttgart	PKW	Diesel	EUR 4	fc	[l]	0.5	20.5	9.131×10^{-11}	-1.052×10^{-8}	5.215×10^{-7}	-1.448×10^{-5}	0.000	−0.003	0.018	−0.070	0.141	0.132	0.151	0.00
Stuttgart	PKW	Diesel	EUR 4	FC	[l/100km]	0.5	20.5	5.594×10^{-10}	-7.621×10^{-8}	4.361×10^{-6}	0.000	0.003	−0.033	0.263	−1.313	3.892	−6.399	19.014	0.01
Stuttgart	PKW	Diesel	EUR 4	CO_2	[kg]	0.5	20.5	2.374×10^{-10}	-2.736×10^{-8}	1.356×10^{-6}	-3.766×10^{-5}	0.001	−0.007	0.046	−0.182	0.366	0.344	0.391	0.00
Stuttgart	PKW	Diesel	EUR 4	CO_2^{avg}	[kg/100km]	0.5	20.5	1.455×10^{-9}	-1.982×10^{-7}	1.134×10^{-5}	0.000	0.007	−0.086	0.685	−3.414	10.121	−16.639	49.445	0.07

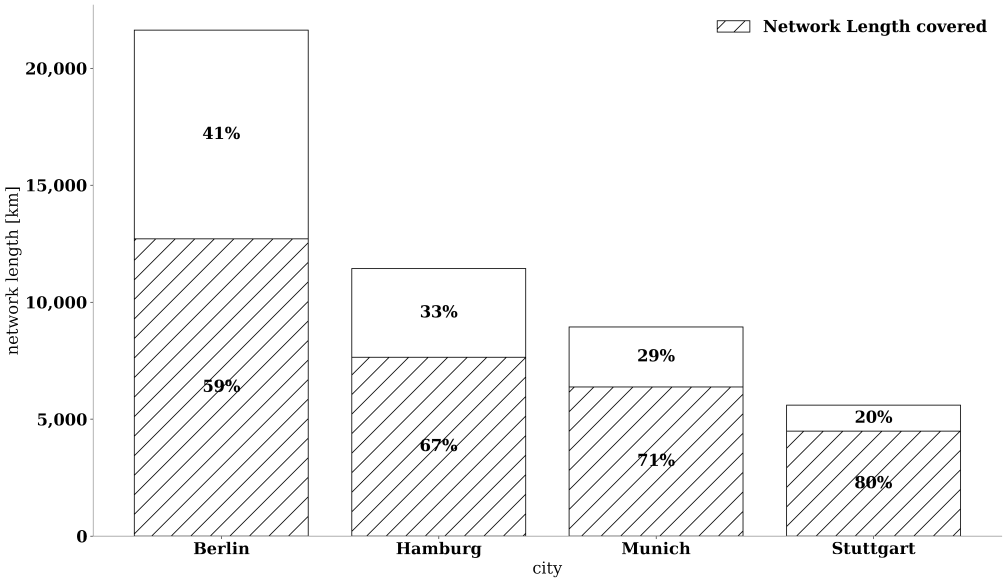


Figure 6.6: Network size comparison and DERNP network coverage.

6.4 Results

The DERNP (Table 6.2) allows for fast and efficient regional comparisons in terms of economical and ecological RNP. Since DERNP relies on air distance measurements as input factors, it seamlessly integrates into existing calculation models. To visualize the impact of differences in RNP between geographical regions, the upcoming section examines four of the largest German cities: Berlin (North-East), Hamburg (North), Stuttgart (South-West), and Munich (South-East). These cities rank highly in the 2021 TomTom Traffic Index [421] but vary significantly in terms of road network size.

Figure 6.6 visualizes the size differences in road network length (measured in kilometers) and the total length of network kilometers traversed for the DERNP generation. Due to the fixed amount of 40 distance classes and the fixed number of $n = 1,000$ generated paths per distance class, larger networks feature less coverage than smaller road networks. Additionally, as depicted in Figure 6.4, DERNP, due to being based on fastest network paths, focuses on larger, arterial roads within networks and tends to ignore smaller residential roads. Even though these smaller roads make up for a large amount of total network length, they can be considered less important for overall RNP as they are less likely to be traversed by a large number of vehicles.

6.4.1 Detour Factor

The detour factor d_f (Equation 6.2) is defined as the increase in road or travel distance d_t compared to a straight-line connection using air distance d_a and measures the infrastructural efficiency of a road network. The less turns and intersections required to overcome a specified air distance, the better the detour factor. A perfectly straight road without turns or intersections corresponds to a detour factor of 1.0.

$$d_f = \frac{d_t}{d_a} \tag{6.2}$$

Figure 6.7 indicates that all investigated detour factors follow a similar pattern. Short distances in a large city introduce a heavy detour penalty due to the densely populated inner-city areas. As air distance increases, larger surrounding roads, also known as arterial roads, are accessible, significantly decreasing the detour necessary to cover air distance. The curve for Hamburg is noteworthy, as it decreases less rapidly compared to the other curves. This indicates a strong deviation from a road network made up of straight connections, which is certainly the case in the city of Hamburg due to the river Elbe and its

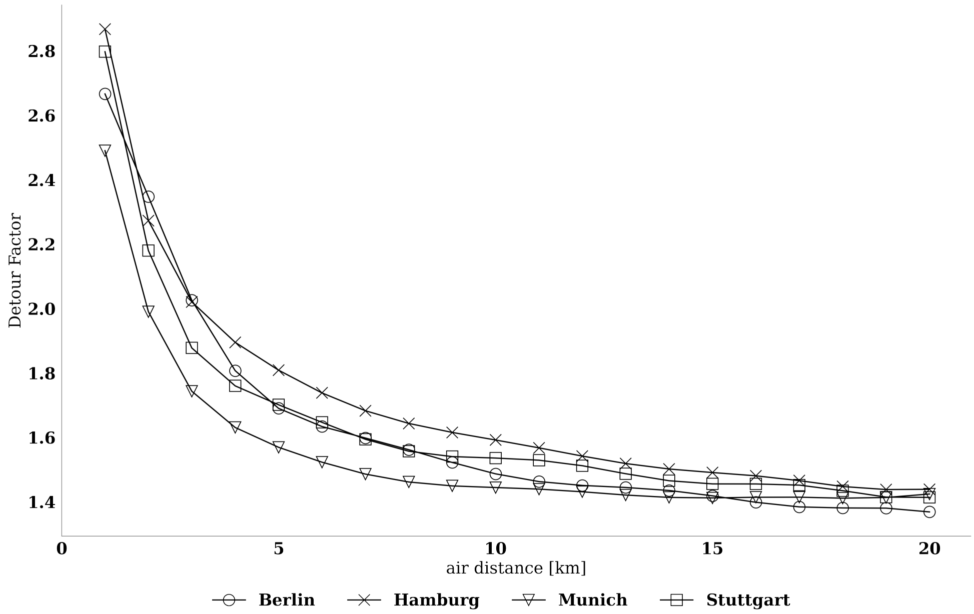


Figure 6.7: City comparison: detour factors.

many waterways inside the inner-city area. Interestingly, Munich's detour factor is significantly lower up to 10 kilometers air distance, indicating a well-built road infrastructure which allows for more direct connections. While Stuttgart's road infrastructure appears to be comparable up to 8 kilometers air distance, a bump can be seen upwards of 10 kilometers air distance. This indicates a below-average road infrastructure at the outer city boundaries, coming close to Hamburg's detour factor. This phenomenon is caused by the city's geographical location within the valley basin of Stuttgart and its unusual city area which extends over an altitude difference of almost 350 meters.

6.4.2 Fuel Consumption and Impact of Network Elevation

The unusual geographical situation in the Stuttgart city area is further supported by examining the fuel consumption per air distance kilometer. As can be seen in Figure 6.8, Stuttgart shows a significantly decreased fuel consumption curve both for (a) the total and (c) the average fuel consumption. This observation is caused by the PHEMLight5 emission calculation methodology which reports a less steep increase in fuel consumption for positive slopes in comparison to its coasting fuel consumption on negative inclines. Therefore, vehicles in areas containing large changes in altitude can save a disproportionately high amount of fuel while coasting in comparison to the increased fuel consumption caused by traversing positive slopes within the network. This hypothesis is further validated by examining Figure 6.9, which depicts the absolute and relative difference in fuel consumption caused by including elevation parameters in the PHEMLight5 calculation model.

Besides Stuttgart, the city of Berlin introduces another interesting observation in terms of fuel consumption. While Hamburg is the most fuel-intensive city for short distances, Berlin overtakes at $d_a = 11$ both in (a) actual and (c) average fuel consumption. This indicates that while most of the inspected cities enable more efficient driving behaviour at longer air distances, Berlin fails to achieve this effect. This is caused by the much larger network size of Berlin compared to the remaining three cities (Figure 6.6), corresponding to a larger diameter of the inner-city area where intersections and traffic stops are much more frequent, resulting in a higher subdivision in driving cycles. This increase in subdivisions, equaling a higher number of stops and acceleration/deceleration phases, significantly increases fuel consumption, rendering driving in Berlin less fuel efficient.

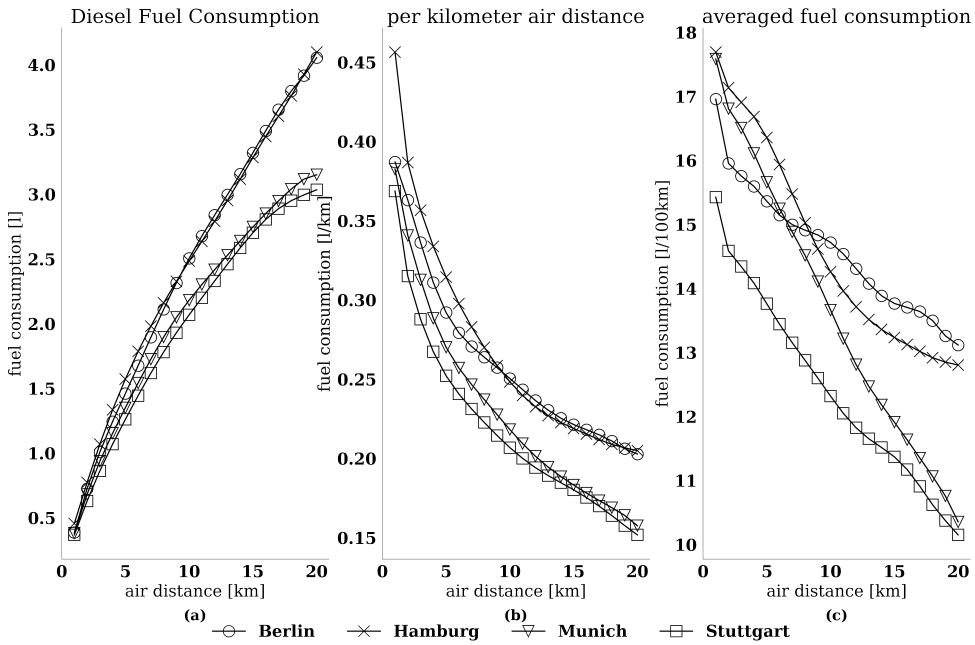


Figure 6.8: City comparison: fuel consumption.

6.4.3 CO_2 Emission

In addition to fuel consumption, PHEMLight5 includes common emission calculation models based on driving cycles, including Nitrogen oxides (NO_x), carbon monoxide (CO), hydrocarbons (HC), particulate matter (PM), particle number (PN), and carbon dioxide emissions (CO_2). This information enables potential CO_2 compensation calculations on a per-vehicle-kilometer basis. Since CO_2 emission per liter Diesel can be described by a ratio of $2.6391 kg/l$ [422], the emission curves depicted in Figure 6.10 follow the same general behaviour as their fuel consumption counterparts (Figure 6.8), leading to identical interpretations. Nonetheless, we include the emission curves for ease of access to CO_2 emission information.

6.4.4 Speed Profiles and Travel Times

Speed profiles and travel time curves provide information on how cities position in terms of infrastructure and congestion measurement. A well-built infrastructure enables longer coasting and less stop times, leading to more efficient driving cycles and a decrease in travel time per air distance kilometer. High levels of congestion decrease the achievable average velocity during these driving cycles, leading to an increase in travel time.

Figure 6.11 depicts achievable travel speeds for each distance class in (a) free flow and (b) congested state as well as (c) the traffic-induced relative decrease in average velocity. Figure 6.12 focuses on the corresponding travel times.

In both free flow and congested state, the city of Hamburg is among the top curves in terms of achievable travel speed. When looking at the traffic penalty curve for Hamburg, the relative increase in travel time (Figure 6.12c) caused by traffic congestion peaks at 17 percent or, in other terms, an average increase of $t_f(20) = 27.5/(1 - 0.17) = 33.13 - 27.5 = 5.63$ minutes when covering 20 kilometers air distance. This indicates that Hamburg suffers from a comparatively low congestion level among most of its network paths, which is in line with average speeds depicted in Figure 6.2 and Figure 6.3. Nonetheless, travel times remain similar to the remaining cities, which is largely caused by the poorly designed infrastructure due to the river Elbe as depicted by Hamburg's detour factor (Figure 6.7).

Interestingly, the city of Berlin suffers the least from congestion (15 percent peak or 5.29 minutes at $d_a = 20$ kilometers) while achieving the slowest travel speed in free flow and the second-to-last travel speed in congested state. Based on this observation in combination with an average detour factor, it appears that Berlin suffers from an almost constantly high level of congestion, influencing the historic

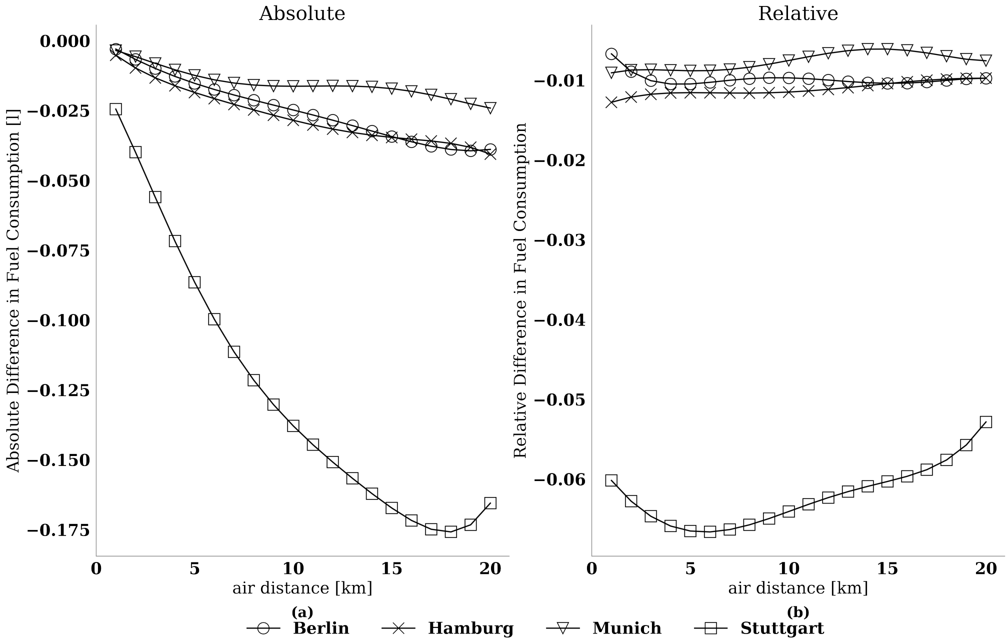


Figure 6.9: City comparison: fuel consumption differences caused via inclusion of elevation data.

free flow speed and significantly reducing the gap between free flow and congested state.

The counterexample to this is Stuttgart. While the travel speed during free flow is akin to Hamburg, it drops significantly when accounting for traffic within the observed time frame, requiring an additional 12 minutes to achieve the same distance of 20.0 kilometers. This effect is also displayed in the relative traffic penalty curve for Stuttgart, with a relative traffic induced time penalty peaking at 30 percent.

The cities displaying the largest variation between free flow and congested state are Munich and Stuttgart, with Stuttgart showing a constant increase in relative loss compared to free flow, indicating a large congestion problem throughout the entire city. Munich, on the other hand, is characterized by an increasing level of relative loss or penalty up to a plateau value of 21 percent (difference in velocity) and 23 percent (traffic induced penalty) where it remains constant. This indicates a large congestion problem for short to medium length travel distances, implying a high level of traffic in inner-city areas, while longer paths upwards of $d_a \geq 17$ allow for improved traffic flow, which might imply access to larger roads with less congestion on the city boundaries.

6.4.5 Transportation Costs

The economic dimension of sustainability of infrastructure, congestion, and detour factor is reflected in total costs of transport. In addition, DERNP allows translating environmental sustainability into economical impact by proposing the inclusion of CO_2 compensation costs into transport cost evaluation. The price per ton CO_2 is set to EUR 180, in line with current political debates by the German Federal Environment Agency [423]. Additionally, we assume EUR 0.7 per kilometer driving costs, an hourly wage of EUR 20.5 as driver costs and EUR 7.5 per hour of vehicle occupation costs, which is in line with other literature [424]. In contrast to comparable studies and based on their heavy impact on transportation costs [306], fuel costs are split from distance-based costs and incorporated on the basis of estimated vehicle fuel consumption derived from PHEMLight5 with a price per liter for Diesel fuel of EUR 1.70.

Figure 6.13 depicts the conglomeration of individual costing factors (a) to (e) in EUR per air distance which account for total costs of transportation in (f) free flow and (g) congested state. Subplot (h) depicts the difference in transportation costs caused by traffic congestion. Free flow data was compared to average traffic data for each city in between July 25 and September 22 of 2022. Traffic-specific results may vary for different time frames. Free flow data constitutes the historical average and is resilient to changes in specified time frames.

The total costs of transportation per air distance kilometer are highest in Hamburg and Berlin both in free flow and congested state. While Hamburg suffers from less travel time loss compared to Berlin,

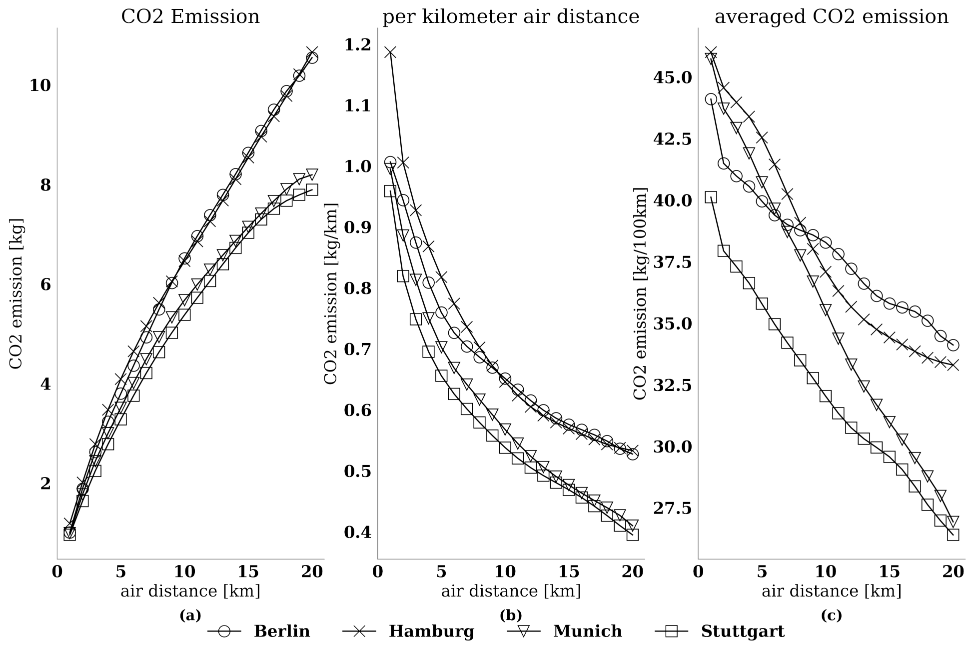


Figure 6.10: City comparison: CO_2 emissions.

the difference is equalized by an increase in travel distance and distance related costs due to inefficient infrastructure as measured by the detour factor. Since both fuel and CO_2 compensation costs correlate only with travel distance, both Hamburg and Berlin inflict a disproportionate cost surplus in comparison to Munich and Stuttgart.

With the exception of fuel and CO_2 compensation costs, transportation is most cost-efficient across all cost components in the city of Munich. A low detour factor due to well-built infrastructure in combination with comparably less congestion and better optimized free flow conditions allow for savings of up to EUR 0.6 per kilometer air distance in Munich compared to Hamburg.

Stuttgart, on the other hand, inflicts higher distance and time related costs than Munich but saves significantly in terms of fuel and CO_2 compensation due to increased coasting possibilities based on its geographical location. Nonetheless, even combined, these savings account for no more than one-third of total distance-related costs, resulting in transportation costs slightly higher than in the city of Munich both in free flow and congested state.

Subfigure (h) depicts the difference in costs per air distance between historical network speeds (free flow) and measured traffic speeds (congestion) within the specified time frame. As explained earlier, Berlin appears to suffer from a constant state of congestion, diminishing most differences between free flow and congested travel speeds. Stuttgart, on the other hand, seems to suffer from a more temporary congestion problem during the seven weeks of observation, accounting for a difference in transportation costs of up to EUR 0.14 per air distance kilometer on short paths. As path lengths increase, the difference between free flow and congestion rapidly decreases due to an increase in availability for alternative routes and faster arterial roads. Converging onto EUR 0.01 per kilometer for paths upwards of $d_a \geq$ 15 kilometers, differences become negligible, removing the need of accounting for time-specific traffic conditions.

6.5 Discussion

The methodology presented in this article adapts and improves on existing methodologies by generating a large set of representative and realistic driving cycles to enable RNP measurement for any geographical bounding box, as long as OSM and HERE Traffic data is available. It therefore manages to overcome a major limitation of previous RNP iterations, which directly depended on a subjective selection of starting locations [255]. The resulting network coverage upwards of 59 percent for most large German cities presents a considerable leap in applicability in comparison to existing studies.

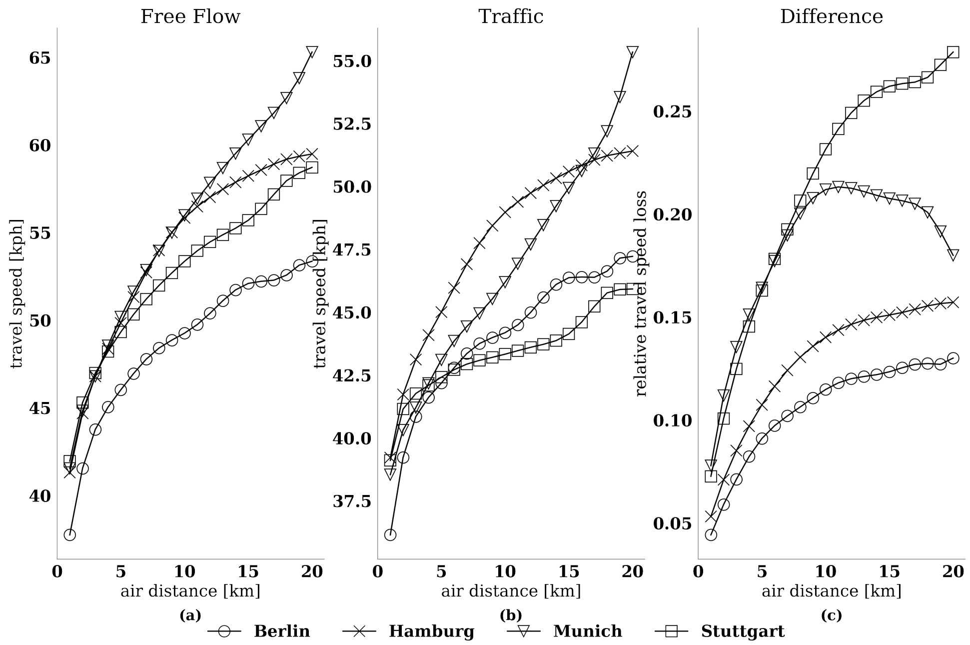


Figure 6.11: City comparison: speed profiles.

Results derived from the DERNP are in line with comparable studies, such as the TomTom Traffic Index [421] or an RNP approach based on reachable range isochrones [255]. By leveraging the PHEM-Light5 [419] emission framework, DERNP provides the first catalogue of combined economic and environmental parameter estimators based on simple air distances. The inclusion of CO_2 compensation costs for sustainable transportation costing based on specific regional geographies can lay the foundation for more realistic and comprehensible approaches to dynamic costing. Studies on the acceptance of congestion pricing indicate that environmental sensitivity is one of the most influential factors that positively affect the acceptability of transport charging policies [425]. As environmental sensitivity can be expected to continually increase over the next decade [426], so does the relevance of CO_2 and congestion pricing strategies [427].

By incorporating realistic driving cycles based on the Worldwide Harmonized Light Vehicles Test Procedure, DERNP manages to improve upon static, mean-based fuel consumption methodologies commonly found in previous studies [89, 255, 256]. Customized driving cycles provide a better estimation of actual traffic behavior as they account for the amount of traffic lights, intersections, roundabouts, and other flow-regulating infrastructural characteristics which are especially important in urban transportation. Our study shows that topology varies heavily between geographic areas, resulting in higher or lower traffic efficiencies and increased or decreased travel costs.

The same is true for the inclusion of elevation data. Even though most major German cities do not contain high variation in geographical elevation, the city of Stuttgart provides a case in point that elevation data, especially in combination with highly detailed emission models such as PHEMLight5, can lead to significant differences in fuel consumption and CO_2 emissions [295].

In addition to the aforementioned aspects, the DERNP confirms and further supports many findings of prior studies on RNP. As previously described, the free flow state in any network includes an accepted delay [318, 331]. Even during free flow state, the maximum allowed speeds are mostly unachievable. This is mainly due to a certain number of simultaneous road users that are considered acceptable during any given time of day. Additionally, certain characteristics of existing infrastructures such as road conditions, traffic lights, and traffic routing considerably influence the maximum speed any road user can be expected to reach. Traffic congestion therefore is not defined by a speed lower than the maximum speed, but as the excessive delay above an agreed upon norm [255].

It remains true that little attention has been paid to the explanation of the detour factor, its determination, and its influencing factors. Nonetheless, our study shows its importance for transport costing as it significantly impacts the cost per air distance kilometer due to the high share of distance-based costs

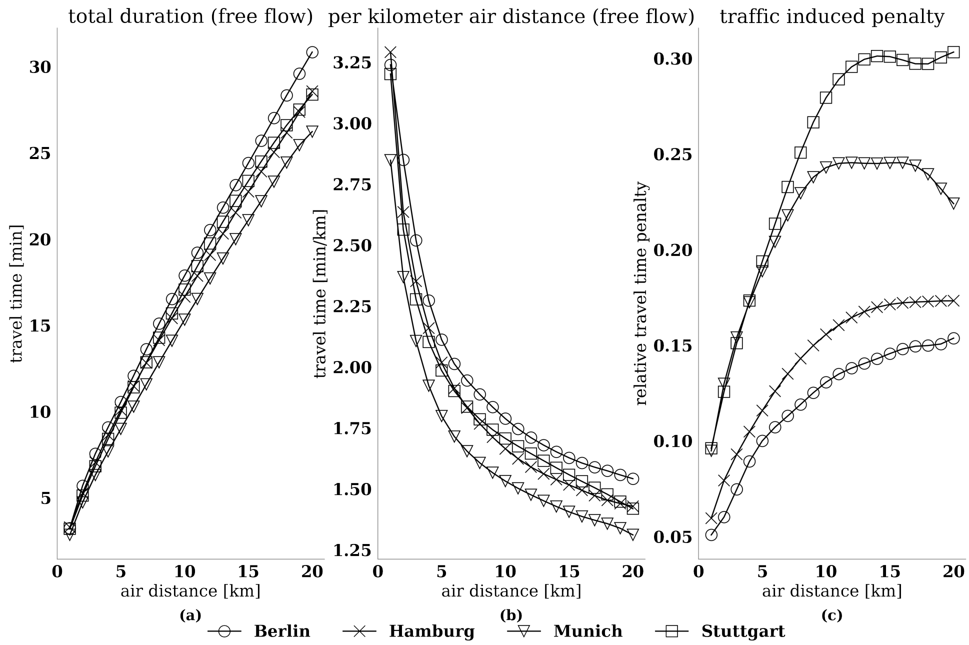


Figure 6.12: City comparison: travel times.

in comparison to total costs of transport. In accordance with previous studies [255], the detour factor decreases with increasing air distance throughout urban areas. This effect is a direct result from the existence of motorways or inner-city highways. These more efficient sections of road networks usually follow a comparably straight or direct course and can be accessed with a higher likelihood as air distances increase. Consequently, when calculating costs, transport companies must take a closer look at short distances, as the costs per kilometer can be many times higher than for longer distances. These short distances occur mainly in distribution between customer locations.

Special care has been taken to account for recent developments in fuel pricing. Previous studies tend to aggregate fuel costs into distance-based costs, obscuring the impact of external fuel price changes and internal cost factors. DERNP deliberately splits and disaggregates distance-based costs from fuel costs, allowing for a better evaluation of internal performance and external, non-adjustable effects.

In general, Section 4 underlines the fact that significant cost differences can arise between different geographical regions. As a practical example, since transport companies mostly charge prices for distribution independent of regional characteristics, the contribution margin of a single shipment might vary significantly between regions [65, 255]. When comparing costs between business units, care should be taken to account for differences in geographical characteristics by referencing the DERNP and adjusting expectations accordingly, i.e., via proportional corrections based on comparative RNP Measurements.

In contrast to prior research [255, 256], DERNP does not define the free flow state by measuring traffic speeds at night. Instead, free flow and traffic speed are compared at identical timestamps, allowing for a comparison between average historic network performance and current network utilization. Most transportation services do not occur at night, rendering free flow results measured during closing hours irrelevant. To allow for a better estimation of occurring traffic costs, the average network performance during delivery hours adjusted by current real-time traffic attributes should be taken into account. Interestingly, when applying the DERNP logic, differences between free flow and congested state diminish in many cases since major German cities tend to suffer from a constantly high level of traffic congestion. Due to this, free flow and congested network performance converges during the relevant business hours.

6.6 Limitations and Further Research

While digitization and open data platforms, such as OSM, provide researchers and analysts with large sets of data, the validity of such crowd-sourced data is a matter of concern. DERNP implements multiple types of validity checks, especially for calculated road attributes. Nonetheless, it fails to account for correctly inserted information by content creators. Several studies found that OSM data is mostly accurate for densely populated areas in developed western countries while accuracy decreases significantly for less developed regions [428–433]. Further studies might be necessary to validate these claims, especially for German road infrastructure referenced during this study as it represents the backbone of the proposed methodology.

In addition to OSM data, traffic information retrieved from the HERE Traffic API is another point of contention concerning the validity of the presented results. In general, further research should evaluate differences in historic traffic data between HERE and other navigation service providers, such as TomTom or INRIX. On a more specific note, external validity could be improved by incorporating additional timestamps throughout the day besides the five timestamps used in this study (08:00 a.m., 09:00 a.m., 12:00 p.m., 02:00 p.m., 04:00 p.m.), albeit at an increase in API requests and the costs associated with it. This change would also allow for a better estimation of isolated infrastructural impact, as performance deterioration inherently caused by network participants can be omitted or minimized at less populated timestamps such as 03:00 a.m. as was shown in previous studies [255].

In the same vein, the selected time frame of July 25 to September 10, 2022 covers the time period of summer vacation for most German states, which might distort the results observed. At the time of writing, the HERE Traffic API does not allow extraction of historic timestamps, severely limiting the availability of data without this distortion. Future research might investigate potential seasonality in network utilization, validating or refuting such concerns.

Another limitation to the validity of the provided results can be seen in the novel approach to driving cycle generation based on the WLTP. While the WLTP certainly provides accurate estimations for laboratory studies in vehicle emission behaviour, the applicability to real-world driving scenarios requires additional research. As Greenwood [316] points out, predictions of fuel consumption based on generated driving cycles may differ by up to 25 percent in comparison to data extracted from equipped single cars. Due to this, future studies should focus on validating and improving the customized driving cycles contained within the driving cycle catalogue by extensive field testing or comparative studies. Introduction of a smoothing factor to allow for better merging of individual road sections might improve accuracy to real-world driving behaviour.

In its current version, DERNP only includes RNP estimators for EURO 4 light passenger vehicles. While general performance patterns between cities will likely remain identical, specific emissions and cost factors will change significantly when incorporating modern engine models as well as heavy duty vehicles. Therefore, future research should focus on acquiring modern vehicle models and updating the provided results, either via licensing through TU Graz or by independent generation of suitable vehicle data.

As DERNP is meant as a generic and universally applicable database for RNP estimation, it tries to measure RNP across the entirety of a road network. While theoretically correct, in practice most transportation service providers, commercial or public, will traverse the same subset of individual network paths multiple times per week or day during operation, rendering generic results less representative for specific service areas. Future studies should focus on acquiring and comparing historic vehicle fleet data for specific service areas to general results provided by the DERNP to measure practical applicability in a more comprehensive study. More specifically, DERNP results should be compared to commercial solutions such as PVT Vissim in order to acquire a reliable benchmark for representativeness of open source solutions in comparison to established commercial software packages.

In addition to these proposed changes, research should focus on identifying potentially missing latent parameters relevant to RNP (besides detour, infrastructure, traffic, and elevation), which are not included in either the current or any previous iteration of RNP Measurements. Exploratory studies might also be valuable in incorporating the last remaining dimension of social sustainability into RNP Measurements. As a starting point, DERNP enables the inclusion of vehicle noise emission frameworks such as CoRTN or CONOSSOS on the basis of highly detailed 1Hz customized driving cycles included within the driving cycle catalogue. By combining all required information to implement these frameworks, our method can help to quantify the impact of RNP on urban social sustainability.

6.7 Conclusions

The contribution of this paper is the presentation of an efficient methodology to generate a large set of representative individual driving cycles through OSM road networks by referencing the Worldwide Harmonized Light Vehicles Test Procedure. Based on this driving cycle catalogue, the reference Database for Estimation of Road Network Performance (DERNP) is derived using the PHEMLight5 emission framework and allows for efficient estimation of relevant RNP parameters based on simple air distance calculations. DERNP overcomes many limitations of contemporary RNP research, especially the lack of availability for large and representative vehicle kinematic data, enabling efficient regional comparisons for researchers and practitioners alike.

Using DERNP, we have quantified and shown that when examining the impact of RNP on the economic dimension of sustainability, it is mandatory to consider several types of costs in parallel: distance-based and time-based costs. In addition to previous RNP Measurements, DERNP further differentiates distance-based costs into vehicle usage costs, fuel costs as well as CO_2 compensation costs, effectively integrating environmental sustainability into transport costing.

Future studies could focus on different parts of the presented methodology: (1) integration of the last dimension of sustainability, social sustainability, into the DERNP via implementation of the CoRTN or CONOSSOS frameworks to estimate road noise pollution based on the highly detailed vehicle kinematic data included in the driving cycle catalogue. Additionally, further research is required on (2) validation and improvement of the WLTP-based custom driving cycle logic using extensive field testing or comparative studies. Lastly, (3) researchers might aim to integrate modern vehicles, especially EURO 6 Light Passenger Vehicles as well as heavy duty vehicles, into the DERNP by licensing or generating suitable vehicle models to supply to the PHEMLight5 emission model, increasing external validity and applicability of the presented results.

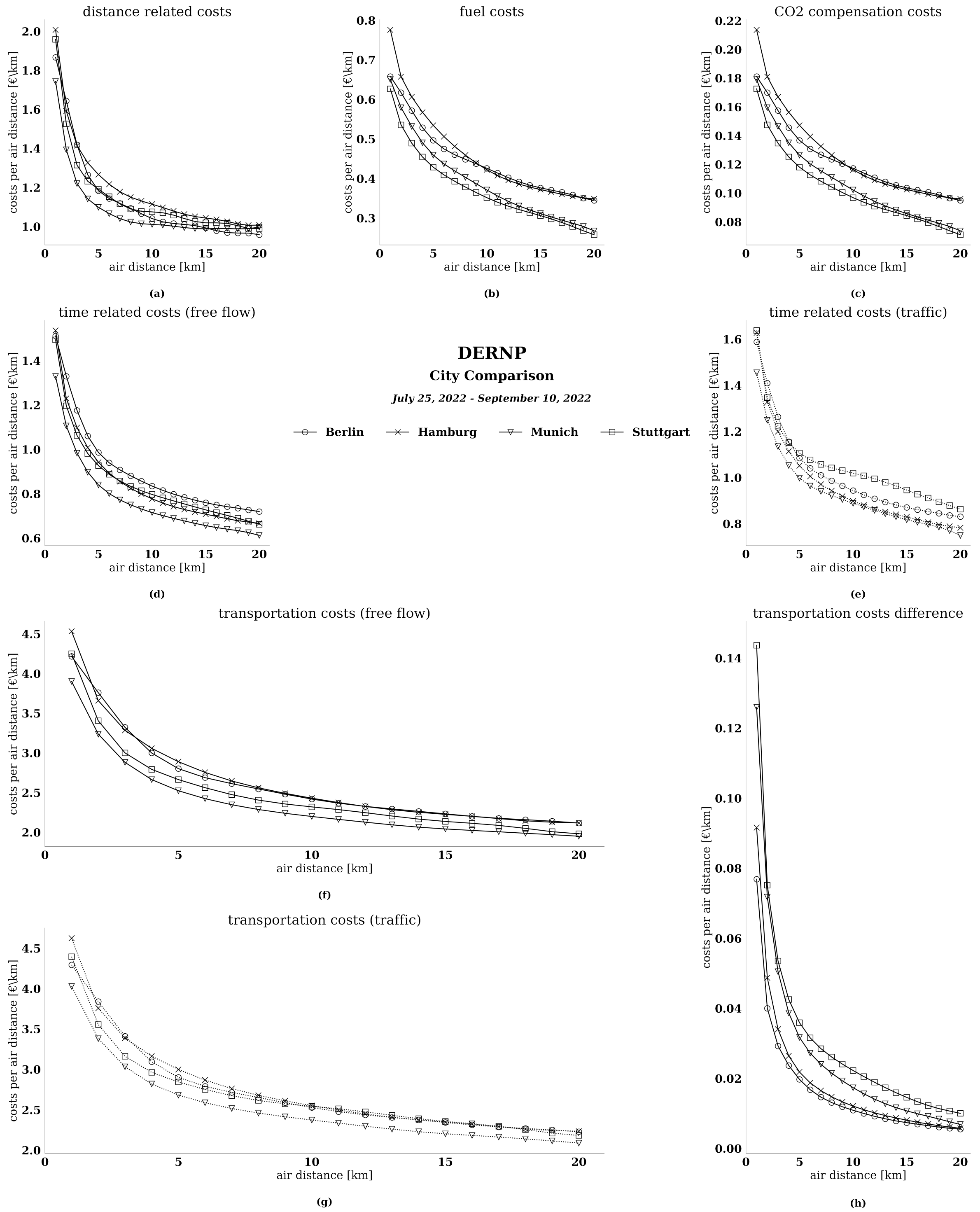


Figure 6.13: City comparison: costs per air distance kilometer.

Part III

Research Impact

CHAPTER 7

Final Conclusion

It is widely known and accepted that the economy of a nation or geographic region depends heavily upon an efficient and reliable transportation system to provide accessibility and promote the safe and efficient movement of people and goods [40]. Measuring and incorporating regional road network characteristics into road transport calculations becomes increasingly important as network usage continually increases while available transport capacities systematically decrease [46, 398, 434]. Both commercial transportation service providers, i.e. freight forwarder and public transport, as well as private road users are required to traverse the same finite infrastructure.

While availability of suitable tools and necessary data has steadily increased, many DSS and calculation models still rely on static information and outdated assumptions about the state of road networks [435]. Existing attempts on RNP calculations are based on individual and selective studies, trying to derive generalizable insights from limited information [305, 436]. What these attempts fail to account for is the highly volatile nature of traffic congestion patterns [237, 437]. Traffic congestion is characterized by significant temporal and geographical variability [7]. Measurements of an identical road section may vary significantly throughout the day, between weekdays and weekends as well as between different seasons of the year. What holds true for a specific road section may have no significance for surrounding road sections within the same geographic area. It is therefore unrealistic to assume that selective studies can derive generalizable and representative insights to enable reliable DSS, resulting in unrealistic cost estimations of road transport in terms of economic, ecological and social sustainability.

To enable reliable DSS, a more cohesive approach to RNP measurement is necessary. Instead of focusing on selective studies, this dissertation approaches the issue of generalizable RNP measurements by leveraging API-based aggregate FCD in combination with crowd-sourced topology data from OSM. By combining both factors, a digital representation of the German road transport network is generated and enriched by historic traffic data. Based on this digital representation, a methodology to efficiently generate and evaluate artificial and representative driving cycles is developed. As a result, this dissertation presents the first representative and publicly available RNP index for all 80 German metropolitan areas.

7.1 Scientific contribution

Due to the cumulative nature of this thesis, the practical and theoretical implications of this new approach to RNP measurements are elaborated separately across all three manuscripts. The upcoming subsection summarizes those implications to draw a broader picture of the presented research. The first paragraph details their general contribution to the overarching research endeavor within this thesis - identifying new approaches to RNP measurements. Bullet points depict additional implications for researchers and practitioners.

7.1.1 Implications of manuscript 1

Manuscript 1 “Towards Sustainable Cities: Utilizing Floating Car Data to Support Location-Based Road Network Performance Measurements” (see Table 3.1 and Chapter 4) solves the problem of determining RNP for geographical regions without reference to selective studies or existing shipment structures. It leverages the potential of aggregate FCD provided as isoline polygon via the so-called TomTom ”Reachable Range” API, which, at the time of publication, had received little attention within the literature. It significantly contributes to the research goal of reliable and generalizable RNP measurements by identifying and efficiently integrating a new data source for historic traffic information. The computational benefits of isoline calculations come at the expense of manual selection of suitable and comparable points of origin. The point of origin is considered a crucial component as a small shift in a certain direction can lead to significant differences in results. Further research is therefore required to either (1) determine an algorithmic or heuristic procedure to automatically identify relevant points of origins for isoline calculations or (2) identify different methodologies besides isoline calculations to efficiently integrate FCD into RNP measurements on a wide geographic scale.

Additional managerial implications derived during the process of integrating FCD into RNP measurements are stated below:

- Due to a high temporal variance in traffic usage patterns, the time of departure highly impacts achievable travel times for OD pairs. Travel time is significantly increased during rush hours in the morning and early afternoon, whereas the hours around midnight are considered traffic-free. These hours can be used as a reference when talking about the so-called free flow state.
- Free flow is characterized by an accepted delay. Even with no additional traffic, inherent restrictions such as infrastructure and traffic signs lead to a lower average travel speed than speed limits alone would induce.
- Little academic attention is paid to the detour factor. The proportion of required travel distance in comparison to covered air distance has a significant impact on travel costs and reflects the efficiency of network configurations. It generally depicts an inverted degressive curve as increasing air distances tend to allow for more efficient, i.e. increasingly straight, road segments such as highways to become available.
- Varying points of origin across different geographical regions lead to significantly different travel costs. A deliberate or unconscious choice of good or bad points of origin can therefore significantly distort RNP measurements but may serve as a good assessment during facility evaluation.

7.1.2 Implications of manuscript 2

Manuscript 2 “Speed Limit Induced CO_2 Reduction on Motorways: Enhancing Discussion Transparency through Data Enrichment of Road Networks” (see Table 3.2 and Chapter 5) explores the possibilities of generating representative digital road network models from crowd-sourced topology data using the Python library OSMnx. The presented methodology manages to integrate OSM topology data as well as aggregate FCD requested from the TomTom routing API and governmental traffic count data across the entirety of the German motorway network to enable transparent and reliable CO_2 emission calculations. Within the political context of motorway speed limit discussions, it delivers a solution to not only support or refute certain claims of CO_2 emission savings but manages to improve upon shortcomings of Manuscript 1, enabling efficient RNP measurements on a wide geographic scale while simultaneously integrating the ecological dimension of sustainability. Manuscript 2 provides palpable evidence that the integration of multiple publicly available data sources concerning road transportation and their mapping onto a network-based dynamic data structure consisting of nodes and edges may serve to successfully overcome shortcomings of existing RNP measurements.

Besides these insights for further research within the context of this dissertation, additional managerial implications concerning speed limits and their impact on CO_2 emission savings can be derived:

- The results show that a general speed limit throughout the German motorway network would lead to significant CO_2 reductions. This is in line with recent literature. Minor improvements were made compared to the official study from the German Environment Agency to allow for improved transparency.

- A flat rate speed limit would impact 70% of total flow kilometer driven whereas more than 3.5 million tons of CO_2 can be saved annually. These savings could be realized by restricting only 50.74% of all network sections through the use of Variable Speed Limits which could possibly lead to much greater acceptance by network participants.
- The calculated CO_2 savings can be seen as a bottom-line estimation. The amount of reduced pollution is potentially much higher as slower driving leads to fewer traffic shock waves, improved traffic flow, less braking and fewer accidents.

7.1.3 Implications of manuscript 3

Manuscript 3 "Sustainable City Evaluation using the Database for Estimation of Road Network Performance" (see Table 3.3 and Chapter 6) builds and improves upon the insights extracted from manuscripts 1 and 2. It solves the remaining problem of obtaining a representative set of OD paths throughout varying geographical areas to allow for generalizable and comparable RNP measurements. The resulting Database for Estimation of Road Network Performance is generated on the basis of a randomized route sampling procedure that utilizes the Worldwide Harmonized Light Vehicles Test Procedure in combination with the tile-based HERE Maps Traffic API v7 and a digital elevation model provided by the European Union's Earth Observation Programme Copernicus to generate a large set of independent and realistic routes throughout OSM road networks. These artificially generated routes are evaluated using the PHEMLight5 framework to provide a comprehensive list of RNP parameters for all German metropolitan areas. All parameters are included as regression coefficients and can be integrated seamlessly into existing calculation models and studies.

Besides the methodological impact, additional findings concerning regional differences in RNP can be derived:

- The significance of the detour factor is further supported by the evaluation of all relevant network paths within a specified region. Short distances in a large city introduce a heavy detour penalty due to the densely populated inner-city areas. As air distance increases, larger surrounding roads, also known as arterial roads, are accessible, significantly decreasing the detour necessary to cover air distance.
- The detour factor adequately reflects inherent network characteristics. The city of Hamburg, due to its proximity to the river Elbe and its many waterways, suffers from a comparatively higher detour factor in its inner-city area. Only after exiting the inner-city area and gaining arterial road access, the detour factor decreases as more direct connections become available.
- The integration of elevation data significantly impacts fuel consumption and CO_2 emissions. Vehicles in areas containing large changes in altitude can save a disproportionately high amount of fuel while coasting in comparison to the increased fuel consumption caused by traversing positive slopes within the network. The city of Stuttgart, due to its geographical location within the valley basin of Stuttgart and its unusual city area which extends over an altitude difference of almost 350 meters, provides a case in point to this phenomenon.
- The city of Berlin underlines the importance of referecing average speeds in comparison to general traffic congestion metrics. Berlin simultaneously suffers the least from congestion in comparison to other German cities while achieving the slowest travel speed in free flow and the second-to-last travel speed in congested state. While at first glance counterintuitive, based on this observation in combination with an average detour factor, it appears that traffic in Berlin is characterized by a continuously high level of congestion due to the sheer amount of traffic participants, influencing the historic free flow speed and significantly reducing the gap between free flow and congested state. This observation is in line with common assumptions and expectations concerning road transportation in the German capital of Berlin.
- The DERNP allows translating environmental sustainability into economical impact by proposing the inclusion of CO_2 compensation costs into transport cost evaluation.
- The total costs of transportation per air distance kilometer are highest in Hamburg and Berlin both in free flow and congested state. While Hamburg suffers from less travel time loss compared to Berlin due to Berlin's general high network utilization, the difference is equalized by an increase in travel distance and distance related costs due to inefficient infrastructure as measured by the

detour factor. Since both fuel and CO_2 compensation costs correlate only with travel distance, both Hamburg and Berlin inflict a disproportionate cost surplus in comparison to Munich and Stuttgart.

- Transportation is most cost-efficient across all cost components in the city of Munich. A low detour factor due to well-built infrastructure in combination with comparably less congestion and better optimized free flow conditions allow for savings of up to EUR 0.6 per kilometer air distance in Munich compared to Hamburg.

- Stuttgart inflicts higher distance and time related costs than Munich but saves significantly in terms of fuel and CO_2 compensation due to increased coasting possibilities based on its geographical location. Nonetheless, even combined, these savings account for no more than one-third of total distance-related costs, resulting in transportation costs slightly higher than in the city of Munich both in free flow and congested state

- As path lengths increase, the difference between free flow and congestion rapidly decreases due to an increase in availability for alternative routes and faster arterial roads. Converging onto EUR 0.01 per kilometer for paths upwards of 15 kilometers air distance, differences become negligible, removing the need of accounting for time-specific traffic conditions.

  While not explicitly described within manuscript 3, the most important managerial implication derived from the DERNP within the context of this thesis is the fact that it has become increasingly feasible to correctly and systematically determine RNP for large geographic areas. It is therefore mandatory for TSPs to increase their efforts on the integration of RNP into decision making, pricing, quoting, monitoring and general optimization of daily operations.

7.2 Limitations and further research

The new approach to RNP measurements described within this thesis constitutes the first cohesive approach to automate the integration of FCD and crowd-sourced topology data in an attempt to improve the capability of existing DSS within German road transport logistics. As is to be expected, this new approach adheres to a set of limitations that should be thoroughly investigated and improved upon by further research. The following subsection concludes the presented research by summarizing the individual limitations across all three manuscripts and provides relevant starting points for additional research.

7.2.1 Discovery and integration of data sources

This thesis and its included manuscripts rely on the integration of external API data and data extracted from Open Data platforms. While these data sources provide aggregate data based on transactional requests, alleviating the issue of data availability that historically hindered the research process within the field of road transportation, they are prone to (1) rapidly changing API specifications and data structures as well as (2) potential errors due to non-validated user input in crowd-sourced data. During the writing process of this thesis, the underlying APIs providing FCD changed multiple times. The tile-based HERE Maps API Version 7, which enabled the underlying methodology in manuscript 3, has been released in its current form in April 2022. The potential it brings with it was unavailable for prior research.

Rapidly changing fields of study require perpetual systematic review of available data sources and capabilities. Currently, no such studies exist in the literature and context of road transportation. In addition, all manuscripts contained within this dissertation rely on either TomTom or HERE traffic data, depending on which provider delivered the most compatible set of data during exploratory data analysis. No comparison is given to similarities and differences of available traffic data between both data providers. Consequently, further studies should focus on a systematic review of applicability between provided data. Included within this review should be additional potential data providers. Due to the self-funded nature of this research, more expensive commercial data providers such as INRIX have been excluded but may deliver more accurate and relevant data to feed into the proposed methodologies, potentially improving results.

In addition to systematic comparisons between API providers, further studies should be dedicated to examine and compare the set of available features within current iterations of FCD APIs, as all research presented within this doctoral thesis focuses only on a small subset relevant to each specific research question.

On the topic of crowd-sourced data, the data provided by OSM has changed significantly during the course of this research endeavor. To allow for comparability and reproducibility, all procedures within each manuscript rely on a fixed or cached set of OSM road network data extracted at specific points in time. Nonetheless, correctness and persistence of data are topics of major concern when working with crowd-sourced data and should be systematically investigated in future studies.

7.2.2 Incorporating historic shipment data

The methodologies presented within this dissertation focus on generalizable approaches to measure RNP on a wide geographic scale, both for the private and commercial sector. They deliberately abstain from incorporating TSP-specific historic shipment structures to avoid distorting the RNP index based on specific characteristics of individual transportation services. Further research might focus on and evaluate the applicability of the provided RNP measurements within a specific TSP context by integrating historic shipment structures and adjusting edge weights within the road network according to day-to-day operations. Additionally, the generation and integration of Heavy Duty Vehicle profiles into the DERNP calculation methodology should be considered to derive a representative set of RNP measurements in terms of fuel consumption and CO_2 emission for commercial truck fleets as these factors differ significantly in comparison to private vehicle fleets.

7.2.3 Improvements on driving cycle generation

Prior approaches to measure RNP within the literature tend to focus on referencing individually measured driving cycles through means of selective study. Manuscript 3 presents a more general approach to the issue of driving cycle availability by deriving artificial driving cycles based on the WLTP and the underlying road network infrastructure extracted from OSM. Nonetheless, as this is the first documented attempt at artificial driving cycle generation, further research is necessary to validate and improve its applicability and representativeness in comparison to real-world driving behavior due to its importance within the DERNP methodology.

7.2.4 Integration of social sustainability, esp. road noise pollution

While this thesis achieves successful integration and quantification of the economic and ecological dimension of sustainability into RNP measurements, in its current form it fails to account for social sustainability. One component of social sustainability is road noise pollution. The DERNP in its current form provides several important components required by road noise pollution calculation models such as CoRTN [337–339]. It entails infrastructural information derived via OSM as well as detailed 1Hz (per-second) driving cycles for a large set ($N = 40,000$) of artificially generated OD paths. Nonetheless, it fails to provide necessary information on road surface characteristics. Future studies should focus on empirical studies and quantitative approximation of road surface characteristics from OSM data and remotely sensed radar data in an effort to incorporate region-specific road noise pollution into RNP measurements.

7.2.5 Transferability of Road Network Performance Measurements

The results presented within this thesis are limited to the German road transportation network. Availability of historic traffic data via API as well as sufficient OSM coverage is an essential driver for the applicability of all presented methodologies. While these data sources are well-developed and therefore suitable for calculation within Germany, applicability should be studied for other geographic regions. In general, all methodologies can be applied to any geographic region as long as the respective API provides data for the specified region and OSM coverage is sufficient. Since the topic of RNP is of relevance to every developed country, comparative studies should be conducted based on the DERNP to reveal differences and similarities between road transport operations and reveal potential improvements based on the impact of underlying network and traffic characteristics to RNP measurements.

In addition to further studies on road transportation networks, the DERNP methodology successfully demonstrates the potential of integrating multiple data sources in combination with digital representations of transportation networks generated via crowd-sourced topology data and the algorithmic evaluation thereof. This inherent potential might not be limited to road transport but can possibly be expanded and transferred to other modes of transport such as railroad networks or bicycle infrastructure included within OSM.

CHAPTER 8

What lies ahead? Closing remarks on the topic of Road Network Performance Measurements

The field of study concerning Road Network Performance, esp. Location Intelligence and Spatial Statistics, is as volatile as the underlying phenomena of traffic usage patterns it tries to evaluate. New sources of relevant data seem to appear on a daily basis. They bring with them an increasingly large number of opportunities. What appears relevant today might already be outdated tomorrow by the discovery of a new and better way of leveraging existing data or the occurrence of a new source of data that falls outside the scope of existing literature.

It is a field of retrospect: Why did we decide to rely on assumptions instead of investigating the actual road network? Because we were unable to do so until this time and age of data availability.

It is also a field of inertia: Knowing that better ways exist, why do we choose to ignore them? Because acknowledgment of better ways coincides with the acceptance that our existing ways might be inefficient or plain wrong - and incorporating all available data might put the blame on us, potentially undeservingly so.

What is possible today in terms of computational capacity and data availability might have been unimaginable a decade ago. The speed of technological achievement is staggering. Almost as staggering as the notion that much of this available potential and intelligence is consciously ignored in everyday-practice.

In order to guarantee long-term profitability, TSPs have to adapt. They need to seize the available opportunities to learn more about the dynamic environment and systematically incorporate these insights into operational, tactical and strategic decision making. The tools exist. They have existed for close to, in some cases even longer than 10 years. And while the last 10 years have been staggering and full of potential, the outlook is potentially even brighter. What we need to learn is how to leverage and rely on external data. It is through this learning that additional value can be generated and sold - and by ignoring it, we purposefully decide to forgoe revenue. The fact is - time is working for this effort. And it will become increasingly fatal to deny and ignore its potential.

In the end, this thesis might be considered just another small step out of many remaining steps on the way to a more digitized and intelligent field of road transportation. Nonetheless, as does the ever-increasing rate at which newly emerging data sources occur, so does the inherent and yet unrealized potential lying dormant within them.

What lies ahead, only time will tell - but as computational capabilities and human creativity converge, one thing is for certain: **We should no longer concern ourselves with having the best or largest amount of data, but with deriving the best decision out of the already endless but ever-increasing corpus of all available data.**

May the smartest data win.

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