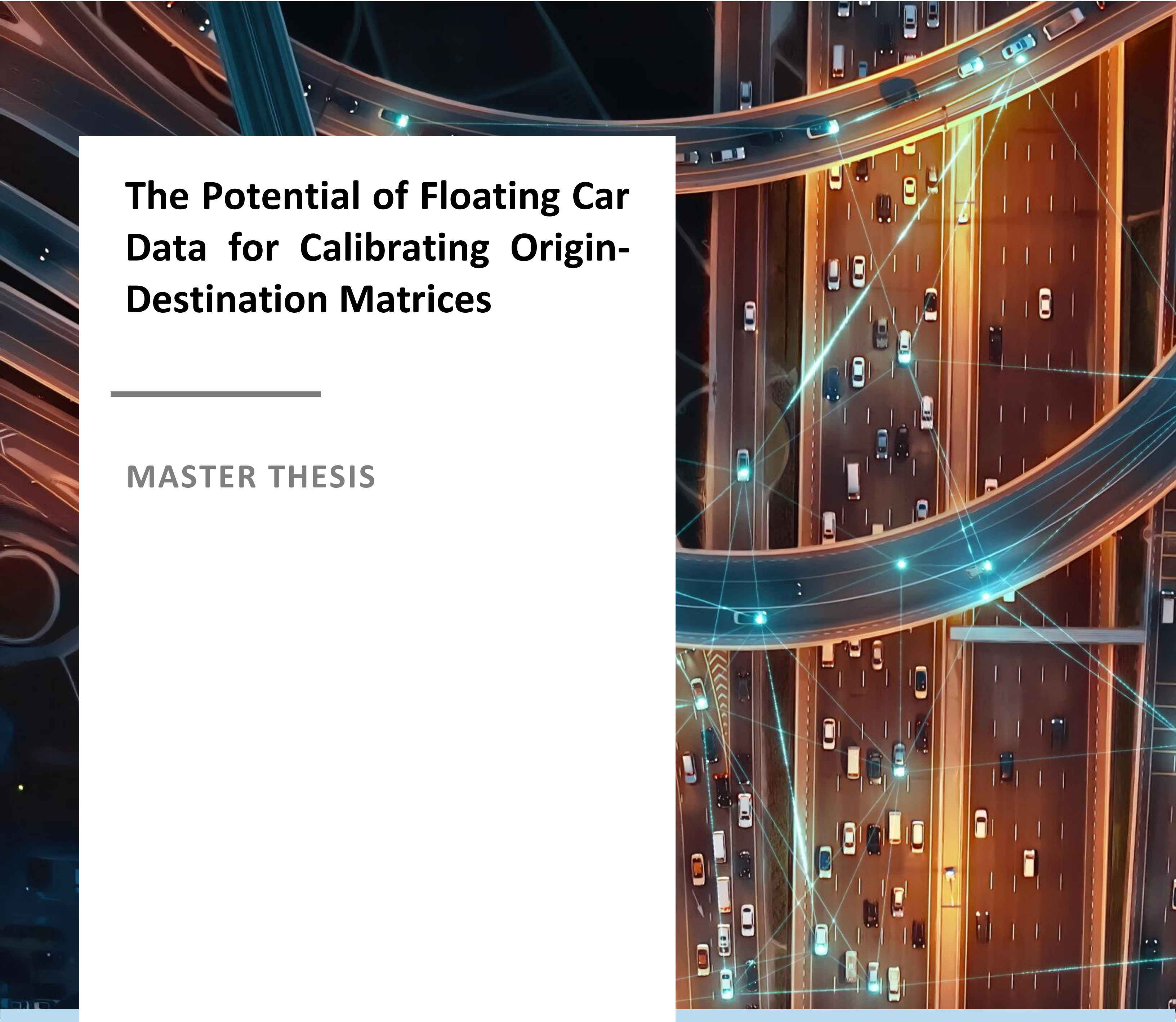

The Potential of Floating Car Data for Calibrating Origin-Destination Matrices

MASTER THESIS

Loes Hazenberg

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The Potential of Floating Car Data for Calibrating Origin-Destination Matrices

Master Thesis – Final report

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Preface

This is the final report of my master thesis titled ‘The Potential of Floating Car Data for Calibrating Origin-Destination Matrices’. This thesis finalises my master’s program in Civil Engineering and Management at the University of Twente. During my research project, I examined the representativeness of Floating Car Data for OD studies, after which I used these results to set up two calibration techniques for the Origin-Destination matrix of passenger cars, which incorporated FCD. I hope that my research contributes to a better understanding of Floating Car Data and its potential applications in Origin Destination calibrations.

During the past months I have learned a lot about the limitations and strengths of Floating Car Data. Furthermore, I gained more insight into how Origin-Destination matrices are estimated and calibrated. Additionally, during my thesis, I had the opportunity to get to know Sweco as an organisation. I want to thank all my colleagues at Sweco for their support and enthusiasm. In particular, I want to thank Roemer Dolman and Koen Blad for making this research possible and guiding me throughout the process. Their enthusiasm, feedback and discussions on the research helped me improve my thesis.

Furthermore, I would like to thank Oskar Eikenbroek and Eric van Berkum for their supervision from the University of Twente. The discussions and feedback helped me to bring the research to a higher level and to gain more insights into research in the traffic engineering field.

Lastly, I would like to thank my family and friends for their support. A special thanks to all fellow students in ‘UT Hok’ for their advice, discussions, and mental support.

Hopefully, you will enjoy reading this thesis!

Loes Hazenberg
Enschede, February 2025

Summary

Origin destination (OD) matrices are model constructs that estimate travellers' movements. As they are model constructs, the correct values of the matrix are unknown and cannot be determined. Typically, the matrix is calibrated with traffic counts, as this should result in an OD matrix corresponding to the actual traffic situation as closely as possible. Research shows that estimating a matrix solely using traffic counts is virtually impossible due to several shortcomings of the calibration process. This led to the question of whether alternative data sources, such as Floating Car Data (FCD), could improve the calibration process.

FCD is trajectory data retrieved from GPS positions of various navigation devices. Therefore, it contains information regarding the origin and destination of trips throughout the whole road network. This could mitigate some of the limitations of the calibration technique using traffic counts. However, as not every vehicle is equipped with a navigation device that is turned on, it is prone to sampling biases. Furthermore, the data is processed to guarantee users' privacy and could contain measurement errors, raising concerns about the data's logical consistency. These two factors could result in (part of) the FCD not being representative. Therefore, this study aims to assess FCD's representativeness and, based on the findings, develop a methodology for incorporating FCD into the calibration process of the OD matrix for passenger cars.

Within this thesis, multiple analyses are conducted to determine the representativeness of FCD. To start with, the estimation of the FCD penetration rate showed that the coverage varies across the different road classes, with a coverage of up to 29% on motorways compared to just over 9% on urban roads. The fact that the distribution of trip types varies per road type and the coverage is not uniform across the road network, illustrates that the FCD contains a sampling bias concerning trip types. This conclusion is also drawn based on a comparison of FCD to travel survey and traffic count data using the trip length distribution, distribution throughout the week and distribution across the day. The comparisons revealed differences between the datasets, indicating that FCD is not representative due to sampling bias or data inconsistencies. The last analysis of the representativeness examined the logical consistency specifically. This analysis revealed that within the data, trips are presented with origins and destinations that are not logical, such as a motorway. This led to the conclusion that FCD regarding the trajectory of a trip is not representative and, therefore, not applicable to OD studies.

Nevertheless, these analyses also revealed that the traffic volume can be roughly estimated using FCD volumes and the penetration rate. Furthermore, the selected link distribution of vehicles taking an off-ramp on the motorway is comparable for FCD and traffic count data. Therefore, these two applications are concluded to be representative and, therefore, suitable for OD matrix calibration. As earlier research revealed that adding more traffic counts leads to a more accurate OD matrix, these applications are used to generate so-called virtual traffic counts. This is done via two approaches: the placement of virtual traffic counts across the road network and virtual traffic counts on the off-ramps of the motorway and trunk road.

The effects of implementation are evaluated using GEH values, screenlines and information regarding the differences between the matrices and traffic assignment. As the results are not unequivocal, no definite conclusions could be drawn regarding the effect of implementing FCD. This leads to the conclusion that it is uncertain whether incorporating FCD via the systematic implementation of virtual traffic counts, positively or negatively impacts the calibration process. However, as some of the results are promising, it is recommended that further research be conducted into the representativeness of FCD and how the FCD can be incorporated within the calibration process of an OD matrix.

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1. Introduction

1.1. Problem context

To gain insight into the number and type of movements within a study area, Sweco has developed a strategic traffic model. The model can be employed to make strategic and tactical decisions regarding traffic and transport by evaluating different scenarios (CROW, 2012). One key output of the model is the generation of Origin-Destination matrices (OD matrices) for a range of transportation modes, including passenger cars. An OD matrix is a representation of a study area that provides estimations regarding the movements of travellers (TU Delft, 2022).

As a model is a simplified representation of a system or process (Cambridge Dictionary, n.d.-a), it is accompanied by limitations. Therefore, it is uncertain how well the results of the strategic traffic model correspond to the actual traffic situation. Ideally, the results, specifically the OD matrices, are compared to the so-called ground truth matrices. Ground truth matrices are defined as the matrices corresponding to the actual situation. Nevertheless, these matrices do not exist, and data is lacking to create them, making it virtually impossible to determine whether the OD matrices accurately represent the actual traffic situation. To ensure that the OD matrix of passenger cars approaches the actual traffic situation as closely as possible, this OD matrix and the associated traffic assignment are calibrated with field data, typically traffic counts (Zhang & Osorio, n.d.). In Figure 1, a schematisation of the calibration technique is displayed.

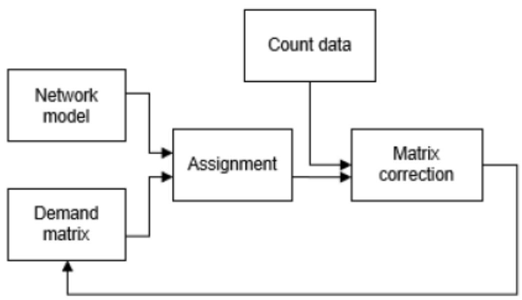

Figure 1: Schematisation of the OD matrix calibration utilising single traffic counts (PTV Group, 2020).

As the figure illustrates, the traffic volume computed by the model is based on the OD matrix and route choice. The traffic volume is, therefore, typically dependent on specific OD pairs of which (a proportion of) the trips pass through a road segment. Consequently, specific OD pairs are updated by comparing a road segment's assigned traffic flow to the traffic counter's measured volume at this road segment.

Although this approach is widely applied, it is subject to shortcomings. For instance, typically, fewer traffic counters are present than origins and destinations, making it impossible to update the OD matrix correctly (Marzano et al., 2009). As the volume of traffic counts also depends on the traffic assignment, the calibrating process is also affected by the accuracy of the traffic assignment. Moreover, some properties of the data sources do not match. For example, the matrix is, in contrast to the traffic counts, purpose-dependent. Also, the OD matrix is deterministic, while the counts include variations due to errors and traffic demand's volatile nature. Due to these limitations, it is desirable to investigate whether other techniques and data sources might improve the calibration process, resulting in a more accurate OD matrix.

A potential data source for this is Floating Car Data (FCD). FCD is data obtained using the GPS positions of various devices, such as navigation systems, mobile phones and tracking systems. This data can be translated into trajectory data of the vehicle from which properties such as the origin and destination of the trip can be computed (NDW docs, n.d.). Furthermore, the data is available throughout the whole network (HERE, 2024b). Due to these properties, FCD may reduce or even eliminate (some of the) shortcomings of the calibration process.

However, since FCD is generated by part of the vehicles that contain navigation devices, known as probe vehicles, certain trip motives may be under or over-represented within the dataset. Moreover, FCD is processed to guarantee user privacy. This and other factors, such as measurement errors, could compromise the logical consistency within the FCD. The under or overrepresentation of specific trip types and inconsistencies might cause the FCD to be not representative concerning the actual traffic situation. Should this be the case, applying (certain parts of) FCD in OD studies may not be possible because it does not lead to reliable and representative results. Therefore, it is desirable to investigate the potential of FCD for OD analysis, or more specifically, OD matrix calibration, by identifying how representative FCD is.

Consequently, the objective of this study is to determine FCD's representativeness in the context of OD analysis and examine how FCD can be implemented into the calibration of the OD matrix for passenger cars while considering its shortcomings.

1.2. Thesis outline

In the remainder of this report, the research conducted for this master thesis is outlined. Chapter 2 describes the results of the literature review. Based on the problem context and research gap, a research structure is formulated in Chapter 3. Chapter 4 outlines the research setup, consisting of a description of the case study, data, and a brief overview of the methodology. In chapters 5 and 6, the methods and results of the two topics central to this study, the analysis of the representativeness of FCD and the implementation of FCD in the OD calibration process are discussed. The report concludes with a discussion and a conclusion in chapters 7 and 8.

2. Literature review

A literature study, of which the results are presented in this chapter, is conducted to better understand the study's background and obtain information from previous studies. The first subsection discusses the importance of OD matrix calibration, the technique to calibrate it, and the drawbacks of the current calibration technique. As FCD plays a significant role in this study, an overview of what exactly FCD is and the advantages and shortcomings of FCD are presented in the second sub-section. This involves an overview of how FCD could overcome the limitations of the current calibration technique and how FCD is already utilised in OD studies, specifically in OD matrix estimations.

2.1. OD matrix calibration

Sweco's strategical traffic model is based on a four-stage model. Even though strategical traffic and transport models, or more specifically four-stage models, are widely applied (for example, by Heyma et al. (1999) and Goudappel Coffeng (2016)), a literature study of Mladenovic & Trifunović (2014) revealed that there are multiple drawbacks to the four-stage method. Some of the limitations addressed by Mladenovic & Trifunović are the fact that usually, within the four-stage model, only a certain amount of trip purposes are considered. Whereas in reality, more trip purposes may be applicable (Johnston, 2014). Furthermore, during the traffic assignment process, all trips are typically assumed to originate and terminate in the centroid of a zone. Another shortcoming addressed by Gu (2004) is that the model represents the average group of travellers. The predictive capabilities of the model are, therefore, marginal, as also indicated by Vuchic (2005).

To ensure that, despite the limitations of the four-stage model, the OD matrix reflects the actual traffic demand as closely as possible, the OD matrix is generally calibrated to fit field data, typically traffic counts (Zhang & Osorio, n.d.). To execute the calibration, the assigned flow per link must be determined using Equation 1.

$$V_a = \sum_{ij} f_{ij} p_{ij}^a$$

Equation 1

In which V_a is the flow assigned by the model to link a, f_{ij} is the number of trips from zone i to zone j resulting from the OD matrix and p_{ij}^a is the proportion of trips from zone i to zone j which travel through link a with $p_{ij}^a \geq 0, \sum_a p_{ij}^a = 1$.

As the equation suggests, the assigned traffic volume results from the OD matrix and route choice. Consequently, the involved OD pairs are updated by comparing the assigned flow of a road segment to the measured volume of a traffic counter on this road segment. Therefore, the number of independent traffic counts should equal the number of OD pairs to create a unique OD matrix. An independent traffic count is a traffic count whose flow cannot be expressed as a linear combination of the flows measured by other traffic counters (Willumsen, 1978). Accordingly, in practice, more OD matrices will lead to satisfaction of the traffic counts, i.e. the accompanying system of equations is underdetermined (Bell, 1991; Cascetta, 1984; Van Zuylen & Willumsen, 1980).

Typically, optimisation techniques are utilised to update the matrix as the calibration usually involves multiple traffic counts, making it a complex problem. Examples of such methods are the entropy maximisation approach developed by Van Zuylen & Willumsen (1980) and statistical inference approaches, including maximum likelihood, generalised least squares, and Bayesian inference (Abrahamsson, 1998). In the case of calibration, constraints are applied to ensure that the structure of the a priori matrix remains relatively unaffected. In addition, it is possible to execute the calibration in an unstructured method where the estimated matrix is not constrained to a feasible space imposed by a structure obtained from, for example, an existing travel demand model (Ortúzar S. & Willumsen, 2011).

2.1.1. Shortcomings OD matrix calibration

Although calibrating OD matrices with traffic counts is widely applied, this approach has some drawbacks. Papola & Marzano (2006) found that, generally, the OD matrix calibration cannot update the OD matrix correctly. Marzano et al. (2009) concluded that this is because the system of equations is underdetermined. Nevertheless, a higher number of independent traffic counters generally increases the quality of the estimated OD matrices (Lam & Lo, 1990; Yang et al., 1991). However, the location of traffic counters also plays a crucial role in OD matrix estimation (Yang & Zhou, 1998). For example, specific OD pairs may have multiple traffic counters on the routes adopted, while the routes between other OD pairs do not pass any traffic counter. As the proportions between the traffic counts and the OD matrix depend on the route choice, multiple structures of the OD matrix could match the traffic counts.

Furthermore, various studies, such as Mohammed et al. (2016),and the Advanced Traffic Analysis Center of the Upper Great Plains Transportation Institute (2023), evaluated different traffic counters. All studies show a difference between the volume counted and the actual traffic volume, implying that the calibration of the OD matrix is based on incorrect traffic volume measurements. However, even if there are no errors in the traffic counts, counts are subject to daily fluctuations due to the volatile nature of traffic flows. While the OD matrix is generally deterministic, representing a defined time period (Hamerslag et al., 1988). These inconsistencies could lead to contradictions in the mathematical equations, resulting in a situation in which the calibration process does not succeed in updating the OD matrix.

Moreover, the OD matrix is typically purpose-dependent, following from the purposes taken into account by the (four-stage) model (Ortúzar S. & Willumsen, 2011; Tsekeris & Tsekeris, 2011), while the traffic counts do not include such information. Therefore, the rationale behind an OD matrix is not considered and the matrix may become obscured.

2.2. Analysis of Floating Car Data

FCD is currently utilised to achieve different objectives, such as improving road safety and minimising disruption during road works (Rijkwaterstaat, n.d.). A significant advantage of FCD compared to traffic counts from stationary sensors, specifically inductive loop detectors, is that it does not require additional investment and maintenance costs. Also, the data collected by FCD is distributed throughout the whole network and not limited to specific locations in the network (HERE, 2024b). Studies have been conducted regarding the accuracy of FCD, for example, by comparing the speed measured by FCD to the speeds measured by stationary count locations like sensors and induction loops (Kessler et al., 2018; Naranjo et al., 2010; Van Der Loop et al., 2019) and by analysing how well FCD can detect traffic jams (Brockfeld et al., 2007; Kessler et al., 2018). These studies illustrated that FCD is reasonably consistent with the other datasets. Nevertheless, these studies do not consider the application of FCD for OD analyses. A literature review on this application reveals that FCD still has some limitations. Meanwhile, FCD has already been applied in OD analyses, and it contains some properties that could reduce the limitations of the current calibration technique.

2.2.1. Limitations FCD

A frequently mentioned drawback in literature is the coverage of the FCD, as not every vehicle has equipment that determines and transmits the GPS location of the vehicle (HERE, 2024b). Therefore, only a portion of the vehicles is included in the FCD, so-called probe vehicles. The problem is not solely that FCD represents only a share of the vehicles but that it is unknown which percentage of vehicles generates Probe Vehicle Data. To understand the penetration rates, volumes based on FCD are compared to those from stationary counting devices. However, it should be noted that a spatial limitation is present within such analysis as the stationary counts are not available for the whole road network (Fourati et al., 2021).

Despite this limitation, Hastig managed to estimate the road intensity based on the volumes of probe vehicle data and the estimated coverage of FCD. In Figure 2, a visual representation of the results is given. The blue line indicates that the estimated intensity corresponds to the measured intensity. The dots indicate the intensities measured at the different traffic counters. Dots near the blue line suggest that the estimated intensity is approximately equal to the measured intensity.

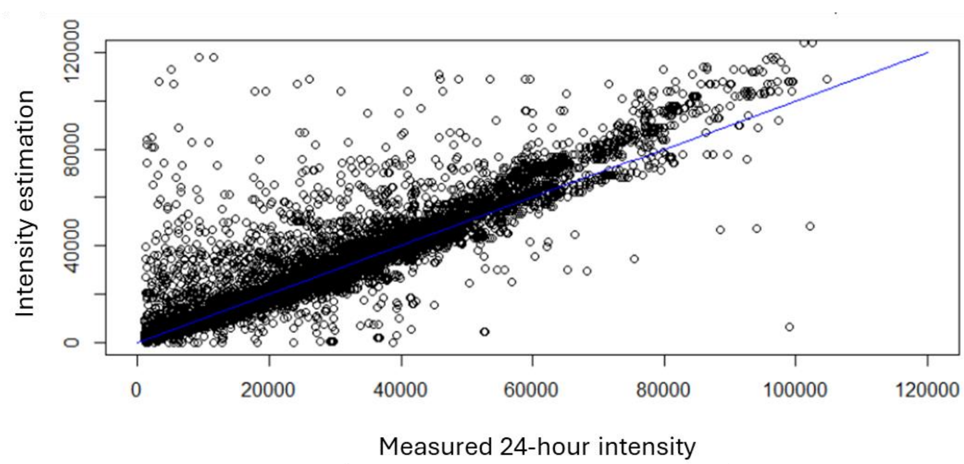

Figure 2: Results of the Intensity estimation method developed by Hastig. The intensity estimated per 24-hour (veh/24-hr) using FCD is displayed on the Y-axis. The X-axis represents the 24-hour intensity (veh/24-hr) measured by traffic counts. The figure is translated from NDW (2023) (Nationaal Dataportaal Wegverkeer, translated: National Road Traffic Data Portal).

It was found that over 90% of the traffic counts differ less than 50% from the estimation. For over 40% of the traffic counts, there was a difference of less than 10%. Additionally, it was concluded that with 24-hour intensities of more than 60,000 vehicles, the intensities are overestimated (NDW, 2023). This is also illustrated in the figure, as at the higher intensities, the dots vary more from the line.

Another limitation of FCD, as mentioned by Van Der Loop et al. (2019), is the sample's selectivity. Not every vehicle is a probe vehicle, so a sampling bias in the data could occur. NDW (n.d.-b) (Nationaal Dataportaal Wegverkeer, translated: National Road Traffic Data Portal) assessed the data quality of FCD retained from TomTom. The study revealed a slight overrepresentation of long-distance trips, which resulted in higher penetration rates on the main roads compared to 'lower' road classes, such as roads within residential areas. It was determined that the penetration rate was occasionally higher than 25% on the motorway, while in specific periods, the penetration rate was less than 5% for residential roads. This indicates variations in penetration rates across different road types and over time. Despite the possible lower penetration rate, the study mentions that analysis on lower-order roads is feasible as long as a longer period is considered.

2.2.2. FCD in OD analyses

Despite its limitations, FCD has several properties that have the potential to mitigate or eliminate some of the drawbacks associated with the current calibration technique. For instance, a benefit of FCD is that it is available throughout the whole network (HERE, 2024). This could facilitate the creation of additional traffic counts based on FCD. This may result in a more accurate matrix, as research indicates that an increased number of independent traffic counts leads, in general, to a more precise estimation of the matrix (Lam & Lo, 1990; Yang et al., 1991). The creation of traffic counts based on FCD, which is referred to as virtual traffic counts in the remainder of this study, appears to be a realistic approach as the traffic volume of a road segment can be estimated based on FCD (NDW docs, n.d.). Moreover, Sweco tested this approach in a scenario where the OD matrix appeared incorrect after calibration. After adding virtual traffic counts, the OD matrix seemed to correspond better to the actual traffic situation, indicating the potential for adding it systematically.

Even though adding virtual traffic counts can potentially mitigate one of the limitations of the current calibration technique, FCD also contains information which could mitigate other limitations. For instance, FCD contains information on the trips' origin and destination, which could mitigate the problem of the current calibration technique involving both the OD matrix and the traffic assignment. The data can, for instance, be used to identify whether the difference between the assigned volume and measured volume originates from the OD matrix or traffic assignment. Multiple studies have already been conducted in which the origins and destinations have been taken into account. Within these studies, existing estimation methods have been extended to include FCD. Vogt et al. (2019) complemented the Information Minimization model by van Zuylen (Van Zuylen & Willumsen, 1980), which is adapted by Pohlmann (2010) and Friedrich & Yun-Pang (2014) with FCD, while Mitra et al. (2020) utilised a data-driven approach. Both approaches have used the FCD to set up an a priori matrix. The results of the different studies vary considerably. Some studies (Ásmundsdóttir, 2008; Vogt et al., 2019) concluded that using FCD to estimate an OD matrix leads to accurate results. However, other studies (Nigro et al., 2018) concluded that OD matrices cannot be directly reconstructed utilising FCD. This is in line with the findings of Ceccato et al. (2022) and Nigro et al. (2018), who concluded that, in particular, the representativeness of probe vehicles affects the accuracy of the estimated matrix. For these studies, it should be noted that, besides Mitra et al. (2020) who tested the performance on the Turin network, OD matrix estimation is only conducted on a small-scale network. This could influence the results as the complexity of an OD matrix increases in a more extensive network.

Although FCD potentially mitigates, or even eliminates, some of the limitations of the current calibration technique, FCD cannot mitigate all of the limitations of the calibration techniques as FCD does not comprise the necessary information. For instance, just like traffic counts, FCD is subject to variations due to, among others, the volatile nature of traffic demand. However, the OD matrix and traffic assignment are typically deterministic. Also, the OD matrix is generally purpose-dependent, while FCD and traffic counts do not include information regarding the purpose of the trip.

2.3. Research gap

From the literature review, it can be concluded that the calibration process of the OD matrix for passenger cars is subject to limitations. Therefore, it is desirable to come up with alternative calibration techniques. As FCD contains much information that could mitigate some limitations, it could be a valuable addition to the calibration process. Currently, multiple studies have been conducted regarding the implementation of FCD within OD matrix estimations (Ásmundsdóttir, 2008; Ceccato et al., 2022; Mitra et al., 2020; Nigro et al., 2018; Vogt et al., 2019). Nevertheless, these studies used an unstructured approach, meaning that the estimation is not constrained to a feasible space defined by an a priori matrix. In the case of the calibration of an OD matrix retrieved from a strategical model, the feasible space is constrained. Therefore, research is needed to investigate the implementation of FCD within the calibration process of the OD matrix of passenger cars.

Additionally, most studies focussed on estimating an OD matrix for a small-scale network like intersections (Ceccato et al., 2022; Vogt et al., 2019) rather than a large-scale road network such as a neighbourhood, city, or region. As many OD matrices are currently created using models of larger areas, it is desired to research whether FCD is also applicable when calibrating such a matrix.

However, before the FCD can be implemented within the calibration process, more insight into its sample bias is desired. Since FCD is based on a proportion of the vehicles, it is possibly subject to sample selectivity (Fourati et al., 2021; NDW docs, n.d.-b; Van Der Loop et al., 2019). As this influences the precision and correctness of the estimated OD matrix (Ceccato et al., 2022; Nigro et al., 2018), it is likely that it also affects the accuracy of the calibration process. Moreover, no literature was found on studies who investigated whether the data of FCD contains inconsistencies due to measurement errors and the processing of data. As this affects the accuracy of the OD data of FCD, it can influence the calibration process. Therefore, more research into the sample bias and logical consistency of FCD is desired.

3. Research structure

3.1. Research aim

Following the problem context and research gap, a research aim is set up consisting of two parts. The first part focuses on the applicability of FCD for OD analysis. The second part aims to implement the FCD within the calibration process of the OD matrix. Leading to the research aiming to:

1. *Evaluate the representativeness of Floating Car Data for OD analysis compared to alternative data sources;*
2. *Develop a methodology for using Floating Car Data in the calibration process of the a priori OD matrix for passenger cars while accounting for the identified representativeness of Floating Car Data.*

Representativeness, as defined by Cambridge Dictionary (n.d.-b), is 'the fact of a smaller group of people or things representing a larger group accurately'. In this study, however, the representativeness encompasses not only sample selectivity but also the logical consistency of the data. Since FCD is generated exclusively by probe vehicles, the data may be subject to a sampling bias as a result of sample selectivity (Van Der Loop et al., 2019), which can affect the data's representativeness. Sample selectivity can be assessed by examining whether specific trip types are under or over-represented. However, as the actual distribution of trips is unknown, it is impossible to state with certainty which types are under- or over-represented. The sample selectivity can be estimated by comparing the FCD to other data sources, such as traffic count and travel survey data. Additionally, logical consistency plays a role in the representativeness of FCD. As GPS devices are subject to errors and the FCD is aggregated and anonymised to guarantee user privacy (M. Uenk-Telgen, personal communication via email, October 14, 2024). It is possible that errors are present within the dataset, thereby influencing the accuracy of the representation of the actual traffic situation. Moreover, as the research aim already suggests, in this study, the representativeness is only determined for the part of the data that influences OD analysis. For instance, the origins and destinations of trips are considered, while the representativeness of speeds according to FCD is not considered.

Using the FCD's representativeness for OD analyses, the FCD is implemented within the calibration process of the passenger cars' a priori OD matrix. A priori is defined as the matrix determined by the strategical traffic model before calibration. Section 4.1 gives a more detailed explanation of the model and calibration process. The choice to focus solely on this matrix is based on the fact that FCD is mainly based on passenger cars and is, therefore, the most interesting one to implement within this calibration process. After implementation, the results should be evaluated to get insight into the effect of implementing FCD in the calibration process.

3.2. Research questions

Five research questions are formulated to achieve the research aim. The first three questions relate to analysing FCD's representativeness. The other questions relate to implementing FCD within the calibration method.

Research question 1 is formulated to gain insight into the distribution of FCD on the network. By comparing FCD volumes with traffic count volumes, the penetration rate of FCD is determined, indicating its coverage across the road network. This can provide insight into which types of trips are relatively more represented in the dataset, as the trip types vary per road type.

RQ1: '*Can traffic volumes per road section be accurately estimated from Floating Car Data by computing the penetration rate of Floating Car Data?'*

After the coverage of FCD across the road network is determined, the representativeness of FCD for OD studies is further examined by comparing FCD on three indicators to travel survey and traffic count data. These three indicators are used as they give insight into the different trip types included within the data. This includes trip characteristics such as the trip length and departure time/day, as well as trip motives. As the distributions of FCD for the various indicators should be equal to those of the other data sets, a difference in the distribution can identify a sampling bias.

RQ2: '*How does Floating Car Data compare to data retrieved from a travel survey and traffic counters regarding the trip length distribution, distribution throughout the week and distribution across the day?'*

In this study, representativeness encompasses not only sample selectivity but also logical consistency within the data. The third research question aims to quantify this, allowing potential errors within the data to be identified.

RQ3: *'To what extent does Floating Car Data exhibit logical consistency in trip origin and destination patterns?'*

To achieve the second part of the research aim, a methodology has to be developed to incorporate FCD in the calibration process of the OD matrix for passenger cars while addressing its representativeness. Research question 4 aims to achieve this part of the research aim.

RQ4: '*How can Floating Car Data be used in the calibration process of the OD matrix for passenger cars?'*

The last research question aims to evaluate the effects of implementing FCD within the calibration process. The ultimate goal is to improve the accuracy of the matrix. Therefore, it is desirable to evaluate whether this is achieved. Given the absence of a definitive value for the matrix that would correspond to the actual distribution of trips, a range of indicators are employed to evaluate the effect.

RQ5: '*What is the effect of adding data obtained from Floating Car Data at the calibration process of the OD matrix for passenger cars on the model's results?'*

3.3. Research scope

This study focuses on determining the representativeness of FCD for OD analyses and implementing FCD in the calibration process based on these results. To analyse the representativeness of FCD, a comparison is made between the trip length distribution, the distribution throughout the week and the distribution across the day of FCD and the traffic count and travel survey data. In this study, a conscious decision was made to focus exclusively on these three indicators despite the existence of additional indicators for the representativeness of FCD, such as the Yuki-san indicators developed by Cerqueira et al. (2018). This is due to the availability of data to conduct other analyses and the fact that the currently employed indicators are expected to be most relevant for origin-destination information. Even though previous research revealed some bias and (measuring) errors in the traffic counts and travel survey dataset, for this study, it is assumed these are not significantly influencing the results.

As outlined, the second part of the study focuses on implementing FCD in the calibration process of the OD matrix for passenger cars. In this study, the decision is taken to limit the scope of the study to the implementation of FCD in the calibration process and not the model itself. Furthermore, different calibration techniques are applied for the OD matrices of the various transport modes. Given that passenger cars represent the largest proportion of traffic and, therefore, majority of vehicles on the road, this study only considers the OD matrix for passenger cars. Lastly, a case study is set up in this study, including only one model and study area.

4. Research setup

Within this chapter, the research setup is outlined. This entails introducing the case study employed in this study, an overview of the data included in this study and a brief overview of the methodology adhered to.

4.1. Case study

As outlined, within this study, a case study is used, which uses a single study area and model. This subsection introduces the study area, model and the current calibration process for the OD matrix of passenger cars.

4.1.1. Study area

This study uses a traffic model of the municipality Stichtse Vecht. The municipality Stichtse Vecht is located between the cities of Amsterdam, Hilversum and Utrecht within the province of Utrecht in the Netherlands, as indicated in red in Figure 3. The municipality was established in 2011 when the municipalities of Breukelen, Loenen and Maarssen were merged. Nowadays, the municipality exists of 12 centres (Gemeente Stichtse Vecht, n.d.).

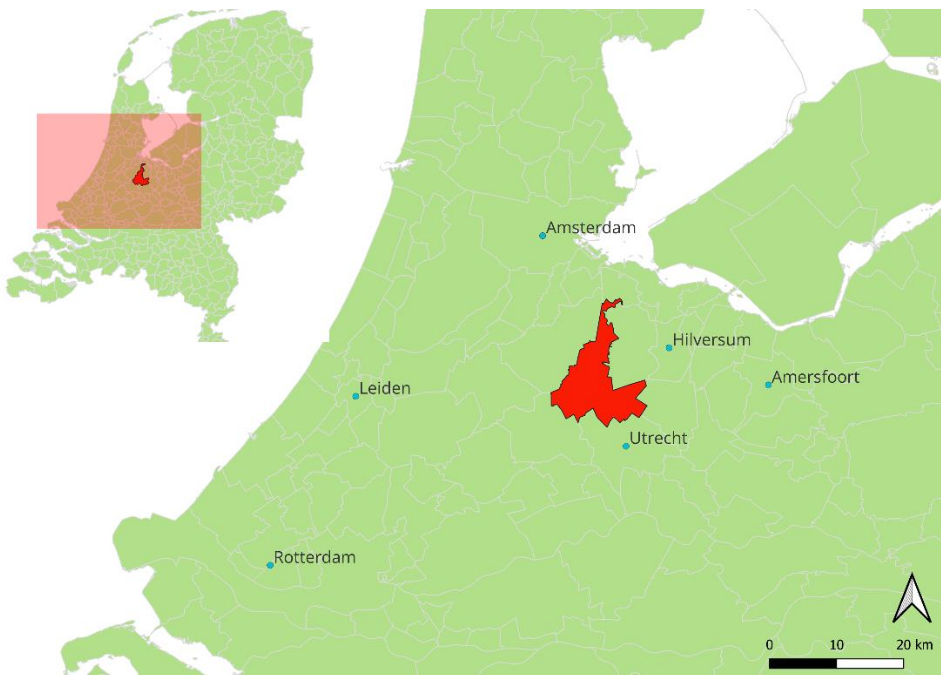

Figure 3: Indication of the location of the study area: municipality Stichtse Vecht (indicated in red) compared to the Netherlands.

In terms of infrastructure, the municipality is crossed by the A2 motorway. Furthermore, multiple provincial roads are situated within the municipality. The road network is dense within the different urban centres, with bigger connecting roads. Within the model, the HERE network is used, which distinguishes six road classes: motorways, trunk roads (in Dutch: autowegen), provincial roads, other rural roads, main roads within built-up areas, and other roads within built-up areas. Figure 4 provides an overview of the road network.

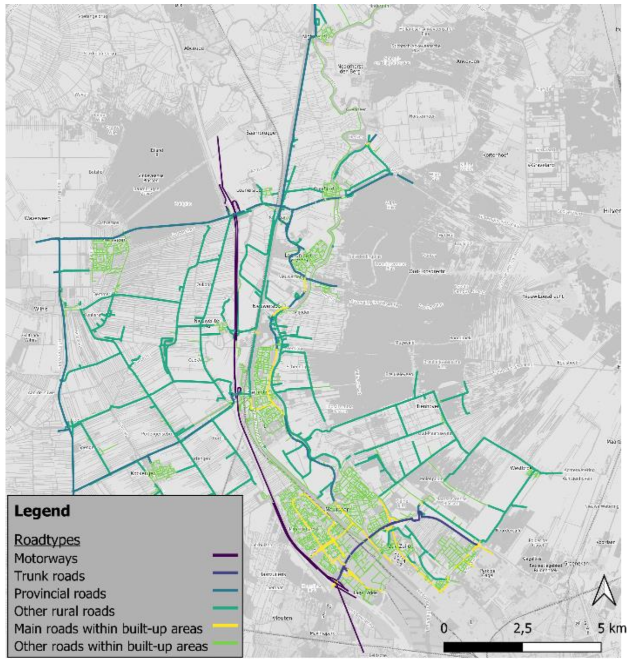

Figure 4: Road types in and around the municipality of Stichtse Vecht.

The model consists of 283 zones, of which 212 are ‘regular’ zones. The other 71 zones are so-called cordon zones. These cordon zones are needed to incorporate trips with a destination and/or origin outside the municipality, as the model is a cutout of a regional model of the province of Utrecht called StraVem. In Figure 5, the ‘regular’ zones are visualised. In this figure, the smaller zones correspond to areas within the municipality's built-up areas.

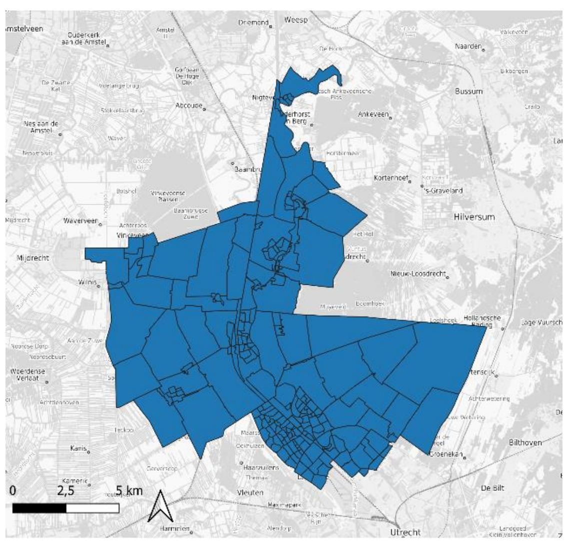

Figure 5: Overview of the different zones within the model of the Municipality Stichtse Vecht.

4.1.2. Model

This study focuses on calibrating the OD matrix for passenger cars determined by Sweco’s strategic traffic model. In this subsection, a more elaborate description of the model is given. All information in this section is retrieved from two internal documents of Sweco (Sweco, 2023, 2024).

The model results in OD matrices and its corresponding traffic assignments for an annual average working day, excluding public holidays, for three time periods: morning rush hour (07:00 – 09:00), evening rush hour (16:00 – 18:00) and residual day (anything but the rush hours). By aggregating the OD matrices for the six trip motives (Work, Business, Education, Shopping, Recreation and Other), an a priori OD matrix per transport mode is determined. The model considers ten transport modes: passenger car (driver), medium-heavy freight traffic, heavy freight traffic, bicycle, bus, train, tram, metro, pedestrians and car passenger, of which the latter two are not assigned to the road network. The access and egress transport modes, which are cycling and walking, are included for public transport.

The model is fundamentally a four-stage model. However, the model is modified, leading to three main stages: preparation (stage 1), demand model (stage 2) and the multi-modality and final assignment phase (stage 3). An overview of the model is depicted in Figure 6.

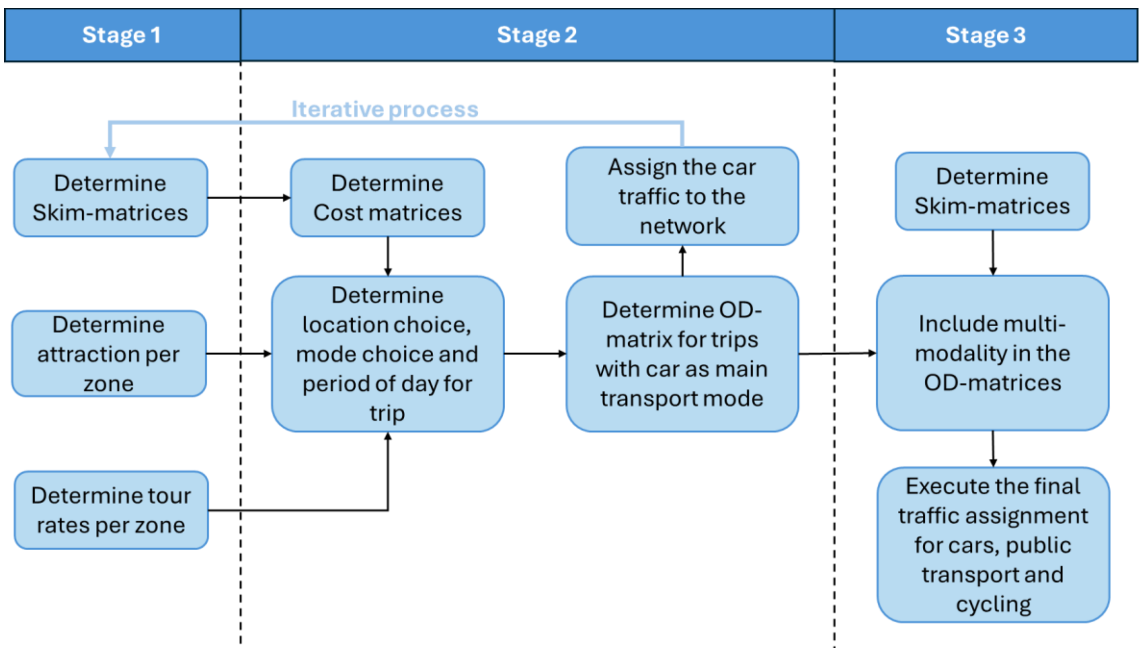

Figure 6: Schematisation of the different stages of the model for the transport mode passenger cars.

4.1.3. Current calibration methodology

As outlined in Section 2.1, the OD matrix is typically calibrated using traffic counts. Instead of adhering to the 'typical' calibration approach, in which the calibration is executed by comparing the count values to the assigned traffic (as described by Van Zuylen & Willumsen (1980) and Bosserhoff (1985)), PTV Visum developed a calibration technique based on the fuzzy sets theory of Rosinowski (1994) (PTV Group, 2020). This method considers the fluctuations within traffic demand by incorporating a tolerance. In Figure 7 and Figure 8 an overview of the entropy of the 'original' and the Tflowfuzzy methodology are displayed.

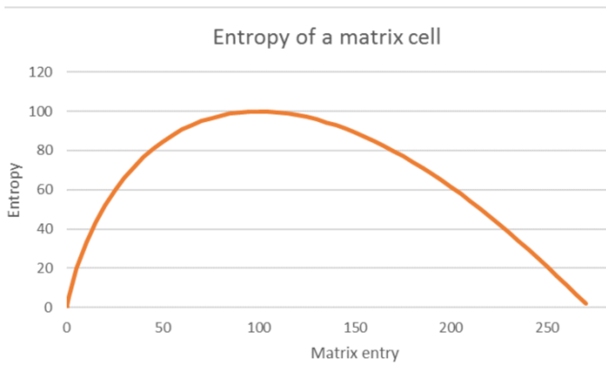

Figure 7: Entropy of the 'original' calibration methodology. The original value of the matrix entry is 100. At this point, the entropy is maximal (PTV Group, 2020).

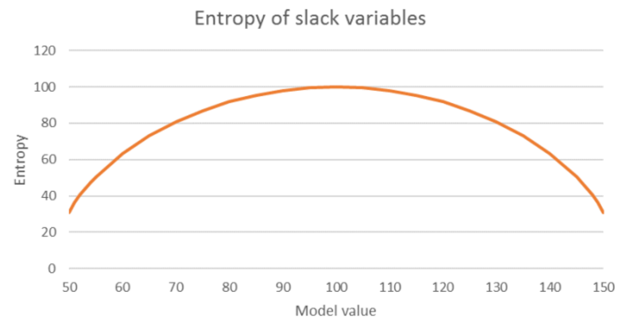

Figure 8: Entropy of the Tflowfuzzy calibration methodology. The original value of the matrix entry is 100, with a variation of 50 (PTV Group, 2020).

The figures illustrate that in the Tflowfuzzy methodology, the entropy corresponds to the interval of the set margin. This allows values within the interval to be accepted, while values in the centre of the interval are preferred. Therefore, the Tflowfuzzy methodology is more applicable in situations with a natural fluctuation in traffic demand.

The calibration methodology can be rewritten as an optimisation problem in which an evaluation function is maximised while constraining the optimisation problem to fit the traffic counts. In PTV Visum, the evaluation function is a combination of entropy and weighting based on the values of the previous OD matrix, resulting in Equation 2. The optimisation problem is, in this case, constrained to the equations which ensure that the assigned traffic is equal to the measured flow by traffic counters (while accounting for a tolerance factor)

$$max\ q(f,r,s) = -\sum_{ij=1}^{n}(f_{ij} \cdot \ln(\frac{f_{ij}}{\hat{f}_{ij}}) - f_{ij}) - \sum_{k=1}^{m}(r_k \cdot \ln(\frac{r_k}{t_k}) - r_k + s_k \cdot \ln(\frac{s_k}{t_k}) - s_k)$$

Equation 2 (PTV Group, 2020)

s.t.

$A \cdot f + r = \bar{c}$ in which $\bar{c} = c + t$

$A \cdot f - s = \underline{c}$ in which $\underline{c} = c - t$

Where f_{ij} is the travel demand from zone i to zone j, $\hat{f}_{ij}$ is the travel demand from zone i to zone j of the previous iteration, r_k and s_k are non-negative slack variables of link k and t_k is the tolerance vector of the traffic count situated on link k. For the constraints apply that A is the flow matrix which indicates the proportion of trips of an OD pair which travels through a particular link containing a traffic counter, f is the OD matrix, and c is the count value vector.

The OD matrix is consequently updated via an iterative process in which the OD matrix entry values and routes travelled between OD pairs are changed to fit the traffic count. By setting constraints to the number of iterations and the allowed deviation from the previous OD matrix, such as the maximum deviation of the sum of the entry values, the importance of the a priori matrix can be regulated.

After the calibration, the GEH value is determined to evaluate whether the calibrated matrix, specifically its assigned traffic, corresponds to the volumes measured by traffic counts. The GEH statistic is a way to represent the goodness-of-fit of a model by comparing the observed flow with the modelled flow. The inventor of the formula is Geoffrey E. Havers, after which the formula is named. The GEH statistic is an empirical formula rather than a true statistic (Bash, 2015). In Equation 3, the formula of the GEH statistic is displayed.

$$GEH_j = \sqrt{\frac{2\left(K_j - M_j\right)^2}{K_j + M_j}}$$

Equation 3
(Bash, 2015)

In which GEH_j is the statistic at link j, K_j is the observed flow at link j, and M_j is the modelled flow at link j. A GEH value below 5 indicates a good degree of similarity, while a value above 10 suggests a weaker match (Aly et al., 2022; Bash, 2015).

4.2. Data

This study uses multiple data sources: Floating Car Data, ODiN data, and traffic counts. This sub-section provides more information about these data sources.

4.2.1. Floating Car Data (FCD)

As described, this study utilises FCD obtained through TomTom Move. TomTom Move is an application of TomTom, a navigation manufacturer. The FCD of TomTom has a market coverage in the Netherlands from 2008 onwards (*Traffic Stats API | TomTom*, 2022). TomTom has several APIs and tools that provide data regarding both real-time traffic situations and historical traffic data. In this study, the historical traffic data retrieved from the Traffic Stats and O/D analysis features is utilised (*Developer | TomTom* , n.d.).

The data of both features is retrieved from TomTom navigation devices, in-dash systems, and apps, resulting in millions of measurement devices. These devices send anonymous data to the servers of TomTom (*O/D Analysis | TomTom* , 2022; *Traffic Stats API | TomTom*, 2022). The data retrieved from TomTom devices is supplemented with data from various data providers. In the Netherlands, this involves around 50 data sources (M. Uenk-Telgen, personal communication via email, October 14, 2024). All data is anonymised, de-identified and aggregated, making the exact origin and destination of vehicles untraceable (*Privacy - Drive | TomTom*, n.d.). Different data providers employ various methods to ensure customers' privacy. Most providers cut part of the beginning and end of a trip based on, for example, a part of the travel time, road class, or distance. However, there is currently no insight into how the different providers process the data (M. Uenk-Telgen, personal communication via email, October 14, 2024).

This study uses the traffic density feature from the Traffic Stats API. In this feature, the number of probe vehicles per road segment is returned for a defined area, date range and time slice (*Traffic Stats API | TomTom*, 2022). Additionally, TomTom's O/D-analysis API is used to provide insight into the distribution of traffic between user-defined origin and destination regions. The API contains three main features, of which two are employed within this study. The first feature is a selected link analysis, which provides insight into the origin and destination of traffic passing through a specific link for a defined range of dates and time slices. The second feature provides, per defined range of dates and time slice, an OD trip matrix for the zones included in the analysis (*O/D Analysis | TomTom* , 2022).

4.2.2. ODiN data

Every year, CBS (Centraal Bureau voor de Statistiek, translated: Central Statistical Office) conducts a travel survey to gain insight into the daily movements of the Dutch population named ODiN (Onderweg in Nederland, translated: On the Road in the Netherlands) (CBS, 2022). The travel survey retrieves trip information and includes background variables (CBS, n.d., 2022). This leads to 166 variables being defined in the dataset. However, not all data is helpful for this study. Table 1 lists the variables in the dataset of ODiN 2019 used during this study.

Table 1: The data relevant for this study which can be obtained from the ODiN dataset of 2019.

Desired information	Data from ODiN
Date	• Weekday
Motive	• Classification of Motive
Mode	• Mode category
Travel distance	• Travel distance within the Netherlands
Timing	• Departure hour

The survey was conducted by taking a sample of the Dutch population. Therefore, the results may be subject to a sampling bias. An analysis revealed that a sampling margin of 1.9% (at 95% confidence) applies to the number of passenger kilometres in the Netherlands per year as determined by the travel survey of 2017 (CBS, n.d.). Additionally, research shows that respondents of travel surveys underestimate the number of trips and the travel distance while overestimating travel time (Stopher et al., 2005, 2015). Furthermore, by comparing reported trips with smartcard data, it was found that routine trips are over-reported and non-routine trips are underreported (Spurr et al., 2015).

A potential explanation for the inaccuracies is the reliance on respondents' memory, as ODiN is designed to report all trips at the end of the day. This includes the arrival and departure location, the departure time and the travel time. Consequently, the reliability of the data depends on how accurately people remember the details of the trips (KiM, 2017). It is also possible that respondents do not want particular types of trips to be known and, therefore, deliberately conceal them in the survey (KiM, 2017). A memory jogger (auxiliary diary) can help to increase the accuracy of the reported trips (KiM, 2017). Nevertheless, these are not included in the ODiN survey.

Another explanation for the inaccuracy of ODiN results is that the response rates vary per demographic group. For example Smit et al. (2017) conducted a non-response analysis, which revealed that the elderly and non-Western immigrants have lower response rates via the web-based reporting method. Various response rates could lead to a sampling bias, as travel behaviour could vary across demographic groups.

4.2.3. Traffic counts

As previously outlined, traffic counts are currently employed to calibrate the OD matrix of passenger cars. For this study, two sets of traffic counts are available. The first one is a dataset retrieved from the municipality Stichtse Vecht. In March 2023, the municipality executed 185 periodical traffic counts. This resulted in an average hourly value for each traffic count location, determined for each time period (morning rush hour, evening rush hour, etc.) based on all working days within the count period. The other dataset is data originating from NDW. This dataset contains 68 permanent traffic counts on provincial roads, trunk roads and motorways. NDW data has a higher resolution, with traffic counts up to a level of volume per minute. Figure 9 displays an overview of all traffic counts on the road network.

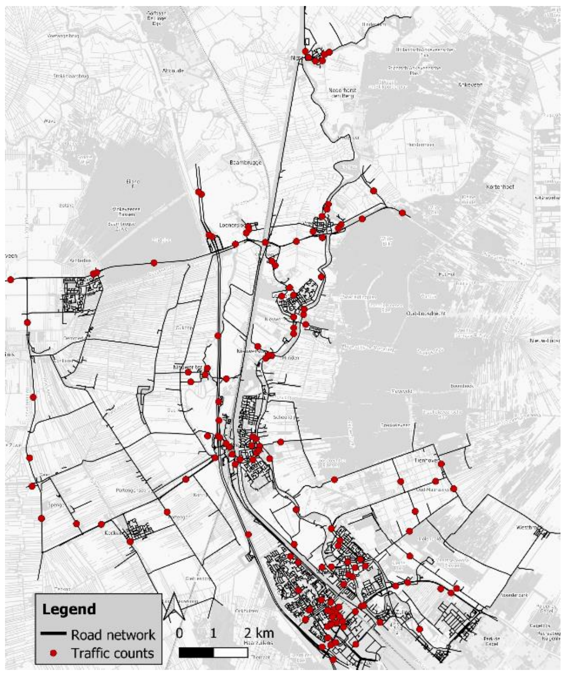

Figure 9: 'Regular' traffic counts taken into account in this study.

4.3. Methodology

The methodology of this study is schematised in Figure 10As the research aim consists of two parts, the methodology is also split into two parts: the analysis of FCD and the implementation of FCD in the model's calibration method. This structure is also adhered to in the remainder of this report.

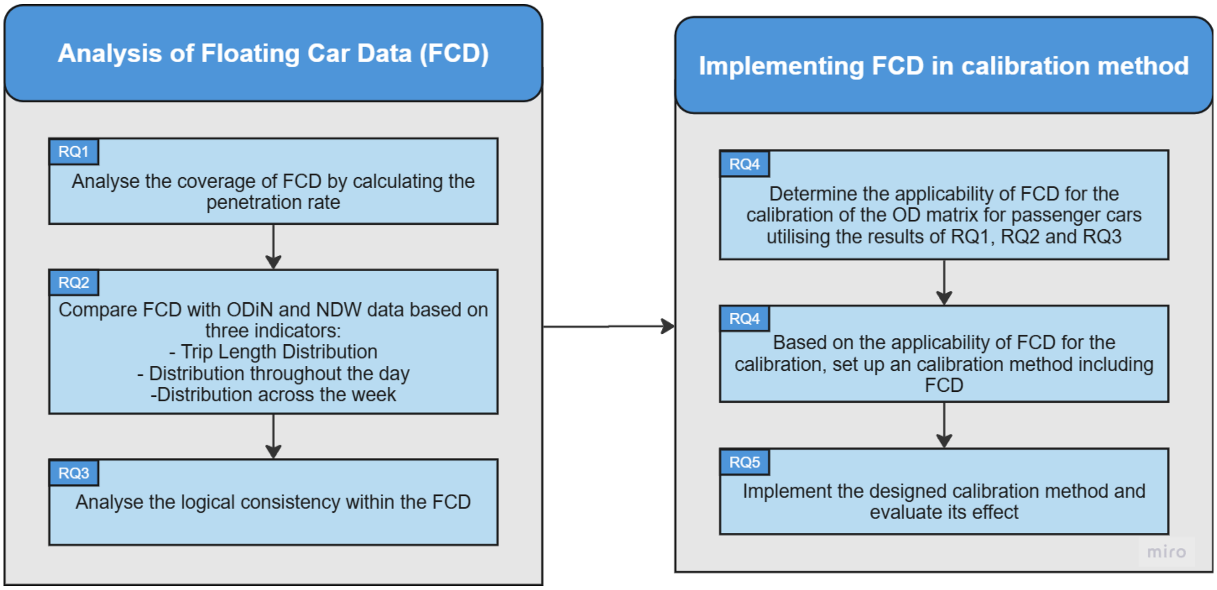

Figure 10: Schematisation of the methodology applied in this study.

5. Analysis of FCD

As mentioned, this study can be distinguished into two parts. This chapter discusses the methodology and results of the first part, which aimed to determine the representativeness of FCD for OD analyses. As outlined, FCD is representative if there is no sample bias in the type of trips the data covers and if the data is logically consistent. This is achieved by answering research questions 1, 2 and 3. This chapter outlines the methodology and results for each research question. The chapter concludes with a conclusion regarding the representativeness of FCD.

5.1. Coverage of FCD

The first research question aims to determine the coverage of FCD, as this gives insight into whether certain types of trips are under or over-represented within FCD. If the FCD does not contain a sampling bias and thus represents the actual situation accurately, the penetration rate on all road types should be equal. When this is not the case, it suggests that certain trip types are under or over-represented since the usage of various road types is linked to different trip types. For instance, long-distance trips have a substantially higher usage of the main roads like motorways and trunk roads, while residential roadways are significantly more travelled by other trip types (Sun et al., 2020). Additionally, the coverage of FCD can be used to translate FCD volumes to actual traffic volumes, which could be helpful for the OD matrix calibration.

5.1.1. Methodology

A visual inspection of the data, in which the FCD volume is plotted against the volume measured by traffic counters, indicated a linear relation regarding the penetration rate. Accordingly, multiple linear relations between the data sets are evaluated, which illustrates that the coverage of FCD can be best described using the average penetration rate per time period per road type. In Appendix A, an overview of the various relations and results can be found.

As the average penetration rates are estimated using a linear relation, Equation 4 and Equation 5 are employed. As can be observed in Equation 4**,** no intercept is present in the formula as the line must pass through the origin to ensure that the estimated volume is zero when the FCD volume is zero.

$$TC_i = Slope * FCD_i$$

Equation 4

$$Slope = \frac{\sum_{i=1}^{n}(FCD_i * TC_i)}{\sum_{i=1}^{n}(FCD_i * FCD_i)}$$

Equation 5

In which n is the total number of traffic counters taken into account, FCD_i is the FCD volume at traffic counter i and TC_i is the volume measured by traffic counter i.

Utilising these equations, the penetration rate is calculated through an iterative process to identify and remove outliers. According to the method of Lewis (n.d.), the sample standard deviation of the penetration rate is employed. Within this analysis, the estimated average and individual penetration rates at the locations of the traffic counters are compared. Based on empirical testing, it has been found that if an individual penetration rate deviates from the estimated average by more than 2.5 times the sample standard deviation, the data point should be labelled as an outlier.

As the goal of the first research question is also to investigate whether FCD volumes can be used to estimate the actual traffic volumes, a visual comparison of the estimated average penetration rate and the penetration rate per traffic count location is made. If the individual traffic counts are on or close to the line indicating the estimated average, it can be concluded that the penetration rate is a good and precise estimation. The penetration rate is a rough estimation if the individual traffic counts vary significantly from the line.

5.1.2. Results

In Table 2, the estimated penetration rates are displayed as computed using Equation 4 and Equation 5**.**

Table 2: Estimated average penetration rate per road class per time period.

Road type	Penetration rate morning rush hour	Penetration rate evening rush hour	Penetration rate residual day
Motorways	29.44%	26.78%	28.32%
Trunk roads	19.98%	19.56%	20.11%
Provincial roads	21.87%	20.44%	21.75%
Other rural roads	12.18%	12.88%	12.14%
Main roads within built-up areas	14.78%	14.24%	14.39%
Other roads within built-up areas	12.24%	9.15%	9.84%

The results illustrate that the penetration rate differs across the various road types, indicating that the FCD contains a sampling bias since the usage of different road types varies among the various trip types. The results in the table demonstrate that 'higher' road classes generally have a higher penetration rate. Since long-distance trips have a substantially higher usage of the main roads (Sun et al., 2020), it is expected that the difference in penetration rate is due to an overrepresentation of long-distance trips in FCD. Nevertheless, other factors may also have influenced these results. For example, the proportion of vehicles with built-in navigation may be greater on a particular road type. As these vehicles will always generate FCD, regardless of whether the navigation is utilised (M. Uenk-Telgen, personal communication, October 3, 2024), a higher proportion of these vehicles thus automatically results in a higher penetration rate. Another factor could be the processing of FCD to safeguard the privacy of road users, which is typically executed by removing the start and end of a trip (M. Uenk-Telgen, personal communication via email, October 14, 2024). As it is more probable that the beginning and end of a trip are situated on a road with a 'lower' road class, the removal automatically reduces the penetration rate.

Furthermore, the results show that the penetration rate varies across different periods. The penetration rate is generally slightly higher in the morning rush hours compared to other periods. These variations could indicate an over-representation of trips within this time period or an under-representation of trips during the other periods. A potential explanation for the over-representation is the fact that people tend to turn on their navigation more often during trips where part of the route is unknown (Schaap & Jorritsma, 2015), which is expected to occur more during the morning rush hour as people leave their homes for another (possibly

unfamiliar) location. However, the variations are minimal, making it uncertain whether the penetration rate is different or whether this is due to the volatile nature of traffic demand.
In Figure 11, the results of the visual comparison between the estimated penetration rate and the penetration rate per traffic count location for the morning rush hour are presented. The figures for the other time periods can be found in Appendix A.

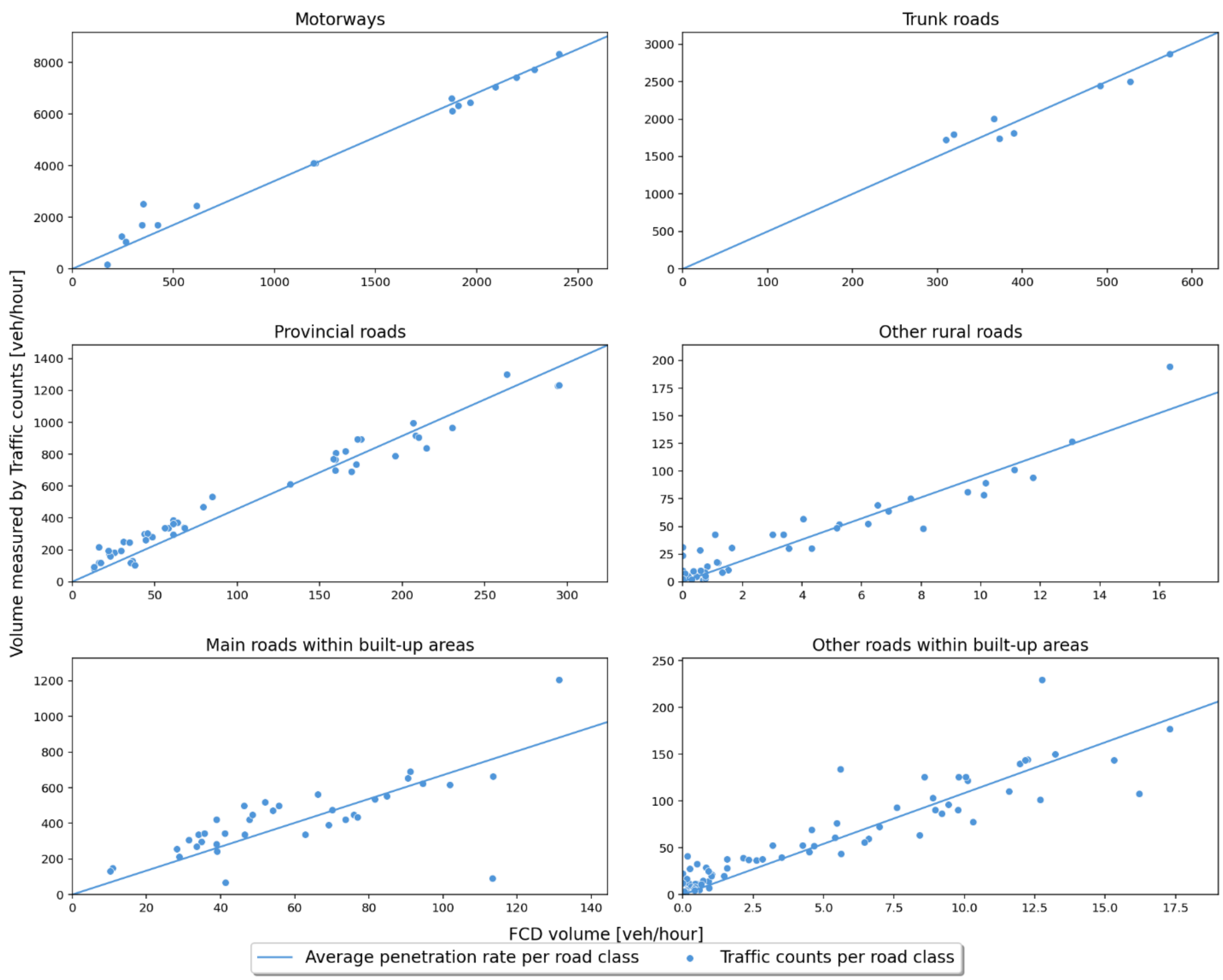

Figure 11: Indication of the average penetration rate of FCD on the different road types during the morning rush hours.

The figure illustrates that the estimated average penetration rate grossly aligns with the penetration rates at the various traffic count locations. Nevertheless, at low FCD volumes, no (linear) trend is visible between the FCD and traffic count data. A possible explanation for this is that some trips' first and last parts are cut off to guarantee users' privacy. As a result, part of the FCD volume may be removed at a specific location, resulting in an incorrect ratio to the actual number of vehicles. Another plausible possibility is that due to the low volume of cars utilising the road section, barely any probe vehicles, of which the data is available via TomTom, pass the section. Therefore, whether a vehicle is a probe vehicle is rather random, making it impossible to estimate the penetration rate.

Consequently, based on these results, it can be concluded that the calculated penetration rate is an accurate, albeit rough, estimate of the actual coverage of FCD. Nevertheless, whether the discrepancies result from inaccuracy in the FCD or in the traffic count data is uncertain. As the quantity of data, more specifically the number of traffic counts is relatively limited, it could be beneficial to execute a more elaborate analysis utilising more data to gain more insight into this. Furthermore, it is advised that estimations of traffic volumes based on FCD volumes should not be conducted at locations where the FCD volume is low, as at low FCD volumes the estimated penetration rate does not correspond. Moreover, the analysis of the penetration rate revealed that the origin-destination information of FCD is not representative, as the penetration rate is not uniform across the road network. This indicates that certain trip motives are under or over-represented.

5.2. Comparison of trip-related metrics

This research question compares FCD to travel survey and traffic count data to identify whether FCD is representative. Initially, an attempt is made to execute this comparison by generating a model that could predict the most probable trip purpose based on trip characteristics and demographic data. The ultimate goal of this model is to apply it to FCD to ascertain the primary trip motives of FCD and to compare these with the primary trip motives derived from the travel survey data. The output did not yield accurate results despite testing multiple techniques to set up such a model. Appendix B discusses a detailed explanation of the method used to set up such a model and the corresponding results.

Consequently, the comparison of FCD to travel survey and traffic count data is executed using three trip-related metrics: the trip length distribution, distribution throughout the day, and distribution across the week. If the distributions for FCD and travel survey or traffic count data align for all indicators, it can be concluded that FCD does not contain sampling bias and is, therefore, representative. Conversely, if the distributions do not match, a sampling bias is present, suggesting that the FCD is not representative. If the distributions do not match, the distributions per trip motive according to travel survey data are analysed. This gives more insight into which trip types are under or over-represented. It should, however, be noted that traffic count and travel survey data are also associated with sampling biases and errors, as described in greater detail in section 2.1 and 4.2.2, which could affect the results of this research question.

5.2.1. Methodology

The data sources are compared by visually analysing the various distributions. To do so, the different data sources should be transformed into the distributions for each trip-related metric. An explanation of how the distributions are computed is given for each indicator. In Appendix C, an extensive explanation of the procedure for creating the various distributions is given.

Trip length distribution (TLD)

The comparison of the trip length distributions gives insight into the under or over-representation of specific trip lengths within FCD. The comparison for this indicator is made solely between FCD and travel survey (ODiN) data, as data regarding the trip lengths is desired to make this comparison, which is not the case for traffic count data. The TLDs are also transformed into cumulative TLDs to ensure that possible fluctuations in ODiN data due to respondents rounding up the trip distance (Witlox, 2007) do not impact the results. The TLDs are created based on all trips recorded within 2019 with an origin and/or destination within the region of the municipality Stichtse Vecht. This choice is based on restrictions for gathering the FCD from TomTom, which are also discussed in Appendix C.

Distribution throughout the week

For the distribution throughout the week, FCD is compared to travel survey (ODiN) and traffic count (NDW) data. The comparisons are based on data from 2019 (excluding public holidays), which distinguishes three time periods: work days, weekend days, and all days combined. To facilitate a comparison between FCD and travel survey data, relative distributions of the departing hours are generated. The comparison with the traffic count data is executed using the relative distribution of the volume at a given time. Within the comparison to traffic count data, three specific locations are selected:

1. Motorway A2 in between off-ramps 4 and 5
2. N201 in between Vreeland and Loenersloot
3. N402 in between Maarssen and Breukelen

These locations are selected as they represent different types of roads: a motorway, a provincial road which crosses the motorway and a provincial road between two town centres. In Figure 12, the locations are indicated on a map of the municipality of Stichtse Vecht. The comparisons are made for both directions of the road.

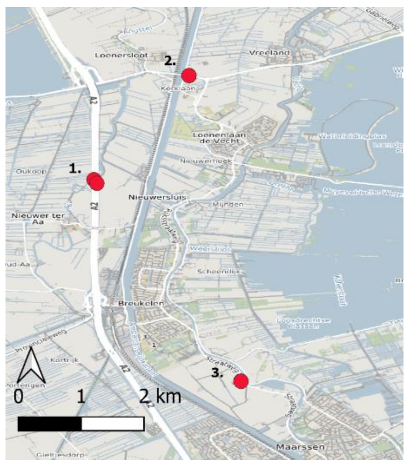

Figure 12: Overview highlighted locations for the comparison of the FCD and traffic count data using three distributions.

Distribution across the week

For this metric also applies that a comparison is made with both travel survey (ODiN) data and traffic count (NDW) data based on data from 2019 (excluding public holidays). For the latter one, the data of the locations highlighted in Figure 12 is utilised. The three datasets (FCD, ODiN data and NDW data) are configured towards a distribution of the relative number of trips per day compared to the other weekdays. As it is uncertain how the ODiN data needs to be transformed to a distribution across the week (see Appendix C for more explanation), two distributions are calculated: the number of trips per day compared to the number of respondents per day and the number of trips per day compared to the total number of trips.

5.2.2. Results

Trip length distribution

In Figure 13, the TLD retrieved from travel survey (ODiN) data is displayed. Figure 14 illustrates the TLD retrieved from FCD. The cumulative TLDs of both datasets are visualised in Figure 15. In Figure 16, the cumulative TLD, based on ODiN data, per trip motive is illustrated.

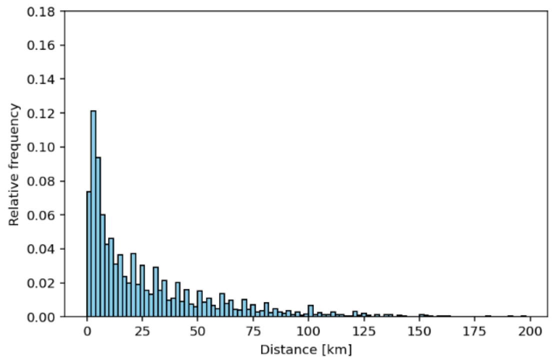

Figure 13: Trip length Distribution of the region in and around the municipality Stichtse Vecht according to ODiN data.

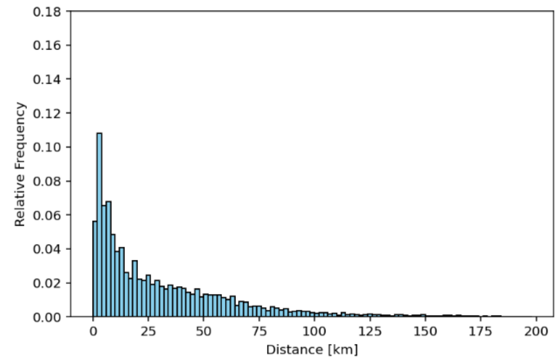

Figure 14: Trip length Distribution of the region in and around the municipality Stichtse Vecht according to FCD.

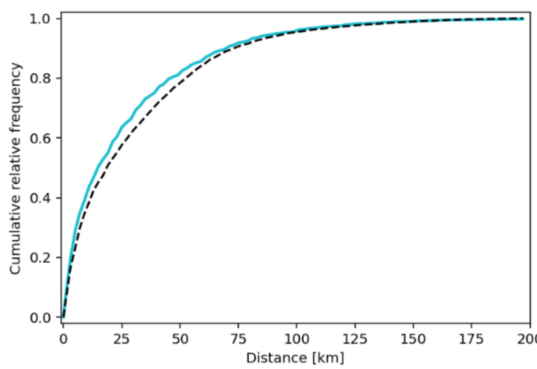

Figure 15: Cumulative TLD of both FCD and ODiN data.

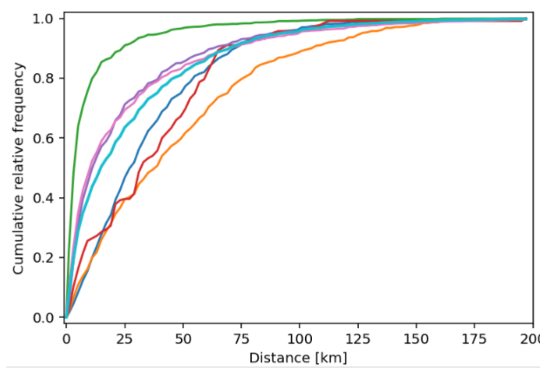

Figure 16: Cumulative trip length distribution per trip motive according to ODiN data.

Figure 13 and Figure 14 show that the trip length distributions of both datasets are comparable as both distributions contain a peak at low distances, after which the relative frequency decreases. Nevertheless, when the distributions are compared in more detail, it is noticeable that the height of the bins is not the same. Particularly at smaller distances, the relative frequency of FCD is lower than that of ODiN data. This result also emerges from Figure 15, which illustrates that FCD underestimates (compared to ODiN) the number of trips less than 75 km long.

This difference is expected to be caused by an under or over-representation of specific trip motives within FCD. As illustrated in Figure 16, there are variations between the different TLDs of the various trip motives. For example, TLDs with a steep slope from the origin, such as the TLD of shopping, indicate that the dataset includes primarily trips with relatively short distances. TLDs with a flat slope, such as the TLD of the trip motive recreation, indicate a dataset that predominantly includes trips with longer distances. Therefore, an under or over-representation of certain trip motives could affect the TLD. This can be argued by the fact that the usage of navigation systems is higher for specific trips than for other trips. Schaap & Jorritsma (2015) revealed that people tend to turn on their navigation particularly on unfamiliar trips. As, for instance, a trip to the supermarket generally takes place within a familiar neighbourhood, it is plausible that these trips are less frequently registered and thus included in FCD than other trip motives.

Nevertheless, the TLD could also be influenced by the processing of FCD to guarantee user privacy. Removing the start and end of a trip could remove trips with a small distance in their totality. Furthermore, this processing could lead to a shifted TLD when the trip length is modified so that the trip culminates in another distance bin. Even though this factor probably plays a role, it primarily impacts trips with a distance less than 10 kilometres, and to a lesser extent those between 10 and 75 kilometres, since removing a part of the trip of trips with a small distance has more impact than on longer trips. Consequently, this is not expected to be the primary factor responsible for the observed discrepancy.

Even though it is uncertain which factor contributes to the difference, the difference implies that the TLD of FCD is not representative. Moreover, the TLD's results are coherent in the context of the estimated penetration rates. The penetration rate revealed that there is a low number of probe vehicles measured on ‘lower’ road classes. As these road classes are generally closer to home and, therefore, more frequently used by shorter trips, these results coincide with the TLD's results, which indicate that the number of shorter trips is underestimated compared to longer trips

Distribution throughout the day

In Figure 17, the relative distribution of the number of departures per hour for both FCD and ODiN are depicted. In Figure 18, the distributions are also visualised, including the distribution per trip motive according to ODiN data. The distributions in these figures are based on working days. In Appendix D, the results of the weekend days and all weekdays combined are given.

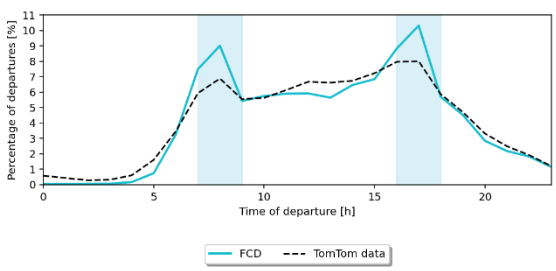

Figure 17: Distribution across the weekdays according to TomTom and ODiN data.

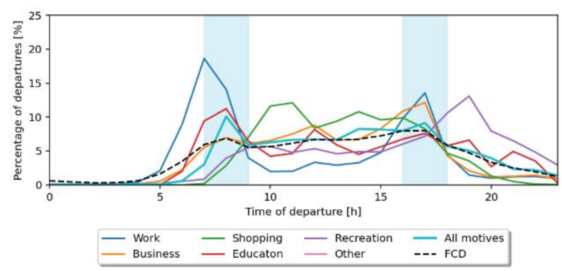

Figure 18: Distribution across the weekdays according to TomTom and ODiN data per trip motive.

Figure 17 illustrates a correlation between the overall trend of FCD and ODiN data regarding departure times. Both datasets indicate that the highest number of trips depart during peak hours, while the fewest trips depart at night. However, it is noticeable that FCD measures the peaks less strongly, while proportionally, more trips are measured during the day (between rush hours) and at night.

Assuming the accuracy of the ODiN dataset, it can be concluded from these results that FCD is not a representative dataset since the distribution of FCD over the day does not match that of the travel survey data. As Figure 18 demonstrates, the distribution throughout the day varies per trip motive, suggesting the possibility of under or over-representation of certain motives. However, the specific motives involved and the extent to which they are under or over-represented cannot be determined. Nevertheless, as research shows that sampling biases and errors are associated with the travel survey dataset, as described in section 4.2.2, it is uncertain how accurate these results and conclusions are.

For this reason, the distribution of FCD throughout the day and the distribution of traffic count data are also compared. This data source is, however, also subject to errors. Nevertheless, this error is minimised as an average value is taken over a longer period of time. In Figure 19 and Figure 20, the relative distribution across the day for two of the three locations considered, see Figure 12, are displayed.

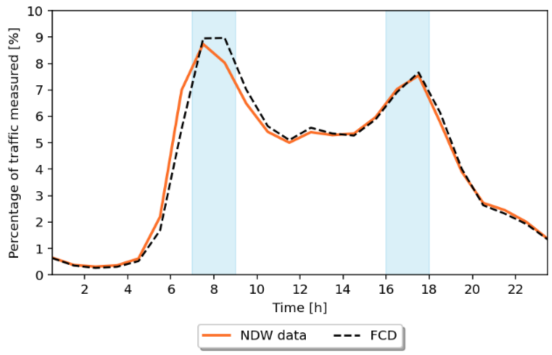

Figure 19: Traffic count on the motorway A2 in the direction South to North.

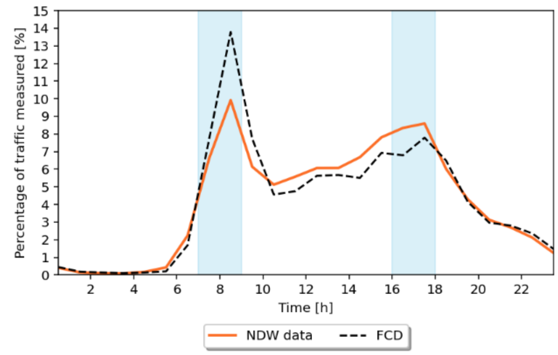

Figure 20: Traffic count on the N402 in between Maarssen and Breukelen in the direction South to North.

When Figure 19 is analysed, it emerges that the FCD volumes across the day by FCD are comparable to the volumes measured by traffic counters. This applies to both the trend in general, so the timing of the peaks, as well as the values associated with them. However, when analysing Figure 20, this conclusion is not supported. This figure illustrates that the trend of FCD in terms of the timing of peaks corresponds to the trend of NDW data, but the distribution values do not entirely match. Especially during the day (between 7 and 19), it can be seen that there is a difference between FCD and NDW data. A plausible explanation for this difference is the fact that Figure 20 visualises the volumes of a ‘lower’ road class. It is anticipated that there is a greater diversity of trip motives and trip distances on 'lower' road classes. This variation can affect the quantity of FCD available and thus result in a different distribution throughout the day. Moreover, processing trips to guarantee users' privacy might also impact the distribution. As some trips will be removed, the FCD volume and the relative distribution will be affected.

Based on these results, it can be concluded that FCD's distribution throughout the day is not representative since the distribution of the travel survey and traffic count data is (significantly) different from that of FCD.

Distribution across the week

Figure 21 displays the distribution of FCD across the week compared to the distribution of ODiN data. The ODiN data is represented according to the two calculation methods discussed in Section 5.2.1.

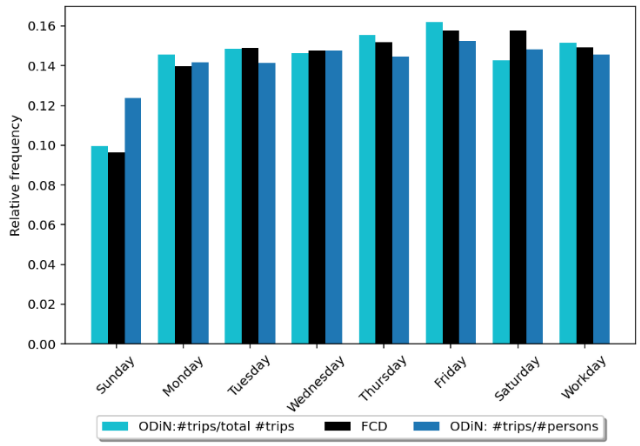

Figure 21: Comparison of distribution across the week of FCD and ODiN data.

The figure demonstrates that the distribution of FCD is relatively similar to that of ODiN data. The most notable difference between FCD and ODiN data is observed on Sundays, particularly for the dataset presenting the average number of trips per person. Minor, inconsequential differences emerge between the distributions of ODiN data and FCD on the remaining days, including the comparison to the average working day. However, whether these (minor) differences occur due to a sampling bias in FCD or ODiN data is uncertain. Therefore, and because it is unclear which of the two ODiN distributions best reflects reality, a comparison to NDW data is made. The results of the comparison of one of the traffic count locations can be found in Figure 22. The results are comparable for the other locations and, therefore, not included in the report.

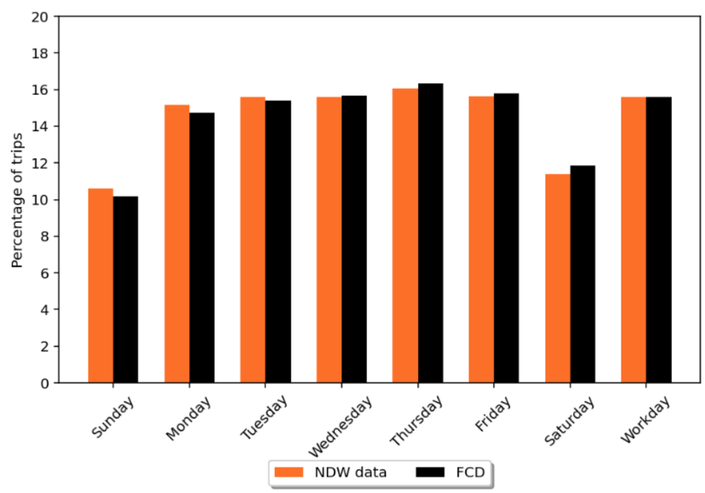

Figure 22: Comparison of distribution across the week of traffic count on the motorway A2 in the direction South to North.

From the figure above, it can be concluded that the distribution throughout the week for both datasets is reasonably comparable. A slight inconsistency is visible on the individual weekdays. Nevertheless, when comparing the results for an average working day, both datasets indicate the same average number of trips. This is favourable since the model assumes an average working day.

An analysis, whose results can be found in Appendix D, revealed that the distribution of trips throughout the week differs per trip motive. Therefore, the minor differences on individual weekdays could indicate that certain trip motives are under or over-represented in FCD. However, as the differences are minimal and no clear trend is visible, no unequivocal conclusion can be drawn regarding the representativeness of this indicator.

5.3. Logical consistency FCD

As discussed in Section 3.1, this study defines the representativeness of FCD not solely as the sampling bias but also to what extent the data is subject to errors that affect logical consistency. Therefore, this research question aims to ascertain whether FCD exhibits logical consistency using a range of indicators. It is desirable to identify these potential inconsistencies as they can affect the accuracy of how well FCD reflects reality. The identification can clarify which part of the data can be used for OD studies and if inconsistencies are present, how the data should be processed to overcome them.

5.3.1. Methodology

The logical consistency is examined using three indicators: consistency in the number of vehicles, logical origins and destinations of trips and a comparison of the distribution on off-ramps.

Consistency in the number of vehicles

For this analysis, data of locations where it is plausible that no (additional) traffic will enter or exit the road, such as a motorway between an on and off-ramp, are analysed. At three of these locations, which are indicated in Figure 23, it is examined for both directions whether the number of vehicles according to the traffic density feature of TomTom exhibited consistent values across the road section and whether the selected link indicated that all traffic remained within this road section. If this is not the case, it is concluded that FCD is inconsistent and, thus, not representative. This study utilised FCD volumes acquired on working days from the 6th of March 2023 until the 20th of April 2023, excluding public holidays.

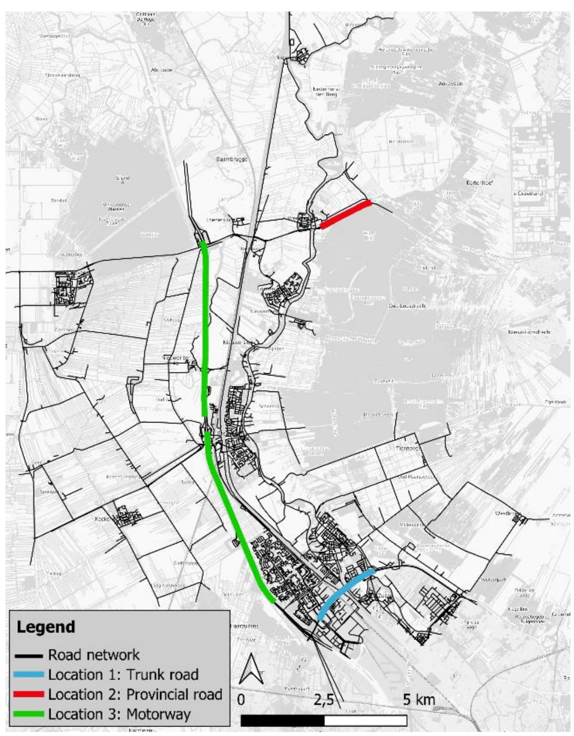

Figure 23: Locations for the logical consistency of the number of vehicles measured by FCD.

The variation in Floating Car Data (FCD) volume is compared to the variation in volumes measured by traffic counters on the same road segment using GEH values. As described in Section 4.1, the GEH value is a metric that indicates how well an assigned volume aligns with the measured volume. If there is significant variation in the measured volumes, it may happen that the assigned volume does not match the measurements from one traffic counter but does correspond with another counter or the average of multiple counters on the same segment. This can lead to incorrect conclusions when there is considerable variation in the traffic volumes measured. To quantify this variation, the standard deviation is used, as it indicates the range of volumes that are likely to occur. The observed average volume across a road segment is considered the baseline value, while the assigned value is determined by adding the standard deviation to this average volume.

Logical origins and destinations of trips

To provide an estimation of the number of trips that, according to FCD, start or end in locations that are not logical (such as on a motorway or trunk road), zones are selected, which are depicted in Figure 24. An OD matrix is generated using these zones and zones within built-up areas (such as Maarssen, Loenen aan de Vecht, and Vreeland). This matrix gives insight into the number of trips departing and arriving in the various zones according to FCD. If (a significant number of) trips depart or end within the zones classified as not logical, the FCD is labelled as inconsistent and, therefore, not representative since the data contains errors in that case.

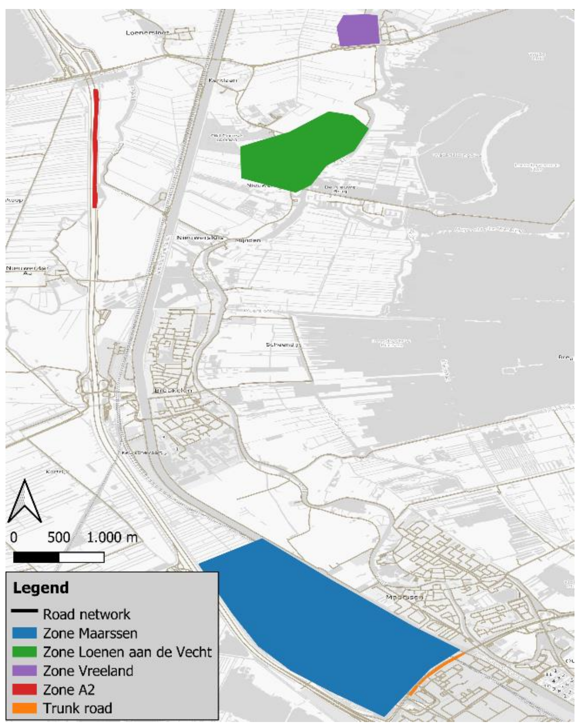

Figure 24: Zones for OD analysis regarding logical origins and destinations of trips.

Comparison distribution on off-ramps

The last indicator involves analysing whether the proportion of vehicles exiting the motorway via an off-ramp is equal according to FCD and traffic count data. Additionally, to ascertain whether the proportion according to the selected link analysis of FCD remains constant, the distribution is determined for various links situated at a greater distance from the off-ramp. A statistical test is executed via a chi-square test to compare FCD and NDW data distributions properly. In this equation, the NDW data is stated as the observed data, while the distribution of FCD serves as the expected dataset. If the distributions of both datasets are not significantly different, it can be concluded that the distribution of FCD is logical and thus representative. Several off-ramps, indicated in Figure 25, on which traffic counters are present, are used to compute this analysis.

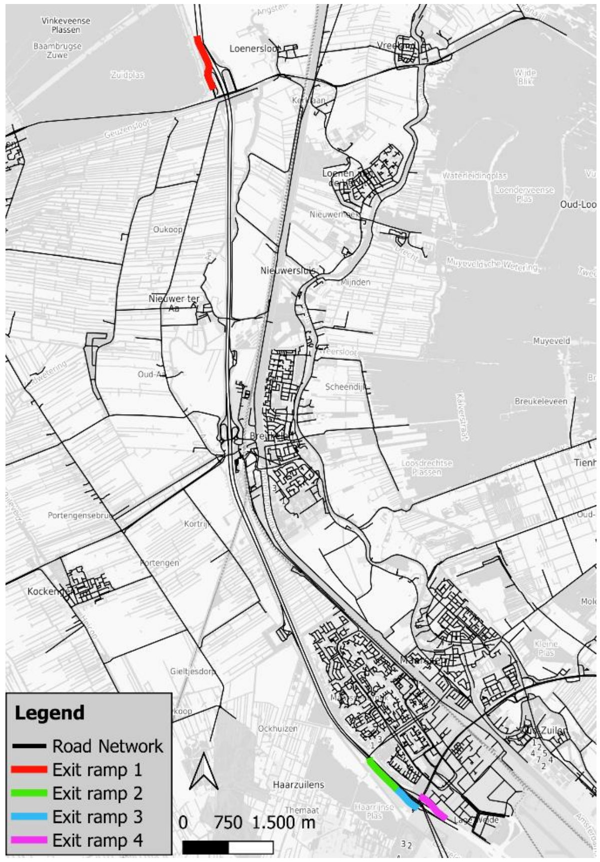

Figure 25: The off-ramps taken into consideration for the comparison of the distribution of FCD and NDW data.

5.3.2. Results

Consistency in the number of vehicles measured

In Figure 26 and Figure 27, the results of the FCD traffic volumes are visualised for the road section on the motorway. The analysis revealed that the results are similar for the various locations highlighted in Figure 23. Therefore, only the results of one location are presented in this report.

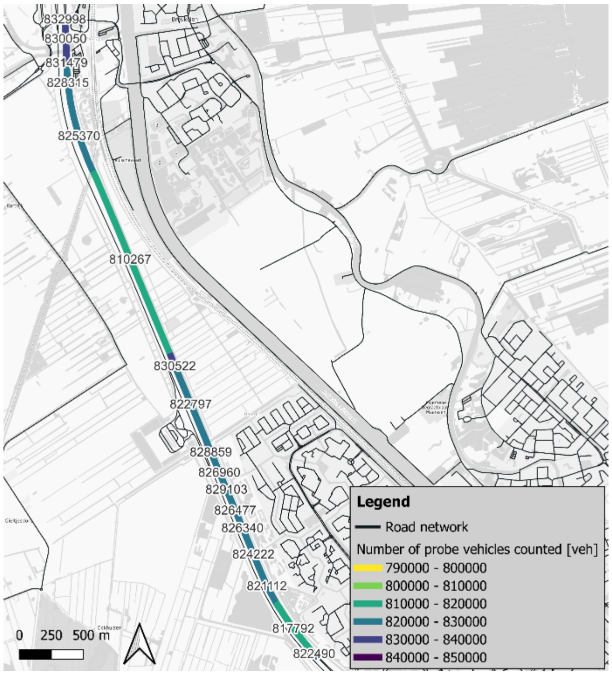

Figure 26: Consistency within FCD volume A2 South to Northbound.

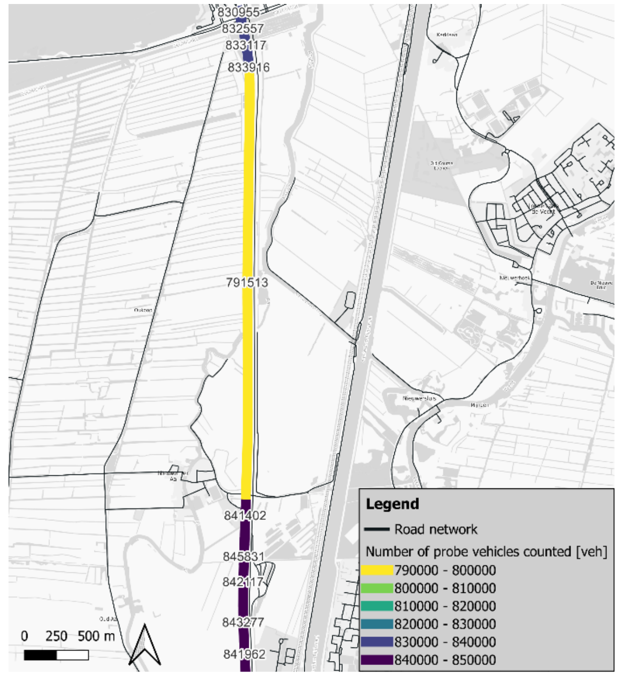

Figure 27:Consistency within FCD volume A2 North to Southbound.

The figures demonstrate a random variation in the amount of (probe) vehicles measured at the different locations within the same road section. This indicates that the FCD is inconsistent and, therefore, not representative. However, with more traditional ways of counting traffic, such as loop detectors, there can also be variation within the traffic counts. For example, Mohammed et al. (2016) revealed that loop detectors are subject to (measurement) errors. Therefore, the variation of the measured volume of FCD is quantified by calculating the standard deviation's GEH value for both FCD and NDW data. The results of this can be found within Table 3.

Table 3: GEH value of the standard deviation for both directions of the motorway A2.

Location	GEH value FCD	GEH value NDW
A2 south to northbound	0.40	0.53
A2 north to southbound	0.83	0.31

The table illustrates that both datasets have comparable GEH values, indicating that virtual traffic counts are equally representative as ‘regular’ traffic counts. Nevertheless, the variation in volumes should be considered when implementing virtual traffic counts.

In contrast to random variation in the FCD volume, a clear trend is visible within the selected link analysis. In Figure 28 and Figure 29, the selected link analysis results on the motorway A2 are visualised.

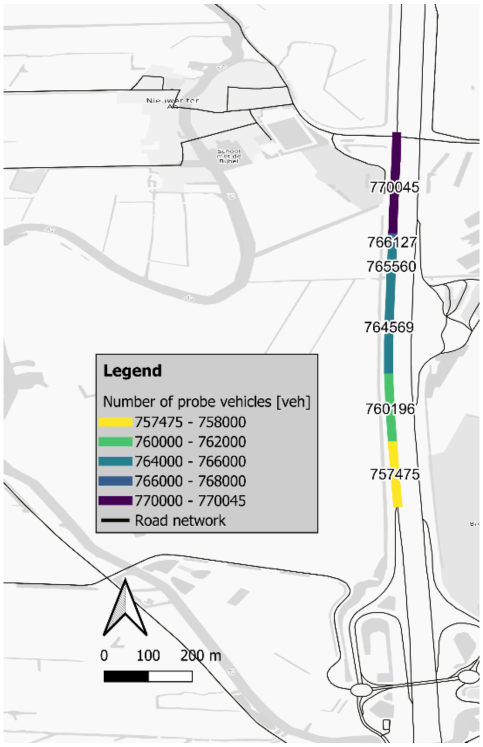

Figure 28: Selected link analysis A2 North to Southbound.

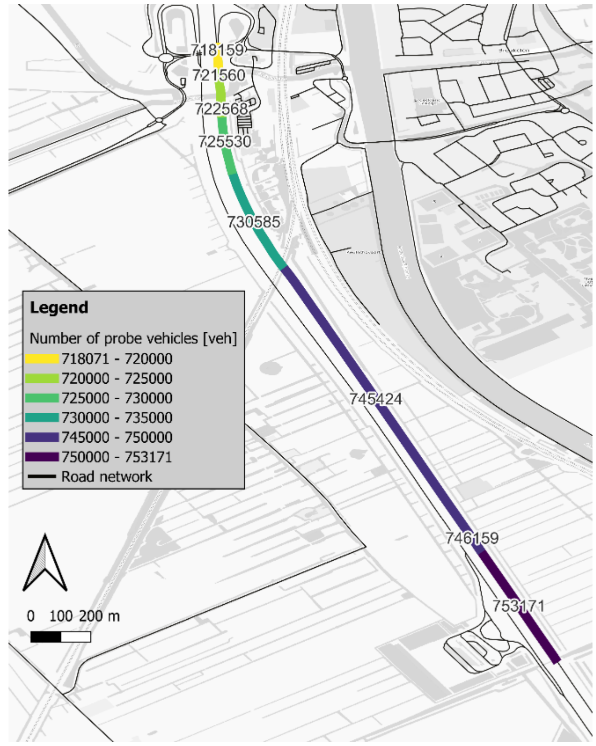

Figure 29: Selected link analysis A2 South to Northbound.

The figures demonstrate that as the distance to the selected link increases, the number of measured (probe) vehicles decreases. However, in practice, ending the trip on the motorway is not feasible. It is expected that this trend is the result of GPS connections dropping out, people turning off their navigation before the end of the trip, and how FCD is processed to guarantee user privacy. Furthermore, it is evident that the number of vehicles measured utilising the selected link feature is less than the traffic density indicated in Figure 26 and Figure 27. Consequently, it can be concluded that the data gathered from the selected link analysis on straight road segments is inconsistent and, therefore, not representative.

Logical origins and destinations of trips

In Table 4, the results of the OD analysis are displayed. The values also include the number of trips with their origin or destination outside the zones included in the OD matrix.

Table 4: Results of the OD analysis of the different zones as shown in Figure 24 for the period 6th of March 2023 until 20th April 2023, excluding public holidays.

Location	Number of trips departing	Number of trips arriving
Zone A2	5295	7326
Zone trunk road	1067	1026
Zone Maarssen	79135	80935
Zone Loenen aan de Vecht	11052	12783
Zone Vreeland	2839	3160

From the table, it emerges that there are instances where the origin or destination of a trip is in a location that is not feasible, such as on a motorway or trunk road. When comparing the number of trips departing and arriving according to FCD within the zone on the motorway (5000-7000) to the number of probe vehicles measured to pass the motorway (800000), the number of trips departing and arriving at the zone is insignificant. However, when these numbers are compared to the number of trips departing and arriving in other zones, such as the zones in Maarssen, Loenen aan de Vecht and Vreeland, the values are significant. Therefore, it is concluded that TomTom's OD analysis is not representative.

Just like the selected link analysis, these results are expected to be a consequence of processing the data to safeguard the users' privacy, users turning off navigation systems earlier or turning them on later, or the presence of GPS errors (such as disconnection) within the data.

Distribution on off-ramps

In contrast to the aforementioned results, the analysis of the proportion of vehicles taking an off-ramp reveals that the FCD distribution aligns with that of NDW data. Table 5 displays the distribution of straight-through traffic compared to traffic taking the off-ramp for the various locations under study for FCD and NDW data. The analysis of the distribution for different links at varying distances from the off-ramp revealed that the distribution remains consistent. Therefore, only the results of the selected link analysis closest to the off-ramp are displayed in the table.

Table 5: Comparison of distribution off-ramp motorway A2 NDW and FCD.

Location	Percentage straight-through		Percentage exit	
	NDW data	FCD	NDW data	FCD
Off-ramp 1	95.93%	88.62%	4.07%	11.38%
Off-ramp 2	65.63%	66.80%	34.37%	33.20%
Off-ramp 3	47.96%	48.52%	52.04%	51.48%
Off-ramp 4	46.83%	53.29%	53.17%	46.71%

The data in the table indicates that the percentages of traffic exiting the motorway are relatively similar for the different data sources. The statistical analysis revealed that the distribution of the percentage of straight traffic has a p-value of 0.70, and the percentage of exit traffic has a p-value of 0.13. Both values exceed the 0.05 significance level, indicating that the null hypothesis, which states that there is no difference in distribution between FCD and NDW data, cannot be rejected.

Given these results, it can be concluded that the FCD is a representative and suitable data source for determining the percentage of vehicles utilising a given off-ramp on a motorway. However, it should be noted that the analysis was limited to motorway off-ramps. It is, therefore, unclear whether the FCD also reflects the correct distribution at intersections.

5.4. Conclusion

The first three research questions aim to determine the representativeness of FCD for OD studies through multiple comparative analyses. To start with, the penetration rate of FCD is estimated. This analysis revealed that the coverage of FCD is not the same across the road network. In general, the coverage increases as the road class increases, resulting in a penetration rate ranging from 9% to 29%. These results are in line with the results of a study conducted by NDW (n.d.-b). This study revealed that the penetration rate was occasionally higher than 25% on the motorway, while in specific periods, the penetration rate was less than 5% for residential roads.

The small differences in penetration rates can be explained by the fact that the coverage of FCD varies across the Netherlands (M. Uenk-Telgen, personal communication, October 3, 2024). NDW (n.d.-b) also revealed a slight overrepresentation of long-distance trips. This is also in line with the results of this study. If FCD is a representative dataset for OD analysis, all trip types should be included similarly, resulting in a uniform penetration rate across the road network. As this is not the case, it can be concluded that the FCD contains a sampling bias probably due to the under or over-representation of certain trip motives. Therefore, according to the penetration rate, FCD is not representative for OD analysis.

Nevertheless, the study reveals that the estimated penetration rate is a good tool for estimating the traffic volume. This conclusion also emerges from the analysis in which the consistency of the FCD volume on a single road segment is examined. This analysis revealed that the FCD volume contains some variation but is of comparable amplitude as the variation between stationary traffic counters on a single road segment. Consequently, it is concluded that FCD is suitable for creating virtual traffic counts. However, It should be noted that on roads where few probe vehicles have been measured, it is more challenging to estimate the actual traffic volume accurately. Without probe vehicle measurements, it is impossible to do so at all.

After the coverage of FCD is examined, three trip-related metrics are computed based on FCD and are compared to the trip-related metrics computed by travel survey and traffic count data. The comparison of the trip length distribution and distribution throughout the day illustrated that the distribution based on FCD differed from the distribution based on travel survey and traffic count data. The comparison of the distribution across the week also revealed a difference. However, the differences in this comparison are minor. If the FCD is representative, the distributions based on FCD should be similar to those based on the other datasets. Therefore, it is concluded that the OD analysis of FCD is not representative. This is likely caused by an under or over-representation of specific trip motives. However, the fact that trips are not entirely included in the FCD due to processing or errors could also play a role. This is in line with the results of the penetration rate and, therefore, with the study of NDW (n.d.-b) .

Lastly, the logical consistency of FCD is examined using a range of indicators. By analysing FCD from locations where no trips should depart or arrive, it becomes clear that, according to FCD, several trips start or end at these locations. As this is not logical and even impossible, it is concluded that the OD analysis of TomTom is not representative. It is anticipated that this is a result of the FCD processing to guarantee users' privacy. However, other factors, such as connection losses or users switching on/off the navigation systems later/earlier, could also lead to these inconsistencies. In contrast to the OD analysis, the turn volumes on off-ramps on motorways according to FCD are representative, as compared to the distribution of stationary traffic counters, which revealed that the distributions of both datasets are equal. It should, however, be noted that the assumption is made that the traffic count data accurately reflects the actual situation. Also, for other road types, no data is available to compare. Therefore, it is assumed that FCD also correctly represents the distribution of these road types.

To summarise, based on the results of the first three research questions, it can be concluded that the location of origins, location of destinations and routes retrieved from FCD are not representative for OD analysis. It contains a sampling bias due to the under or over-representation of certain trip motives, and the logical consistency is affected by, among others, the processing of data, connection losses or users switching on/off the navigation systems later/earlier. However, more research is recommended to identify the biases and errors more accurately to overcome them.

Nevertheless, the results revealed that virtual traffic counts based on the penetration rate per road class per time period are equally representative as volumes measured by stationary traffic counters. Additionally, the proportion of vehicles taken an off-ramp according to the selected link feature is equal to the proportion according to stationary traffic counters. It is therefore hypothesised that these data applications may be suitable for OD studies.

6. Implementing FCD in the calibration method

As FCD provides much information of interest for OD studies, including origins, destinations and travelled routes of trips, it is evident that utilising this information for OD calibrations is desirable. However, the comprehensive analysis of FCD, as outlined in the preceding chapter, revealed that not all components of FCD are suitable for OD studies. The results identified that certain trip types are either under or over-represented in the data and that not all origins and destinations of trips are accurately represented in the data. Therefore, it is concluded that the origin and destination information provided by TomTom move is inadequate for OD studies. Consequently, its implementation in the calibration process of the OD matrix is not desirable.

Nevertheless, the results presented in Chapter 5 illustrated that two applications of the FCD give a representative overview of the traffic situation, namely the estimated penetration rate and the proportion of vehicles taking an off-ramp according to the selected link analysis of TomTom. Therefore, it is decided to use these applications to develop and test two calibration techniques which involve the placement of virtual traffic counts. It is expected that these techniques lead to more accurate OD matrices as more independent traffic counts lead to a more precise estimation of the actual OD matrix (Lam & Lo, 1990; Yang et al., 1991).

This chapter discusses the methods and results for answering the last two research questions. The first subchapter, in which research question 4 is answered, offers an overview of the developed calibration techniques. The subsequent subchapter, which answers research question 5, discusses the effects of implementing the developed calibration techniques.

6.1. Implementation calibration methodology

The goal of the fourth research question is to develop methodologies that implement FCD within the calibration process. This section discusses a methodology for developing the two calibration techniques mentioned before. Then, the calibration techniques are displayed.

6.1.1. Methodology

The first technique places virtual traffic counts on suitable roads across the road network. These virtual traffic counts are generated by multiplying FCD's volume with a multiplication factor based on the penetration rate as determined in Section 5.1. As illustrated in Figure 11, at low FCD volumes, the estimated penetration rate is not applicable as there is no linear relationship between the measured FCD volume and the volume measured by the traffic counters. Therefore, using the correlation coefficient, the minimum required FCD volume is determined to identify which road sections are suitable for virtual traffic counts. The correlation coefficient is a metric that reflects the degree of coherence between two variables (van Heijst, 2022). In this study, the Pearson correlation coefficient, whose formula is depicted in Equation 6, is employed.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}}$$

Equation 6
(Turney, 2022)

In which r is the Pearson correlation coefficient, n is the number of data points, x is the FCD volume at the location of the traffic counter and y is the volume measured by the traffic counters.

To determine the minimum FCD volume, the correlation coefficient of all data points of traffic count locations for which the measured FCD volume is below a certain threshold is determined. In Figure 30, a schematisation of this threshold is given. In this situation, the correlation between the traffic counts on the left of the threshold (the red dots) is calculated.

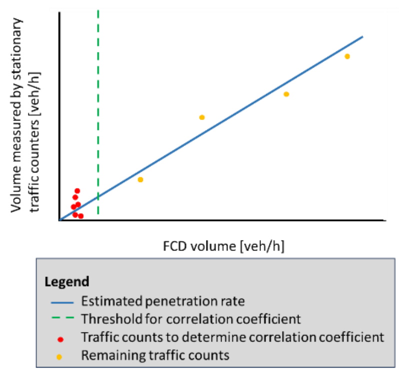

Figure 30: Visualisation of the method to determine minimum FCD volume for virtual traffic counts.

This threshold is increased incrementally (a shift of the line to the right in the figure), resulting in an overview of the correlation coefficient per threshold value. As a correlation coefficient of 0.5 or more indicates a strong linear (positive) relationship (Turney, 2022), the FCD volume at which this correlation coefficient is exceeded is considered the minimum FCD volume. The method described is applied to the lowest ('Other roads within built-up areas') road class, as this is the road class at which the dispersion is most significant. Consequently, it is assumed that the minimum FCD volume calculated based on this road class also applies to the other road classes.

Subsequently, a virtual traffic count is implemented on 10% of the suitable road sections per road class. The locations for virtual traffic counts are selected randomly, excluding road sections on which a 'regular' traffic count is present, to ensure no inconsistencies appear in the dataset. The 10% figure is selected to avoid excessive information that could lead to inconsistencies within the data while ensuring that sufficient FCD is included to have an effect. If there are too many traffic counts, the matrix may be overshaped by the counts, resulting in an overdetermined system that is not solvable or a system that does not reflect the situation correctly anymore. Furthermore, the virtual traffic counts are subject to variation, which could lead to inconsistencies. This could result in the calibration method failing to produce a result. This is partly taken into account by the slack variables in the optimisation process, but the variation of the slack variables is only limited. For the same reasons, and because many traffic counts are already present on the higher road classes, virtual traffic counts have not been incorporated on the 'higher' road classes (motorways, trunk roads or provincial roads).

Based on TomTom's selected link analysis, the second technique incorporates virtual traffic counts on all off-ramps on the motorway and trunk road that do not have 'regular' traffic counts. The rationale behind this technique is that when the distribution of traffic on the main roads is correct, the other road will automatically be more correct. The percentage of traffic that takes the off-ramp can be determined by placing a selected link just before the off-ramp. As PTV Visum can only calibrate the OD matrix with absolute traffic counts, the distribution is transformed into a traffic volume utilising a (virtual) traffic count on the main road (motorway or trunk road).

After the virtual traffic counts are determined for both techniques, they are implemented within the calibration methodology utilising the PTV Visum software. During the implementation phase, the focus is solely on the evening rush hour, as this period is typically the busiest period of the day (Rijkswaterstaat, 2023). It can be hypothesised that the results obtained also apply to the other periods.

6.1.2. Results

Utilising the correlation coefficient, it is found that road sections where FCD recorded an average of at least 4 vehicles/hour during the evening rush hour are suitable for virtual traffic counts. An overview of the road segments suitable for virtual traffic counts, when the 4 vehicles/hour is taken as threshold, is given in Figure 31.

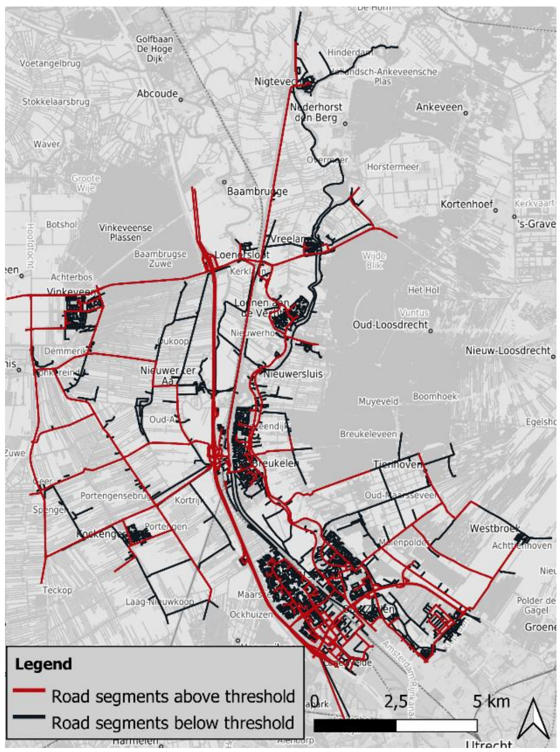

Figure 31: Overview of the road segments suitable for a virtual traffic count depending on the threshold of 4 vehicles/hour on average during the evening rush hour.

As previously mentioned, on 10% of these road segments, virtual traffic counts are added randomly, with the exclusion of road sections with already a 'regular' traffic count present. A total of 3 scenarios are created using this technique, and these results can be found in Figure 32.

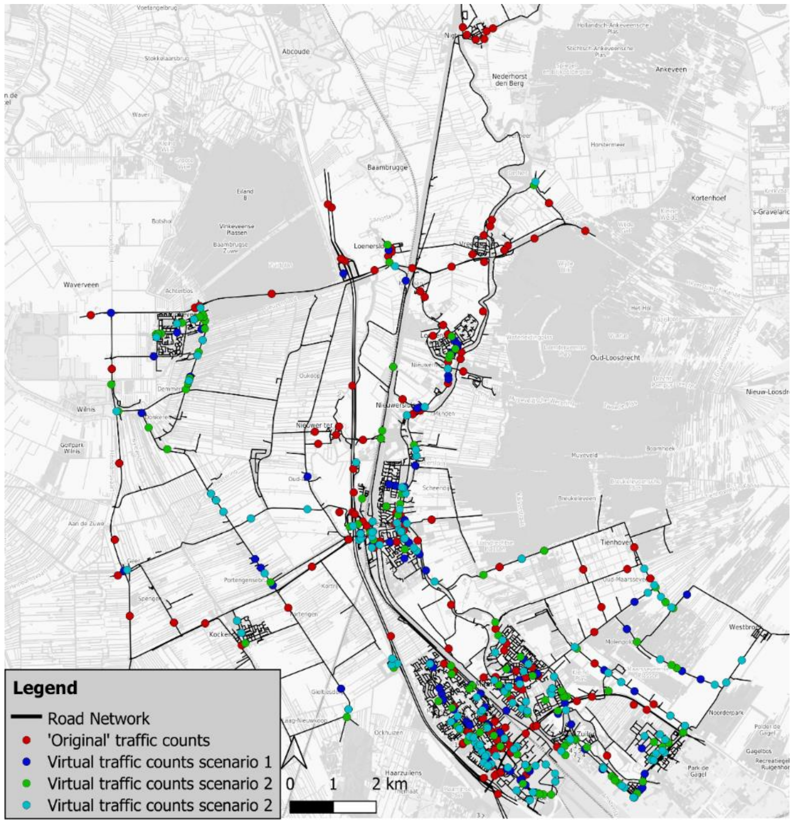

Figure 32: Location of the virtual traffic counts for each of the different scenarios.

In addition, a technique is employed whereby virtual traffic counts are added so that information about the number of vehicles utilising each off-ramp of the motorway and trunk road is available. Figure 33 shows the virtual traffic counts involved.

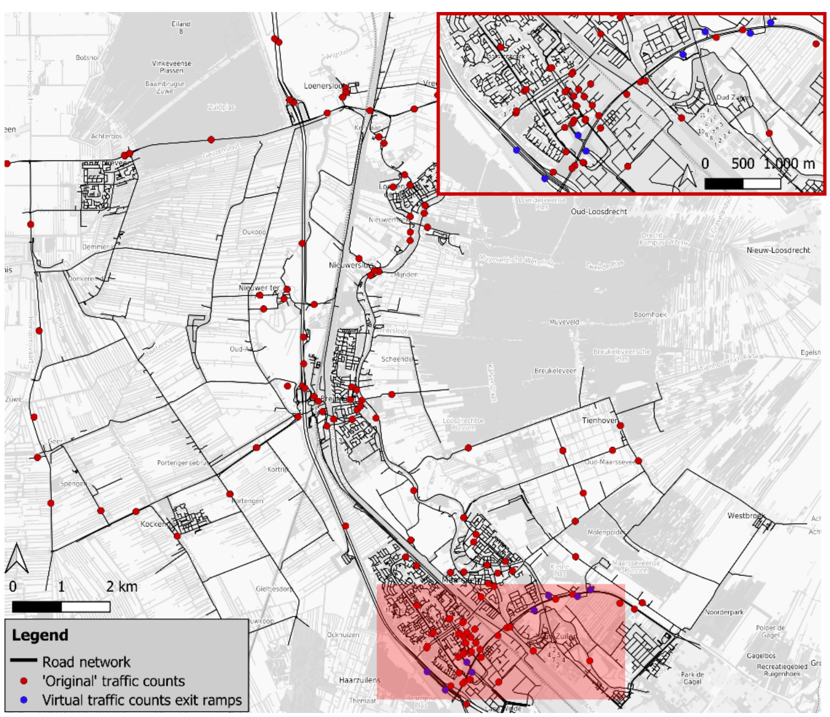

Figure 33: Location of the virtual traffic counts for the technique in which virtual traffic counts are added to off-ramps which do not contain count information.

This figure demonstrates that virtual traffic counts are particularly added on the trunk road. This can be attributed to the fact that data is available regarding the proportion of traffic taking most off-ramps on the motorway.

6.2. Evaluation of effects of implementation

The last research question aims to evaluate the effect of implementing the calibration techniques that use FCD. It is important to evaluate the effect since it is desirable to conclude which OD matrix is most accurate. As the ground truth OD matrix is unknown, the evaluation is based on two indicators: GEH values and screenlines. For both indicators, some metrics determine which OD matrix best describes the actual traffic situation and, thus, is the most accurate OD matrix. Based on these metrics, it can be determined which OD matrix is most accurate.

6.2.1. Methodology

The effect has been analysed after the FCD is implemented within the calibration process. As different techniques are created, multiple scenarios are executed to derive which calibration technique results in an OD matrix which most accurately reflects reality. By creating multiple scenarios, the effect of outliers is minimised. Therefore, the effects of implementing the various techniques can be evaluated most accurately. In Table 6 an overview of the various scenarios is given. Underneath the table, an explanation regarding the various scenarios is given.

Table 6: Overview of the scenarios implemented in order to evaluate the effects on the OD matrix.

Scenario number	'Regular' traffic counts	Virtual traffic counts
1	Set 1 of 70% of counts	-
2	Set 2 of 70% of counts	
3	Set 3 of 70% of counts	
4	Set 1 of 70% of counts	Set 1 of virtual traffic counts across network
5	Set 2 of 70% of counts	
6	Set 3 of 70% of counts	
7	Set 1 of 70% of counts	Set 2 of virtual traffic counts across network
8		Set 3 of virtual traffic counts across network
9	Set 1 of 70% of counts	Set of virtual traffic counts on off-ramps
10	Set 2 of 70% of counts	
11	Set 3 of 70% of counts	

Scenarios 1 to 3 are based on the current calibration technique, which is solely based on 'regular' traffic counts. As part of the 'regular' traffic counts are desired to be used to measure the implementation effect, the current technique is executed with 70% of the 'regular' traffic counts. This percentage is chosen as empirical studies revealed that 20-30% of the data is an optimum size as a validation set (Gholamy et al., 2018)For each scenario, the traffic counts used in the calibration technique are altered by randomly including 70% of the traffic counts per road class.

Scenarios 4 to 8 are related to the technique which implements virtual traffic counts across the road network. In this study, this technique is split into two methodologies, as the accuracy of the results depends on both datasets. Therefore, in a situation where one of the sets of (virtual) traffic counts contains outliers, the results could be skewed. Setting up two methodologies eliminates outliers as much as possible, making the results more accurate. The first methodology, which is the basis for scenarios 4 to 5, examined scenarios where the different sets of regular traffic counts are used while the virtual traffic counts remain constant. This technique is called the ‘Variation regular & virtual’ methodology. In the second methodology, referred to as the ‘Variation virtual’ methodology, scenarios 5 to 8 are generated by keeping the set of regular traffic counts constant while altering the set of virtual traffic counts across the road network.

Scenarios 9 to 11 are based on the technique involving virtual traffic counts on off-ramps. As the locations of the virtual traffic counts remain constant, the scenarios are generated by altering the set of ‘regular’ traffic counts according to the scenarios of the current calibration technique. Based on these scenarios, the effects are analysed according to various indicators.

GEH values

As outlined in Section 4.1, the GEH value serves as an indicator of the degree to which the assigned traffic volume aligns with the measured traffic volume. As Bash (2015) and Aly et al. (2022) indicate that a GEH value of less than 5 suggests a good degree of similarity, and a value higher than 10 implies a weaker match between the assigned and measured volume; the number of traffic counts falling within these categories is determined. In addition, the average GEH value of all traffic counts is determined. To ensure robust validation, only 30% of the traffic counts that are not utilised within the calibration are considered in this analysis. Subsequently, the OD matrix with the highest percentage of GEH values below 5, the lowest percentage of GEH values above 10, and the lowest average GEH value, is most accurate according to these indicators.

Screenlines

Screenlines are utilised to examine the effect of implementing FCD. A screenline can be defined as an imaginary line drawn on the network, thereby creating a division by a natural or manufactured boundary with only a few crossings (Ortúzar S. & Willumsen, 2011). One of the screenlines is placed at a neighbourhood in Maarssen where two entrances and exits are present, as illustrated in Figure 34. Consequently, vehicles must travel through these specific road sections to exit or enter the neighbourhood. Therefore, the total number of trips whose origin is within the neighbourhood and whose destination is outside of the neighbourhood should be equal to the sum of vehicles utilising the exit roads of the neighbourhood. However, this calculation must exclude vehicles utilising one exit and re-enter the neighbourhood via the other entrance. In this situation, this was only a few percent. The selected link feature of TomTom is utilised to determine the proportion of the volume to which this applied. The same procedure was applied to the entry roads, albeit with the origin and destination reversed.

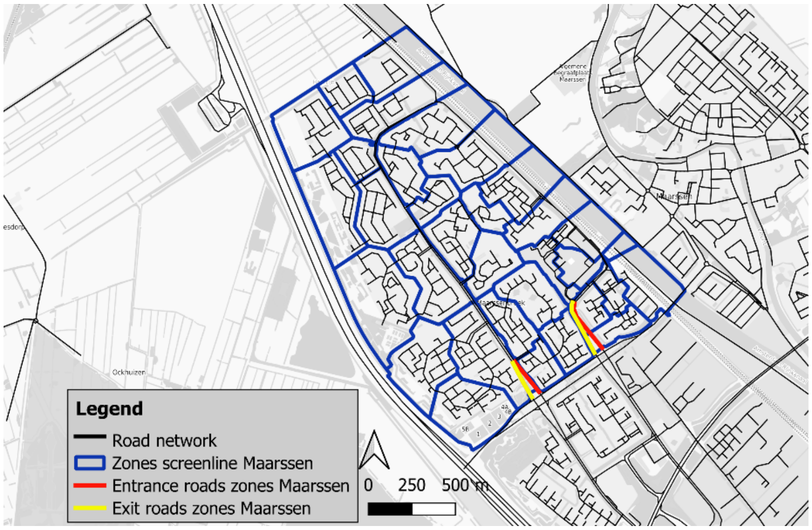

Figure 34: Visualisation of the zones included in the screenline of Maarssen.

The second screenlines are positioned where the A2 motorway enters and exits the study area. As all vehicles with an origin or destination within the cordon zone associated with this road segment must travel through this segment, the (virtual) traffic count should be equal to the total sum of the number of trips departing or arriving at this cordon zone. In addition to the traffic counts, the selected link feature of TomTom is utilised to ascertain the proportion of traffic which did not exit the A2 during the entire length of the study area. This approach facilitates a more precise examination of the validity of the OD pairs within the study area, which are associated with the A2 cordon zones.

Consequently, the OD matrix, in which the summed entry values lead to the value closest to the traffic count value, is the most accurate according to that screenline. Therefore, per screenline, it can be determined which OD matrix is most accurate.

Differences matrices and assigned flows

In addition to the evaluation of the accuracy of the effects, a general analysis of the effects is conducted. This analysis aims to further understand the impact of implementing FCD within the calibration process and is not aimed at evaluating which OD matrix is most accurate. Moreover, this analysis could provide insight into the factors that impact the other indicators' results. This general analysis is conducted by examining the differences between the matrices and assigned flow from the various calibration techniques. Therefore, the average values of the three scenarios per calibration technique are compared using the following three indicators:

- Total number of trips;
- Difference in trip ends (number of trips arriving and departing) per zone compared to the current calibration technique;
- Difference in assigned flow per road segment compared to the current calibration technique.

In addition to the aforementioned indicators, the geographical distribution of the GEH values and a comparison to a map made by NDW, which reveals the estimated intensities for the road network, are considered. Nevertheless, the results of these analyses are not considered conclusive and are, therefore, not included in this report.

6.2.2. Results

GEH values

In Table 7, the percentage of count locations with a GEH value lower than 5 or higher than 10 and the average GEH value across the traffic counts are presented for the various calibration techniques. This table provides an overview of the results for each analysis, in which red and green indicate the calibration techniques with the poorest and best scores for each indicator, respectively.

Table 7: Average results of the GEH values for the different calibration techniques. Red indicates the technique that scored poorest for that indicator; green indicates the technique that scored best.

	% of GEH-values <5	% of GEH-values >10	Average GEH-value
Current technique	90.35	2.19	2.26
Variation 'regular' & virtual counts	86.40	3.95	2.58
Variation virtual counts	87.28	3.07	2.32
Virtual traffic counts on off-ramps	90.48	1.90	2.18

From the results outlined in the table, it can be concluded that the technique which calibrates the OD matrix utilising virtual traffic counts on the off-ramps leads to the best fit concerning the traffic counts. The techniques in which virtual traffic counts are added across the road network, particularly in which different sets of 'regular' traffic counts are applied within the calibration, result in a poorer fit of the validation traffic counts. Nevertheless, it should be noted that the differences among the various techniques are marginal. Therefore, conclusions cannot be drawn with certainty. Furthermore, it is uncertain whether the observed differences in the scores for the various indicators indicate an improvement or deterioration of the accuracy of the OD matrix or whether it is caused by a change in the traffic assignment due to the incorporation of additional traffic counts.

Screenlines

As outlined, various screenlines are compared to get an idea of the accuracy of the OD matrices resulting from the different calibration techniques. In Table 8, the results of these analyses are presented. The upper section of the table presents the results of the Maarssen screenline. The middle and lower sections show the results of the screenline of the A2. The results in the middle section correspond to the total screenline. The lower section presents the results of traffic with a destination or origin zone that is not the cordon zone of the A2 motorway. For all parts of the table, the 'Traffic count' line represents the value measured by the traffic count and, thus, the actual traffic situation. Consequently, the technique that has the result closest to this value is the best match to reality. Again, the calibration techniques with the poorest and best scores for each indicator are indicated in red and green.

Table 8: Average results of the screenlines for the different calibration techniques and screenlines. Red indicates the technique that scored poorest for that indicator; green indicates the technique that scored best.

Neighbourhood Maarssen	**Origin within neighbourhood**		**Destination within neighbourhood**	
Traffic count	***1349.22***		***1865.45***	
Current technique	1162.55		1773.61	
Variation 'regular' & virtual	1193.79		1783.37	
Variation virtual	1186.40		1728.08	
Off-ramps	1156.19		1777.37	
A2 Motorway	**S to N bound: Destination North**	**S to N bound: Origin South**	**S to N bound: Origin North**	**S to N bound: Destination South**
Traffic count	***6253.50***	***3905.30***	***6299.00***	***4377.89***
Current technique	6005.22	3771.05	6984.74	3582.52
Variation 'regular' & virtual	6038.86	3795.00	7056.82	3599.78
Variation virtual	6069.90	3860.72	7299.40	3643.89
Off-ramps	6004.28	3425.86	6759.78	3574.53
A2 Motorway study area	**S to N bound: Destination North**	**S to N bound: Origin South**	**S to N bound: Origin North**	**S to N bound: Destination South**
Traffic count	***3084.85***	***502.61***	***3592.95***	***794.59***
Current technique	3162.99	636.65	3850.34	740.29
Variation 'regular' & virtual	3178.27	611.89	3945.81	748.52
Variation virtual	3191.88	668.92	3930.74	752.81
Off-ramps	3204.67	650.76	4089.43	778.66

In contrast to the findings related to the GEH values, the outcomes of the screenlines are less definitive. The most effective technique varies for the different screenlines. Moreover, the differences between the techniques are marginal. It is, however, noteworthy that in all cases, a substantial difference is observed between the traffic count and the OD matrices. It is particularly remarkable that this observation also applies to the OD matrix in which the calibration technique is based on virtual traffic counts on the off-ramps, as the primary focus of this calibration is on the main roads of the study area. A potential explanation for these substantial deviations is the constraints of the calibration process. To ensure that the matrix structure is not significantly altered, restrictions are imposed on the extent to which the matrix may deviate from the a priori matrix. For instance, it is restricted how much the sum of a zone's attraction or production values can alter per iteration. Furthermore, the calibration process is constrained by the number of iterations permitted. It is possible that an increase in the number of iterations would result in matrices that more closely resemble the values of the screenlines. Moreover, it is possible that the virtual traffic counts on the off-ramps are inaccurate and, therefore, do not match the actual counts.

Differences matrices and assigned flows

As the GEH analysis and screenlines demonstrated that the results of the various scenarios differ only marginally, the differences between the matrices are also examined. The first analysis compares the total number of trips.

This is calculated by taking the sum of all matrix entry values. The results of this analysis are presented in Table 9.

Table 9: Total number of trip ends resulting from the different calibration techniques.

Calibration technique	Total number of trips
Current technique	33125.98
Variation ‘regular’ & virtual counts	34652.29
Variation virtual counts	34409.26
Virtual traffic counts on off-ramps	32630.03

The table demonstrates that the number of trips is almost 5% higher for the technique using virtual traffic counts across the road network compared to the current calibration technique. In contrast, adding virtual traffic counts on off-ramps leads to a slight decrease of approximately 1%. This aligns with the size of the differences for the GEH values and screenlines. Nevertheless, it is noticeable that the differences in the results of the screenlines are sometimes negative and sometimes positive compared to the current calibration technique. Therefore, more insight is needed into how the differences are distributed across the study area. This is done by examining the differences in the OD matrix's entry values and the traffic assignment differences. Since the two techniques involving the addition of virtual traffic counts across the road network provide comparable results regarding the differences, the results of one of the techniques are presented in the report.

In Figure 35 and Figure 36, the results of the percentage differences between the number of trips arriving per zone resulting from the technique involving FCD compared to the current calibration technique are presented. In these figures, a negative percentage (indicated in blue) reveals a drop in the number of trips arriving in the zone. In contrast, a positive percentage (indicated in red) indicates an increase in the number of trips arriving in the zone. When analysing these figures, it should be noted that the distribution of colours is not equal in both figures. As an analysis revealed that the trend of differences is comparable for the number of trips originating and arriving in a zone, only the results of the number of trips arriving in a zone are presented in the report.

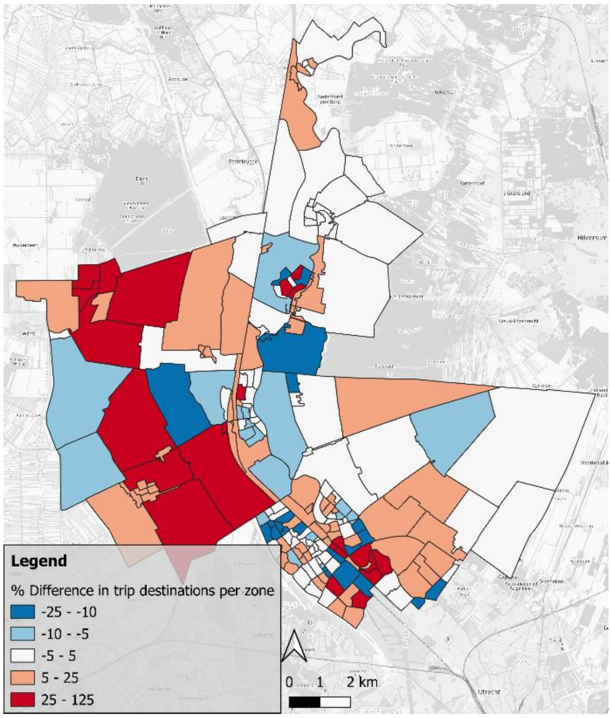

Figure 35: % Difference in the number of trips arriving at a zone for the calibration technique involving virtual traffic counts across the road network compared to the current calibration technique.

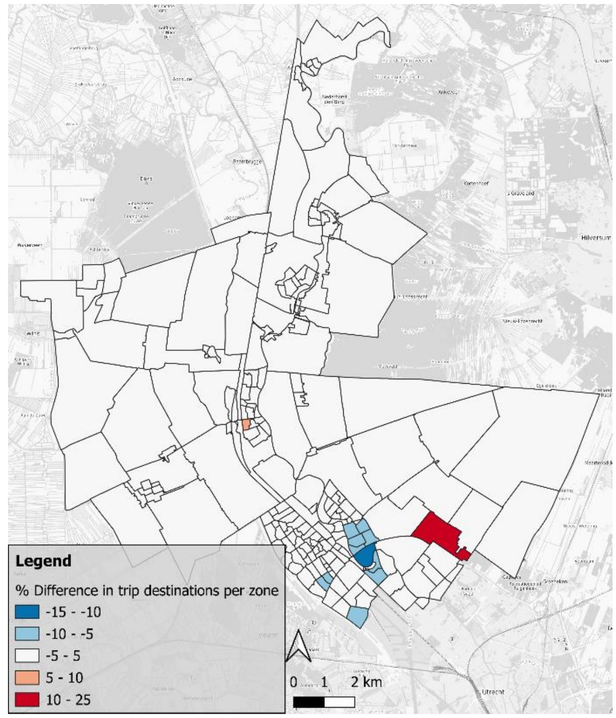

Figure 36: % Difference in the number of trips arriving at a zone for the calibration technique involving virtual traffic counts on off-ramps compared to the current calibration technique.

Figure 35 demonstrates, particularly in comparison to the results presented in Figure 36, a substantial difference between the current technique and the technique involving virtual traffic counts across the road network in numerous zones. It should be noted that the difference is expressed in percentages. Therefore, a minor adjustment in the matrix could lead to a significant percentage difference in a zone where the number of trips arriving is low. A notable observation in Figure 35 is that clusters of zones exhibit similar trends, signifying an increase or decrease in the number of trips arriving at a zone. Nevertheless, no particular explanation is identified, such as the urbanity of the zone or the location of virtual traffic counts, that could explain the increase or decrease. Figure 36 shows that the differences occur mainly in the surroundings of the trunk road. This observation is consistent with the input data, as virtual traffic counts are mainly located at the trunk road's off-ramps.

In Figure 37 and Figure 38, the percentage differences between the assigned traffic volume per road section resulting from the technique involving FCD and the current calibration technique are displayed. In these figures, a negative percentage (indicated in blue) reveals a drop in assigned traffic volume, while a positive percentage (indicated in red) indicates an increased traffic volume. When analysing these figures, it should be noted that the distribution of colours is not equal in both figures.

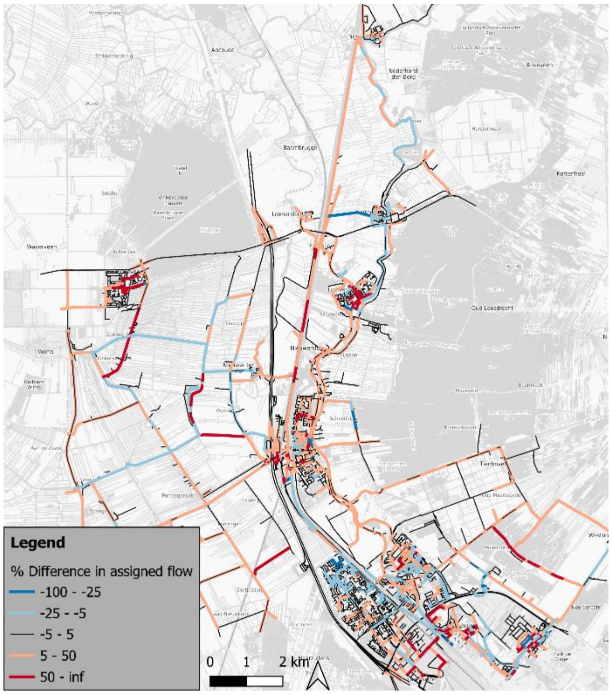

Figure 37:% Difference in the volume of the assigned traffic per road section for the calibration technique involving virtual traffic counts across the road network compared to the current calibration technique.

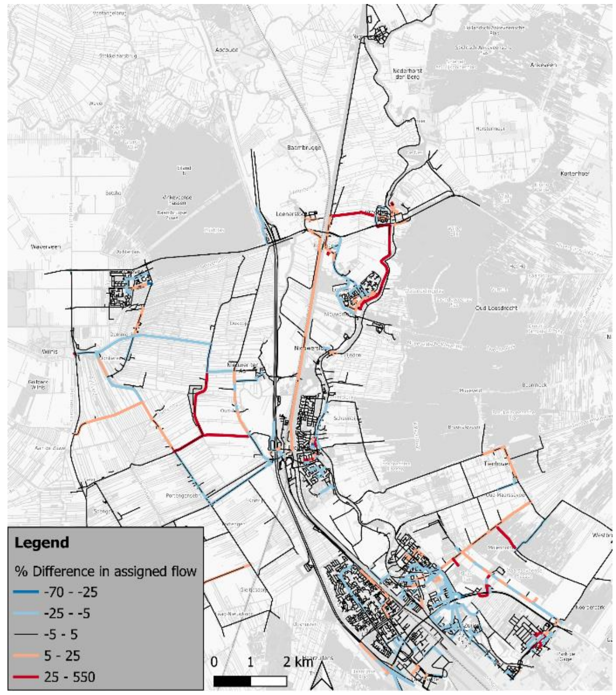

Figure 38: % Difference in the volume of the assigned traffic per road section for the calibration technique involving virtual traffic counts on off-ramps compared to the current calibration technique.

As with the number of arriving trips per zone, adding virtual traffic counts across the road network leads to the most significant change in the number of assigned traffic volumes. The off-ramp technique primarily affects the traffic assignment around the trunk road. Since the assignment is based on the OD matrix, it is logical that the traffic assignment results match the results of the difference between the OD matrices.

Based on these analyses, it can be concluded that the technique in which virtual traffic counts are placed across the road network causes more significant changes to the OD matrix and, thus, to the traffic assignment. However, no clear trend is visible regarding the locations of these changes. Therefore, it is unfeasible to conclude that these changes are logical and result in a more accurate OD matrix. The calibration technique, which places virtual traffic counts on off-ramps, causes the main differences to occur around the trunk road. This is logical as the virtual traffic counts are mainly placed at these off-ramps. Nevertheless, whether the OD matrix resulting from this technique is more accurate is unclear.

6.3. Conclusion

In this study, two techniques are employed to implement FCD within the calibration process of the OD matrix for passenger cars. The first technique involved the placement of virtual traffic counts across the road network. Within this technique, a virtual traffic count is included on 10% of the roads (with a low road class) classified as suitable for virtual traffic counts. The study revealed that a road section is suitable if FCD recorded an average of at least 4 vehicles per hour during the evening rush hour. Within the second technique, virtual traffic counts are implemented on the off-ramps of the motorway and trunk road where no count information is available within the regular set of traffic counts.

Utilising the GEH values, screenlines and information regarding the differences between the matrices and traffic assignment, the effect of the implementation of FCD is evaluated. According to the GEH values, the off-ramp technique scored best in terms of accuracy. Nonetheless, the differences between the various are marginal. In contrast, the results of the screenlines were not unequivocal, thus leading to an indefinite conclusion. The analysis of the differences between the matrices and traffic assignment revealed that the calibration technique involving virtual traffic counts across the road network influenced the OD matrix and traffic assignment the most. Nevertheless, whether this corresponds with a more accurate OD matrix and traffic assignment could not be ascertained. These results are not in line with earlier studies that concluded that the accuracy of an OD matrix increases when the number of independent traffic counts increases (Lam & Lo, 1990; Yang et al., 1991). A possible explanation for this difference is that the traffic volumes of the virtual traffic counts are not accurate enough or that the location of the virtual traffic counts is not beneficial for the calibration. Additionally, it is possible that the matrix is already of such an accurate level that adding the virtual traffic counts overshapes the matrix.

Consequently, based on these results, it cannot be concluded whether the virtual traffic counts positively or negatively impact the accuracy of the OD matrix for passenger cars. Therefore, further research is recommended, such as testing more scenarios and techniques in other study areas. Section 8.2 elaborates further on this and provides additional recommendations concerning further research.

7. Discussion

Since decisions are made regarding the scope of this study, some aspects are not considered, leading to limitations and generalisations. This section addresses some of these attention points.

7.1. Transferability of results

The first point of discussion is that the study's outcomes could vary considerably if an alternative study area or model is used. Since there are variations in the amount of FCD available, specifically in the coverage of FCD across the Netherlands (M. Uenk-Telgen, personal communication, October 3, 2024), the trip types covered within FCD may differ for other study areas. Consequently, the representativeness of FCD, specifically the sampling bias of FCD, could be affected by this. Furthermore, a different study area or model may influence the accuracy of the estimation of the OD matrix and the impact of virtual traffic counts. For example, in instances where only a few traffic counts are located on main roads, virtual traffic counts may improve the calibration process to generate an accurate OD matrix. For the model applies that the calibration method could also affect the results. For instance, the restrictions on how much the matrix is allowed to change per iteration and the number of iterations can affect the final OD matrix and, thus, the effect of implementing FCD. As the study only focuses on one model, this is not considered.

Furthermore, implementing FCD within the calibration process is only applied to the OD matrix regarding the evening rush hours. While the results are expected to not differ for the other time periods, this has not been researched. Therefore, it could be possible that implementing FCD in the calibration process of the other time periods could lead to more or less accurate results. Particularly since the analysis of the coverage of FCD revealed that the penetration rate is different for the different time periods, this is a possible scenario.

In addition to examining a particular case study, the study focussed on FCD obtained from TomTom. Nevertheless, there are other suppliers of FCD, such as HERE (2024a) or Be-Mobile (NDW docs, n.d.-b). It is plausible that the representativeness of the FCD varies between these suppliers due to differences in the probe vehicles on which the data is based and the procedure on how the data is processed. For instance, even though HERE (2024a) also anonymizes the data by removing a trip's first and last parts. The part of the trip which is removed varies each time and could be different from TomTom's. Furthermore, data from sparsely populated areas is also removed by HERE. Therefore, it is unclear whether the conclusions drawn in this study also apply to other FCD datasets.

7.2. Indicators representativeness FCD

To determine the representativeness of FCD, the data is compared with travel survey and traffic count data based on the trip length distribution, the distribution throughout the week and the distribution across the day. However, the analysis is conducted based on isolated indicators and does not provide a comprehensive study into a possible correlated bias. For instance, if there is an overrepresentation of longer trips during the morning rush hours, while during the evening peak hours there is an underrepresentation of longer trips, this is not presented by the current indicators. Furthermore, it is possible that other indicators may better uncover the representativeness of FCD.

In addition to the indicators itself, a point of discussion outlined before is that there is a bias in the two datasets to which the FCD is compared. As outlined in Section 4.2., particularly in the travel survey (ODiN) data, a bias is present, as revealed by multiple studies (KiM, 2017; Smit et al., 2017; Spurr et al., 2015; Stopher et al., 2005, 2015). Nevertheless, traffic counts are also subject to bias and measurement errors (Mohammed et al., 2016). Due to these biases and errors, the travel survey and traffic count data themselves also do not accurately represent the actual traffic situation. Therefore, it is possible that the three distributions (trip length distribution, distribution throughout the day, and distribution across the week) produced based on these datasets are skewed and thus not representative. If this is the case, the conclusion drawn regarding the representativeness of FCD could have been affected and therefore be inaccurate.

7.3. Number of scenarios

The final point of discussion is that implementing FCD is restricted to several scenarios. This study selected only two techniques to implement FCD within the calibration process. However, alternative approaches, particularly variations of the technique involving the placement of virtual traffic counts across the road network, may result in more accurate OD matrices. For instance, techniques involving different percentages of roads on which virtual traffic counts are placed or techniques in which more restrictions are applied on the placement of the virtual traffic counts.

In addition to considering only two techniques, the effects are analysed utilising three scenarios per technique. The rationale behind multiple scenarios is to eliminate outliers in the results, such as the random selection of incorrect locations for virtual traffic counts. However, when calculating the number of replications required, for instance, using the method involving the relative error (Law, 1983), a higher number than three is obtained. Nevertheless, due to temporal constraints, it was decided to proceed with three scenarios. It is, therefore, possible that the effects on the OD matrix are different with more replications.

8. Conclusion & recommendations

This chapter reflects upon the different research questions to achieve the research aim. Additionally, recommendations are presented. These entail practical recommendations on how the results of this study can be used in practice and recommendations for future research.

8.1. Conclusion

RQ1: *Can traffic volumes per road section be accurately estimated from Floating Car Data by computing the penetration rate of Floating Car Data?*
The study has demonstrated that a linear relationship between FCD volume and the volume measured by traffic counters per road class per time period can be used to estimate the penetration rate of FCD to a certain extent. From this penetration rate, it has become clear that the FCD coverage varies significantly across the different road classes, with a coverage of up to 29% on motorways compared to a coverage of just over 9% on urban roads. The results show that generally, 'higher' road classes exhibited higher coverage rates. This indicates that the FCD is subject to a sampling bias as the penetration rate is not uniform across the road network. This is in line with the results of NDW (n.d.-b), which reveals that the penetration rate varies across the road network, indicating an overrepresentation of long-distance trips. Therefore, it is concluded that the FCD is not representative for OD studies according to the penetration rate. Nevertheless, the estimated penetration rate can be used to estimate the traffic volume based on traffic volume. However, it should be considered that at low FCD volumes, the linear trend, and thus the penetration rate, is not evident.

RQ2: *How does Floating Car Data compare to data retrieved from a travel survey and traffic counters regarding the trip length distribution, distribution throughout the week and distribution across the day?*
By comparing FCD with ODiN data and NDW data based on the trip length distribution, distribution throughout the week and distribution across the day, it emerged that the FCD generally aligns with these datasets. For the trip length distribution and distribution throughout the day, the distribution trend based on FCD corresponds to the distribution of the other data sources. Nevertheless, the height of the FCD distribution varies from the other distributions. The distribution comparison across the week revealed minor differences between the datasets. The analysis of the distributions per trip motive revealed that the difference is plausibly caused by an under or over-representation of certain trip motives. However, based on the study's findings, it is impossible to determine for which trip motive this applies and to what extent the representation is skewed. Another factor that may be at play is that the data does not cover the entire trip. This is attributed to multiple factors, including data processing to guarantee user privacy, the user switching on/off the navigation system later/earlier, and the disconnection of the GPS location of the navigation system.

Although it can not be ascertained which aspect of the FCD is responsible for the differences, the indicators indicate that the origin-destination information from FCD is not representative.

RQ3: *To what extent does Floating Car Data exhibit logical consistency in trip origin and destination patterns?*
Based on different techniques, it is examined whether the FCD exhibits logical patterns. The results, however, reveal that this is not entirely the case. In particular, the origins and destinations of trips are not always logical within FCD. For example, the OD analysis of TomTom indicated that trips depart or arrive on a motorway. This is probably because FCD does not incorporate the entire trip, as also outlined in the conclusion of RQ2.

Furthermore, it can be concluded that the traffic volumes counted by FCD are reasonably consistent, especially when compared to the variations within stationary traffic counters. Also, the distribution of vehicles taking an off-ramp on the motorway is comparable for both FCD and NDW data. Therefore, it is concluded that the FCD's origin-destination information is not representative but that the FCD volumes and proportions of vehicles taking an off-ramp, according to FCD, are representative.

Together, these research questions ensured that the first part of the research aim was attained, namely:
Aim: *Evaluate the representativeness of Floating Car Data for OD analysis when compared to alternative data sources.*
Based on the results of the first three research questions, it can be concluded that the origin-destination information of FCD is not representative. This is caused by specific trip types being under or over-represented. Also, (a proportion of) trips are not fully represented within the data. It is, however, important to note that this conclusion is based on the assumption that the other data sets are accurate and reflect the actual situation. This may not always be the case, as discussed in Section 0. Nevertheless, the study revealed that the traffic volumes according to FCD and the proportions of vehicles taking an off-ramp are accurately represented. Therefore, these two applications are suitable for OD studies.

Based on this conclusion, the subsequent two research questions have been addressed.

RQ4: *How can Floating Car Data be used in the calibration process of the OD matrix for passenger cars?*
Since the first three research questions identified that the origin-destination information of FCD is not representative, and more independent traffic counts lead to a more precise estimation of the actual OD matrix (Lam & Lo, 1990; Yang et al., 1991)It was decided to incorporate FCD using virtual traffic counts. As the FCD volume and the proportions of vehicles taking an off-ramp are accurately represented, two techniques for including the virtual traffic counts are formulated: placement across the road network and placement on off-ramps of motorways and trunk roads.

The first technique involved the placement of virtual traffic counts on 10% of the roads (with a low road class), which are classified as suitable for virtual traffic counts. Utilising the correlation coefficient, it is found that if FCD recorded an average of at least 4 vehicles per hour during the evening rush hour, a road section is suitable for virtual traffic counts. The FCD is transformed into a traffic count by applying the penetration rate calculated in research question 1. The second technique placed virtual traffic counts on the off-ramps of the motorway and trunk road for which no count information is available. The volume of traffic taking the off-ramp is estimated by utilising the distribution according to the selected link feature and a (virtual) traffic count on the main road.

RQ5: *What is the effect of adding data obtained from Floating Car Data at the calibration process of the OD matrix for passenger cars on the model's results?*
As the ground truth values of the OD matrix are not known and cannot be determined, the effect of implementation is evaluated according to three indicators: GEH values, screenlines and information regarding the differences between the matrices and traffic assignment. While the GEH values illustrated that the technique of the off-ramps scored best in terms of accuracy, the results of the screenlines do not reflect this. These results are ambiguous as the various screenlines result in different conclusions. Moreover, the analysis regarding the differences between the matrices and traffic assignment showed that the placement of virtual traffic counts across the road network influences the OD matrix and traffic assignment the most. However, no clear conclusion

can be drawn from this analysis. Following these results, no definite conclusion can be drawn regarding the effect of implementing FCD within the calibration process, as the results are not unequivocal.

Together, the answers to these research questions lead to a conclusion regarding the second part of the research aim:

Aim: *Develop a methodology for using Floating Car Data in the calibration process of the a priori OD matrix for passenger cars while accounting for the identified strengths and limitations of Floating Car Data.*

Based on FCD's identified representativeness, it was decided to use FCD by adding virtual traffic counts to the current set of 'regular' traffic counts. However, at this point, it cannot be concluded whether the virtual traffic counts positively or negatively impact the calibration process since the results regarding the accuracy of the OD matrices are not definitive. Therefore, further research is recommended on this matter.

8.2. Recommendations

8.2.1. Practical recommendations

The results of this study indicate that incorporating FCD in the calibration process in a systematic way is currently not desirable, as it has not been demonstrated that doing so results in a more accurate OD matrix. Consequently, it is not recommended that the FCD is implemented using any of the techniques tested in this study. However, the research demonstrated that the actual traffic volume could be estimated using FCD and the penetration rate. Therefore, adding a virtual traffic count at a location where no 'regular' traffic count is present but where a traffic count is deemed essential for the calibration process is feasible. This way, it is not implemented systematically but in specific locations where necessary. However, it is recommended to assess per study area whether the estimated penetration rate is a good measure as the coverage of FCD differs per location (M. Uenk-Telgen, personal communication, October 3, 2024).

Moreover, FCD can be utilised to evaluate the OD matrix and traffic assignment. For instance, the selected link analysis can be employed to verify whether the proportion of traffic taking an off-ramp is correct. Additionally, the FCD volumes can be utilised to check the allocated traffic volumes at different locations in the road network. Based on these comparisons, parameters in the model can be adjusted to ensure that the results match the FCD. Further research is recommended to determine whether it is desirable to incorporate FCD systematically or to use FCD in other ways to improve the accuracy of the OD matrix.

8.2.2. Recommendations for future research

In this study, the representativeness of FCD is examined by comparing it to ODiN and NDW data and analysing the logical consistency inherent in FCD. The results of these analyses indicated the presence of differences, revealing that the origin-destination information of FCD is not representative. Nevertheless, the methodologies employed do not determine exactly what causes the sampling bias and its size. Therefore, it is recommended that further insight into the representativeness of FCD for OD studies be gained by utilising alternative indicators and different datasets. For instance, in this study the indicators have been analysed in isolation while a correlation could be possible between them. For example, the trip length distribution may be different at various times. Other datasets, such as plate registration data or traffic cameras, could provide other information on which a comparison can be made. Furthermore, these datasets may have fewer errors or fewer biases than travel survey and traffic count data, leading to more accurate results. Furthermore, as the study revealed that the distribution of the selected link feature is consistent at off-ramps, it is recommended to investigate whether this applies to the distribution of intersections as well. By comparing the selected link distribution of FCD to traffic control system (TCS) logging data (in Dutch: verkeersregelinstallatie-logging data (V-log data)), which comprises information regarding the intensities per turn at an intersection with TCS (NDW docs, n.d.-a), it can be identified whether the selected link feature can be used to calibrate flows at intersections.

Additionally, it is recommended that the current implementation techniques be investigated further to ascertain whether they have the potential to result in more accurate OD matrices. As the number of replications per technique is only three, executing more experiments with these techniques in this study area is recommended to ensure robust conclusions. Furthermore, testing the methods in other study areas to ascertain the effects of implementation in different contexts is recommended. In particular, it is interesting to select a study area in which less regular traffic counts are available (on main roads) as the developed techniques are expected to have a more significant impact on the accuracy of the OD matrices in these situations.

Furthermore, it is recommended that more research be conducted regarding other applications of the developed techniques. For example, the percentage of roads suitable for virtual traffic count on which a virtual traffic count is placed could be adjusted. It would also be interesting to conduct more research on the effect of the constraints associated with the calibration. For instance, the margin surrounding a traffic count, as outlined in Section 4.1, could be adopted for virtual traffic counts as the uncertainty of this traffic count is probably more significant. For the same reason, a methodology could be developed in which the matrix is first calibrated solely based on the regular traffic counts, after which it is calibrated using all traffic counts (including the virtual traffic counts). In this way, a greater weight is given to the regular traffic counts. Furthermore, instead of including the virtual traffic counts across the road network, an optimisation approach, such as developed by Yang & Zhou (1998), could be used to determine the optimal locations for virtual traffic counts.

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Appendices

Appendix A Results Penetration rate

As mentioned in Section 5.1.1, multiple techniques are employed to find the most accurate penetration rate of FCD. These are the following:

- Average penetration rate per 24-hours for all road types combined
- Average penetration rate per time period for all road types combined
- Average penetration rate per 24-hours per road type
- Average penetration rate per time period per road type

In this section, the results of these different techniques are visualised and analysed. In the first two figures, Figure 39 and Figure 40, the remaining results of the technique which is found most suitable to estimate the penetration rate are visualised. In these figures the penetration rate for the different road types and different time periods, evening rush hour in Figure 39 and residual day in Figure 40, are visualised.

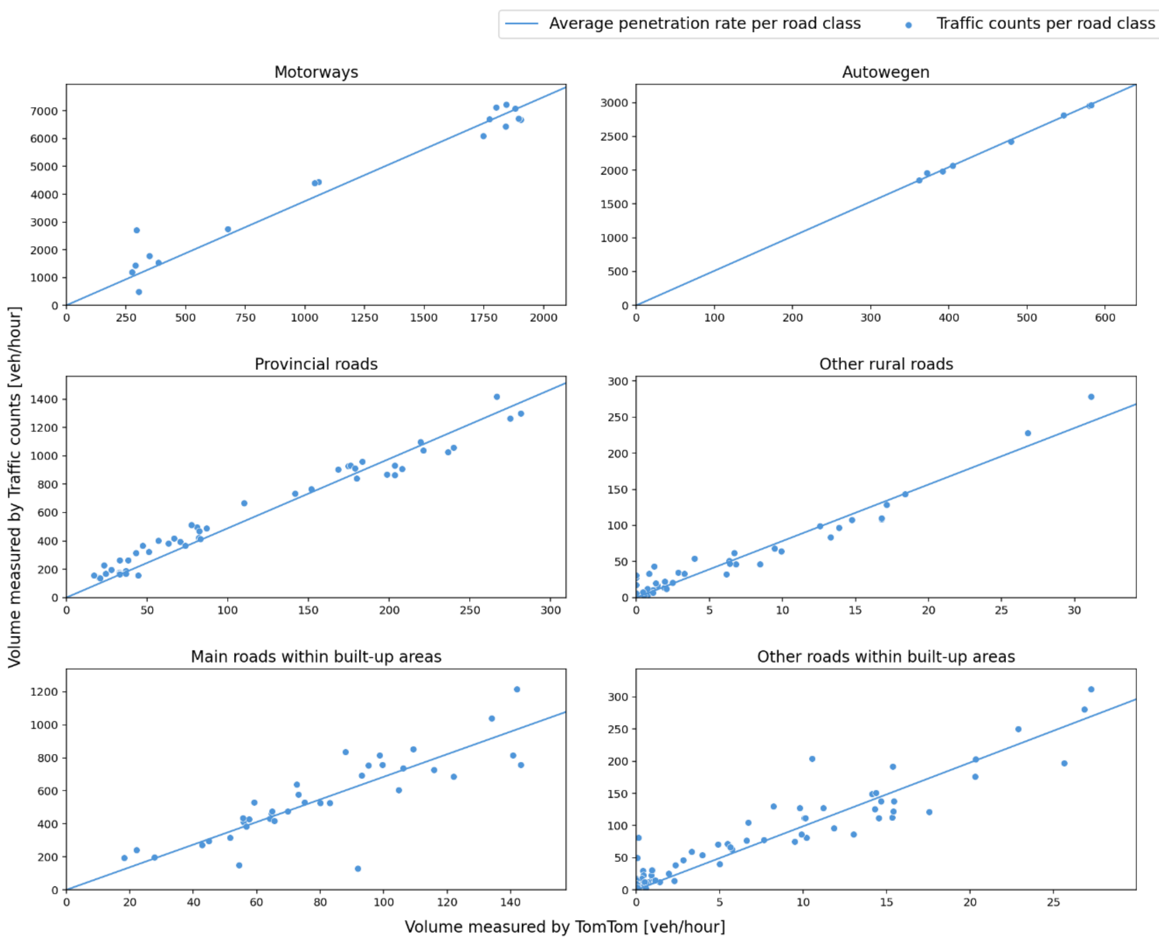

Figure 39: Indication of the average penetration rate of FCD on the different road types during the evening rush hours.

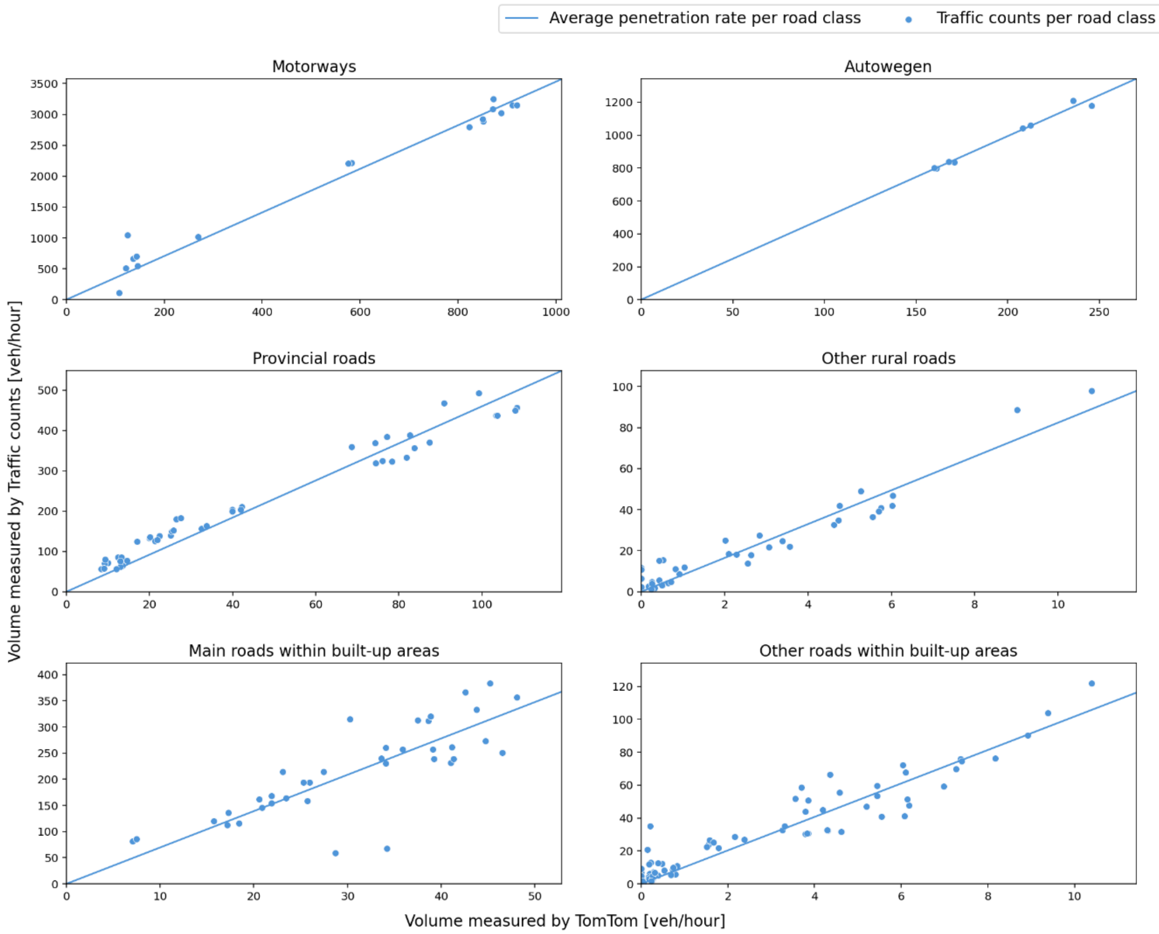

Figure 40: Indication of the average penetration rate of FCD on the different road types during the residual day.

As can be seen, the same conclusions can be drawn as discussed in section 5.1.2, namely that the penetration rate determined according to this method is an accurate but rough estimation of the actual coverage of FCD.
In addition to the technique in which the average penetration rate is calculated per time period per road class, two techniques are employed in which the penetration rate is determined without making a distinction between different road types, namely: average penetration rate per 24 hours and the penetration rates per time period. Figure 41 displays the results of the technique in which the average penetration rate is calculated per 24 hours. In Figure 42 and Figure 43, the results are displayed in which the average penetration rate is calculated per time period.

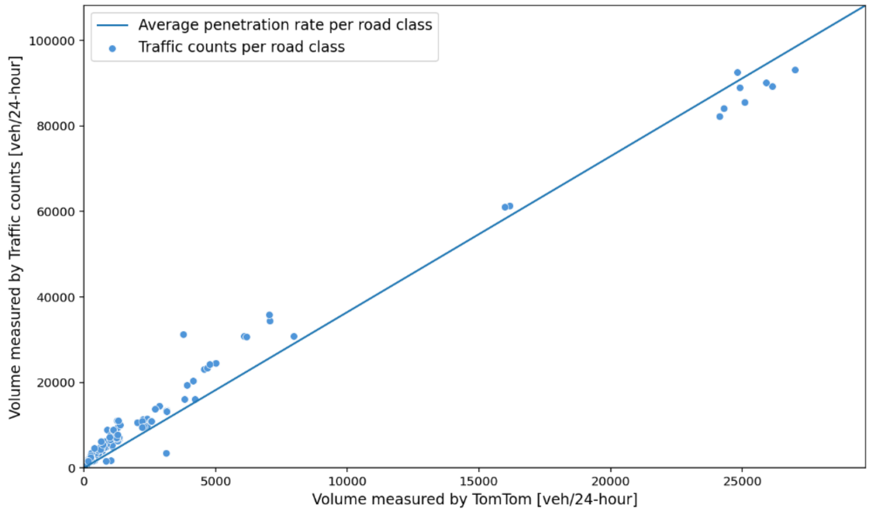

Figure 41: Indication of the average penetration rate of FCD on all road types combined for the intensity per 24-hour.

Figure 42: Indication of the average penetration rate of FCD on all road types combined during the morning rush hours.

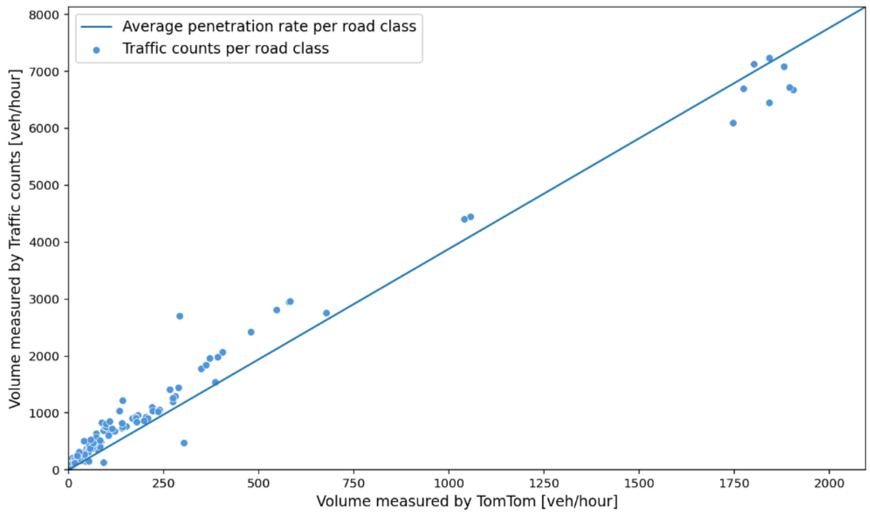

Figure 43: Indication of the average penetration rate of FCD on all road types combined during the evening rush hours.

When analysing the figures above it stands out that the calculated penetration rate overestimates the coverage in FCD. Especially at the lower (FCD) volumes, the line is located below the traffic counts indicating an overestimation of the penetration rate. Therefore, it was concluded that the technique which calculates the penetration rate per road type per time period results is a more accurate estimation of the penetration rate. Additionally, the average penetration rate was calculated per road type per 24-hours. The results of this technique can be found in Figure 44.

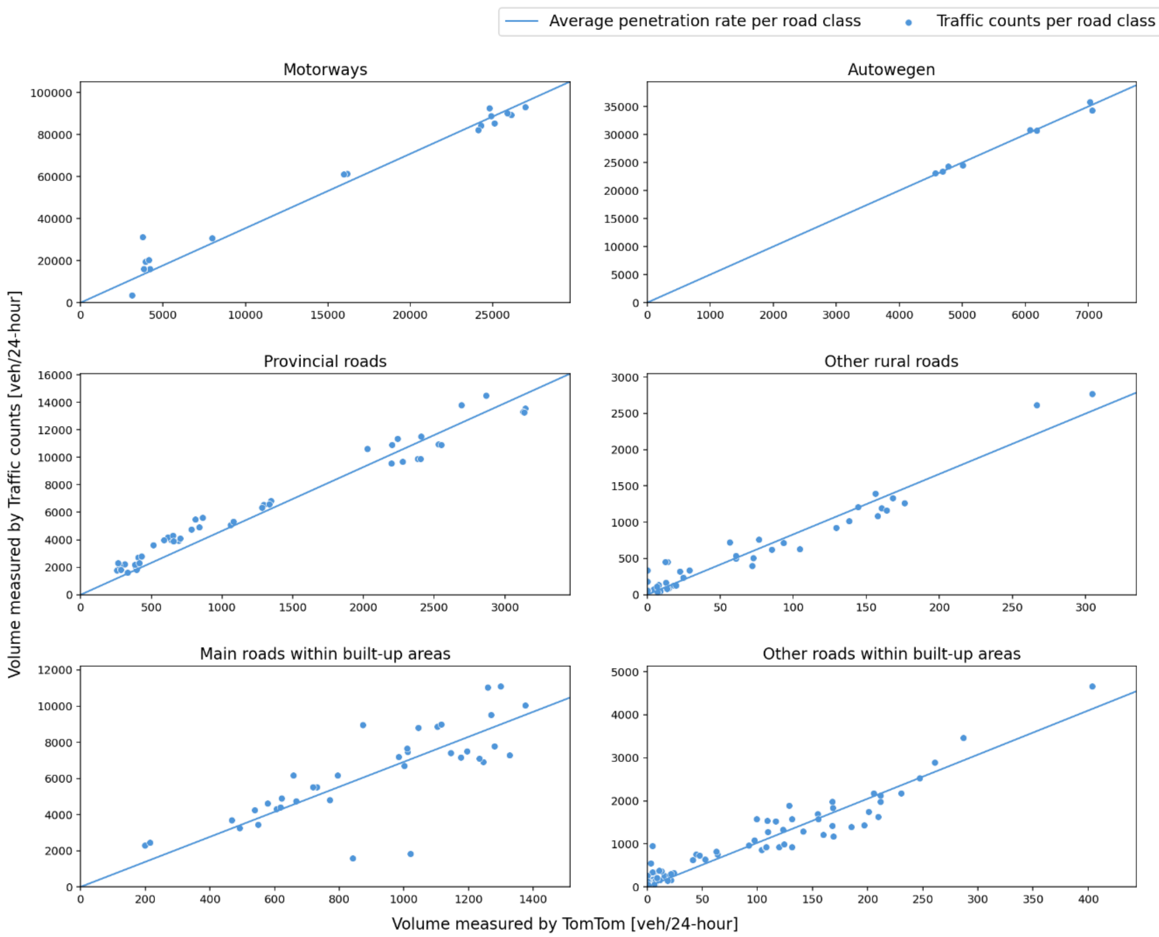

Figure 44: Indication of the average penetration rate of FCD on the different road types for the volume per 24-hour.

A review of the results presented in the above figure indicates that the estimated penetration rate for FCD is reasonably accurate. However, a more detailed examination of the results in which the results are compared to the results of the other techniques revealed that the technique in which the penetration rate is determined per road type per time period provided a more accurate representation of the penetration rate as the different datapoints are closer to the trend line.

Appendix B Prediction most probable trip motive

As discussed in Section 5.2.1, an attempt was made to build a model that could predict the most probable trip motive based on trip characteristics and demographic data of the origin and destination zone. Nevertheless, the results of this model were inconclusive. In this section an overview of the method employed and the results retrieved are presented.

Methodology

The goal of the model was to utilise explanatory variables to ultimately predict the most probable trip motive. Such models can be established utilising a machine learning algorithm. Based on OViN data of 2017 and ODiN data of 2019, multiple techniques were employed to fit a model. From the data, 70% was utilised to fit the model and 30% of the data was utilised to evaluate the model (Gholamy et al., 2018). Utilising this data, two models were tested: one that predicts what the most probable trip motive is and another one that predicts for each motive individually whether a trip has that particular trip motive. For both models, various tests were executed utilising different algorithms and combining different data(sets). In Table 10 an overview of all employed algorithms and data(sets) can be found.

Table 10: Overview methodology most probable trip motive.

Algorithms	Data	Trip characteristics of OViN/ODiN
• Decision tree • Random forest classifier • Gradient boosting • Neural network	• CBS landuse • CBS statistical data per PC4 • NRM demographic data	• Distance • Departure & arrival hour • Weekday • Urbanity

To evaluate the performance of the model, 30% of the survey data was utilised. The explanatory variables accompanied to the trips within this datasets were entered into the model with the objective of making a prediction regarding the most probable trip motive. These predicted motives were compared to the actual motives. Based on this comparison, the total number of true positives, true negatives, false positives and false negatives could be calculated. These numbers were then transferred to the three evaluation parameters utilised in this study: the precision, recall and F1-score. These evaluation measures give an indication regarding the number of predicted values which are correct compared to the number of false predicted values. The values of the evaluation parameters vary between 0 and 1, where 1 indicates a perfect model with no errors in the prediction and 0 indicates a model where all predictions made are incorrect. In Equation 7, Equation 8, and Equation 9 the formulas of these parameters are displayed.

$$Precision = \frac{True\ positive}{True\ Positive + False\ Positive}$$

Equation 7

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Equation 8

$$F1 = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

Equation 9

Results

From the various tests, the technique in which the random forest classifier is applied utilising all data available yields to the best results. This technique led to an accuracy of 0.54. This indicates that the model almost half of the times does not successfully predict the correct trip motive. Nevertheless, for some individual trip motives, the model was better at predicting the right motive. In Table 11 the results of the evaluation parameters associated with this approach are presented.

Table 11: Best results of the trip motive prediction model. The model is based on a random forest classifier utilizing all datasets as explanatory variables.

Trip motive	Precision	Recall	f1-score
Work	0.62	0.72	0.67
Business	0.56	0.07	0.13
Shopping	0.55	0.57	0.56
Education	0.61	0.09	0.16
Recreation	0.51	0.31	0.39
Other	0.47	0.58	0.52

From this table can be concluded that there is a big difference in performance between the different motives. Nevertheless, the highest performance, which is acquired for the work motive, is still only correct in approximately 2/3th of the cases. This indicates that the model is not applicable to predict the most probable trip motive.

Nevertheless, Zhao et al. (2024) conducted a similar study in which a machine learning algorithm was applied to predict the trip purpose utilising travel survey data from the Chengdu Houshold Travel Survey and POI, resulting in an accuracy of 0.788. A potential explanation for the difference in accuracy, is the fact that the size of the PC4 areas is such that multiple landuse typed are incorporated in each area. If the study of Zhao et al. utilised smaller zones, it could potentially have less variation in the landuse types. Additionally, it is possible that the mix between landuse types is less in Chengdu compared to the Netherlands. This will automatically lead to less variation within the origin and destination zones of the model.

Appendix C Elaborated explanation trip-related metrics

Trip length distribution

To get an idea of the possible bias in FCD, the TLD of FCD was compared to the TLD of travel survey (ODiN) data. For both datasets, the TLD was constructed based on a bar plot wherein the bins had an interval of 2 kilometres with a range from zero to the maximum distance measured in both datasets. To make a proper comparison, the frequencies per bin were divided by the total number of datapoints to retrieve the so-called relative frequency. Besides the TLD, also the cumulative TLD was computed for both datasets. This was executed by summing the relative frequency of all bins covering a distance which was smaller.

To determine the height of the bin for the TLD of FCD, the O/D analysis API of TomTom was utilised. Ideally, an OD matrix with small zones would have been created that covers the whole of the Netherlands to construct the TLD. However, the O/D analysis API of TomTom restricts that the OD matrix consists of a maximum of 600 zones that covers an area of maximum 40000 km^2. Therefore, another method was developed to construct the TLD of FCD utilising multiple OD matrices.

The first step of this approach was to generate an OD matrix with zones that cover the whole of the Netherlands to ensure that long trips are also properly included in the TLD. To this end, a zoning was shaped which include square zones with a side length of 10 kilometres. 150 zones were identified which are closest to the centre of the municipality Stichtse Vecht. These zones were quartered, resulting in a grid matrix of 600 5 by 5-kilometre squares. This process was then repeated twice more with the newly generated zones, resulting in OD matrices comprising square zones with side lengths of 2.5 and 1.25 kilometres. Figure 45 provides an overview of the different zones per OD matrix. The zones with smaller areas overlap those with larger sides, as illustrated in the visualisation of all 10 kilometre zones displayed in the bottom right corner of the figure.

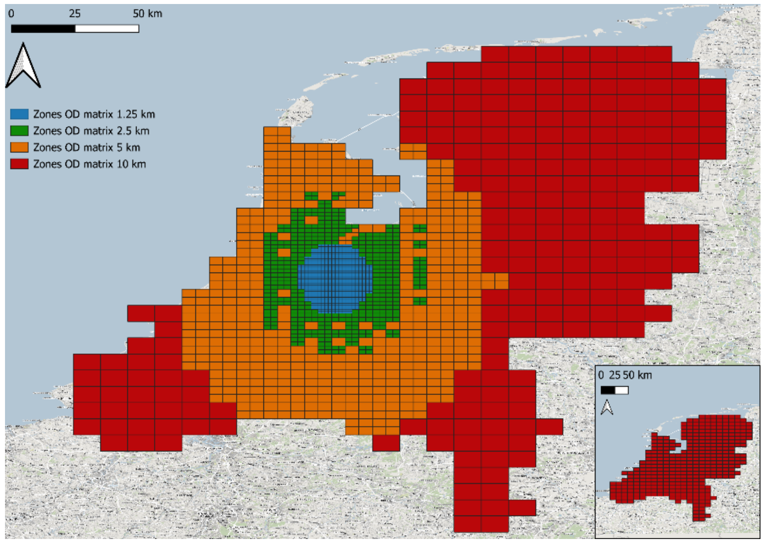

Figure 45: Zoning OD matrices for TLD of FCD.

To ensure that long distance trips are not overrepresented in the data and that short trips are not included twice, only OD pairs with an origin or destination within the area of the 1.25 km OD matrix were incorporated. From the OD matrix 1.25 km, all OD pairs were incorporated. Subsequently, the TLD can be constructed. The distance between OD pairs was calculated based on the shortest network distance between the centroids of the two zones in question. It should be noted that it is possible that some trips could end up within the wrong bin as in reality, the trips do not start and/or end at the centroid of a zone.
For the ODiN data, the number of datapoints within each bin was determined utilizing the travel distance variable. This parameter is filled in by the respondents and indicates the travel distance according to the respondent. As the TLD of FCD is solely based on trips having their origin and/or destination in and around the municipality Stichtse Vecht, the TLD of ODiN data was also generated based on trips with origins and/or destination in and around Stichtse Vecht. In addition to the TLD of all ODiN data combined, TLDs were made for the different trip motives individually. These TLDs were computed to provide insight into the difference between the various trip motives and to compare them to the TLD computed based on FCD.

Distribution throughout the day
The second indicator, is the distribution over the day. For this indicator, FCD was compared to both ODiN data as well as traffic counts, or more specifically NDW data.

<u>Comparison ODiN data</u>
For the comparison between FCD and ODiN data, the O/D analysis API of TomTom was utilised. Per departing hour, OD matrices were generated for the whole of the Netherlands utilising the zones of the 10 kilometre matrix displayed in Figure 45. The OD matrices were based on data of the year 2019 (excluding public holidays) distinguishing three time periods: weekdays, weekend days and all days combined. The distribution was generated based on the relative frequency, which was calculated by dividing the sum of all cells in the matrix corresponding to a departure hour by the sum of all matrices corresponding to the time period combined.

The distribution throughout the day retrieved from ODiN data was computed by dividing the total number of trips measured for each departure hour by the total amount of trips measured per day. For this dataset, also the three time periods (weekdays, weekend days and all days combined) were distinguished. Moreover, distributions were generated in which a distinction was made between the various trip motives present in the dataset to identify potential bias. To ensure that the sample size is big enough, data of 2017 and 2019 is combined.

Comparison Traffic counts

As the traffic counts do not indicate the departure time of trips, but give an indication regarding the traffic volume at a certain time, the distribution throughout the day is based on the relative traffic volume measured per hour. The distribution for FCD was computed utilising the Traffic Stats API of TomTom. The FCD volumes were determined per hour for all weekdays in 2019 (excluding public holidays). For each road section, the measured volume for each hour was divided by the measured volume per day resulting in the relative frequency. The distribution for traffic counts was created by dividing the average hourly aggregated data of NDW by the average volume per day. The data was, just as for FCD, gathered for all weekdays in 2019 (excluding public holidays). This method was applied to three traffic count locations:

1. Motoway A2 in between exit 4 and 5
2. N201 in between Vreeland and Loenersloot
3. N402 in between Maarssen and Breukelen

These locations were highlighted as they represent different types of roads: a motorway, a provincial road which crosses the motorway and a provincial road in between two town centres. In Figure 12 the locations are indicated on a map of the municipality Stichtse Vecht. The comparisons were made for both directions of the road.

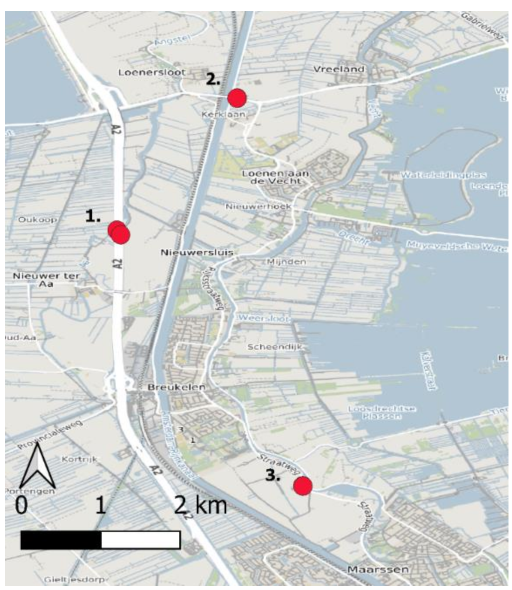

Figure 46: Overview highlighted locations.

Distribution across the week

For the distribution across the week, the FCD is again compared to travel survey data as well as traffic counts.

Comparison ODiN data

To determine the distribution for FCD, the same approach was applied as explained in the paragraph regarding the distribution throughout the day. Instead of computing an OD matrix per departure hour, an OD matrix was generated per day. The relative distribution was subsequently calculated by dividing the sum of the daily matrix by the sum of all daily matrices combined. For this distribution, data from 2019 was utilised.

For ODiN data, the distribution was computed via two techniques. In the first method, the average number of passenger car trips per person was calculated by dividing the number of passenger car trips recorded per day by the number of respondents per day. However, an analysis of the data revealed that the number of respondents differed significantly. On Sundays in particular, significantly fewer people completed the survey (1816 compared to 2174-2428 on the other days). It was expected that there is significantly less traffic on the roads during the weekends resulting in less average trips per day during the weekends. Nevertheless, the calculated average trips per day resulted in minor differences between the days. In addition, the question could be asked whether the lower number of responses on Sundays is because fewer respondents were asked, or whether fewer respondents completed the survey. If the latter was the case, it was deemed plausible that individuals did not make any trip and consequently did not fill in the survey. Therefore, the ratio of passenger car trips per day to the total number of passenger car trips for the whole week was also examined.

Comparison Traffic counts

For the comparison with traffic counts, the method explained in the paragraph regarding the distribution throughout the day was utilised. Instead of summing up the data per hour, the data was summed per day and divided by the total sum of all days combined. The comparison was also executed utilising data of the year 2019 (excluding the public holidays) for the three locations highlighted in Figure 12.

Appendix D Additional analysis trip-related metrics

As outlined in Section 5.2, representativeness of FCD is determined utilising three trip-related metrics: trip length distribution, distribution throughout the day and distribution across the week. In this appendix additional results are given regarding these indicators.

Distribution throughout the day

As mentioned in Section 0, the distribution throughout the days is conducted for weekdays, weekend days and all days combined. In the figures below, the results for these analysis can be found. The figures on the left show the distribution of all ODiN datapoints combined. On the right, the distributions per trip motive are visualised.

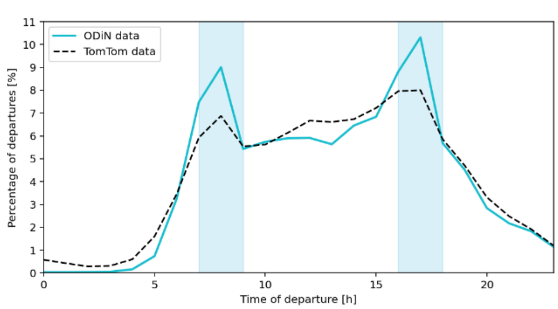

Figure 47: Distribution across the weekdays according to TomTom and ODiN data.

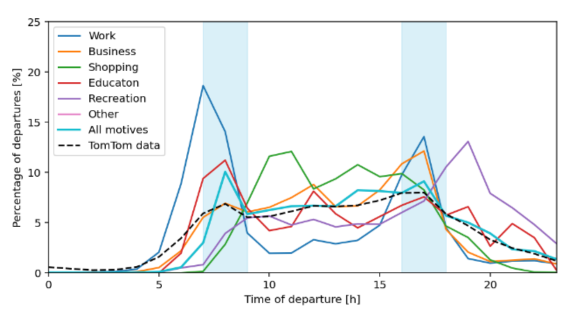

Figure 48: Distribution across the weekdays according to TomTom and ODiN data per trip motive.

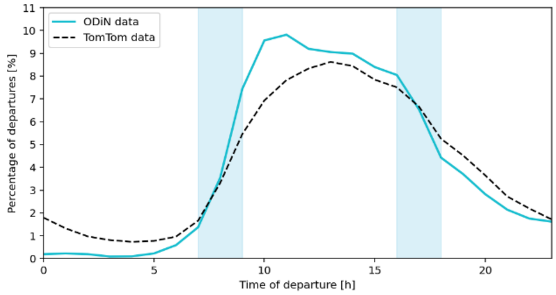

Figure 49: Distribution across the weekend days according to TomTom and ODiN data.

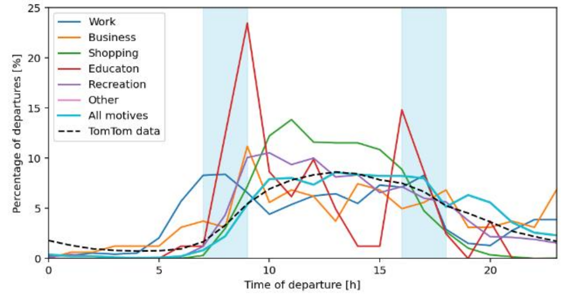

Figure 50: Distribution across the weekend days according to TomTom and ODiN data per trip motive.

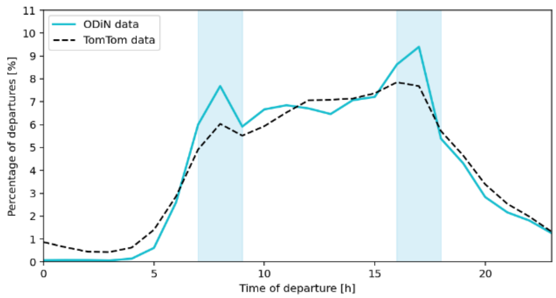

Figure 51: Distribution across all days (week and weekend days) according to TomTom and ODiN data.

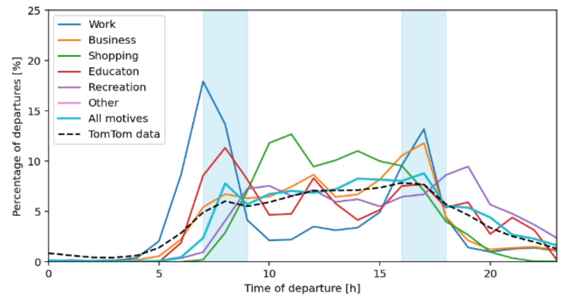

Figure 52: Distribution across the all days (week and weekend days) according to TomTom and ODiN data per trip motive.

From the figures it becomes evident that the distribution throughout the days is different for weekdays as for weekend days. Nevertheless, the trend of FCD is in both cases similar to the trend of ODiN data. When analysing the distributions for the different motives in more detail, it stands out that it varies a lot per motive how the trips are distributed throughout the day. This indicates that an under or over-representation of certain trip motives is present within FCD. Nevertheless, it is not possible to ascertain for which motives this applies and how skewed this representation is.

Distribution across week

In Figure 53, the distribution across the week is visualised per trip motive. In this figure the average number of trips per person per day is given for each trip motive.

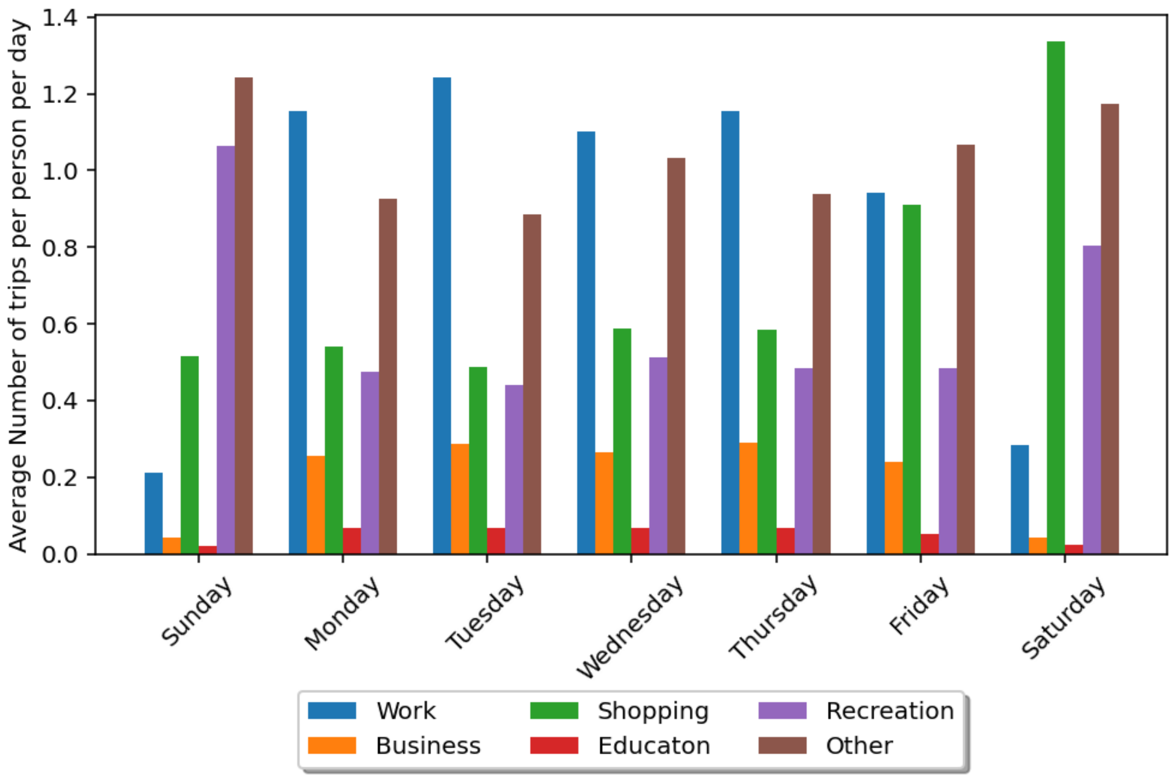

Figure 53:Distribution across the week per trip motive according to ODiN data.

From the figure, it can be concluded that specific trip motives, such as work and education, occur mostly during the week, whereas other motives, such as recreation and shopping, are more prevalent on weekends. The difference between the distribution of FCD and ODiN data may therefore indicate that specific motives are either under or over-represented. Similarly, if the distribution is equal, it does not necessarily follow that the distribution is identical. It is possible that the two distributions will cancel each other out.