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Assessing the Accuracy of Average Travel Speeds from Floating Car Data on Urban Street Facilities

Torben Lelke[a]*, Lea Fuchs[b], Bernhard Friedrich[a], Peter Vortisch[b]

[a] *Institute of Transportation and Urban Engineering, TU Braunschweig, Hermann-Blenk-Straße 42, 38108 Braunschweig, Germany*
[b] *Institute for Transport Studies, Karlsruhe Institute of Technology, Otto-Ammann-Platz 9, 76131 Karlsruhe, Germany*

Abstract

To improve traffic flow on regularly congested roads in a network, the performance of these roads has to be evaluated. The average travel speed is a crucial indicator of traffic quality and is used in several performance evaluation methods. Floating Car Data (FCD) obtained from vehicles equipped with GPS offers continuous and ubiquitous data acquisition, making it a potential alternative to conventional speed detection methods. However, the limited penetration and representativeness of detected vehicles pose challenges. This work investigates the suitability of commercially available FCD for determining accurate space-mean speeds. Ground truth data was collected using Automatic Number Plate Recognition (ANPR), and a comparison analysis was performed with FCD-derived travel times and space-mean speeds. Different statistical measures were applied to evaluate the accuracy of FCD data. The results indicate a generally acceptable correlation between the two data sources, but deviations occur, especially for time intervals with a low number of detected FCD trajectories. Subsequent analyses suggest that a minimum number of five trajectories per hour are sufficient to derive valid space-mean speeds. Based on these findings, it is possible to accurately assess the performance of roads exclusively using commercially available FCD.

Keywords: Probe Vehicle Data; Automatic Number Plate Recognition; Comparative Analysis; Urban Main Roads;

* Corresponding author. *E-mail address:* t.lelke@tu-braunschweig.de

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1. Introduction

In many urban transportation systems, especially in metropolitan areas, increasing traffic volumes lead to congestion on the road infrastructure. This results in overall reduced mobility and accessibility within the cities and the production of avoidable emissions. To facilitate an improvement of the traffic flow, transportation planners must identify problematic elements of the roadway system and quantify their current performance. Various methods are available for this performance evaluation based on different traffic state variables (Afrin & Yodo, 2020). Especially for urban areas, the average speed is essential in evaluating the performance of road segments and facilities that span multiple road segments and intersections (Jenelius & Koutsopoulos, 2013). The importance of speed as an input parameter for road performance evaluation is also reflected in the methodology of the American Highway Capacity Manual (HCM) for evaluating performance, in which the determination of the Level of Service (LOS) is based on the through-vehicle travel speed (National Academies of Sciences, Engineering, and Medicine, 2022). The German Highway Capacity Manual (HBS) adopted a similar method. Here, a speed index is calculated based on a target speed for the present road category, and a design speed calculated from measured traffic volumes (FGSV, 2015).

To evaluate road performance, it is, therefore, first necessary to obtain travel speeds on the road system element under consideration. Conventionally, speeds are recorded using point detectors, which detect the presence of vehicles in fixed locations (Mori et al., 2015). The most widely used point detectors are inductive loops embedded into the road surface and detect the disturbance of a magnetic field generated by the loop. Using a pair of these loop detectors with a short distance in between makes it possible to detect speed values by considering the time between the two detections (Leduc, 2008). The data is then aggregated and averaged for a predefined time period, producing time-mean speed values. Because of the widespread use of inductive loops, this method is often used to obtain base data for performance evaluation of the roads on which the detectors are installed. However, the time-mean speeds obtained from this methodology refer only to the point where the detector is installed. Accordingly, these values are unsuitable for evaluating the performance of longer road segments or road facilities (Soriguera & Robusté, 2011).

For an accurate evaluation that considers the entire length of the roadway system element, it is necessary to obtain the space-mean speed. This value can be defined as the division between the total distance traveled by a set of vehicles within the considered time period and their total travel time (Mori et al., 2015). Therefore, the space-mean speed is not directly measured but instead calculated from travel time. This travel time can be measured using interval detectors, which can be subcategorized into Automatic Vehicle Identification (AVI) systems and Floating Car Data (FCD).

AVI systems are similar to point-based detectors in that they are set up at fixed locations along the road. However, they not only detect the presence of a vehicle but can also identify individual vehicles based on distinctive characteristics. A typical example of AVI systems are Automatic Number Plate Recognition (ANPR) devices that identify passing vehicles through their license plate (Kazagli & Koutsopoulos, 2013). If a vehicle with a certain license plate is detected at two detectors positioned in succession, the travel time between the two points can be calculated directly. This functionality makes AVI systems very suitable for the short- or long-term collection of travel times along a predefined section. However, many individual devices are required for consistent travel time measurement over a wide network area, which is very time-consuming and cost-intensive (Leduc, 2008).

Floating cars, also known as probe vehicles, are equipped with Global Positioning Systems (GPS) and record their position, the current time, and other information, such as the current speed. The data is recorded at regular intervals or significant events, such as stopping or accelerating. The trajectory can be reconstructed by relating a vehicle's individual data points. On this basis, estimating the travel time between any two points in the network is possible. Jenelius and Koutsopoulos (2013) presented a methodology for estimating travel time using low frequency FCD.

Compared to stationary detectors (both point and interval), FCD has the benefit of continuous data acquisition in space and time, and the data is almost ubiquitously available. Therefore, in theory, FCD could replace the established methods to measure travel time and space-mean speed. However, FCD has the downside of limited penetration, which means that not all vehicles are detected. In addition, it is often unclear in what type of vehicle the respective GPS receiver is installed. Therefore, no conclusion can be drawn about the vehicle mix in most data sets. There is a possibility that, for example, heavy traffic from commercial vehicle fleets is overrepresented, which would influence the distribution of travel speeds. Due to these uncertainties in data quality, it is not trivial to assume that an FCD sample's space-mean speed exactly represents the space-mean speed of the total traffic.

This research aimed to investigate this issue and determine the suitability of commercially available FCD for determining space-mean speeds. For this purpose, ground truth travel times were collected for urban street facilities in three German cities using ANPR. We then compared the travel times and resulting hourly space-mean speeds for the ground truth data with the same values derived from an FCD dataset. The following section discusses the selected road sections and our methodology for calculating travel time from FCD trajectories. Afterward, we present the analysis results, for which we apply different statistical measures to evaluate the accuracy of the travel times and space-mean speeds from FCD compared to the ground truth values. The final section discusses the results and provides recommendations for further investigations regarding the usage of FCD for road performance evaluation.

2. Data processing

This section presents the methodology we used for data gathering and processing. To obtain ground truth and FCD-based space-mean speed values, it is first necessary to determine travel times along the road facilities. For the ground truth data, we selected ANPR devices to obtain these travel times because they allow nearly complete detection of all passing vehicles. We used raw GPS tracks to calculate travel times for FCD, which were obtained from a commercial provider.

2.1 Collection and processing of ground truth travel time data

Ground truth travel times were detected on four road facilities in the German cities of Hanover, Braunschweig, and Karlsruhe. Various requirements were considered when selecting the analyzed road facilities. The selection was limited to urban main roads since congestion is especially frequent here, and a comparatively high FCD penetration rate is also expected. In addition, different infrastructural conditions were considered to analyze whether an influence on the validity of the space-mean speeds from FCD can be determined. The selected road facilities and key information about them are presented in Table 1.

Table 1: Considered road facilities

#	Road facility	City	Length [m]	Speed Limit [km/h]	Lanes per direction
1	Celler Strasse	Braunschweig	2400	50	2
2	Vahrenwalder Strasse	Hanover	2300	50	1
3	Kriegsstrasse	Karlsruhe	500	30	1
4	Fiduciastrasse	Karlsruhe	2200	50	2

We conducted the ground truth measurements using ANPR devices situated on the roadside. The road facilities were divided into sections, with a device placed at the start and the end of the sections. Since the measurements were performed in both directions of travel, we detected the ground truth travel times for a total number of 14 sections. After completion of the measurements, the recorded data was processed and then analyzed. The data from all the measuring devices was combined into a total data record per survey day and direction of travel. The data points were then grouped according to the recorded license plate and sorted by time to identify travel times from the individual recordings. During this process, duplicate records and license plates that were only detected by one ANPR device were deleted. Afterward, we formed individual journeys through the road facility by connecting the timestamps of a license plate that were consecutively detected by the ANPR devices within a time period of 30 minutes. We chose this threshold to eliminate outliers such as vehicles that stopped their journey through the road facility and, therefore, do not produce a valid travel time. The data set resulting from this preparation step is then used to calculate travel times as the difference between the timestamps at the detection points for each section.

2.2 FCD processing

FCD was acquired from a commercial provider and included only data from the respective day of data collection for each road section. The data was map-matched using the Hidden-Markov algorithm presented by Newson and Krumm (2009). Afterward, the data format was adapted to derive travel times from the trajectories. First, a reference point is defined for distances along the respective route, which is located at the first ANPR detection point. Subsequently, the course of the investigation route is defined as a sequence of edges in the network. For this purpose, the respective edges are selected in the network model. Using this approach, we could identify the trajectories of only those vehicles that traversed the entire section. The resulting dataset contained the spatial distance between each GPS point and the defined starting point of the road section, representing the driving distance between the points rather than the direct beeline distance. We then defined a second point at the subsequent ANPR detection to determine the travel time along the road section. For each trajectory, the travel time between these two points was then calculated by interpolating the timestamps for each point from the available data. Each travel time in the resulting data set was linked to the time it was recorded. This linkage makes it possible to extract travel times within defined time intervals and to evaluate these values separately. To eliminate outliers, which can be caused by errors in the GPS detection or the map-matching, we excluded all trajectories with a travel time longer than 30 minutes and all trajectories with a higher average speed than 75 km/h.

2.3 Calculation of space-mean speed

With both datasets processed, we used the obtained individual travel times to calculate the space-mean speed. For this calculation, we used the definition of Mori et al. (2015), where space-mean speed v_s is defined as the quotient of the total traveled distance d by a set of vehicles n within a considered time period and their total travel time t. This can be formulated as the following term:

$$v_{s,n} = \frac{\sum_{i=1}^{n} d_i}{\sum_{i=1}^{n} t_i} \quad (1)$$

The set of vehicles we consider for calculating space-mean speed values is defined by the hour of the day a vehicle passes the initial detection point. We chose an interval of one hour because hourly average values are used in most regulatory frameworks, such as HBS and HCM, to assess road performance. In addition, due to the typically low penetration rate of FCD, the interval should not be too short to avoid overweighting of possible outliers or measurement errors. The result of the data processing is a dataset containing individual travel times for all detected vehicles and the hourly space-mean speeds for both detection techniques.

2.4 Analysis of FCD penetration

To contextualize the quality of the FCD we used in our comparative analysis, we first calculated the penetration rate for each hourly interval by dividing the number of detected floating cars by the number of detected ANPR trips. An example of this analysis is shown in Table 2. The penetration rate on all road facilities varies significantly throughout the day. Overall, the penetration of the FCD lies between 0.4% and 4.5% of the total traffic. It must be considered that the penetration rate and the number of trajectories recorded do not correspond directly. The dependence of the penetration rate on the total traffic means that one detected floating car in an hour could lead to a penetration rate of 0.4% on the road facility in Braunschweig or 2% on the road facility on the Fiduciastraße in Karlsruhe. In the following analyses, another objective was to evaluate which of these two values is better suited to define a minimum value to achieve reliably accurate values from FCD.

Table 2: Hourly penetration rates for the road facility in Hanover

Hour	ANPR detections	FCD detections	Penetration Rate [%]
07:00 – 07:59	413	7	1,69
08:00 – 08:59	410	18	4,39
09:00 – 09:59	297	15	5,05
10:00 – 10:59	278	9	3,24
11:00 – 11:59	304	9	2,96
12:00 – 12:59	273	5	1,83
13:00 – 13:59	327	10	3,06
14:00 – 14:59	335	10	2,99
15:00 – 15:59	333	14	4,20
16:00 – 16:59	305	12	3,93
17:00 – 17:59	283	14	4,95

3. Comparative analysis and results

After the data processing, the individual recorded travel times and the hourly space-mean speeds are available for both detection techniques. In the following section, all these values are used to assess how well FCD represents the overall situation and evaluate the usability of the space-mean speed values obtained from FCD to assess road performance. The first step in comparing the two data sets was a visual analysis of the recorded travel times throughout the day. As an example of this comparison, Figure 1 shows the diagrams for the second section when traveling southwards on the road facility in Hanover. It can be seen that the pattern of the travel times is similar in both diagrams. Only the afternoon peaks are less pronounced in the FCD-based travel times than in the ground truth data.

a) b)

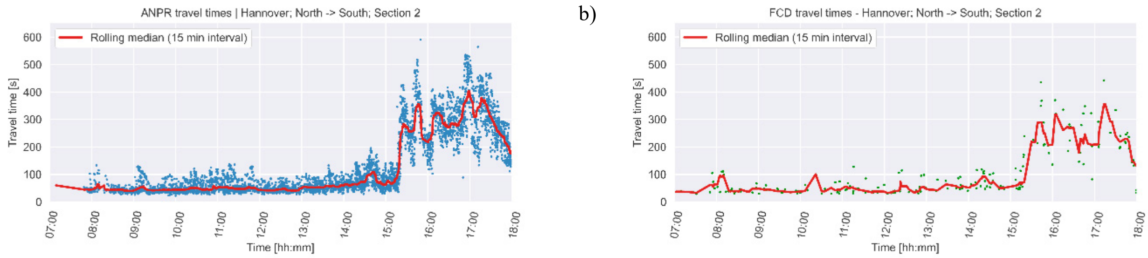

Figure 1: Visual comparison of travel times from (a) ANPR and (b) FCD detection throughout the day

After confirming that the travel times derived from FCD are generally consistent with the actual data, we continue the analysis by focusing on the calculated space-mean speed values. First, we perform a correlation analysis of the hourly speed values for all 14 sections. Figure 2 shows the resulting correlation diagram. It can be seen that the speed values from the two sources for the same time intervals generally show an acceptable correlation. Pearson's correlation coefficient reaches an acceptable value of 0.69. However, it is also evident from Figure 2 that some speed pairs lie far from the bisector and thus differ more significantly. The data points in the plot shown are colored according to the number of floating cars detected within each hour. The analysis focuses on this parameter since the penetration rate of commercially available FCD is usually unknown. At the same time, the number of trajectories per hour can be derived from the data sets in any case. A darker data point color represents a higher number of floating cars. The figure shows that fewer detections also characterize the hours with the most significant deviation between travel times. However, there are also some speed values from hours with a high number of detected floating cars that show a high correlation.

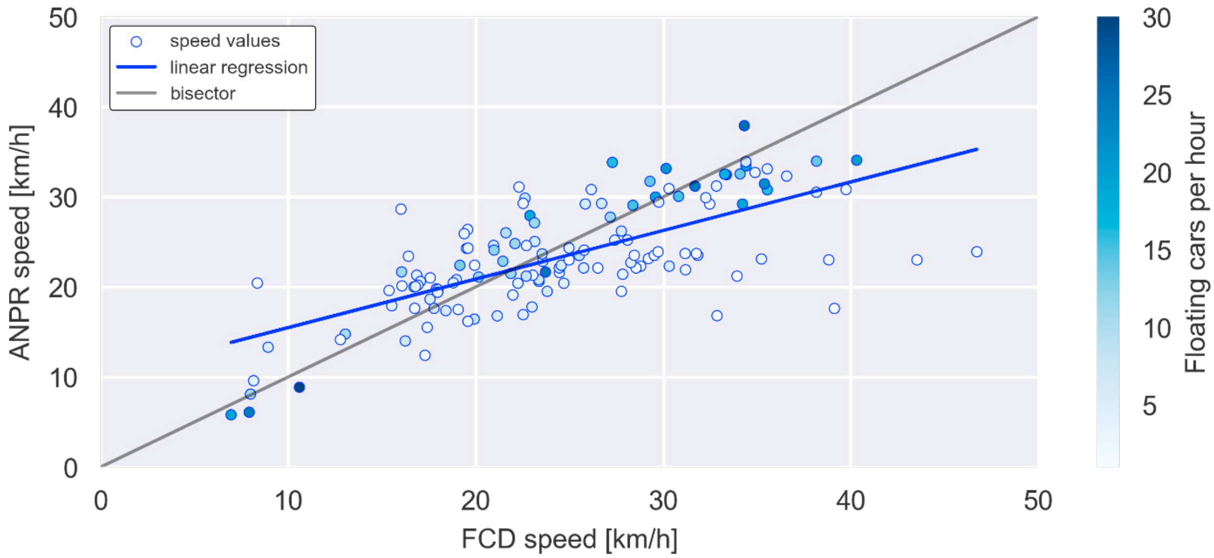

Figure 2: Correlation diagram for space-mean speed calculated from ANPR and FCD

The correlation analysis indicates a more thorough similarity evaluation of the values is necessary. We, therefore, use the "Scalable Quality Value" (SQV), which was defined by Friedrich et al. (2019), to quantify the similarity of individual speed pairs from the two datasets. The primary advantage of using the SQV lies in its being scalable and can be adjusted to the available data. Additionally, the SQV allows a direct evaluation of the similarity of two values because it ranges between 0 and 1, with the latter representing a perfect match. In their work, Friedrich et al. also define ranges to directly evaluate the quality of fit, with an SQV of 0.8 representing an acceptable match of the compared values. The SQV for a speed pair p is calculated as follows:

$$SQV_p = \frac{1}{1 + \sqrt{\frac{(v_{s,p,FCD} - v_{s,p,ANPR})^2}{f * v_{s,p,ANPR}}}} \quad (2)$$

The variable f represents the scaling factor whose magnitude should be coupled to the expected value of the variable under investigation (Friedrich et al., 2019). For the evaluation of space-mean speeds, we chose a scaling factor of f = 30 km/h, since this value relates approximately to the aspired speed on urban main roads according to the HBS (FGSV, 2015). We subsequently calculated the SQV for each hourly speed value pair and consolidated the results to obtain a general view of the similarity between FCD and ANPR speeds. For this purpose, the arithmetic mean of all SQVs on each section is used. Similarly, using the arithmetic mean, we calculated the average number of detected floating cars and the average penetration rate for each section. It should be noted that hours without recorded FCD trajectories were also used for averaging. Therefore, for some sections, less than one trajectory per hour is given as the average value. The result of this analysis is shown in Table 3.

Table 3: Summary of the comparison

#	Road facility	Direction	Section	Length [m]	Avg. floating cars per hour	Avg. Penetration Rate [%]	Avg. SQV
1	**Hanover** Vahrenwalder Strasse	North → South	1	750	8.9	2.44	0.942
2			2	489	20.8	2.98	0.906
3		South → North	1	495	19.3	2.82	0.927
4			2	801	10.8	3.52	0.883
5	**Braunschweig** Celler Strasse	North → South	1	1320	6.1	2.39	0.935
6			2	750	3.6	1.73	0.892
7		South → North	1	898	1.1	1.07	0.770
8			2	1260	3.6	2.59	0.853
9	**Karlsruhe** Kriegsstrasse	East → West	1	533	3.0	1.26	0.881
10		West → East	1	498	4.8	2.34	0.891
11	**Karlsruhe** Fiduciastrasse	North → South	1	791	0.6	0.78	0.634
12			2	737	2.4	1.80	0.761
13		South → North	1	763	2.3	1.64	0.920
14			2	810	0.9	1.22	0.833
		Total Mean			**6.61**	**2.24**	**0.869**

The overall evaluation shows that the mean SQV of 0.869 over all sections lies in the previously defined acceptable range. Therefore, the average space-mean speeds calculated for FCD represent the ground truth values well. However, when considering the average results of individual sections, it becomes apparent that significantly less satisfactory results are also achieved. As was indicated by the analysis presented in Figure 2, this difference can be related to a low number of floating cars during these hours. The analysis also supports the assumption that the number of detected FCD trajectories is a better indicator of the quality of the space-mean speeds than the penetration rate. In the last step of our analysis, we focused on the relation between the quality of fit, indicated by the SQV of the space-mean speeds, and the number of detected FCD trajectories. For this purpose, we first consider all hours from the total set of space-mean speeds and analyze the distribution of SQVs and the correlation coefficient. Then, we exclude all hours in which less than two floating cars were recorded and repeat the same analyses with this subset of the data. We continue this process until the maximum number of detected floating cars is reached. Figure 3 presents the results of this analysis. In this, each subset is defined by the minimum number of detected floating cars. The figure includes a distribution of SVQ values shown in a boxplot and the development of the correlation coefficient with an increasing number of minimum trajectories per hour.

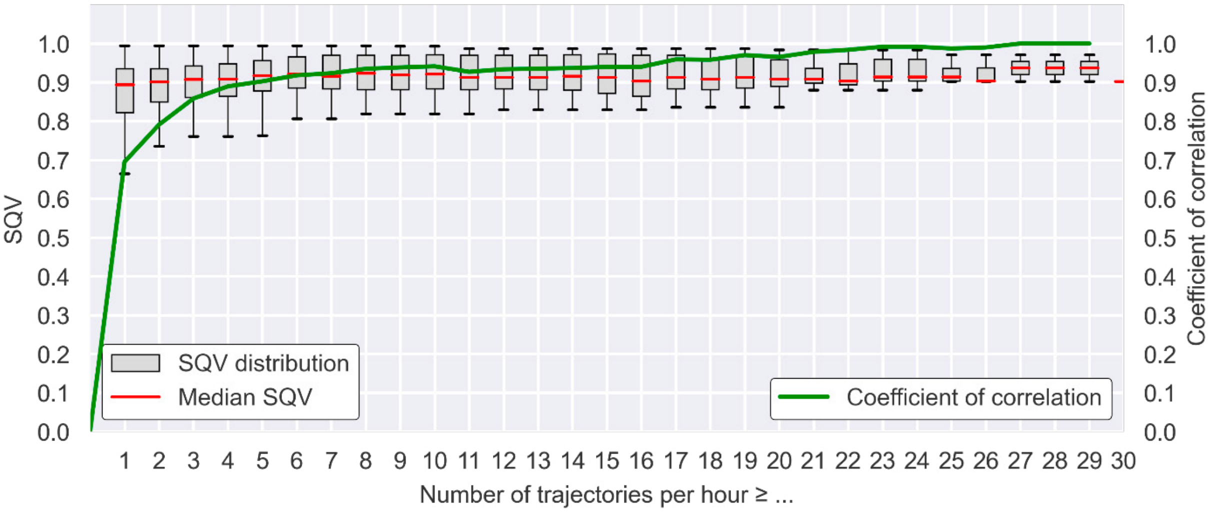

Figure 3: Analysis of SQV and coefficient of correlation for sets with differing minimum number of detected floating cars

Several statements can be made based on the analysis shown in Figure 3. The median of the SQV is almost constant across the various subsets. However, it can be seen that, especially in the subsets containing hours with a low number of floating cars, outliers in speed lead to the correlation coefficient not being in a satisfactory range. When looking at the course of the correlation coefficient, it becomes clear that the quality of the fit between the speed values from the ground truth ANPR data collection and the FCD improves with increasing numbers of floating cars recorded per hour. The correlation coefficient improves significantly for the data set without the hours with only one recorded FCD trajectory. It is noticeable that from a minimum of 5 floating cars per hour, both the median of the SQV and the correlation coefficient do not drop below a value of 0.9. This value is an SQV representing a very good match between the compared values (Friedrich et al., 2019) and a very high correlation (Schober et al., 2018).

4. Discussion and outlook

The analysis performed in this paper represents a crucial first step when working with commercial floating car data. Since the exact vehicle mix and the penetration rate is typically unknown, it is often difficult to judge whether data calculated using FCD reproduces the same values as the ground truth data. Therefore, we focused on the accuracy of space-mean speed values, which we calculated from FCD. This assessment was performed using ground truth space-mean speed values we calculated from measured travel times using ANPR detection.

The analysis results show that space-mean speeds from FCD generally match well with the ground truth data. The average SQV over all considered road facilities is within the acceptable range, and the correlation analysis resulted in a similarly acceptable value for Pearson's correlation coefficient. However, the subsequent analysis of the relation between the minimum number of detected floating cars per hour in a dataset and the quality of fit for the space-mean speeds shows that these values can be significantly improved when only considering hours with five floating cars or more.

Several ideas presented in this paper can be adapted into performance evaluation methods in the future. Firstly, the performed analyses show that obtaining valid space-mean speed values is possible even from the generally small sample size that commercially available FCD provides. This suggests that road performance evaluation using only FCD as input is valid, facilitating more consistent evaluations within networks. The determined minimum number of five floating cars per hour, necessary for a very high correlation between ground truth and FCD speeds, is also a practical value for the future assessment of FCD. Furthermore, the paper discusses the difference between the number of detected floating cars in a time interval and the penetration rate of the FCD. We argue that for future quality assessment of FCD, the average number of detected floating cars per hour better indicates the accuracy of some parameters calculated from the data. Therefore, the penetration rate and the number of detected floating cars per hour should be considered.

Some factors influencing the quality of FCD-based space-mean speeds were not studied within the scope of this paper. This includes the type of road system element on which the data is analyzed. This work's considered sections of road facilities included at least one signalized intersection. The variance in travel times introduced by the signal programs may contribute to a lower correlation between ground truth and FCD-based space-mean speeds. The minimum number of necessary FCD trajectories may be lower on road segments without intermediate signalized intersections. Additionally, the analysis in this work was only performed using data from one provider. A similar study with FCD from other providers should be conducted to verify our results. Another possible direction for further research concerns the application of the developed methodology to performance evaluation methods. These methods are usually based on a singular value representative of the traffic on this road system element. Since we proved that the space-mean speed values from FCD are generally accurate, the next step would be to formulate a methodology to obtain such a representative value.

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