Spatio-Temporal Speed Metrics for Traffic State Estimation on Complex Urban Roads

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Abstract. With this paper, we aim to make two main contributions. Firstly, we present a detailed overview of performance metrics used for estimating traffic conditions in urban settings. Compared to highway situations with relatively stable traffic conditions, Traffic State Estimation in urban environments exhibits several challenges, which we discuss in depth. Secondly, through a simulation study, we utilize Eclipse MOSAIC to assess the capabilities and limitations of these metrics. Therefore, we have developed an open-source suite of applications and add-ons for MOSAIC, that will be documented in this paper. Utilizing the publicly available BeST traffic scenario, which encompasses 24 h of realistic urban traffic in Berlin, we present a comparative analysis of average speeds observed on various types of urban roads. Importantly, we made these implementations available to the open-source community, providing a valuable resource for traffic scientists and others who are interested in our contribution.

Keywords: Traffic State Estimation · Simulation · Eclipse MOSAIC

1 Introduction

Road traffic networks in urbanized areas are vulnerable to congestion, especially during morning and evening rush hours. Precise, timely, and robust Traffic State Estimation (TSE) is a crucial means to identify bottlenecks and circumnavigate afflicted areas. Finding suitable metrics to describe the traffic state is a non-trivial task and often multiple metrics are calculated. A substantial body of research regarding TSE was performed for highway settings, which are characterized by relatively consistent traffic patterns, with fewer intersections and traffic signals. Consequently, the traffic state within this context has been extensively studied, yielding diverse models of traffic behavior and associated metrics. Krajezewicz et al. [1] describe common unambiguous metrics used to describe the traffic state.

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As the first objective of our paper, we review and summarize related research on TSE in a short survey. We lay our focus on the mean speed as it is one of the key measurements of traffic performance [4] and can also easily be used in cost functions for routing algorithms. Nonetheless, the mean speed measures presented are seldom used in isolation; instead, they serve as inputs for more advanced systems dedicated to traffic state estimation and prediction.

One effective approach for developing such systems is through simulation. Over the past decade, we have been actively engaged in the development of Intelligent Transport Systems using the Eclipse MOSAIC simulation environment [10]. A notable recent outcome of this effort is the open-source BeST scenario, a calibrated representation of 24 h of motorized traffic in Berlin, Germany [11].

The second objective of this paper is to put the theoretically discussed metrics into practical use, specifically within the simulation context. To achieve this, we have implemented a suite of applications and add-ons for MOSAIC. These implementations are utilized in conjunction with the BeST scenario to conduct a thorough comparison, thus assessing the capabilities and limitations of the identified metrics. It is noteworthy that we have also made these implementations available to the open-source community, rendering this paper a concise guide to our code contributions.

The paper is structured as follows. We give a broad introduction to relevant topics of traffic dynamics in Sect. 2. Secondly, we explain the most commonly applied sensor modalities and their implications for mean speed estimation in Sect. 3. Afterwards, in Sect. 4 we conduct an empirical test to highlight differences in the mean speeds. Finally, in Sect. 5 we summarize our findings and highlight our future research interests.

2 Fundamentals of Traffic Dynamics

In the following section, we build on common traffic theory terminology and encourage newer readers to look up the following references [5,7,12] if you encounter difficulties.

Traffic dynamic research often uses so-called space-time diagrams to explain spatio-temporal relations of the traffic flow [12]. Figure 1 depicts two such space-time diagrams. Conventionally, we plot the time on the abscissa and the space on the ordinate. Each of the purple lines represents the trajectory of a vehicle moving along a given route, where steeper segments indicate faster speeds and less steep segments indicate lower speeds. From a given trajectory it is trivial to calculate the average velocity for a segment of its route using Eq. (1).

$$\bar{v} = \frac{\Delta s}{\Delta t} \tag{1}$$

As the traffic state is a highly fluctuations measure, deviating both over space (i.e., different roads/road segments) and over time (i.e., morning and evening peaks vs. midday lows), any statement about it has to be made on segments

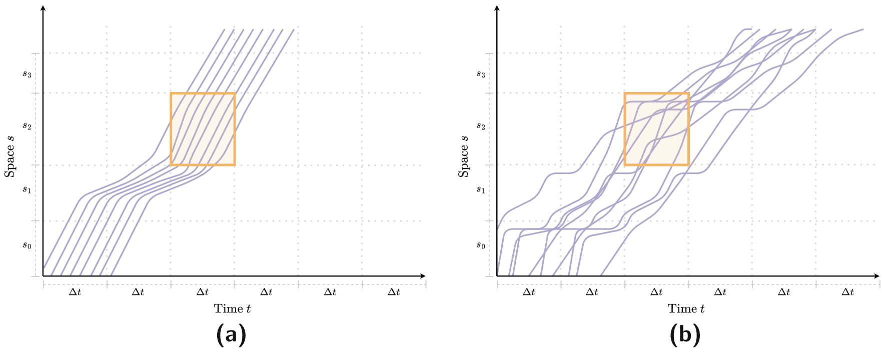


Fig. 1. Exemplary space-time diagrams. (a) shows typical vehicle trajectories on a highway. Whereas, (b) highlights large deviations in vehicle trajectories in urban areas. (Color figure online)

in space and time. Empirically speaking, this means that we consider separate time intervals and traffic network segments, leading to spatio-temporal measurements. This also implies that over these intervals and segments, some form of aggregation has to be applied. Usually, one sets a constant aggregation interval (T) and separates roads into smaller chunks (e.g., from junction to junction, or fixed-length segments). In Fig. 1 this indicated by the Δt's of constant size and the set of road segments $S \coloneqq \{s_0, \ldots, s_3\}$. With these spatial and temporal segments, many spatio-temporal aggregation intervals have to be considered, one being indicated by the orange squares in Fig. 1. When trying to extract a mean speed for the spatio-temporal interval indicated by the orange square, one faces a couple of issues. In a scenario where we would have access to all exact vehicle trajectories, we would calculate the aggregated average velocity by taking the arithmetic mean of all average velocities within the marked time frame on the marked road segment as shown in Eq. (2).

$$V = \frac{1}{n}\sum_{i=0}^{n} \bar{v}_i = \frac{1}{n}\sum_{i=0}^{n} \frac{\Delta s_i}{\Delta t_i} \tag{2}$$

where V declares the aggregated average velocity and n the amount of vehicles that drive on the marked segment within the marked time interval. Consequently, for each vehicle i, s_i and t_i denote the driven distance within the marked time interval and the time spent on the marked road segment respectively.

However, depending on the sensor modality used vehicle trajectories can at best be estimated and are often only available for a small subset of all vehicles, leading to an incomplete measurement.

When looking at the exemplary trajectories in Fig. 1a and Fig. 1b, it becomes obvious that estimating the traffic state on highways is a much simpler venture compared to urban surface roads [4]. Where we can expect fairly consistent driver behavior on highways, we have to consider large variances in speed, acceleration, and braking behavior on urban roads, due to additional variables like traffic signals, second-row parking, and other obstructions increasing the complexity of an urban scenario. Additionally, Fig. 1 doesn't consider any turns and assumes that all vehicles travel on a concurrent road segment. Turning vehicles further complicate the task of estimating the traffic state.

3 Sensor Modalities

In this section, we will describe the basic functionality and implied use cases of the sensor modalities under test, starting with induction loops in Sect. 3.1 and moving on to Floating Car Data (FCD) in Sect. 3.2. We explicitly regard these sensor modalities separately and omit considerations of fusing the acquired sensor data, as we aim to make out strengths and weaknesses independently. The interested reader may find approaches for fusing sensor data in TSE applications in literature [6,13].

3.1 Induction Loops

The most widespread, traditional sensor modality comes in the form of induction loops, also known as spot or loop detectors. They function by insetting two metal coils within a short distance from each other below the surface of a road. Using the principle of induction it is possible to detect when a vehicle passes a coil. By knowing the distance between the two coils and stopping the time at passing it is possible to determine the spot speed of a vehicle with high precision.

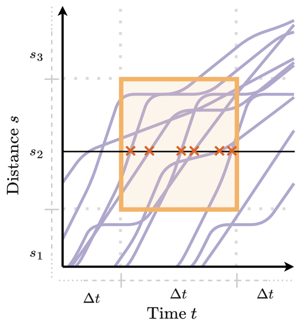
Due to the high installation price, loop detectors are very sparsely installed and mostly cover major road arteries. Additionally, road administrators usually abstain from installing more than one detector per road segment, which may lead to limited insight into the roads' traffic.

Knowing about how induction loops operate and their cost limitations, we can revisit the space-time diagram from Sect. 2 and illustrate how one would aggregate the mean speed using a loop detector. Figure 2a depicts this by drawing a cross-section through the middle of s_2. The orange crosses along the cross-section indicate the measured spot speeds using the slope of the respective vehicle trajectory at the point of passing. This is a slight simplification as induction loops do not measure spot speeds but rather the average velocity over a very short distance. However, for our purposes, we consider the speed of vehicles over that distance as constant and continue using spot speeds.

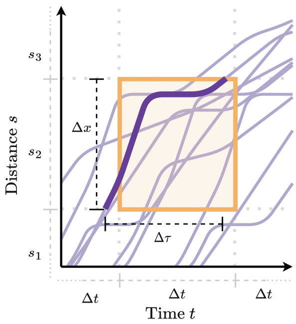
Intuitively, to aggregate the marked spot speeds within the marked Δt-interval one would use the arithmetic mean (see Eq. (3)).

$$V_{TMS} = \frac{1}{n} \sum_{\alpha=1}^{n} v_\alpha \tag{3}$$

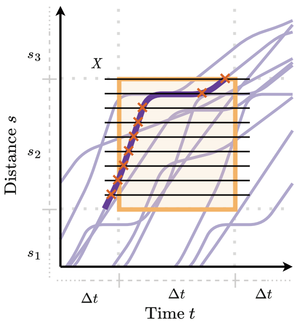
where n denotes the number of vehicles that pass the detector within a given time interval and v_α the speed of a single vehicle at the time of passing. This arithmetic mean is known in the literature as the *Time Mean Speed* as it aggregates the speeds for a certain duration of time. However, when considering the



(a) Loop Mean Speeds



(b) Temporal Mean Speed



(c) Spatial Mean Speed

Fig. 2. (a) illustrates how the samples for the time and space mean speeds are measured. (b) illustrates the calculation of the temporal mean speed Whereas, (c) depicts the calculation of the spatial-mean-speed.

traffic density ρ often the *Space Mean Speed* is used instead of the time mean speed as it delivers better density estimates. The space mean speed considers the same variables but uses the harmonic mean instead of the arithmetic mean (see Eq. (4)).

$$V_{SMS} = \frac{n}{\sum_{\alpha=1}^{n} v_\alpha} \tag{4}$$

Note, that even though both presented speeds, especially the space mean speed, are intensively used in practical traffic density analysis, they rarely deliver correct results for density. In reality, density estimates using the time mean speed tend to underestimate the actual density, whereas estimates using the space mean speed tend to overestimate the actual values. For in-depth explanations on these circumstances see [12, Chapter 5].

Another important aspect of the time- and space mean speed is that they originate from traffic-flow theory, which treats moving vehicles similar to a hydrodynamic process in which flow, density, and speed of particles (i.e., vehicles) have a strong correlation. Treating vehicles as particles works sufficiently well on highways, where there is little variance in vehicle speeds and a certain degree of predictability in vehicle movements. In urban scenarios, however, using a single point of measurement will often fail at giving a meaningful insight into the realizable mean speed. The inhomogeneous trajectories in Fig. 2a further visualize this potential flaw.

3.2 Floating Car Data (FCD)

With the increasing availability of GNSS-enabled (Global Navigation Satellite System) devices and broader cell coverage people began to use vehicles as moving (i.e., floating) sensors in the early 2000s [9]. By periodically transmitting position, speed, and heading data to a central service via the cellular network, many vehicles provide a data set called Floating Car Data (FCD). This method of data collection became the de facto standard for many traffic services and is applied in current-day navigation applications like Google Maps and TomTom.

Nonetheless, utilizing the data received from connected vehicles comes with a set of difficulties. On the one hand, sensor inaccuracies, especially those of GNSS sensors, impose a large threat on the validity of collected data. Instead of just trying to improve sensor technologies (e.g., by fusion of GNSS and Inertial measurement systems) an approach called Map-Matching [2] is applied, where the vehicle trajectories are combined with a digital map to infer their most probable positions regarding coordinates but also respective edge and lane positions. The second major difficulty is that crowd-sourced systems such as FCD require a certain percentage of market penetration to deliver broad and reliable estimation results. It is hard to find an exact reference for the minimum penetration rate required, as this depends on the inspected road type and applied algorithms, however, commonly cited thresholds range from 5% to 10% market penetration [4] for reliable highway estimation, meaning every 20th vehicle needs to be connected. In an urban city scenario, this value increases due to higher fluctuations and less coverage in residential areas.

When using FCD as the data source, multiple approaches for mean speed estimation can be applied. These approaches typically examine and aggregate each road segment (i.e., edge or sub-edge) individually by recognizing traversals of said segments.

Commonly, some form of curve fitting is applied using either interpolation or regression (i.e., using polynomial splines) to estimate vehicle movements between received FCD samples. A lower frequency of samples imposes higher uncertainty on the fitted curves. These fitted curves can then be used to infer speed values along a given edge for given vehicles. Yoon et al. [14] introduce the *Temporal Mean Speed* and the *Spatial Mean Speed*, which are calculated using the curve-fitted trajectories of vehicles. These values are calculated separately for each vehicle and later aggregated for specified time intervals, which is depicted in Fig. 2.

The temporal mean speed is simply defined as *"[...] the average speed over time [...]"* [14]. It captures the average speed for a single vehicle for one edge, which is formalized in Eq. (5) and visualized in Fig. 2b.

$$v_{\text{temporal}} = \bar{v} = \frac{\Delta x}{\Delta \tau} \tag{5}$$

Yoon et al. define the spatial mean speed as *"[...] the average speed over location [...]"*. However, compared to the temporal mean speed, the spatial mean speed follows a more difficult definition as shown in Eq. (6). In this equation, x separates that edge into equidistant segments and X declares the number of these segments spanned within an edge (see Fig. 2c). The distance x typically ranges from 10 m to 15 m. Finally, $v(x)$ defines the instantaneous (i.e., spot) speed at point x derived by the tangential. By averaging these segment speeds, the goal is to gain a perspective on how a vehicle moves in space. For example, if the spatial mean speed of a given vehicle traversal is lower than its temporal mean speed, a more "stop-and-go"-like traffic can be assumed.

$$v_{\text{spatial}} = \frac{1}{X} \sum_{x=1}^{X} v(x) \tag{6}$$

As mentioned in Sect. 2 one is usually interested in an aggregated view of the traffic state as compared to those of individual vehicles. Aggregating the temporal and spatial mean speed for a given time segment has the caveat that traversals of the inspected edge may start before a given time segment. This issue is also visualized in Fig. 2b where the highlighted vehicle trajectory driving on segment s_2 starts within the previous time interval. Most commonly, this issue is disregarded and traversals are accounted towards the aggregation interval in which they finish. It is noteworthy though that this can lead to intervals being more sparsely populated, especially if traffic signals come into play and introduce traffic waves. For this paper we thereby compute V_{temporal} and V_{spatial} for a given edge and a given interval according to Eq. (2) where n includes all vehicles that traversed the edge within the given interval.

$$V_{\text{temporal}} = \frac{1}{n} \sum_{\alpha=1}^{n} v_{\text{temporal}}(\alpha) \tag{7}$$

$$V_{\text{spatial}} = \frac{1}{n} \sum_{\alpha=1}^{n} v_{\text{spatial}}(\alpha) \tag{8}$$

Alternative approaches may omit the curve-fitting step and directly average and aggregate collected samples. These approaches do not face the aforementioned issue, though they can tend to oversimplify the TSE task as only temporal features will be regarded.

4 Simulation Approach

To evaluate, compare, and parameterize a TSE model simulation-based tests can be an effective tool before considering a real-world deployment. Simulation not only allows to catch potential errors and privacy threats at a much lower cost, but it also allows an evaluation of necessary market penetration rates for a functioning system.

4.1 TSE Applications for Eclipse MOSAIC

For simulative tests to deliver significant results simulators for traffic, communication, and other environmental influences have to be modeled as close to reality as possible. The MOSAIC simulation framework [3,10] couples industry-leading FOSS (Free and Open-Source Software) simulators from these domains using a runtime infrastructure based on the IEEE standard for High-Level Architecture (HLA). MOSAIC, additionally, provides a powerful application simulator that allows for fast prototyping and integration of applications in the domains of smart mobility including V2X Communication via ITS-G5 and LTE/5G, autonomous vehicle perception, and e-mobility.

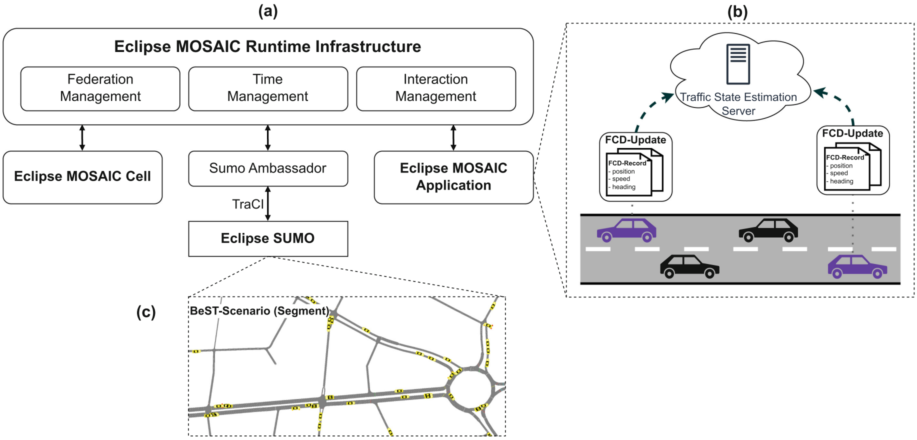


Fig. 3. This diagram gives an overview of all relevant simulators and how they are utilized in hand the TSE applications. **(a)** shows a simplified version of MOSAIC's architecture based on the HLA. **(b)** depicts how the vehicle applications interact with the Traffic State Estimation server using FCD. Finally, **(c)** indicates the functionality of the traffic simulator SUMO. We map our applications on the vehicles controlled by SUMO, which provides realistic FCD traces.

For our evaluation purposes, we couple the microscopic traffic simulator Eclipse SUMO [8] with MOSAIC's integrated Application and Cell simulators. Based on the general FCD approach we modeled the system using MOSAIC's Application simulator (see Fig. 3). The model includes a vehicle application that periodically sends FCD Updates consisting of individual FCD Records and a server application that receives, processes, and aggregates said traces. The server has been designed to be extensible with many processing units, that can act based on newly detected edge traversals or in an event-based manner. The default setup comes enabled with a processor for calculating the Relative Traffic Status Metric (RTSM) defined by Yoon et al. [14], which uses the spatial and temporal mean speed in a threshold-based approach to rate the traffic state. The results of this processor will be stored in a local SQLite database for post-processing and investigation of the collected data. All relevant parameters for both the vehicles, the server, and its processors can be configured using respective JSON configurations, to inspect different key aspects of the system.

In addition to the application-based speed measures (v_{temporal}, v_{spatial}), we configured the traffic simulator SUMO to write ground truth speeds (v_{GT}) and measured speeds of placed induction loops (v_{TMS}, v_{SMS}), which are later used for the comparative study. To ensure reproducibility, the complete application suite as well as all configuration files have been published to GitHub under the following link:

https://github.com/mosaic-addons/traffic-state-estimation.

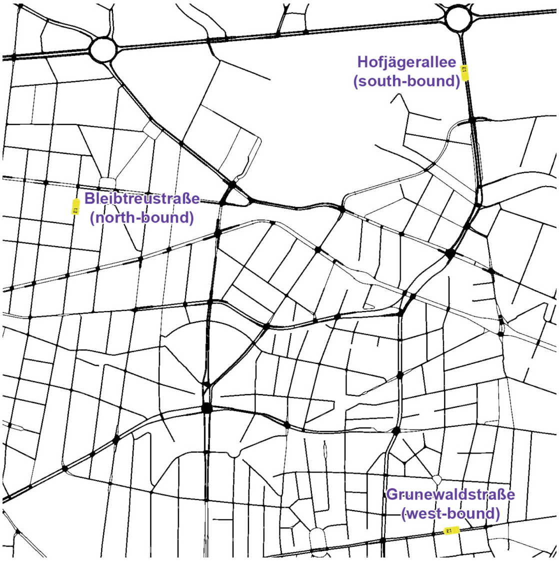


Fig. 4. A map of Charlottenburg indicating loop detector positions for time and space mean speed estimations.

4.2 Experiment Setup

To validate developed applications and the mean speed measurements a traffic scenario has to be established, which mimics real-world road networks and traffic behavior in an urban environment. Therefore, we utilize the BeST scenario [11] which has been modeled for MOSAIC and SUMO and encompasses 24 h of individual motorized traffic in Berlin with around 2.25 million individual vehicle trips.

As we are not focusing on a city-wide evaluation we set up our simulation within the Charlottenburg area of the BeST scenario and simulated an entire day of vehicle movements with 200 000 independent trips. In this test, we configured 100% of vehicles with our FCD solution and set up loop detectors on the marked road segments in Fig. 4 and collected estimations for the time and space mean speed using the configured SUMO output. We selected the marked roads intentionally, to obtain insights on how different measures react to different road types and sizes. Relevant markers for these roads are depicted in Table 1, which indicates how these roads differ from one another. Lastly, we configured SUMO to write a file with reference speed values in the form of edge-wise data which acts as our ground truth. All outputs were aggregated for 15 min intervals as this window size offers a good trade-off between sufficient sample sizes and detailed enough granularity.

4.3 Results

Results of the initial experiment are visualized in Fig. 5 and in Table 2. We colored the measures based on the utilized sensor technology, the ground truth is colored in orange, measures from the induction loops are colored in yellow, and measures retrieved from FCD are colored in purple. We focus on the hours between 6 am to 10 pm as the night hours the network is only sparsely populated and traffic measurements become spotty and irrelevant.

It is apparent that depending on the road type (compare Table 1) the different mean speeds respond differently. On the segment of the *Hofjägerallee* where there are no traffic lights at the end of the edge all measures behave similarly. This is due to the highway-like properties of the road where we can expect nearly constant free-flow speeds along the entirety of the edge on all lanes.

On the segments of the *Grunewaldstraße* and *Bleibtreustraße* a clear split in the measures can be noticed. While the time, space, and spatial mean speeds remain close to the speed limit, the ground truth and temporal mean speeds drop to around 40 km/h on the *Grunewaldstraße* and 22 km/h on the *Bleibtreustraße*. For the time and space mean speed this is easily explained, as the samples are measured close to the center of the segment, where vehicles typically drive close to free flow speed. The spatial mean speed, however, emits this behavior because the distance that vehicles spend in the queue at the traffic signal is small compared to the distance spent driving at free-flow speed.

As the BeST scenario delivers a road network and traffic demand without any major obstructions and slow downs, we are only able to observe measures that reflect this behavior. Figure 5 clearly indicates this as we were only able to measure speeds at and around the speed limit, with expected slowdowns at signalized edges. Also Table 2 shows that average speeds close to the speed limit can be reached. While it is important to be able to measure the free flow characteristics, it is often more relevant to measure impaired traffic situations, as these are the locations one potentially would circumnavigate. How to model these situations and how the TSE system responds to them is part of ongoing research.

In an attempt to highlight the impact of the penetration rate in FCD-based systems, we ran the same scenario with different ratios of (5%, 10%, 30%, 100%) equipped CVs (Connected Vehicles). For this experiment, we solely looked at the temporal mean speed (v_{temporal}) as it resembled the ground truth more closely than the spatial mean speed. Results of this test are visualized in Fig. 6.

Table 1. Key markers of the inspected road segments.

street	length	#lanes	speed limit	signalized
Hofjägerallee	399.96 m	3	50 $\frac{\text{km}}{\text{h}}$	no
Grunewaldstraße	185.37 m	2	50 $\frac{\text{km}}{\text{h}}$	yes
Bleibtreustraße	182.34 m	1	30 $\frac{\text{km}}{\text{h}}$	yes

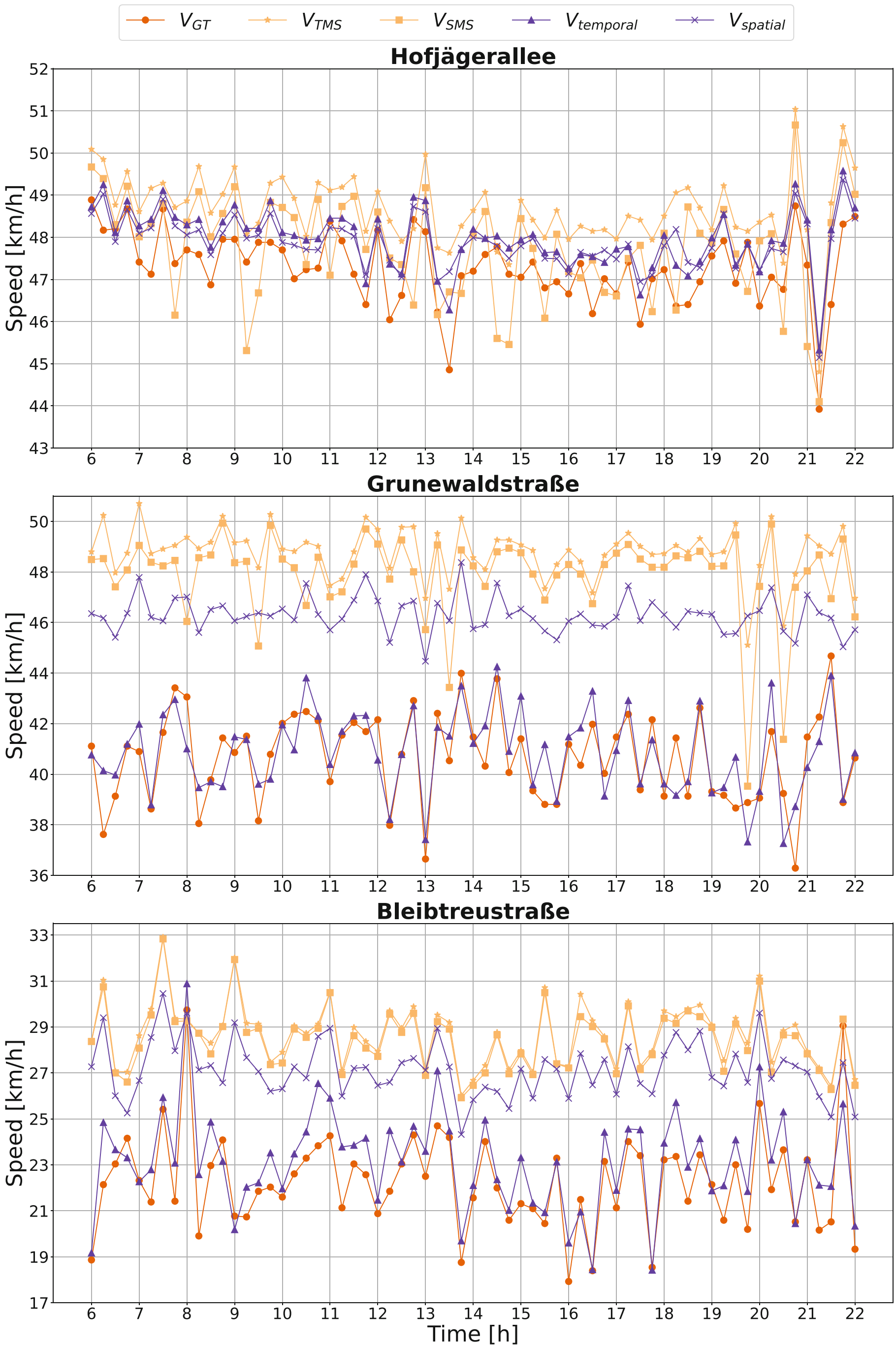


Fig. 5. Different mean speed measures aggregated over 15 min intervals for the street segments highlighted in Fig. 4 using 100% market penetration.

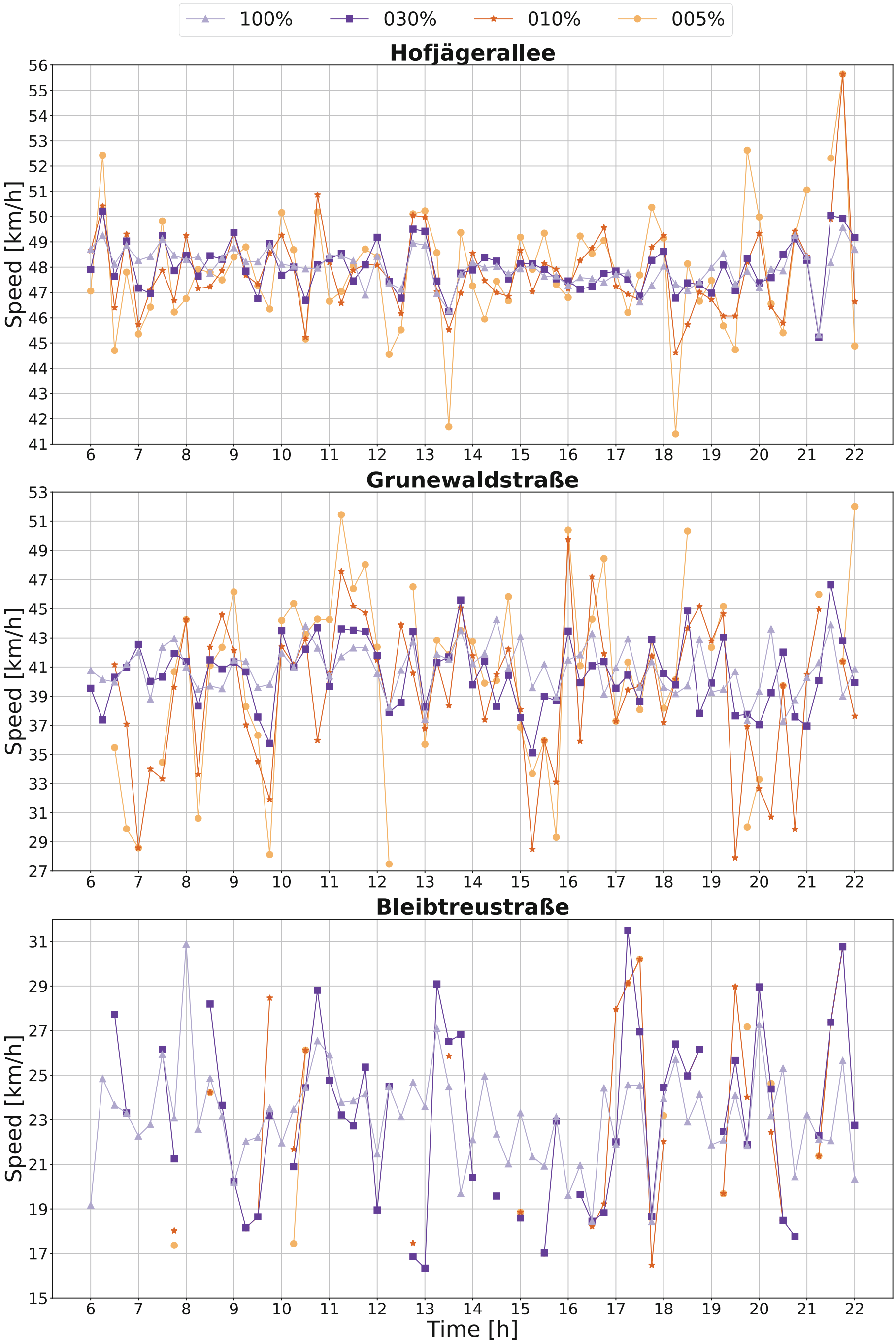


Fig. 6. Temporal mean speed measured with different rates of equipped CVs aggregated over 15 min intervals for the street segments highlighted in Fig. 4.

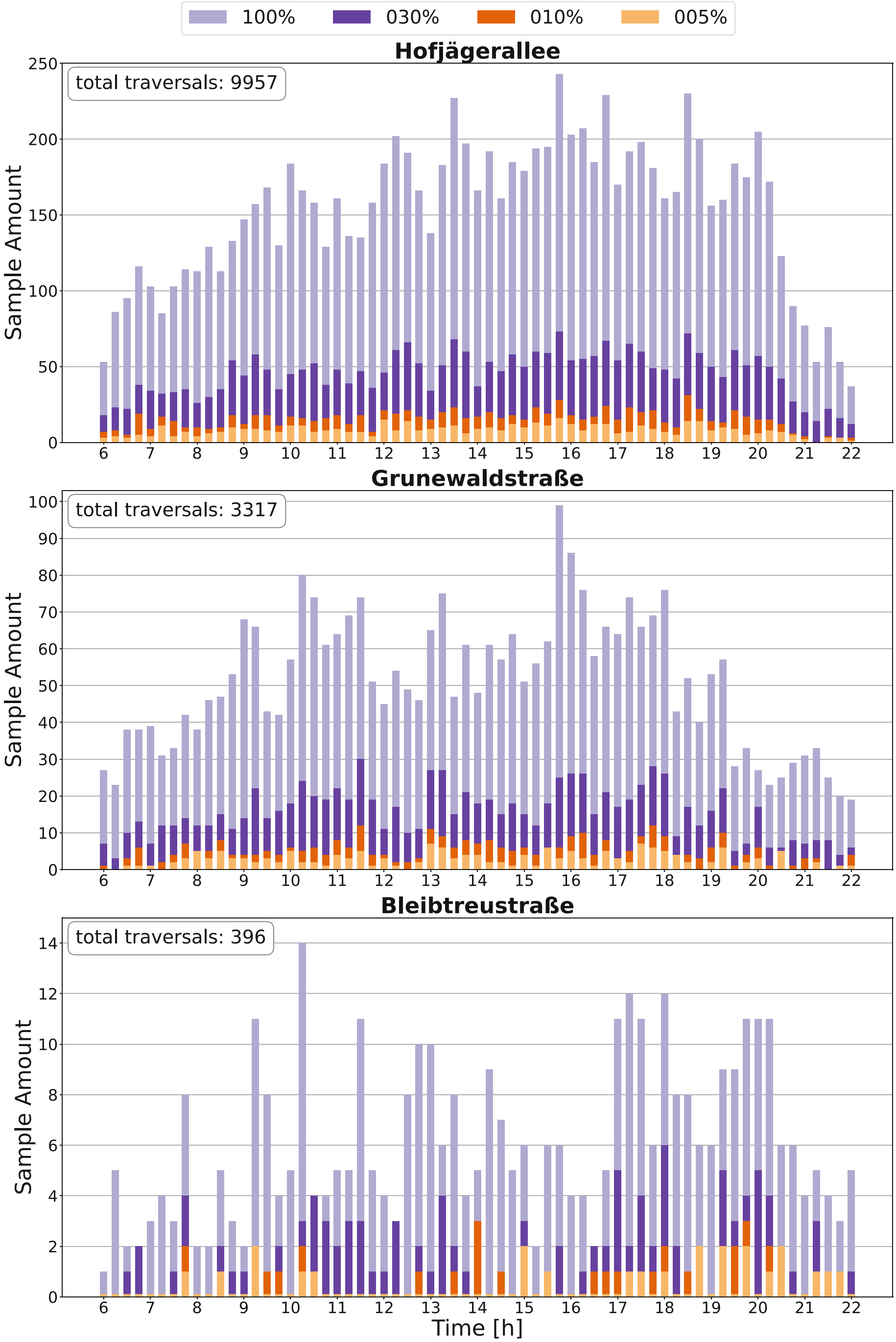


Fig. 7. Samples collected using Floating Car Data aggregated over 15 min intervals for the street segments highlighted in Fig. 4.

Table 2. Measured mean speeds on inspected roads averaged from 6 am to 10 pm.

street	$\bar{V}_{\mathrm{GT}}$	$\bar{V}_{\mathrm{TMS}}$	$\bar{V}_{\mathrm{SMS}}$	$\bar{V}_{\mathrm{temporal}}$	$\bar{V}_{\mathrm{spatial}}$
Hofjägeralle	47.3 $\frac{\mathrm{km}}{\mathrm{h}}$	48.7 $\frac{\mathrm{km}}{\mathrm{h}}$	47.7 $\frac{\mathrm{km}}{\mathrm{h}}$	48.0 $\frac{\mathrm{km}}{\mathrm{h}}$	47.9 $\frac{\mathrm{km}}{\mathrm{h}}$
Grunewaldstraße	40.9 $\frac{\mathrm{km}}{\mathrm{h}}$	49.0 $\frac{\mathrm{km}}{\mathrm{h}}$	48.0 $\frac{\mathrm{km}}{\mathrm{h}}$	40.9 $\frac{\mathrm{km}}{\mathrm{h}}$	46.3 $\frac{\mathrm{km}}{\mathrm{h}}$
Bleibtreustraße	22.4 $\frac{\mathrm{km}}{\mathrm{h}}$	28.6 $\frac{\mathrm{km}}{\mathrm{h}}$	28.4 $\frac{\mathrm{km}}{\mathrm{h}}$	23.2 $\frac{\mathrm{km}}{\mathrm{h}}$	27.2 $\frac{\mathrm{km}}{\mathrm{h}}$

It is evident that the road type and thereby the amount of recorded traversal have a large impact on estimation quality. On the Hofjägerallee even with penetration rates as low as 5% decent estimation is still possible. The Grunewaldstraße on the other hand, seems to reach its threshold between 10% and 5% with more outliers and unsampled intervals. Compared to that, the system fails to collect enough samples on the Bleibtreustraße to get a meaningful speed estimate even at penetration rates around 30%. The acquired estimates at market penetrations of 10% and 5% are only sparsely usable. On the Hofjägeralle and the Grunewaldstraße, the number of outliers increases with decreasing penetration rates and even at 10% we start to see outliers with a significant magnitude. The cited penetration rate thresholds for highway speed estimation of 5% to 10% can only be applied to the Hofjägerallee, due to its highway-like character. On the other two streets, measures based on basic FCD reach their limit sooner.

Figure 7 offers more detailed insights into why a meaningful speed estimation might not be possible at lower penetration rates. While both the Hofjägerallee and the Grunewaldstraße are traversed thousands of times throughout the day, the Bleibtreustraße is only traversed 400 times with intervals where merely two traversals are recorded. This makes it highly unlikely for a CV to traverse the Bleibtreustraße even at penetration rates as high as 30%. Usually, as roads like the Bleibtreustraße don't experience large traffic volumes anyway, less frequent samples aren't influential. Yet, for use cases like incident detection consistent sampling becomes more relevant.

4.4 Summary

To summarize the results, we demonstrated that the published application suite can act as a basis for a simulative assessment of TSE systems, delivering expected results for implemented metrics. We found that on large, heavily frequented roads (e.g., Hofjägerstraße, and highways) loop detectors can deliver decent results and might be worth the investments. However, on these roads, very comparable results can be achieved even with a low market penetration of CVs. Speed estimation on highly frequented, signalized urban street segments is more difficult as speeds fluctuate between and within traversals. Single loop detectors fail to produce proper speed estimations, while an FCD-based solution can still closely reconstruct the actual mean speed on those edges. On smaller, less frequented edges both loop detectors as well FCD-based approaches face difficulties. Despite that, even small amounts of FCD can give an insight into the traffic state throughout the day, while no traffic agency would consider loop detector installation on such roads due to costs. Consequently, for smaller roads, the relevancy of a constantly available TSE has to be considered. For these roads, little traffic is expected anyway and obstructions are rare, meaning that most of the time it is possible to accelerate close to the speed limit and an estimation is not required regardless. However, if a major incident happens even on a smaller road, users would expect a timely reaction by the TSE system to circumnavigate the afflicted area.

5 Conclusion and Outlook

In this paper, we initially offered a review of existing speed metrics for Traffic State Estimation (TSE) and categorized the challenges one faces when considering complex urban environments compared to highways. Due to much larger fluctuations in individual vehicle behavior, metrics have to be chosen more carefully and potentially from multiple sensor sources for urban applications.

Nonetheless, mean speed estimations always offer insights about the traffic state and are highly important for urban TSE. We identified different commonly used sensor modalities, which lead to different mean speed measures as different assumptions have to be made when aggregating lossy data from sensors. We classified the *Time Mean Speed* and the *Space Mean Speed* as common derivations when dealing with induction loop data. More recent applications based on Floating Car Data often rely on curve-fitted approaches, for which we identified the *Temporal Mean Speed* and *Spatial Mean Speed*, derived from the work of Yoon et al. [14].

To empirically test these measures, we pursued a simulation approach (see Sect. 4), utilizing the strengths of Eclipse MOSAIC [3]. We developed an open-source MOSAIC application suite to calculate the aforementioned mean speed metrics for any traffic scenario. The code for these applications is published on GitHub[1], together with configuration files for a simulation setup within the Charlottenburg area of the BeST scenario [11].

Based on the published resources, we conducted a comparative study with urban traffic demand provided by the BeST scenario. We found that inner city speed estimations are dependent on the road that they are measured on. The length, speed limit, lane amount, and traffic signal occurrence at the end heavily influence the magnitude of realizable speeds as well as the variability. Time and space mean speed measured by single loop detectors often fail to capture the latter, as these are limited to a single observation point.

We furthermore showed that FCD-based approaches like the temporal and spatial mean speed are better at capturing the characteristics of entire road segments. As FCD-based systems rely on vehicles as mobile sensors, the equipment rate has to be considered. Our study showed that at rates lower than 15% only partial observations can be made, especially on smaller roads. In the future, we

[1] https://github.com/mosaic-addons/traffic-state-estimation.

aim to tackle this research question by enriching the FCD set to improve the data quality and enable smaller fleets to provide a sensible TSE. Concisely, we aim to utilize additional information from perception sensors.

Furthermore, a large-scale, scenario-wide evaluation of implemented TSE metrics is of high importance. While initial efforts have been made in that direction, finding appropriate assessment strategies is a non-trivial task due to the heterogeneous nature of traffic patterns, both in spatial and temporal regards. In addition, we aim to construct and study scenarios with disruptive traffic patterns (e.g., incidents, second-row parking, etc.) in more detail as these are often most relevant for road users and should be detected by any form of TSE.

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