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## Incident detection on urban roads - A case study using synthetic floating car data

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### Abstract

Within the scope of this paper we examine incident detection on inner-city roads using floating car data (FCD) under different traffic conditions and data qualities. We used synthetic FCD to analyze incidents under variable conditions, such as different traffic volumes. They are generated from microscopic traffic flow simulations with the software tool PTV Vissim. Automated processing of the synthetic FCD gained from the microsimulation models also makes it possible to analyze different data qualities resulting from the choice of penetration rate and transmission frequency. We investigated the recognizability of the incidents using five laboratory examples, which depict different traffic incidents, and a real inner-city road in Karlsruhe, Germany. Graphical and quantitative evaluations are used for incident detection, whereby violin plots and the proposed incident indicator have the most reliable detection rate. Incident detection decreases significantly if several incidents overlap, the severity of the incidents or the traffic volume is reduced, the data quality decreases, or if there is no current speed information in the data. For additional insights, we recommend considering the different figures created in the graphical analysis alongside the incident indicator used in the quantitative analysis.

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**Keywords:** floating car data (FCD); synthetic FCD; incident detection; microscopic traffic flow simulation

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### 1. Introduction

Traditionally, traffic quality has been determined using data from loop detectors. However, since they do have many disadvantages like the costly installation and tuning process of the detectors, their high failure rate, the extensive maintenance, and that they can only cover single locations, previous studies examined whether FCD are a better alternative [8]. FCD are data collected by vehicles moving in traffic using position detection technology. In addition to the position, they usually contain time and speed information. FCD offer finer spatial information than detectors, but low penetration rates have hindered their use in the past [5]. Since the data quality and latency have improved

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over the past years, FCD are now being used more and more frequently. Still, the data quality requirements for traffic quality analysis, in this case, for detecting incidents, have yet to be investigated. The following provides an overview of current research in the field of FCD for detecting incidents.

Petty et al. [8] proposed an incident detection algorithm. Because loop-based algorithms have many disadvantages, as mentioned above, the authors use data from probe vehicles participating in traffic. To detect incidents, accelerations above a certain threshold and up to a certain speed are identified to determine where vehicles accelerate to the free-flow speed after passing the incident. However, only accidents can be detected in 70 % of the cases on a freeway, and the detection rate of the incident types police ticketing and breakdowns is relatively low. Houbraken et al. [5] investigate the usage of FCD in live automated incident detection systems, which generally rely on conventional traffic sensors, as FCD have low data coverage due to their low penetration rates. The study uses FCD covering approximately 5.93 % of all vehicles. The authors compare the traditional detection system using detector data with the newly developed FCD system relying on current average speeds to detect incidents on two highways in the Netherlands. They conclude that FCD can be used for live incident detection systems with appropriate differences and are thus a less costly alternative to systems based on loop detector data. A similar study is presented by Zhao et al. [11]. To detect incidents, the changes in speed and the differences between upstream and downstream travel speeds of FCD are analyzed. Tested on an expressway in Beijing, 87 % of incidents are detected.

In contrast to the previous work, Liang et al. [7] attempt to detect congestion incidents with FCD for urban intersections. They utilize the GPS coordinates provided by the FCD to calculate the vehicle's time of stay at the intersection. Coupled with the intersection's signal data, it is determined whether the intersection is congested or not. Tested in Ningbo City, China, the algorithm can accurately detect congestions and dissipations. Also, the incident detection by Zhu et al. [12] is applied to an urban arterial road in Beijing. Their method is based on outlier mining, which uses the average speed on the link. The proposed approach results in a detection rate of 81.5 %.

In most research studies, the use of FCD is limited to motorways [5, 8, 11]. Here, they provide better results in detecting incidents than on inner-city roads with a more challenging environment due to the increased occurrence of traffic signals, intersections, entrances, exits, and other disruptive points, such as public transport stops, speed controls, etc. Therefore, higher penetration rates are required to detect traffic conditions on inner-city roads than on motorways [6]. Furthermore, in most studies, a map matching process is carried out before analyzing the data, requiring additional time and effort [5, 7, 11]. In the presented studies incident algorithms based on the analysis of accelerations, average speeds and travel times are presented. However, there is a lack of a qualitative, graphical examination which could potentially provide further insights beyond quantitative evaluations. In most cases, the incidents are not distinguished based on their source. To address these research gaps, this paper investigates the possibility of using FCD to detect incidents on urban roads and, if so, examines the required data quality in terms of penetration rate and transmission interval. Moreover, the study explores the detection rates for different types of incidents. In contrast to the presented algorithm-based methods, a qualitative approach is presented. In addition, a quantitative incident index is introduced. Both methods can be applicable without requiring map matching and are tested on a real urban measurement section.

## 2. Method

In order to test the graphical and quantitative incident detection using data of different qualities, we generate synthetic FCD using microscopic traffic flow simulation models and Python scripts. Synthetic FCD have the additional advantage of a known ground truth, in contrast to real FCD, where locating the origin of incidents is challenging with the added complexity of potential overlapping incidents. To ensure that the proposed incident detection method, examined with synthetic FCD due to their easy modifiability, is applicable to real FCD, the synthetic FCD must closely resemble real FCD in terms of their statistical properties. Therefore, this chapter describes the analysis of real FCD as well as the generation and processing of synthetic FCD. Additionally, the graphical and quantitative evaluation is presented.

### 2.1. Generation of Synthetic FCD

Significant limitations in the use of FCD are that the position of the vehicles is not available continuously but only at specific points in time (transmission interval), that only some of the vehicles send data at all (penetration rate), and

that the reported values such as position and speed are subject to errors. These three aspects should be considered when generating synthetic FCD and must therefore first be analyzed using real data. Therefore an FC data set of a German inner-city main road is purchased from a commercial provider, examined, and compared with the synthetic FCD. For a reliable data basis to determine the characteristics of the real FCD, all Tuesdays, Wednesdays, and Thursdays of September 2021 are taken into account. A comparison to travel time measurements using number plate recognition indicated sufficient reliability of the data. The real FCD contain the following information: vehicle number, date, time of day, position as longitude and latitude, angle of alignment, and current speed. The data contain positional inaccuracy due to the inaccuracy of the GPS. In addition to this, it is also noticeable that individual vehicles systematically deviate from the route recorded on the digital map. This may be due to defects in individual GPS units. To generate synthetic FCD, which provide complete information about the traffic flow (ground truth), simulation models must be created using simulation software, such as PTV Vissim. The necessary processing steps for generating synthetic FCD, which in the best case are indistinguishable from real FCD, are explained in the following.

In Vissim, a local Cartesian **coordinate system** is used where a reference point is set as point zero in the background map when the first network object is created. To ensure that the FCD from the simulation can be processed universally, the Vissim coordinates are converted into the WGS 84 coordinate system. A random selection of vehicles is made to achieve the desired **penetration rate** while removing all other vehicles and their information. Upon analyses of the real FCD, it was observed that the **transmission intervals** are subject to fluctuations. Therefore they should be kept variable to assess the impact of the different intervals. Because the set time resolution of the simulation can only be increased but not decreased afterwards, Vissim is configured to write an entry in the vehicle record every second for each vehicle. The desired transmission interval is then generated by deleting all entries that fall between the selected frequency. In addition, each vehicle is assigned a random start time between 0 s and the duration of the selected transmission interval, ensuring that not all vehicles transmit at the same second after entering the road section. As mentioned earlier, real FCD are subject to a **position error** due to the inaccuracy of the GPS. The synthetic FCD, which so far have been located exactly on the route, must also be equipped with this. As we cannot determine the position error from the real FCD due to the unknown precise location of the transmitting vehicles, we rely on a previous study which has evaluated the accuracy of GPS-based position reports to estimate the spatial uncertainty [3]. Upon reproducing the stated position error distribution with a mean value of approx. 0.75 m, it becomes apparent that it is insufficient to replicate the real FCD when compared to them. This may be due to the fact that the GPS accuracy in urban areas tends to be lower than in open areas, as the GPS signals are reflected due to buildings and fail to reach the receiver directly. As a result, the previous position error distribution is doubled. It is then reproduced by randomly selecting one value from the distribution and an angle between 0° and 360° to indicate the direction in which the points should be moved. Additionally, the synthetic FCD account for the already described offset present in the real FCD by including it in some of the vehicles. The synthetic FCD, which are now affected by the penetration rate, transmission interval, and position error, show a high degree of similarity to the real FCD. In addition to that, a **direction of travel** is assigned to each vehicle resulting from the alignment angles. With the help of these, the **travelled distance** in relation to a specified route starting point for each direction of travel is calculated.

## 2.2. Incident Detection Approaches

With the previously created synthetic FCD, we want to investigate whether and under which data qualities a detection of incidents is possible. This investigation is initially carried out using laboratory examples modelled in Vissim, each consisting of a straight road with only one incident at a time. The incidents examined are a bus stop, an intersection with and without signal control, a pedestrian crossing and parking spaces. To investigate different severity levels of the incidents, one driving direction is modelled with higher disturbance levels such as reduced green times or increased pedestrian traffic. Furthermore, different vehicle volumes are tested by increasing the volumes from 400 to 700 vehicles per hour in steps of 100 vehicles. After creating the simulation models, synthetic FCD with varying data qualities are generated. The investigation covers the optimum (100 % penetration rate and 1 s transmission interval) as well as nine other scenarios created by combining a penetration rate of 2 %, 5 % or 10 % with transmission intervals of 5 s, 10 s or 15 s. The transmission intervals are based on the intervals found in the real FCD. Since, as it turns out later, a 10 % penetration rate together with a 5 s transmission interval result in a similar incident detection rate as the optimum, there is no need to further improve data quality. In addition to the laboratory examples, we investigate a real inner city road in Karlsruhe. First, a graphical evaluation is carried out, followed by a quantitative one.

### 2.2.1. Graphical Evaluation

Various forms of presentation can be used to identify incidents. The simplest option is to plot each point on a map using colors to indicate the speed. Alternatively, the density of the points can be color-indicated, since lower speeds generate more data points in the same location resulting in a higher density if an incident occurs. However, utilizing the density requires a constant transmission interval distribution, and should therefore only be used if no speed information is available in the data. Figure 1 displays a point plot with the position error applied, allowing for the detection of the priority-controlled intersection as well as the higher severity of the direction from west to east.

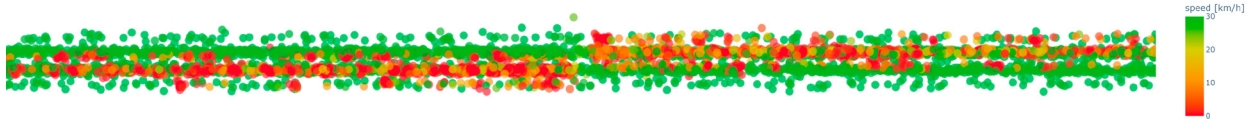


Fig. 1: Point diagram with color-coded speed of the priority-controlled intersection with 10 % penetration rate and 10 s transmission interval

Another form of visualization are path-time diagrams, although data without map matching can only be displayed to a limited extent. It is possible to display trajectories or points, whereby the latter can again be colored according to speed. For example, the discrete path-time diagrams of the laboratory example of the signalised intersection with different data qualities are shown in Figure 2. If the points are connected to form trajectories, the gradient is evaluated. Hereby, an incident can only be detected if it causes significant time losses or if the transmission interval is sufficiently short. In addition, this form of representation is more suitable for single-lane routes without overtaking possibilities, as otherwise the trajectories would overlap and the diagram would appear confusing.

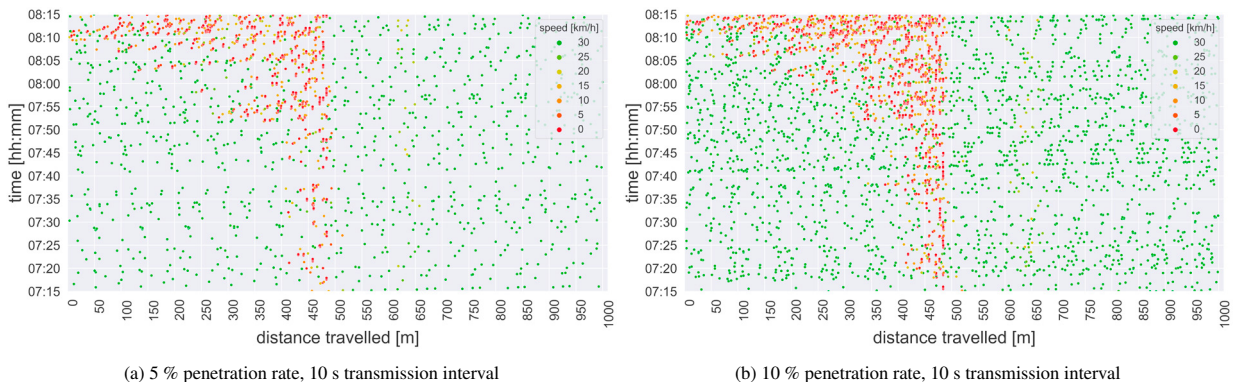


Fig. 2: Path-time diagrams of the signalised intersection

To overcome the discrete character of the individual data points and their varying spatial and temporal density, heat maps present themselves as a quasi-spatial-temporal interpolation. The individual data points are not shown in these illustrations, but an average speed is formed for individual space-time areas. At low penetration levels, however, one must assume that sufficient plausible speed information is not available for every space-time segment. It should be ensured that the selected time intervals are greater than the cycle time of the signal system to avoid a strong dependency on it. During the evaluation, route segments of 10 m and time intervals of 5 min turned out to be suitable sizes. Violin plots are a useful tool for visualizing the statistical distribution of quantitative data in general. In the case of FCD, they summarise speed distributions along a route during an observation period. The diagram no longer reflects the course over time. The path is divided into small segments in which the speeds are aggregated. Violin plots are similar to box plots, which are often used in statistics, but they provide more information. While box plots only show summary statistics like the mean, median and interquartile ranges, violin plots display the data's full distribution as the bars' thickness. An exemplary heat map and violin plot of the signalised intersections are illustrated in Figure 3. In cases where speed information is not provided in the FCD, heat maps and violin plots can still be used. This requires calculating the travel speed using the distance between two position reports and the time elapsed between them, and then apportioning this among the sections travelled through. The calculations are based on those of Rahmani et al. [9].

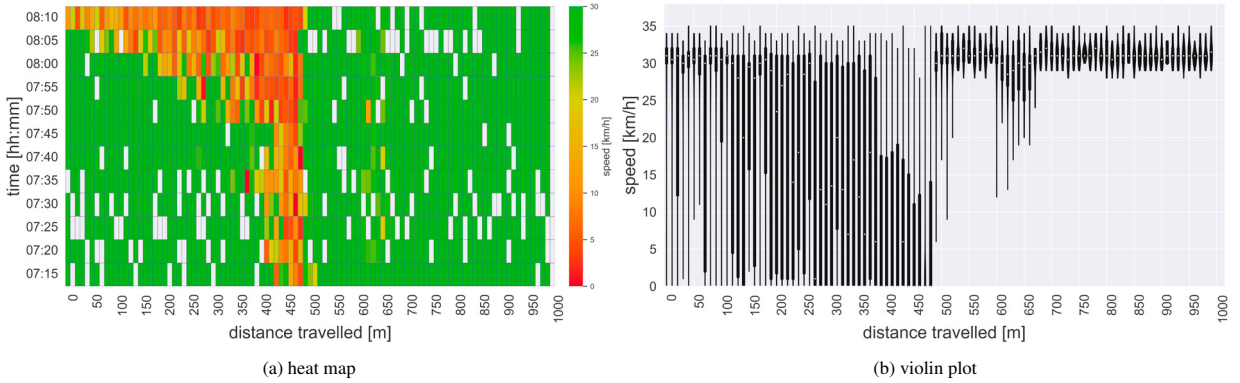


Fig. 3: Plots of the signalised intersection with a penetration rate of 10 % and a transmission interval of 10 s

The presented diagram types are then visually inspected to determine how clearly the incidents can be recognized across all parameter combinations of the laboratory examples and the real measurement section. In summary, eight diagrams are created for each of the simulated cases:

- point diagrams displaying the reporting vehicles' position along the route with color-coded density or speed;
- path-time diagrams displaying vehicle trajectories or points with color-coded speed in the path-time plane;
- heat maps showing the calculated or the current speed;
- violin plots showing the calculated or the current speed.

### 2.2.2. Quantitative Evaluation

To provide a comprehensive evaluation, it is important to include both graphical and quantitative analyses. This will allow for the identification of three different traffic conditions: consistently high speeds indicating no incident, a mix of high and low speeds, and consistently low speeds indicating an incident. As a first approach, we used the unreliability index, which is a key performance indicator (KPI) for the assessment of traffic flow qualities on the German motorway network [1]. It indicates the dispersion of the travel time distribution, whereby the 10 % fastest and slowest vehicles ( $p_{10}$ ,  $p_{90}$ ) as well as the median ( $p_{50}$ ) are considered. These considerations are adopted for the determination of an incident indicator, whereby speeds are used instead of travel times (Equation 1). The higher the incident index, the more likely there is an incident. A weakness of this incident indicator is that it only considers the width of the speed distribution, not the absolute level of the speeds. On a road section where the speed is consistently low, the 10 %, 50 % and 90 % percentiles will be close together, resulting in a small incident index despite ongoing disruptions. To address this issue, the incident index is extended by a factor that additionally considers the quotient between the median and the maximum permissible speed  $v_{per}$  (Equation 2). This is only applicable if the value of  $v_{per}$  is known.

$$\text{Incident indicator} = \frac{p_{90} - p_{10}}{p_{50}} \quad (1)$$

$$= \frac{p_{90} - p_{10}}{p_{50}} \cdot \frac{v_{per}}{p_{50}} \quad (2)$$

The extended incident indicator is calculated for all parameter combinations and laboratory examples as well as the real measurement section. To ensure comparability with the visual inspection, three degrees of malfunction are defined:

$$\text{Incident} = \begin{cases} \text{occures} & \text{incident indicator} < 1, 0 \\ \text{occures sometimes} & 1, 0 \leq \text{incident indicator} < 2, 0 \\ \text{does not occure} & \text{incident indicator} \geq 2, 0 \end{cases}$$

### 3. Results and Discussion

#### 3.1. Results of the Graphical Evaluation

Upon analyzing the diagrams, we observed that the **priority-controlled and signalised intersections** are detectable in almost all data quality cases and forms of presentation. Even the otherwise poorly performing point diagram color coding the density is able to detect the intersections (except for the priority-controlled one with the lowest data quality (2 %, 15 s)), which is related to the severity of the incident. The impact of traffic volume is most evident in the evaluation of the intersections, as higher traffic volumes lead to more noticeable upstream congestions. This is only visible in the path-time and heat map diagrams, as the other diagram types do not contain a time reference and therefore cannot distinguish between different traffic volumes. When analyzing the laboratory examples of the **bus stop** and the **pedestrian crossing**, there are great similarities in the recognizability of the incidents. Figure 4 displays the incident recognizability of the pedestrian crossing in the various diagrams forms and data qualities. Light grey indicates detectability, dark grey represents limited detectability, and black that no incident is detectable anymore. It can be seen that the point diagrams showing the density and the path-time diagram illustrating the trajectories as lines are only helpful in very few cases. In contrast, path-time diagrams showing color-coded points can be well utilised for almost every data quality. When using the heat map diagrams, there is a clear difference between the use of the current or calculated speed, as the latter is less reliable in recognizing incidents. Both point diagrams and path-time diagrams, color-coded by speed, and violin plots, whether showing the calculated or current speed, exhibit nearly perfect detection rates. The **parking incident** is detected the least frequently as the parking process is brief, resulting in minimal traffic disruption, and the disruptions do not always occur at the exact location. This is also supported by Riel's research [10]. Similar to the previous incidents, it is possible to detect parking incidents using violin plots, except for cases with very low data qualities. Also, path-time diagrams showing color-coded points can detect parking incidents in most data quality cases. Other diagram types do not allow for the detection of parking operations.

| Data quality | Point diagram        |               |                    |               | Path-time diagram |               |                    |               | Heat map         |               |               |               | Violin plot      |               |               |               |
|--------------|----------------------|---------------|--------------------|---------------|-------------------|---------------|--------------------|---------------|------------------|---------------|---------------|---------------|------------------|---------------|---------------|---------------|
|              | Density colour-coded |               | Speed colour-coded |               | Trajectories      |               | Speed colour-coded |               | Calculated speed |               | Current speed |               | Calculated speed |               | Current speed |               |
|              | Low severity         | High severity | Low severity       | High severity | Low severity      | High severity | Low severity       | High severity | Low severity     | High severity | Low severity  | High severity | Low severity     | High severity | Low severity  | High severity |
| 100 %, 1 s   |                      |               |                    |               |                   |               |                    |               |                  |               |               |               |                  |               |               |               |
| 10 %, 5 s    |                      |               |                    |               |                   |               |                    |               |                  |               |               |               |                  |               |               |               |
| 10 %, 10 s   |                      |               |                    |               |                   |               |                    |               |                  |               |               |               |                  |               |               |               |
| 10 %, 15 s   |                      |               |                    |               |                   |               |                    |               |                  |               |               |               |                  |               |               |               |
| 5 %, 5 s     |                      |               |                    |               |                   |               |                    |               |                  |               |               |               |                  |               |               |               |
| 5 %, 10 s    |                      |               |                    |               |                   |               |                    |               |                  |               |               |               |                  |               |               |               |
| 5 %, 15 s    |                      |               |                    |               |                   |               |                    |               |                  |               |               |               |                  |               |               |               |
| 2 %, 5 s     |                      |               |                    |               |                   |               |                    |               |                  |               |               |               |                  |               |               |               |
| 2 %, 10 s    |                      |               |                    |               |                   |               |                    |               |                  |               |               |               |                  |               |               |               |
| 2 %, 15 s    |                      |               |                    |               |                   |               |                    |               |                  |               |               |               |                  |               |               |               |

Fig. 4: Graphical evaluation of the incident pedestrian crossing under various data qualities

Overall, it can be stated that violin plots are particularly helpful for identifying incidents. Regardless of whether velocity information is known or not, the incidents are recognized most reliably in almost all cases, even with low penetration rates and long transmission intervals, except for parking incidents with low data quality. In contrast, point plots displaying the density are the least suitable for detecting incidents. In general, the availability of speed information increases the probability of detecting incidents regardless of the diagram type. An increase in the severity of the interference source also positively affects recognizability. It is important to mention that the incidents are typically located downstream of the speed drop. Also, it should be noted that the temporal variability, such as the frequency of public transport vehicles, is only recognizable in the path-time and heat map diagrams. This can be advantageous for determining the type of incident.

#### 3.2. Results of the Quantitative Evaluation

In addition to the graphical evaluation, incident indices are analyzed across all laboratory examples. The large upstream congestions of the two **intersections** are particularly apparent, with the signalised intersection frequently showing higher incident figures than the priority-controlled intersection. Also, the dispersion of the congestion at a distance upstream from the incident location is recognizable. Figure 5 shows the incident indicators for the priority-controlled intersection as an example. Only the distances between 100 and 520 m are shown as the incident occurs

at 500 m. The calculated values are colored as follows: Red coloring indicates that an incident is detected (incident indicator  $\geq 2$ ), green means no incident (incident indicator  $< 1$ ), and orange shows that the indicator is in between. The upstream congestion and the reduction of the congestion with increasing distance to the incident are recognized at all data quality levels. Congested sections near the incident may go unrecognized at penetration rates as low as 2 %. In the laboratory example of the **bus stop**, speed reductions are also visible far upstream of the incident location. In contrast, almost no upstream congestions are visible in the laboratory example of the **pedestrian crossing**. The difference in the severity of the disruption is because the public transport vehicles not only pull over at the bus stop but also have a lower acceleration compared to the passenger cars. At a pedestrian crossing, vehicles stop for comparatively less time, which is why many short disruptions occur. **Parking** operations cannot be detected with the incident indicator.

| Data quality | Travelled distance [m] |     |      |     |     |      |     |     |     |     |     |     |     |     |     |      |      |      |      |      |     |     |     |     |      |      |      |     |     |      |      |      |      |      |      |      |      |      |      |     |     |     |     |     |  |  |  |  |  |  |  |  |
|--------------|------------------------|-----|------|-----|-----|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|-----|-----|-----|-----|------|------|------|-----|-----|------|------|------|------|------|------|------|------|------|------|-----|-----|-----|-----|-----|--|--|--|--|--|--|--|--|
|              | 100                    | 110 | 120  | 130 | 140 | 150  | 160 | 170 | 180 | 190 | 200 | 210 | 220 | 230 | 240 | 250  | 260  | 270  | 280  | 290  | 300 | 310 | 320 | 330 | 340  | 350  | 360  | 370 | 380 | 390  | 400  | 410  | 420  | 430  | 440  | 450  | 460  | 470  | 480  | 490 | 500 | 510 | 520 |     |  |  |  |  |  |  |  |  |
| 100%, 1 s    | 1.1                    | 1.1 | 1.1  | 1.1 | 1.1 | 1.1  | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1 | 1.1  | 1.2  | 1.3  | 1.6  | 2.0  | 1.8 | 2.4 | 2.1 | 2.5 | 2.9  | 2.9  | 3.6  | 2.9 | 4.0 | 3.6  | 3.4  | 4.4  | 3.9  | 4.4  | 5.0  | 5.0  | 6.0  | 4.1  | 9.0  | 1.9 | 0.2 | 0.2 | 0.2 |     |  |  |  |  |  |  |  |  |
| 10%, 5 s     | 1.0                    | 0.9 | 1.1  | 1.1 | 1.1 | 0.6  | 1.1 | 1.1 | 1.1 | 1.0 | 1.0 | 1.0 | 1.1 | 1.0 | 1.1 | 2.0  | 1.1  | 1.0  | 32.0 | 1.6  | 1.6 | 1.1 | 0.9 | inf | 2.5  | 3.4  | 1.9  | 3.1 | 2.3 | 15.5 | 1.4  | 2.9  | inf  | 3.1  | 15.5 | 2.8  | 6.0  | 2.6  | 13.3 | 5.6 | 1.8 | 0.3 | 0.1 | 0.2 |  |  |  |  |  |  |  |  |
| 10%, 10 s    | 1.1                    | 1.1 | 1.2  | 1.0 | 1.2 | 1.0  | 1.0 | 1.1 | 1.1 | 1.1 | 1.2 | 2.2 | 1.1 | 0.5 | 1.1 | 0.9  | 33.0 | 2.4  | 3.2  | 1.3  | 1.9 | inf | 2.7 | 1.7 | 2.6  | 2.7  | 2.2  | 7.8 | 3.1 | 1.9  | 6.2  | 2.6  | 3.3  | 3.8  | 7.3  | 3.1  | 3.1  | 37.0 | 1.1  | 0.2 | 0.3 | 0.1 |     |     |  |  |  |  |  |  |  |  |
| 10%, 15 s    | 1.0                    | 0.2 | 0.7  | 1.1 | 1.0 | 1.1  | 1.1 | 1.1 | 1.6 | 0.4 | 1.0 | 1.1 | 0.3 | 1.7 | 1.3 | 3.1  | 1.0  | 32.8 | 31.6 | 2.8  | 1.5 | 2.7 | 6.3 | 1.4 | 32.0 | 2.1  | 2.7  | 1.9 | 2.2 | 1.5  | 4.1  | 3.5  | 15.3 | 30.0 | 5.5  | 14.2 | 19.3 | 13.5 | inf  | 2.6 | 0.2 | 0.1 | 0.1 |     |  |  |  |  |  |  |  |  |
| 5%, 5 s      | 0.6                    | 1.1 | 0.8  | 1.1 | 0.8 | 1.0  | 1.0 | 1.1 | 1.3 | 1.1 | 1.1 | 1.1 | 0.8 | 1.1 | 4.4 | 2.3  | 0.7  | 1.0  | 82.0 | 0.8  | 1.3 | 1.1 | 2.9 | 5.6 | inf  | 2.4  | 1.0  | 1.9 | 8.4 | 3.6  | inf  | inf  | 8.7  | 1.7  | 1.5  | 2.0  | 4.4  | 2.6  | 6.5  | 2.8 | 0.2 | 0.3 | 0.1 |     |  |  |  |  |  |  |  |  |
| 5%, 10 s     | 1.1                    | 0.6 | 34.0 | 0.7 | 0.6 | 32.5 | 1.0 | 0.3 | 1.0 | 2.8 | 1.1 | 0.9 | 0.8 | 1.1 | 1.1 | 1.1  | 1.5  | 0.9  | inf  | 16.4 | 1.7 | 1.1 | 1.4 | 1.4 | 1.0  | 1.1  | 31.7 | 1.3 | inf | 1.4  | 31.5 | 1.6  | 1.9  | 3.3  | 3.4  | 5.0  | 3.4  | inf  | 3.4  | 1.4 | 0.2 | 0.1 | 0.2 |     |  |  |  |  |  |  |  |  |
| 5%, 15 s     | 0.3                    | 1.1 | 0.1  | 1.1 | 0.6 | 1.7  | 0.8 | 0.5 | 2.2 | 2.7 | 2.2 | 0.8 | 7.9 | 4.2 | 1.2 | 1.3  | 2.7  | 0.6  | 0.8  | 2.3  | 6.3 | 0.7 | 1.1 | 5.9 | 2.6  | 0.0  | 2.4  | 2.5 | 1.6 | 2.2  | 7.9  | 04.0 | 1.0  | 4.4  | 28.3 | 3.0  | 4.2  | 20.0 | 10.1 | 1.0 | 0.1 | 0.1 |     |     |  |  |  |  |  |  |  |  |
| 2%, 5 s      | 0.4                    | 0.5 | 0.1  | 0.2 | 0.7 | 0.3  | 1.1 | 0.3 | 0.5 | inf | 1.1 | 0.8 | 0.1 | 0.2 | 2.5 | 16.0 | 8.0  | inf  | 2.4  | 5.5  | 0.7 | 6.4 | 2.1 | 2.3 | inf  | 1.5  | 4.7  | 2.5 | 2.9 | 0.9  | 2.3  | 8.0  | 30.4 | inf  | 3.7  | 4.3  | 2.4  | 2.8  | 3.7  | 4.3 | 0.2 | 0.1 | 0.1 |     |  |  |  |  |  |  |  |  |
| 2%, 10 s     | 0.1                    | 0.1 | 0.5  | 0.6 | inf | 0.5  | 0.0 | 0.1 | 0.0 | 0.4 | 1.1 | inf | 1.3 | 0.1 | 0.1 | 0.9  | 1.1  | 1.0  | inf  | 3.4  | 0.3 | 1.7 | inf | 1.2 | 31.0 | 2.4  | 1.4  | 0.9 | 2.7 | 1.6  | 0.9  | 1.0  | 0.7  | 1.0  | 9.7  | 1.6  | 11.8 | 1.9  | inf  | 2.3 | 0.1 | 0.1 | 0.1 |     |  |  |  |  |  |  |  |  |
| 2%, 15 s     | 0.0                    | 0.1 | 1.6  | 1.1 | 1.1 | 0.0  | 0.1 | 0.5 | 0.9 | 1.3 | 1.7 | 1.1 | 2.7 | 0.5 | 1.4 | 0.2  | 0.7  | 0.8  | 1.1  | 30.5 | 0.5 | 0.8 | 1.5 | inf | 0.3  | 30.3 | 1.6  | inf | 1.5 | 1.2  | 0.9  | 0.8  | 2.1  | 0.3  | inf  | inf  | 2.7  | 1.5  | 3.9  | 1.1 | 0.1 | 0.1 | 0.1 |     |  |  |  |  |  |  |  |  |

Fig. 5: Incident indicators of the priority-controlled intersection under various data qualities

Based on the laboratory examples, it can be stated that at traffic volumes of 400 vehicles/h and above, a penetration rate of 5 % and at traffic volumes of 500 vehicles/hour and above, a penetration rate of 2 % is recommended. For longer transmission intervals over 10 s, larger traffic volumes may also be required. However, it is impossible to define generally applicable minimum requirements for data quality. It is remarkable that across all laboratory examples in the driving direction with the higher severity, even at the lowest penetration rate in combination with the lowest reporting frequency (2 %, 15 s), a significant detection is still possible, provided that the disturbance is detectable at all, i.e. it is detectable with perfect data quality (100 %, 1 s). It is evident from both the quantitative and graphical analyses that detecting incidents like public transport stops, pedestrian crossings and roadside parking can be challenging because they result in relatively short waiting times, especially when compared to waiting times at intersections. This confirms the findings of a Swiss research project [2].

### 3.3. Results of the Real Measurement Section

When analyzing the real measurement section in Karlsruhe, which includes multiple intersections, a pedestrian traffic light, and two bus stops, the intersections clearly stand out in both the graphical and quantitative evaluation. One intersection leads to particularly high speed reductions, which can be attributed to the public transport stop and pedestrian signal located behind it. In both evaluations, it is securely possible to detect the signalised and priority-controlled intersections with moderate turning flows with a minimum penetration rate of 5 %. Detecting priority-controlled intersections with low turning flows can be challenging since speeds are not significantly reduced. The parking spaces and public transport stops cannot be identified as separate incidents, but the latter certainly affect the intersection's recognizability at this location. Contrary to expectations, detection is also possible at low traffic volumes. Although the total number of data points decreases, speed reductions are more noticeable and not overshadowed by other sources of interference. At a penetration rate of 2 %, data is increasingly no longer available in some time and space intervals or consists of only one FCD point. Especially in the quantitative evaluation, speed drops that cannot be attributed to a particular source are identified. In general, the underlying data quality is unknown in reality. Therefore, the interpretation of the evaluation becomes more difficult, especially in aggregated plots.

## 4. Conclusion and Further Research

This study demonstrates the possibility of detecting incidents on inner-city roads using FCD. Both graphical and quantitative methods are used for evaluation. Synthetic FCD are generated using microscopic traffic flow simulations to analyze different data qualities regarding penetration rates and transmission intervals. With these generated

synthetic FCD, numerous other analyses are conceivable besides detecting incidents. It is recommended to consider both graphical and quantitative evaluations for incident detection, as they provide different insights and benefits depending on the research question. The evaluation of laboratory examples with different incident sources, data qualities, severities of incidents, and vehicle volumes shows that intersections, regardless of whether they are priority- or signal-controlled, have the highest detection rates due to the severity of the incident. The most reliable graphical incident detection is possible with violin plots. In general, aggregated forms of visualization, such as heat maps or violin plots, are advantageous for identifying incident locations. However, they may not effectively recognize the incident type, as these aggregate the data over time. In this case, discrete visualization forms like point plots or path-time diagrams with color-coded points based on speed are more helpful. Unlike several diagram types, the incident indicator cannot estimate speed distribution. This and the lack of time differentiation make it difficult to recognize the incident type in the quantitative evaluation. On the other hand, the incident indicators allow for evaluating larger networks, in contrast to the graphical evaluation, which is only useful for precisely analyzing incidents due to the great effort involved. In the graphical and quantitative evaluation, it should be noted that slow-moving vehicles are over-represented, as they transmit more frequently than faster vehicles at the same transmission frequency due to their slow speed. However, this does not negatively affect the detectability of incidents, as it amplifies them. The availability of current speed information and map-matching improves recognizability during evaluation. Identifying the incident source becomes more complicated when multiple incident sources overlap. Also, determining a general level of data quality is difficult as the necessary penetration rate and transmission frequency for incident detection vary based on traffic volume and the severity of the incident source. Further research is needed to assess the application and plausibility of the incident indicator and to analyze the superposition of several incident sources in greater depth. Based on similar incident indicators, a further investigation of city-wide networks has already been carried out in order to identify problematic road segments [4]. These can then be further analyzed by applying the presented methods.

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