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Comparison of the Accuracy of Traffic Flow Intensity and Speed Measurement Using a Camera System and Measuring Devices Such as Sierzega and SDR on a Congested Road

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Abstract: This study investigates the accuracy of traffic flow and speed measurements using two radar-based devices, Sierzega and SDR, against manual video-based traffic counts. The measurements were conducted over a 12-h period on a congested urban road section characterized by variable traffic conditions and frequent vehicle stops. The results revealed that the SDR device generally provided lower deviations compared to manual counting, especially in measuring traffic flow. In contrast, the Sierzega device demonstrated greater and more inconsistent deviations, particularly in vehicle categorization and traffic density estimation. The observed discrepancies were primarily attributed to vehicle stopping and queuing, influencing length estimation and classification errors. Despite these limitations, SDR provided sufficient accuracy for practical applications, such as monitoring traffic trends or supporting long-term traffic planning in urban environments.

Keywords: vehicles; traffic flow measurement; radar sensors; traffic monitoring



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1. Introduction

Traffic surveys and road traffic monitoring constitute fundamental tools for effective transportation planning, traffic management, and the enhancement of road safety [1–3]. Data on traffic volume, vehicle speeds, vehicle categorization, and the temporal distribution of traffic flow enables road administrators, traffic engineers, and municipalities to make informed decisions concerning traffic organization, infrastructure investments, and the implementation of traffic restrictions. Accordingly, the accuracy and reliability of this data are therefore crucial. Inaccurate data may result in erroneous conclusions and lead to inefficient decision-making [4–6].

Currently, various methods exist for collecting traffic data, along with the most widespread including passive radar devices (such as Sierzega and SDR), camera systems, loop detectors, and mobile applications. Each method possesses specific advantages and limitations. Although radar devices allow for immediate and automated measurements, their accuracy can be affected by technical limitations, installation methods, and the characteristics of traffic flow, such as density, smoothness, and vehicle spacing [7–9].

In addition to these widely used technologies, traffic data can also be collected using fixed spot measurement methods, including inductive loops, pneumatic tubes, detectors, video cameras, and radars. Furthermore, probe vehicle data systems, such as floating car data (FCD), represent another important approach for collecting traffic information. These methods provide complementary insights and have become essential tools in traffic monitoring and management.

Another method for traffic data collection is the “moving car observer method” (MOM), also known as the “moving car observer” (MCO) technique, which was developed by Wardrop and Charlesworth in 1952. This method involves the use of a moving vehicle to observe and record traffic flow rates along a specific road section. It offers an alternative approach to fixed-point and probe vehicle data methods and has recently been explored in combination with modern deep learning techniques [10].

Manual evaluation of camera recordings is more time-consuming, often yields the most detailed and accurate data and is therefore used as a reference method in studies validating technical devices [11–13].

The need for data collection has become increasingly critical in contemporary times. This trend is primarily driven by the implementation of the Smart City concept, where possessing the most comprehensive and accurate data is fundamental for effective urban management [14–16]. High-quality data collection is ensured by intelligent technologies capable of adapting and learning under real-world conditions [17–19].

The significance of this study lies in addressing a notable gap in current research: the lack of detailed comparisons of measurement device accuracy in highly congested urban traffic scenarios. By focusing specifically on conditions where vehicle stopping and queuing occur frequently, this research provides data that are directly applicable to the optimization of traffic monitoring systems in real-world congested environments.

Comparing the accuracy of various measurement methods is essential when selecting the most appropriate solution for specific applications. In urban environments characterized by frequent traffic jams and congested roads, it is essential to have devices capable of capturing the actual traffic conditions even under complex circumstances [20,21]. At the same time, it is necessary to ensure the correct identification of the direction of travel and the vehicle category (passenger cars, trucks, buses, heavy goods vehicles, etc.), as these factors directly influence traffic engineering decisions. Since the measuring devices used in this study distinguish vehicles solely based on their length, motorcycles represent a problematic vehicle category, as they cannot be reliably distinguished, for example, from bicycles. However, recent studies have shown that this issue could be addressed through systems based on deep learning, which enable effective urban traffic monitoring with a focus on the detection and tracking of motorcycles using embedded hardware [22]. By identifying discrepancies between these detection methods, the study not only contributes to the development of traffic load monitoring detectors but also supports advancements in autonomous vehicle technology, which necessitates highly accurate data to prevent traffic accidents [23,24].

This research focuses on comparing the accuracy of traffic volume and vehicle speed measurements across three different methods: the Sierzega device, the SDR device, and the manual evaluation of traffic surveys using camera recordings. Both the SDR and Sierzega devices operate based on radar technology, which is particularly advantageous for traffic monitoring as it remains unaffected by environmental conditions such as fog, rain, and snow [25,26]. Today, it is standard practice for camera recordings to be evaluated using software tools [27,28]. Nevertheless, for the purposes of this study, camera recordings were evaluated manually, as careful manual assessment yields an almost negligible error rate. The measurements were carried out over a 12-h period on a section of road with heavy traffic volume. The collected data include the number of vehicles in time intervals, direction of travel, vehicle length, and vehicle speed.

The main objective of this study is to calculate and compare traffic volume and density on a selected road section using three different measurement methods: the Sierzega device, the SDR device, and manual counting based on camera recordings. The results will then be graphically processed and analyzed in terms of differences between the individual methods.

The goal is to identify measurement discrepancies, assess the accuracy of each device under real-world conditions, and determine the factors that have the greatest influence on the differences in the recorded data.

Such research holds practical relevance, particularly for municipalities, cities, and road administrators when deciding upon the most suitable types of monitoring systems to implement. Furthermore, it contributes to the professional discourse on the effectiveness of various technologies in the field of traffic research.

Today, most cities and municipalities face the challenge of increasing traffic loads, which negatively affect traffic flow, air quality, and the overall comfort of residents [29]. In response to these issues, the concept of Smart Cities has emerged, utilizing modern technologies and digital solutions to optimize the functioning of urban infrastructure. An important component of this concept is intelligent traffic management, based on the collection, processing, and evaluation of data in real time [30–32].

While this study evaluates specific radar-based devices (SDR and Sierzega), the results are not intended to generalize the performance of the entire category of radar sensors. Instead, they provide a practical insight into the behavior of two widely used devices under real-world traffic conditions with frequent congestion and queuing. These specific conditions are often underrepresented in validation studies, despite being common in Smart City environments. Notably, the selected devices are typically designed for locations with smoother traffic flow, and this study aims to evaluate their suitability in more complex urban situations.

2. Materials and Methods

This chapter describes the procedures undertaken to conduct the traffic survey, including the methodology employed, and the technical means utilized for data collection. It focuses on the measurement location, the time frame of data collection, the characteristics of the deployed devices, and the parameters monitored during the measurement. It also outlines the methods of data processing and evaluation, which provide the basis for comparing the accuracy of the individual methods in the following sections.

Measurement Location and Duration

The traffic survey was carried out on a local road in the city center, directly adjacent to a shopping center generating significant traffic volumes throughout the day. This location was deliberately chosen due to its high and variable traffic flow, which includes passenger cars, freight vehicles, deliveries, and transit traffic. To improve the traffic situation in such areas, it is advisable to encourage as many residents as possible to use public transportation. In addition to reducing congestion, this would also enhance safety and decrease emissions [33–35].

Measurements were conducted on 6 March 2025, from 6:00 a.m. to 6:00 p.m., thereby covering both morning and afternoon peak hours. The measurement location and its surroundings are illustrated in Figure 1.

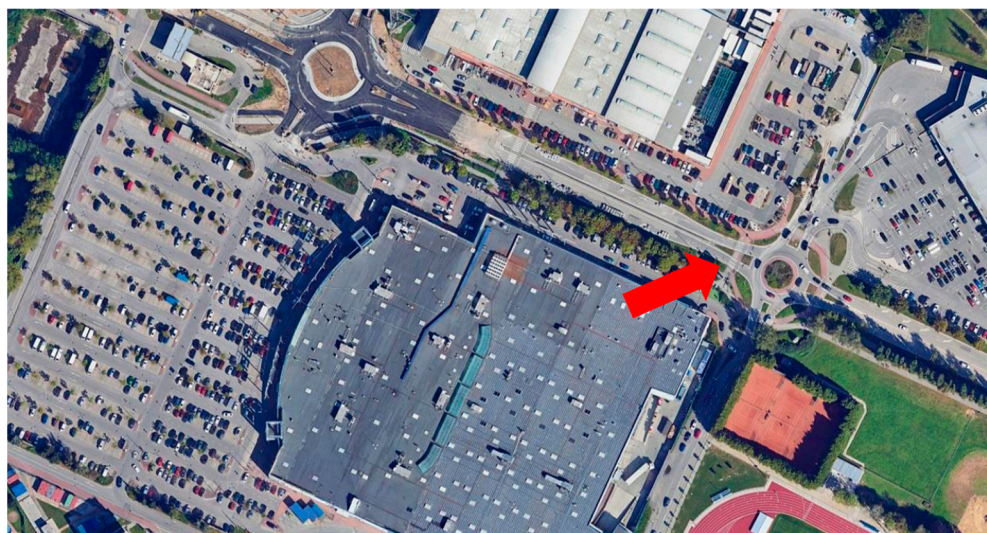


Figure 1. Orthophoto map. Source [36] processed by authors.

The red arrow in the figure indicates the exact location where the Sierzega device, the SDR device, and the camera were placed during the traffic survey. The site is located between a turbo roundabout on the left and a small roundabout on the right. While roundabouts pose greater challenges for data collection compared to standard T-junctions or cross intersections, they significantly enhance safety by reducing collision points [37,38]. This location is characterized by frequent congestion, especially during rush hours, with uneven traffic flow patterns influenced by the nearby roundabouts and the proximity of the shopping center. Urban traffic congestion in cities is a factor that directly affects residents' quality of life, and cities should aim to prevent it [29,39]. Recent developments in artificial intelligence have introduced new tools that assist in minimizing congestion risks [39,40]. Additionally, the development of the Internet of Things facilitates real-time decision-making and supports the evolution of cities [41,42]. However, these systems also require the most accurate data possible.

The SDR and Sierzega devices were installed on the same pole, with the SDR positioned above the Sierzega device, following the instructions provided by the device manufacturers. Although this arrangement ensured that both devices covered the same measurement area, there is an assumption that placing the SDR even higher might have resulted in slightly more accurate data. However, this was not possible in the current location. Both devices are designed to measure traffic parameters in two traffic lanes, which corresponds to the monitored road section. The measurement was conducted on a narrowed part of the road between a turbo roundabout and a small roundabout, where only two lanes were present. This setup ensured that both devices operated within their specified capabilities for dual-lane measurements.

Devices and Data Collection Methods Used

To compare the accuracy of traffic measurement, three different data collection methods were used during the survey: the Sierzega radar device, the SDR radar sensor, and a camera system with subsequent manual evaluation of the recordings. All devices were installed at the same location and configured to monitor the same traffic lanes. This setup ensured a high level of comparability of the results and eliminated the risk of differences arising from varying measurement conditions.

Sierzega

The Sierzega device is a portable radar unit designed for the automatic recording of vehicle speed, direction of travel, and vehicle length. It operates on the principle of the

Doppler effect and allows for basic differentiation between vehicle categories based on their length. Such devices are commonly used in practice owing to their relatively high data accuracy at a low operational cost [43]. The device was positioned approximately 1 m above the roadway and angled at 30 degrees to ensure proper calibration. Traffic was measured in two lanes, recording both directions of travel. Specifically, the Sierzega device recorded the following:

- the exact time of passage,
- speed [km/h],
- travel direction,
- vehicle length [m].

After the survey was completed, the data were exported and subsequently processed using MS Excel software.

The Figure 2 below presents the opened Sierzega device, revealing both the measuring unit and the battery.



Figure 2. Sierzega.

SDR (Smart Data Recorder)

The SDR is a modern radar system capable of automated traffic data collection. It functions similarly to the Sierzega device but offers enhanced flexibility in data processing and filtering. The SDR was installed at a height of 1.6 m and positioned at a 45-degree angle on the same pole as the Sierzega device.

Just like the Sierzega device, it recorded the following data:

- the exact time of passage,
- speed [km/h],
- travel direction,
- vehicle length [m].

An advantage of the SDR device is its more detailed recording of vehicle movements, facilitating improved vehicle categorization. The following Figure 3 shows the measuring device opened.



Figure 3. SDR.

Camera System and Manual Evaluation

The third measurement device was a camera system that provided a continuous recording of the traffic situation throughout the entire 12-h period. The camera was statically positioned to have a clear view of the same traffic lanes monitored by the radar devices, as well as the small roundabout. After completing the measurement, the recording was divided into 15-min intervals and manually analyzed. The manual evaluation provided data on:

- the number of vehicles according to their direction of travel,
- vehicle category
- The manual analysis served as a reference method, enabling verification of the accuracy and reliability of automated devices and rush hours [44]. To further ensure reliability, the manual counting was reviewed to minimize potential counting errors.

All three methods were synchronized. The Sierzega and SDR devices were aligned using the time set during their calibration. The video recording timestamp was synchronized retrospectively.

Data Processing and Evaluation

From the obtained data, the following traffic engineering parameters were subsequently calculated:

- Traffic flow (veh/h),
- Traffic density (veh/km),
- Average speed (km/h),
- Rush hour.

3. Results

This chapter presents the results obtained from the SDR device, the Sierzega device, and the manual evaluation of camera recordings. Each method generated an independent dataset, which was then processed and analyzed in terms of traffic flow, speed characteristics, and vehicle categorization.

The results are presented separately for each method, facilitating an objective comparison and enabling the identification of each technology's strengths and weaknesses.

SDR

During the twelve-hour traffic survey, the SDR radar device recorded a total of 11,490 vehicles traveling in both directions along the measured section. The device provided data on passage time, speed, direction of travel, and vehicle category based on vehicle length. In addition to length-based categorization, modern sensors are also capable of classifying vehicles by their shape [45]. Given the measurement point's proximity to the intersection and the shopping center, the results exhibit significant variability in vehicle speeds. A total of 11,490 vehicles were recorded. During the monitoring, two main rush hours were identified:

- the morning rush hour, between 10:45 and 11:45 a.m.,
- the afternoon rush hour, between 3:15 and 4:15 p.m.

These time periods correlate with increased visitor traffic to the adjacent shopping center. Thus, the traffic load in the area is influenced not only by commuting patterns but also by commercial activities.

In addition to the standard morning and afternoon rush hours, a significant increase in traffic volume was observed between approximately 10:00 a.m. and 1:00 p.m. This phenomenon can be classified as a secondary rush hour. During this period, there is an increased occurrence of travelers outside of commuting mobility, mainly related to dining, shopping, deliveries, and leisure activities. Given the location of the measured section near a shopping center and administrative facilities, it is likely that service and delivery vehicles also contribute to part of this traffic volume. This type of rush hour is typical for urban environments and adjacent civic zones. This phenomenon can also be observed in the following Figure 4.

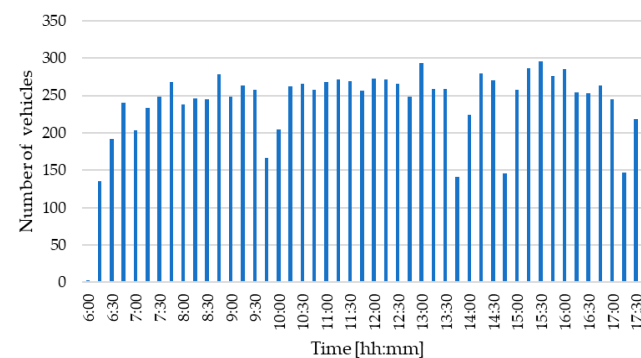


Figure 4. Number of vehicles during the day according to SDR.

The graph displays the actual number of vehicles traveling on the selected section in 15-min intervals.

From the recorded data, vehicles were classified into four groups based on their length. The specific classification groups and the corresponding number of vehicles recorded during the survey are presented in the following Table 1 and Figure 5.

Table 1. SDR summary.

Vehicle Type	Number of Vehicles
Cars	9486
Trucks	1028
Motorcycles/bicycles	914
Heavy goods vehicles	62

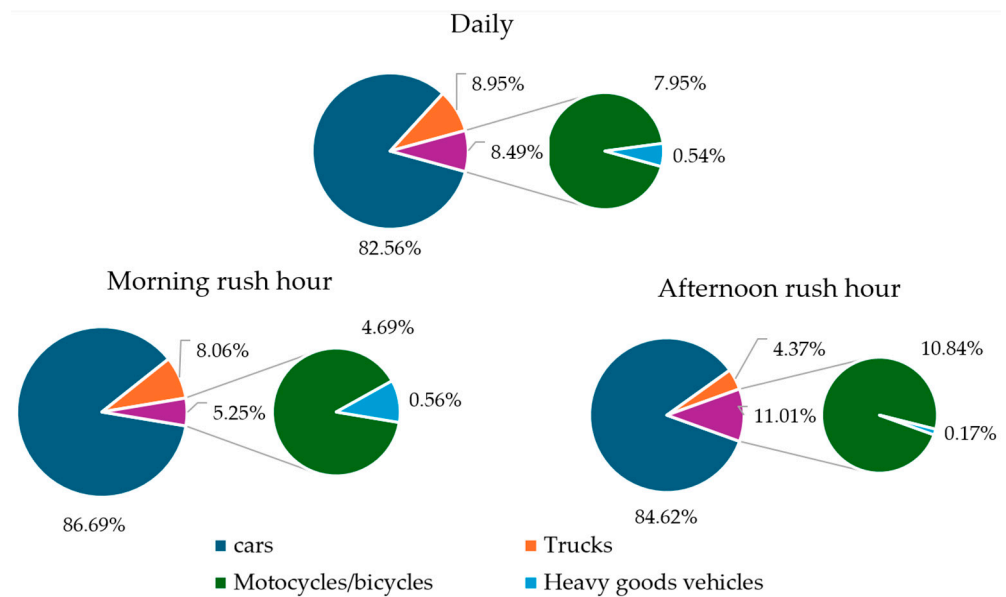


Figure 5. Traffic flow composition according to SDR.

In the previous figure, three graphs can be seen: the upper graph shows the overall composition of vehicle categories throughout the day. Purple color represents a summary of motorcycles/bicycles and heavy good vehicles. The two lower graphs show the composition of traffic flow during the morning rush hour (10:45–11:45 a.m.) and the afternoon rush hour (3:15–4:15 p.m.).

Subsequently, we can proceed with calculating traffic density and flow both during the rush hours and over the entire survey period.

Daily traffic flow

The following formula will be used to calculate traffic flow, along with a sample calculation of the daily traffic flow for both directions of traffic.

$$Traffic\ flow_{day} = \frac{number\ of\ vehicles}{time\ interval} = \frac{11490\ veh}{12\ hours} = 957.5\ veh/hour \quad (1)$$

Traffic flow was calculated for both rush hours using the same method. The specific results are presented in Table 2.

Table 2. Traffic flow and density based on SDR.

Traffic Parameter	Number of Lanes	Flow	Traffic Parameter	Number of Lanes	Density
Daily flow	Both	957.5 [veh/h]	Daily traffic density	Both	29.92 [veh/km]
	Lane 1	588.17 [veh/h]		Lane 1	21.78 [veh/km]
	Lane 2	369.33 [veh/h]		Lane 2	9.23 [veh/km]
Morning rush hour flow	Both	17.78 [veh/min]	Morning rush hour traffic density	Both	34.4 [veh/km]
	Lane 1	10.3 [veh/min]		Lane 1	24.46 [veh/km]
	Lane 2	7.48 [veh/min]		Lane 2	11.53 [veh/km]
Afternoon rush hour flow	Both	19.07 [veh/min]	Afternoon rush hour traffic density	Both	37.43 [veh/km]
	Lane 1	12.12 [veh/min]		Lane 1	29.10 [veh/km]
	Lane 2	6.95 [veh/min]		Lane 2	10.35 [veh/km]

Daily traffic density

Similar to traffic flow, density will be calculated using the following formula along with a sample calculation of the daily traffic density for both directions.

$$\text{Traffic density}_{\text{day}} = \frac{\text{Traffic flow}}{\text{average speed}} = \frac{957.5 \text{ veh/hour}}{32 \text{ km/hour}} = 29.92 \text{ veh/km} \quad (2)$$

It should be noted that the relationship used to calculate density as the ratio of flow to average speed is a fundamental concept in traffic engineering. However, this relationship is strictly valid only under uninterrupted and stationary traffic conditions. In urban environments characterized by frequent stopping, queuing, and other disturbances, the application of this formula provides only approximate estimates.

The following Table 2 presents the traffic density and traffic flow results for both directions, covering the entire day and the rush hours.

The table presents an overview of traffic flow and density based on data from the SDR device, comparing the results for both traffic lanes, namely Lane 1 (approaching the small roundabout) and Lane 2 (exiting the roundabout). The results show that both traffic flow and density were consistently higher in the direction toward the small roundabout, which can be attributed to the lower average vehicle speed when approaching the intersection. Over the entire day, the highest density was recorded during the afternoon rush hour (37.43 vehicles/km), followed by the morning rush hour (34.4 vehicles/km), reflecting the increased traffic load characteristic during these periods.

Sierzega

The Sierzega device recorded a total of 12,465 vehicles during the twelve-hour traffic survey. Although the data volume is comparable to other methods, inconsistencies appeared in the dataset, particularly in the vehicle length measurements, which in some cases reached unrealistic values. This finding highlights potential accuracy limitations of the device that must be considered in the final method comparison. The following Figure 6 illustrates the vehicle counts recorded throughout the day.

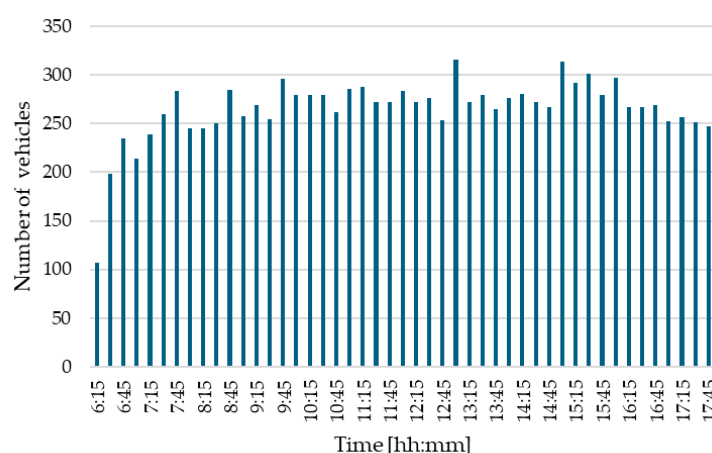


Figure 6. Number of vehicles during the day according to Sierzega.

In numerical terms, the rush hours can be defined as:

- the morning rush hour: 9:45–10:45 a.m.,
- the afternoon rush hour: 3:00–4:00 p.m.

The graph shows that the device recorded a relatively uniform distribution of traffic flow throughout the measured day, without significant fluctuations or the usual rush hours. This phenomenon may be attributed to a higher proportion of slow-moving vehicles, which

this type of radar can detect more frequently. It is also possible that the device records vehicles traveling in close succession as multiple entries, which could artificially smooth out the traffic flow distribution.

Based on the collected data, the following Table 3 and graphs depicting the traffic flow composition were generated, as shown in Figure 7.

Table 3. Sierzega summary.

Vehicle Type	Number of Vehicles
Cars	8174
Trucks	2521
Motorcycles/bicycles	410
Heavy goods vehicles	1360

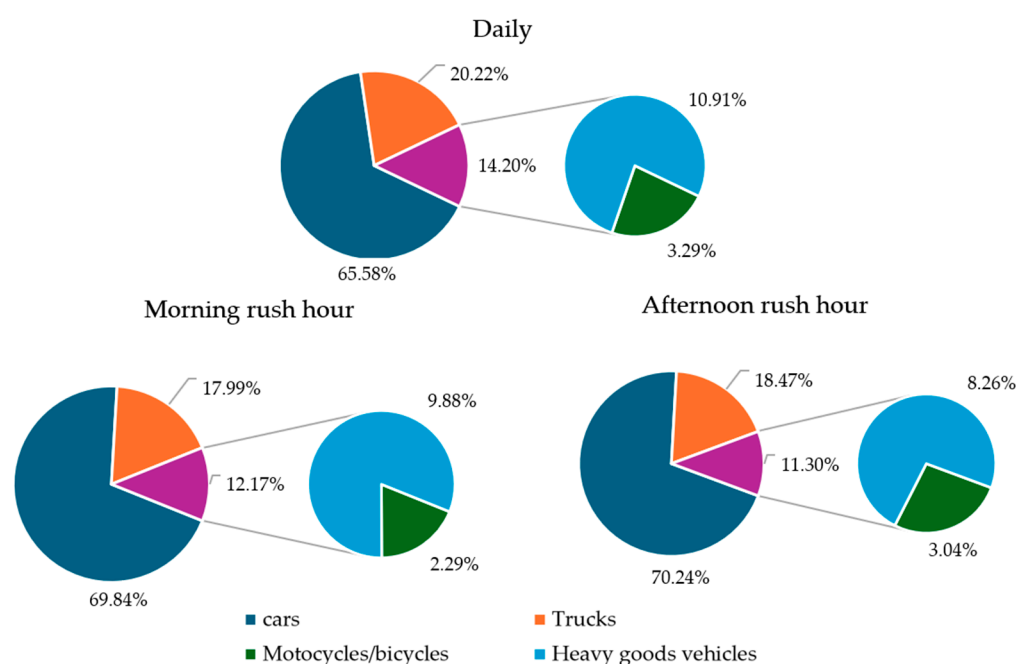


Figure 7. Traffic flow composition according to Sierzega.

In comparison, it is immediately apparent that the Sierzega device recorded an unusually high number of heavy goods vehicles. This is due to Sierzega's inability to accurately determine vehicle length when vehicles were stationary at the intersection approach.

The graphs show the composition of traffic flow recorded by the Sierzega device over the entire day, as well as during the morning and afternoon rush hours. Purple color represents a summary of motorcycles/bicycles and heavy good vehicles. Passenger cars accounted for the largest share (65.58%), followed by trucks (20.22%), motorcycles and bicycles (10.91%), and heavy goods vehicles (3.29%). However, the device recorded an increased occurrence of trucks compared to other methods, which may result from inaccuracies in measuring vehicle length and subsequent miscategorization. These discrepancies must be considered when interpreting data from the Sierzega device.

The traffic flow and density will also be calculated in this case using Formulas (1) and (2). The results will be grouped in the following Table 4.

The table summarizes the traffic flow and density calculated from the Sierzega device data. The overall average daily traffic flow reached 1038.75 vehicles per hour, corresponding to a density of 49.87 vehicles per kilometer. The lane distribution shows that the direction toward the small roundabout is consistently more loaded than the exit lane at every

observed time. During the morning and afternoon rush hours, the highest density value of 59.9 vehicles per kilometer was recorded, indicating increased traffic pressure during these periods. These results support the conclusion of uneven lane loading and underscore the need to consider methodological differences between the technologies when interpreting the data.

Table 4. Traffic flow and density according to Sierzega.

Traffic Parameter	Number of Lanes	Flow	Traffic Parameter	Number of Lanes	Density
Daily flow	Both	1038.75 [veh/h]	Daily traffic density	Both	49.87 [veh/km]
	Lane 1	606.75 [veh/h]		Lane 1	34.72 [veh/km]
	Lane 2	432 [veh/h]		Lane 2	16.92 [veh/km]
Morning rush hour flow	Both	18.9 [veh/min]	Morning rush hour traffic density	Both	59 [veh/km]
	Lane 1	11.23 [veh/min]		Lane 1	43.81 [veh/km]
	Lane 2	7.67 [veh/min]		Lane 2	18.52 [veh/km]
Afternoon rush hour flow	Both	19.77 [veh/min]	Afternoon rush hour traffic density	Both	59.9 [veh/km]
	Lane 1	12.23 [veh/min]		Lane 1	45.48 [veh/km]
	Lane 2	7.53 [veh/min]		Lane 2	17.54 [veh/km]

Manual counting

As a reference for comparing the accuracy of the measurement devices, data obtained by manual evaluation of the camera recordings were utilized. During the 12-h measurement period, all vehicles passing the observed section were counted manually and classified by vehicle type and direction of travel. These values represent the most accurate record of the actual traffic flow and serve as the basis for assessing the deviations in the measurements of the SDR and Sierzega devices. Based on the manual count, vehicle numbers were recorded during the morning and afternoon rush hours. The vehicle counts by category are listed in Table 5.

Table 5. Rush hours, manual counting.

Rush Hour	Cars	Trucks	M/B	HGV	Total
Morning (10:30–11:30)	1227	25	6	10	1268
Afternoon (15:15–16:15)	1346	8	18	3	1375

For a more detailed evaluation of traffic flow, vehicles during the morning and afternoon rush hours were also categorized by direction of travel. This processing allows for better identification of differences in traffic composition between the two directions. The vehicle counts by category and direction are presented in Table 6.

Table 6. Traffic flow composition based on lane, manual counting.

Rush Hour	Lane	Cars	Trucks	M/B	HGV
Morning rush hour (10:30–11:30)	1	631	11	2	2
	2	596	14	4	8
Afternoon (15:15–16:15)	1	717	3	11	1
	2	629	5	7	2

The percentage composition of traffic flow during the morning and afternoon rush hours is illustrated in the following Figure 8. The graphs show the share of each vehicle

category (passenger cars, trucks, motorcycles and bicycles, and heavy goods vehicles) in the total count for both the morning and the afternoon rush hours.

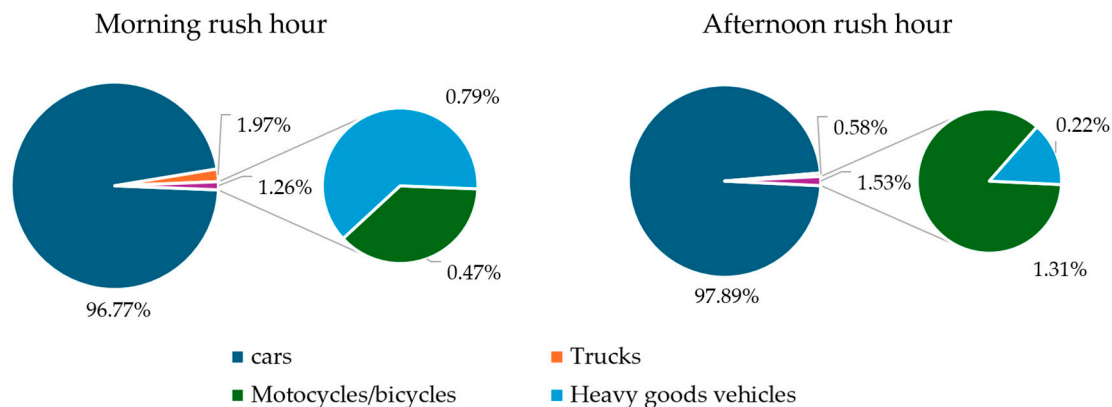


Figure 8. Traffic flow composition according to manual counting.

From the graphs, it is evident that passenger cars constitute most of the traffic flow in both observed periods. The share of motorcycles and bicycles, as well as heavy goods vehicles depicted in purple, was minimal in both cases. A more pronounced share of motorcycles and bicycles was observed during the afternoon rush hour, whereas a higher proportion of heavy goods vehicles occurred during the morning rush hour.

Based on the results of the manual vehicle count and the average speeds measured by the SDR and Sierzega devices, traffic flow and traffic density during the morning and afternoon rush hours were calculated. The results are presented in the following Table 7.

Table 7. Traffic flow and density according to manual counting.

Traffic Parameter	Number of Lanes	Flow	Traffic Parameter	Number of Lanes	Density
Morning rush hour flow	Both	20.45 [veh/min]	Morning rush hour traffic density	Both	46.67 [veh/km]
	Lane 1	10.52 [veh/min]		Lane 1	30.6 [veh/km]
	Lane 2	9.93 [veh/min]		Lane 2	18.64 [veh/km]
Afternoon rush hour flow	Both	22.43 [veh/min]	Afternoon rush hour traffic density	Both	49.85 [veh/km]
	Lane 1	11.95 [veh/min]		Lane 1	34.14 [veh/km]
	Lane 2	10.48 [veh/min]		Lane 2	19.06 [veh/km]

From the results, it is apparent that the afternoon rush hour demonstrated higher traffic flow and density compared to the morning rush hour. The highest traffic density was recorded in Lane 1 during the afternoon rush hour, indicating an increased traffic load at that time.

Comparison

For an objective comparison of the accuracy in measuring traffic composition, percentage differences between the values recorded by the SDR and Sierzega devices and the reference values obtained through manual counting were calculated. The resulting deviations are presented in the following Table 8 and facilitate a detailed evaluation of the reliability of each measurement system under conditions of a congested road section where vehicles frequently stop. Frequent stopping at this section is also caused by the presence of a pedestrian crossing, which, in addition to increasing emissions, directly impacts the safety of the most vulnerable road users [46].

Table 8. Differences between measuring devices and manual counting.

Rush Hour	Source	Cars [%]	Trucks [%]	M/B [%]	HGV [%]
Morning	SDR	−10.42%	+534.92%	+137.56%	−29.11%
Morning	Sierzega	−27.77%	+1327.78%	+517.77%	+189.87%
Afternoon	SDR	−13.53%	+653.45%	+608.50%	−22.73%
Afternoon	Sierzega	−28.22%	+3084.48%	+638.56%	+1272.73%

The results reveal significant deviations in vehicle categorization, with the greatest discrepancies observed in the Sierzega device data, particularly for trucks and heavy goods vehicles. The main cause of this inaccuracy appears to be that vehicles often slow down or stop completely during rush hours. Due to the extended detection time, the device may overestimate vehicle length and misclassify passenger cars as trucks. Given the high proportion of passenger cars in the traffic flow, even small absolute errors can lead to large percentage deviations in the truck categories.

Other factors affecting measurement accuracy include potential calibration errors of the devices, which can lead to incorrect determination of boundaries between vehicle classes. Vehicle proximity in a queue also plays a significant role, as the system may interpret multiple passenger cars as a single long vehicle. In addition, the different detection methodologies of the SDR and Sierzega devices must be considered, since they can influence data evaluation. Overall, the SDR device demonstrated higher accuracy in vehicle categorization compared to the Sierzega device, which showed significant distortion in traffic composition assessment.

It is important to highlight that the analysis was based on a twelve-hour traffic monitoring period and involved detailed manual processing of video footage in 15-min intervals. Each vehicle was individually classified and counted according to direction and category, providing a high-resolution reference dataset. This comprehensive approach enabled the calculation of traffic flow, traffic density, peak hour identification, and category-based deviations between the measurement methods. Given the amount of data processed and the level of manual effort required, the scope of the study extends beyond a standard traffic survey and offers valuable insights into the operational performance of traffic measurement devices under real-world urban conditions.

To evaluate the accuracy of the data measured by the SDR device, percentage differences were calculated relative to the reference values obtained from the manual traffic counts. The comparison was performed for traffic flow and traffic density separately for both rush hours and for each traffic lane. The results are presented in the following Table 9.

Table 9. Traffic flow and density difference, SDR.

Rush Hour	Number of Lanes	Flow Difference [%]	Density Difference [%]
Morning rush hour	Both	−13.05%	−26.26%
	Lane 1	−2.09%	−20.03%
	Lane 2	−24.68%	−38.09%
Afternoon rush hour	Both	−15.38%	−24.92%
	Lane 1	+1.42%	−14.78%
	Lane 2	−33.67%	−45.71%

The results indicate that the SDR device generally slightly underestimated both traffic flow and density compared to the reference manual counts. The smallest discrepancy was observed in Lane 1, where traffic flow differed by only about 2%, whereas in Lane 2 the underestimation exceeded 30%. These deviations can be partly explained by vehicles

stopping and slowing during rush hours, which affects the device's ability to register each vehicle correctly, as well as by reduced accuracy in distinguishing closely spaced vehicles. The radar detection methodology employed by the SDR device may also be particularly sensitive to these conditions. Overall, the SDR provided relatively accurate traffic flow measurements, but its density estimates showed larger errors, especially in the less congested traffic lane.

To assess the accuracy of the data measured by the Sierzega device, percentage differences relative to the reference values from the manual traffic count were calculated similarly to the method applied for the SDR device. The comparison was performed separately for traffic flow and traffic density during the morning and afternoon rush hours, as well as for each traffic lane. The results of this comparison are presented in the following Table 10.

Table 10. Traffic flow and density difference, Sierzega.

Rush Hour	Number of Lanes	Flow Diff [%]	Density Diff [%]
Morning rush hour	Both	−7.59%	+26.41%
	Lane 1	+6.74%	+43.23%
	Lane 2	−22.76%	−0.64%
Afternoon rush hour	Both	−11.85%	+20.16%
	Lane 1	+2.34%	+33.27%
	Lane 2	−28.13%	−7.98%

The comparison results reveal that the Sierzega device achieved higher accuracy in measuring traffic flow than the SDR device in some instances, particularly in Lane 1, where deviations from the reference values were minimal or slightly overestimated. In contrast, in Lane 2, the Sierzega device consistently underestimated traffic flow, with deviations of approximately −28%.

Regarding traffic density, the Sierzega device generally overestimated the results, with the largest overestimation recorded in Lane 1 during the morning rush hour, where density was over 43% higher compared to the reference data. These deviations can be explained primarily by inaccurate device calibration, difficulties in distinguishing vehicles in queues, and differences in detection methodology.

For the comparison of measurement accuracy in traffic flow and density, data obtained from manual counts, the SDR device, and the Sierzega device were analyzed. Reference traffic density values were calculated by determining the average vehicle speed, which was derived as the arithmetic mean of speeds measured by both devices, thus providing a balanced value representative of actual road conditions. The results indicated that the SDR device tended to slightly underestimate both traffic flow and density, with the largest deviations observed in the less congested lane. The Sierzega device sometimes overestimated traffic flow in Lane 1 but overall exhibited larger and less consistent deviations across both parameters.

The primary causes of inaccuracies were vehicles slowing down and stopping during rush hours, which affected the correct measurement of vehicle length and their classification. Problems also arose when vehicles were detected in a queue, where multiple vehicles could be merged into a single object.

Overall, it can be concluded that the SDR device demonstrated better accuracy in measuring traffic parameters compared to the Sierzega device. Despite the observed deviations, the results from the SDR device can be considered suitable for practical purposes, such as preliminary traffic analyses or monitoring long-term traffic trends. However, the results from the Sierzega device would require additional verification and corrections if used for precise traffic analyses.

Despite the observed deviations in measuring traffic flow and density, data from the SDR device can be considered adequate within the Smart City framework, especially for purposes that do not require precise values for individual traffic parameters. In a Smart City environment, it is often more important to monitor trends, identify changes over time, track the load on specific roads, implement adaptive traffic management, or optimize traffic flows based on available data. When designing control strategies, planning infrastructure, or evaluating traffic measures, the SDR device could reliably serve as a primary data collection tool.

Nevertheless, it should be noted that for critical applications requiring high accuracy, such as dynamic lane assignments, direct speed control, or intelligent signaling, it would be prudent to supplement or verify SDR data with other technologies. In typical Smart City applications, where data are processed over longer time periods and the primary goal is trend optimization and congestion reduction, SDR data are sufficient and represent an effective balance between cost and accuracy.

4. Discussion

This study differs from other works by focusing on the accuracy of traffic measurement under highly congested urban conditions. The innovative aspect of our approach lies in evaluating how radar-based devices behave when vehicles frequently slow down, stop, or travel in close proximity to one another. These situations present significant challenges for automated measurement systems and are critical for Smart City applications, yet they are rarely addressed in detail in existing literature. Moreover, the tested devices are not primarily intended for such congested urban scenarios, making this analysis relevant for assessing their practical applicability and limitations under non-ideal conditions.

Although a unified analytical model was not the objective of this study, the presented findings can serve as a practical foundation for the future development of correction models or adaptive filtering methods for radar-based traffic sensors, especially in complex urban environments.

The results of this study highlight that the accuracy of measuring traffic parameters is significantly influenced by the technology used and the nature of traffic flow. The SDR device demonstrated relatively stable and usable results for measuring traffic flow, with deviations from manual counting generally lower than those of the Sierzega device. However, the SDR consistently underestimated traffic density, particularly in the less congested lane, due to radar detection limitations when vehicles are moving slowly or queuing.

The Sierzega device exhibited greater inaccuracies in vehicle categorization as well as in measuring traffic flow and density. The results revealed an overestimation of density, particularly in the direction toward the intersection, indicating problems with interpreting slow-moving or stationary vehicles. This issue is especially critical under high-density traffic conditions, where the device may misclassify multiple vehicles as a single long vehicle or incorrectly assign passenger cars to truck categories.

The misclassifications occurred mainly in slow-moving or queuing traffic and typically involved larger vehicles, such as trucks or buses, which the devices had difficulty distinguishing accurately in congested conditions.

In this study, vehicle parking was not an influencing factor since parking is not permitted on this road section. The entire monitored segment is dedicated to through traffic, and no parked vehicles were present during the measurement period. The presence of parked vehicles could have introduced measurement challenges by creating additional reflections or being incorrectly interpreted by the radar devices as a third lane, which exceeds the measurement capacity of the SDR and Sierzega devices that are designed to monitor two traffic lanes.

Among the main factors affecting measurement accuracy are vehicles slowing down or stopping, which prolongs their passage through the measurement zone and leads to incorrect vehicle length estimates. Vehicle proximity in a queue also plays a key role, as systems may merge multiple vehicles into a single record. Moreover, the different detection methodologies used by each device influence the quality and accuracy of the collected data.

For calculating traffic density in the reference data, the average speed was used, calculated as the arithmetic mean of the speeds measured by the SDR and Sierzega devices. This approach provided a balanced reference value independent of the deviations of individual devices and ensured greater objectivity in comparison. The average speed evaluated in this study corresponds to the time mean speed, which was calculated as the arithmetic mean of the measured speeds obtained from the SDR and Sierzega devices.

Overall, it can be concluded that the SDR device is suitable for monitoring traffic trends and routine analytical purposes in a Smart City environment, where absolute precision of individual measurements is not required. The results indicate that the SDR can reliably serve as a basis for strategic traffic planning, assessment of road loading, and optimization of traffic measures.

In contrast, the Sierzega device requires more thorough calibration, and, in critical applications, its use should be supported by complementary methods or data verification. For dynamic traffic management applications, where very precise and rapid system responses are required, it would be advisable to combine SDR or Sierzega data with additional data sources.

It should also be noted that our study was conducted under generally favorable weather conditions. Although radar-based devices are typically robust against environmental influences such as rain or fog, future research could explore how more extreme weather conditions, including heavy rainfall, snow, or fog, might impact measurement accuracy in real-world scenarios. Future studies could build upon these findings to assess the performance of traffic monitoring devices in a wider range of environmental conditions and develop more comprehensive guidelines for their use in practice.

This study has several limitations, including the specific characteristics of the selected location, such as the presence of roundabouts, the influence of the adjacent shopping center on traffic flow, and the complexity of traffic during the monitored period. These factors may have affected vehicle behavior and, consequently, the measurement results. Another limitation is the duration of the survey: as it covered only a 12-h period, extending the observation to a full 24-h cycle, including nighttime hours when traffic conditions are lighter, would provide a more comprehensive evaluation of device performance.

Another limitation of this study is that it was conducted on a single congested road section located between two roundabouts near a shopping center. Although this location was chosen for its challenging urban traffic conditions, the findings should be considered indicative of similar environments rather than fully generalizable to all urban traffic scenarios. Future studies could expand the scope of data collection to include a larger urban area with multiple road sections to further validate and generalize these conclusions.

Additionally, the application of intersection fundamental diagrams can offer valuable insights for evaluating traffic performance at roundabouts and other intersections [47].

Future studies could involve a wider range of locations and broaden the scope of measurement. It would also be advisable in subsequent research to employ additional measuring devices and, in addition to non-invasive sensors, to utilize invasive detectors or even OCR technologies.

5. Conclusions

This study examined the comparison of accuracy in measuring traffic flow and density using the SDR and Sierzega devices under real-world conditions of high traffic load. Manual vehicle counting via camera recordings was used as the reference method, and the average vehicle speed obtained from the SDR and Sierzega devices was applied in the calculation of traffic density.

To ensure comparability between datasets, the SDR and Sierzega devices were synchronized in advance using calibrated time settings, while video recordings were aligned retrospectively using clearly identifiable reference events. In this study, no extreme values were removed from the datasets. On the contrary, all recorded data were retained intentionally, as a core objective of the research was to evaluate how specific device limitations and measurement inconsistencies affect calculated traffic parameters in real-world urban conditions. This approach allowed for an unbiased comparison of device behavior in complex traffic environments without artificially improving the results through data cleaning.

In the final stage of analysis, percentage deviations between automated device outputs and manual counting were calculated for traffic flow and density. The results showed that the Sierzega device produced deviations of up to 43% in traffic density, while the SDR device showed deviations of up to 33% in traffic flow, depending on the traffic lane and rush hour conditions. These findings support the argument that built-in data filtering or correction mechanisms could significantly improve measurement reliability. Incorporating such functions directly into the device software may help mitigate the impact of misclassification and measurement artifacts in future deployments.

The results showed that the SDR device exhibited smaller deviations compared to the manual counts and provided reliable results for monitoring traffic trends, especially regarding traffic flow. In contrast, the Sierzega device recorded larger and less consistent deviations, particularly in vehicle categorization and traffic density measurements.

The primary factors affecting measurement accuracy were vehicles slowing down and stopping during rush hours, traveling in queues, and the differing detection methodologies of the devices used. These factors primarily led to incorrect estimations of vehicle length and subsequent misclassification.

From a practical standpoint, data from the SDR device can be considered sufficiently accurate for Smart City applications, preliminary traffic analyses, and long-term monitoring of traffic trends. The Sierzega device, on the other hand, would require supplementary data verification and appropriate calibration procedures when used for precise analyses.

It should be emphasized that the findings of this study reflect the performance of the specific devices tested and are not intended to represent all radar-based traffic measurement systems. The conclusions are therefore applicable to the technologies evaluated under the specific conditions described. As the devices were originally intended for smoother traffic environments, their deployment in high-density urban areas requires a thorough understanding of their capabilities and limitations, which this study helps to provide.

For future research, it would be advisable to extend the analysis to include various types of locations and roadways that better represent different traffic conditions. In addition to expanding the measurement scope, subsequent studies could incorporate a wider range of sensing devices, including invasive detectors such as loop detectors or piezoelectric sensors. It would also be beneficial to test advanced technologies, such as OCR systems for license-plate recognition, which could significantly improve vehicle categorization accuracy and real-time traffic monitoring. This approach would allow for a more comprehensive assessment of the reliability of various measurement methods within the Smart City framework.

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