Intelligent bicycle path sensors

Research on intelligent bicycle path sensors that are applied at the Plastic Road at the TU Delft

Bachelor's Final Project

Katrien de Jong

TU Delft

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by

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Preface

I hereby present my final report of my Bachelor Thesis on intelligent bicycle path sensors. This report is submitted in partial fulfillment of the requirements for a Bachelor's degree in Civil Engineering at the TU Delft. The report is written for the section Transport and planning.

As most of the Dutch people, I use my bike every day. When I cycle to the faculty of Civil Engineering, I pass a bicycle path that is claimed to be the most intelligent bicycle path of the world. This road has always caught my attention, partly because it is sometimes difficult not to accidentally get caught in the side slots with your tire, and partly because I wondered what made this road so incredibly smart and what was the purpose of such a smart road.
After doing some research on the Plastic Road and the applied sensors, I was wondering: Is the most intelligent bicycle path as intelligent as is claimed?

I would like to thank Alexandra Gavriilidou and Yufei Yuan for their time and effort in my research. I would also like to thank Winnie Daamen for collecting and sending me the data. Finally, I would like to give my thanks to my group members of Group 2 who not only reviewed my work, but were also there to help me when needed.

Katrien de Jong
Delft, November 2022

Summary

The Plastic Road at the TU Delft is claimed to be the most intelligent road of the world. This road knows what traffic is passing, what the weather circumstances are and much more. But, is the Plastic Road as smart as the company claims? This paper will examine the reliability of the StreetSense sensor, compared to the mm wave sensor, on the field of vehicle counting. Thereafter, an analysis is done on the relationship of weather conditions and vehicle intensity.

In this report, three sensor technologies at the Plastic Road at the TU Delft are investigated. Two of these are vehicle counting sensors, which are compared to each other to conclude which one is more reliable. The third sensor is a weather station, whose datasets have been compared with the datasets of the most reliable vehicle counter to see if an effect can be detected in the sensor data on cycling volume.

To conduct the research, a literature study as well as data-driven analyses were done. The literature study gave information about the sensors that are applied at the Plastic Road and what they can measure. The technology of the sensors that are used for the analyses is explained in more detail.

The results from the literature study show that all sensors generate different variables. On top of that, the study shows that the two vehicle counting sensors, that are used for the analyses, make use of different technologies.

The first data-driven analysis has shown that the vehicle counting data from the underground StreetSense sensors deviates strongly from the data from the above-ground Mmwave sensors. Both sensors work at least partially, since there is a clear difference in week- and weekend days.

The second analysis has shown that there could be a possible relationship between rain and vehicle intensity, but the effect is difficult to determine because many more factors can play a role in the number of cyclists on a day. Also, there was very little rain in April to do enough research. However, there are clear differences in cycling volume between rainy days and non-rainy days, so there is a chance that there is a relationship. It has also been found that the moment it starts to rain, the vehicle intensity temporarily decreases.

The conclusions from this research are:

- 1. The Mmwave sensor is probably more reliable for vehicle counting than the Streetsense sensor.
- 2. The relationship between weather conditions and cycling volumes can be partly deduced from the Davis weather station and the mm wave sensor.

It is recommended to expand this research further and include more datasets, to get a better representative of the functioning of the sensor types applied at the Plastic Road. It would be a good approach to compare datasets from the sensors with ground truth data, which unfortunately was not possible for this research due to broken sensors.

Contents

1 Introduction

The Netherlands is a cycling country. Industry associations BOVAG and RAI estimate that there are about 23.4 million bicycles – out of a population of 17.5 million [1]. According to the KiM, 13 billion kilometers are traveled by bicycle in 2020. The KiM expects that in 2026 bicycle use (distance travelled), as a result of the rise of the e-bike, will increase by 9% compared to 2019 [2]. To accommodate all these cyclists, governments invest in extending and improving cycle networks. The increase in bicycle use is a positive development, because cycling is healthy, convenient and environmentally friendly. However, to keep up with this increase without compromising on safety, bicycle flows need to be properly monitored and managed. This is generally performed by traffic control installations which obtain information from sensors. Bicycle path sensors perceive movement, evasive manoeuvres, stress factors, vehicle types, precipitation etc. These sensors can communicate with other platforms, such as traffic lights, public lighting, dynamic signage and so on. The main goal of smart sensor technology is to reduce traffic congestion and improve safety of road users. By collecting information about the intensity on a bicycle path in a database, the condition of the infrastructure can be monitored.

1.1. Research motivation

A place where various sensor technologies are brought together, is the Plastic Road. This road is claimed to be the most intelligent bicycle path of the world and is located at the TU Delft. Because of the sensors, this road knows what kind of traffic is passing by, and can even communicate with other platforms, such as traffic lights, public lighting, dynamic signage and so on [3]. These types of smart roads make it possible to design and manage cities smarter and more efficiently. But, are the sensors as reliable as is claimed? And do the sensors contribute to traffic knowledge? The answers to those questions are unclear, because the road is relatively new. In this report, research is conducted to partly answer these questions.

The Plastic Road is 25 metres long and contains multiple sensors. The cycle path is equipped with stereo vision cameras, radar, mm wave sensors, a weather station and internal sensors to measure precipitation, speed, movements and wind. This provides a source of information about traffic flows and the behavior of road users [3]. To examine the sensors for its reliability, the datasets of the underground sensors are compared to datasets of the above ground sensors. In this report the reliability will be tested on vehicle counting.
Besides, the sensor's contribution to traffic knowledge is of interest. Because weather is expected to have an effect on cycling volume, [4], an analysis is done on the effect of weather conditions on cycling volume data of the sensors. This analysis will be conducted with datasets of the most reliable vehicle counting sensor, according to the reliability analysis, and datasets of the above ground weather station.

1.2. Research question

In this report a data-driven research is performed on several sensors at the Plastic Road. The process of answering the following research question is reflected in this paper.

Do the sensors in the Plastic Road contribute to reliable traffic knowledge?

To answer this question, the research question will be divided into the following sub questions.

- *Which sensor technologies are applied at the Plastic Road and what do they measure?* In order to be able to perform analyses, an overview must first be made of all sensors that are installed at the plastic road with the variables that these can provide. This makes it possible to determine from which sensors the data will be used to perform the analyses.

- *What is the reliability on vehicle counting of the underground sensors, in comparison to the above ground sensors?* A reliability analysis will be done on the ability of cycling volume tracking of the StreetSense sensor and the mm wave sensor. The mmwave sensor has been in use for some time and it may therefore be interesting to compare the newer sensor with the older sensor.

- *What is the effect of rain on the vehicle counting data of the sensors in the Plastic Road?* If the sensors deliver reliable data, an interesting purpose could be to do research to relationships between weather conditions and intensity. By doing research to this relationship, smart technology might be developed by this information in the future. For this report it was decided to only use rain conditions because the temperature in April did not differ much and it is not expected that the wind will make a significant difference to the traffic intensity.

1.3. Report structure

Before conducting the analyses, research on background information about the sensors needs to be done. This can be found in chapter 2 “Literature Research“. In this chapter the analysed sensor technologies and their data structures are explained. Subsequently, the Methodology for the analyses is explained in chapter 3. This chapter is provided with a detailed approach per analysis. In chapter 4 the analyses are performed and the results are presented. Then, in chapters 5 and 6 the results are discussed and conclusions are drawn. Lastly, recommendations for further research are given in chapter 7.

2 Literature Research

This chapter contains background information on the applied sensor technologies at the Plastic Road. Literature research is done on what information is provided by which sensor.

Because various sensor technologies have been used in the Plastic Road, it is an interesting location for research into sensor technology. The sensors at the Plastic Road can be divided into above ground and underground sensors.

The literature study consists of two parts. First, an overview of all applied sensor types at the Plastic Road and which variables they are able to contribute is given. Thereafter, the used sensors for the further analyses are explained in more detail.

2.1. Sensor types

The Plastic Road is a bicycle path, which is located in front of the faculty of Civil Engineering. The road maps out how much traffic is passing at what speed and at what time by the use of various sensor types. There are three companies that supply underground sensors for the Plastic Road: Strain2data, StreetSense and Wavin.
The Strain2data sensor contains LVDT sensors, strain gauges, load cells and temperature sensors. The StreetSense sensor is a mobility and slipperiness sensor. Wavin supplies a sensor box, the purpose of which is to measure the sludge and water level.
The above ground sensors are mostly from the TU Delft itself. These exist of a camera with stereo vision, a weather station, a radar sensor and mm wave depth sensors.

An overview of which variables can be estimated by the sensors is shown in the table in figure 2.1.

2.2. Used sensors for analyses

For this report, the aim is to do research on the sensors in the Plastic Road. Because not all sensor data was available (in time) or had a link with the transport and planning section, the data of only three sensors is used for the analyses in this report.

The received data exists of the Strain2data, Wavin, StreetSense, mm wave and Davis weather station data. For the analyses, only the underground StreetSense sensor, above ground mm wave sensor and above ground Davis weather station are used. The StreetSense and mm wave sensors are used for a reliability analysis on vehicle counting, because these sensors both generate the number of passing vehicles. The Davis weather station is used for the analysis on the effect of rain on vehicle intensity data of sensors, because this weather station generates data on rain.

As can be seen in figure 2.1, stereo vision sensors, GPS/GNSS sensors and radar sensors, generate data on vehicle counting as well. However, the stereo vision and radar data is not received in time for

Sensors / Variables	Strain2data sensor	StreetSense sensor	Wavin sensor box	Camera with stereovision	Mm wave sensor	GPS / GNSS sensor	Davis weather station	Radar sensor
Vehicle intensity		✓		✓	✓	✓		✓
Speed		✓		✓	✓	✓		✓
Route				✓		✓		✓
Direction								✓
Distance					✓			✓
Temperature in/on road		✓						
Fatigue of the road	✓							
Water /sludge level			✓					
Weather conditions							✓	

Figure 2.1: An overview of which sensor can estimate what variables after processing its data [5, 6, 7, 8, 9, 10].

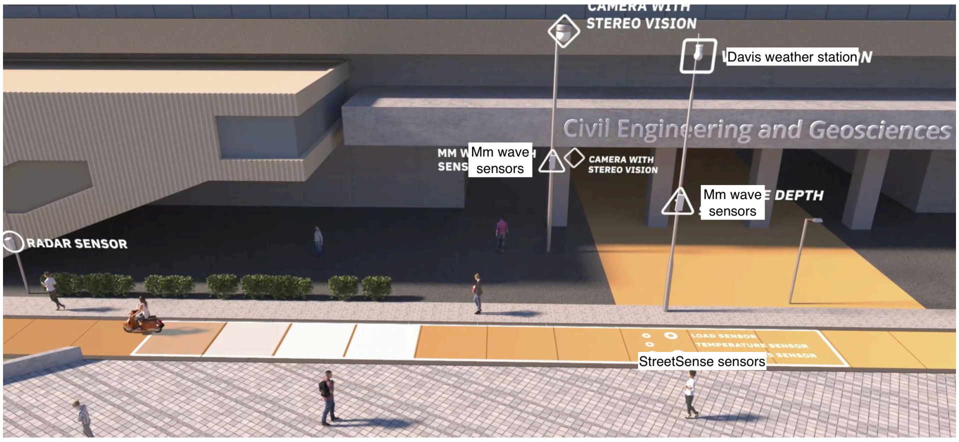

Figure 2.2: Plastic Road and the location of the sensors [14]

the analyses and the GPS/GNSS sensors are not in use yet. On top of that, the mm wave sensor is considered a highly reliable sensor for vehicle counting [11, 12, 13], so is suitable for comparison to the StreetSense sensor data.
The Wavin and Strain2data data sets are not used for the analyses because they both do not contain useful information for this paper. The aim of the Wavin sensor is to measure the water / sludge level and the aim of the Strain2data sensor is to detect fatigue of the road.

The StreetSense sensors provide various information about the road user, among which the cycling volume. The Mmwave sensors provide information about solely the number of passing vehicles and the Davis weather station collects information on weather conditions. For these sensor types it is explained how they work, what they measure and what can be done with their output.

In figure 2.2 the location of the used sensors is shown. The names of the sensors are stated in the white colorboxes. The StreetSense sensor is located underground [14].
A more detailed description per sensor is given below. The technology that is used to generate data and the measurable variables are explained.

2.2.1. StreetSense sensors

The StreetSense sensor is a pod which is applied in the surface of the road. As can be seen in figure 2.1 the StreetSense sensor measures various variables, such as vehicle intensity, speed and temperature [6]. In this paper, the StreetSense sensor is used for an analysis on the reliability in vehicle counting.

The vehicle intensity is measured by the use of a magnetometer, which is located in the top of the StreetSense sensor. The magnetometer works by making use of the earth magnetic field. When a vehicle passes by, the magnetic field is disturbed. The disturbances are detected and converted into counts [15].

2.2.2. Mm wave sensors

The mm wave sensors are located above the Plastic Road. The mm wave sensor measures vehicle intensity. In this paper, the data of the mm wave sensor is used as comparison material to check the StreetSense sensor on its reliability in vehicle counting. The mm wave sensors collect data by using radio-frequency radar technology. Movements are detected by the sensor as dots, by sending wireless signals to the road and capturing its reflection [14]. Mm wave sensor can precisely detect vehicles, such as cars, bicycles and motorcycles, without invading privacy [13].

2.2.3. Davis weather station

The Davis is a wireless weather station with sensors located at a height of 10 meters from the street surface. The Davis weather station measures various weather related attributes, such as rain, temperature, windspeed, humidity, UV and so on [16].

2.2.4. KNMI weather station

As extra validation, KNMI weather station data is used to compare to the data of the Davis weather station. Due to the fact that there is no knmi weather station located in Delft, the data from the nearest weather station is used, which is Rotterdam. The technology of this weather station will not be explained, as it is irrelevant for this paper.

3 Methodology

The aim of this paper is to investigate the reliability on vehicle counting of the sensors that are applied in the Plastic Road, and to investigate what the effect of rain is on the vehicle counting data.
Reliability can be estimated by comparing different versions of the same measurement. The initial set-up for this research would be a comparison of the StreetSense sensor data with ground-truth data. Due to the fact that the sensor is broken at the moment, this is not possible. Instead of ground truth measurements, the StreetSense sensor data is compared to the mm wave sensor data. The effect of rain on vehicle counting data of the sensors is investigated by making use of a data set with rainrate and a data set of vehicle counting data.

This paper will consist of the following analyses:

- Analysis on the reliability of vehicle counting of the underground StreetSense sensor, compared to the above ground mm wave sensor.
- Analysis on the effect of rain on the vehicle counting data of the sensors.

The research is performed by data-driven analyses in Jupyter Notebook, which consists of visual and statistical approaches. The aim of the visual approach is intuition while the aim of the statistical approach is rigor.
This chapter will discuss the methodology for the analyses.

3.1. Collecting data

After completing the literature search, datasets are collected. These datasets are requested from Mrs. Daamen, who is in contact with the Plastic Road company. Because it is currently not possible to receive the most actual data sets, older data sets are used in this study.
As the data will depend on weather conditions, time of day and crowdedness, the data sets are from different time slots and different weather circumstances.
The received data sets consist of the data from the StreetSense sensors, the mm wave sensors and the Davis weather station. Their purpose and output are explained in the former chapter.

3.2. Reliability analysis on cycling volume data

For this analysis the data sets on vehicle counting are used from the StreetSense sensor and the mm wave sensor. The aim of the analysis is to investigate whether the StreetSense sensor is a reliable sensor for vehicle counting, compared to the mm wave sensor.
The analysis consists of two parts: a visual approach and a statistical approach. The visual approach starts with box plots to clean the data from possible false data. Thereafter, bar plots are made with the mean values per day. The statistical approach is done by comparing the distribution functions.

3.2.1. Visual approach

The visual approach consists of cleaning the data, and plotting the cleaned data in bar plots. The datasets need to be checked for inconsistencies and incompleteness. Incorrect data has to be tracked

down and removed. Furthermore, the time windows of the datasets differ. For comparison, the datasets have to be evenly spaced, so they are re sampled. The data cleaning process is vital for the accuracy of this research. The cleaning process will be done by the use of box plots.
Box plots are a useful tool to detect false data because outliers are clearly marked in such plots. However, not all outliers are false data so outliers are checked on significance and time [17]. If outliers cannot be explained, they are removed.
The cleaned data is plotted in bar plots with the mean value per day to investigate if there is a difference in vehicle counting data for weekdays and weekend days. According to these plots, intuitive findings can be discussed.

3.2.2. Statistical approach

The statistical approach is done by calculating and comparing the empirical cumulative distribution functions (ECDF). An empirical cumulative distribution plots the data points from lowest to highest against their percentiles [18]. The ECDF of the data sets are plotted in one graph to see if they are similar. Thereafter, the Kolmogorov–Smirnov test is done to test whether the probability of the two sets of samples are drawn from the same probability distribution. The test calculates the distance between the empirical distribution functions of two data sets. The KS test returns a D statistic and a p-value corresponding to the D statistic. The D-statistic is the maximum distance between the empirical cumulative distributions of the data sets. A close number to zero means that the samples are similarly distributed. The p-value is the level of significance. If the p-value is lower than the chosen level of significane, the null-hypothesis will be rejected [19].

3.3. Analysis on rain versus cycling volume

The aim of this analysis is to investigate the effect of rain on vehicle counting data. Cycling volume data is obtained from the most reliable sensor, according to the prior analysis, and weather data is retrieved from the data sets of the Davis weather station, which is located above the Plastic Road. The data sets were collected in the first two weeks of April 2022.
The analysis consists of two parts: a visual approach and assessing the changes in a macroscopic traffic model through the observation of the diagram describing relationship between vehicle intensity and rain.

3.3.1. Visual approach

The visual approach consists of cleaning the data, and plotting the data in graphs. The data first needs to be re sampled because the time intervals are unequal. For clear plots, the datasets are both re sampled to time intervals of 10 minutes.
For a reliable analysis, the data sets have to be cleaned. Deviating values can be detected by making use of box plots. If outliers cannot be explained, they are removed. For the rain rate data box plots are not useful because all rain peaks are outliers, as it is dry most of the time. To confirm that the rain peaks are no errors, the peaks are checked with data of the KNMI weather station in Rotterdam. This station is the closest to Delft.
Rainy days will be detected by analysing the Davis rain data. A rainy day is a day with rainfall of 2.5 mm or more than that [20]. Finding rainy days is done by simply adding up the precipitation per day. If the precipitation is higher than the limit for a rainy day, 2.5 mm, this day will be qualified as a rainy day. After detecting the rainy days, the rain rate will be plotted against the cycling volume for these days. In this way, a possible decrease in vehicle intensity can be detected in case of a rain peak.

3.3.2. Macroscopic traffic model

Subsequently, the vehicle intensity for the rainy days will be compared to days without rain. For comparison it is important that the days are basically the same, but have the only difference that it rains on one of the days. So a weekday will be compared to the same weekday in the week before or after. Public holidays must also be taken into account, as the university is then closed.
Because it probably did not rain for a whole day, only the time windows are analysed in which it actually rained. For these time windows the difference in vehicle intensity is calculated for the rainy days versus the dry days.

4

Data analyses

This chapter discusses the performed analyses and the results. The two analyses will be discussed separately.

4.1. Reliability analysis on cycling volume data

The analysis consists of two parts: a visual approach and a statistical approach.

4.1.1. Visual approach

The data first needs to be re sampled because the time intervals are unequal. The StreetSense data is received in vehicles per 10 minutes and the mm wave data is received in vehicles per 5 seconds. The data is re sampled to the bigger time interval.
For a first impression of the sensor data the re sampled data sets are visualised, figures 4.2 and 4.1. As can be seen the data sets do not look similar. The values of the mm wave sensor are significantly higher than the values of the StreetSense sensor.
On top of that, in the data from the mm wave sensor, a day and night pattern can be clearly recognized. However, this is not the case in the data from the StreetSense sensor.

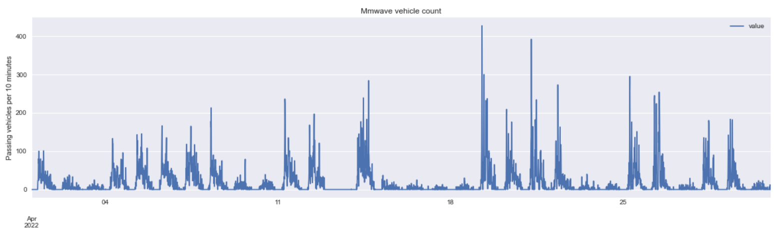

Figure 4.1: Mmwave sensor: The vehicle intensity per 10 minutes for the month April.

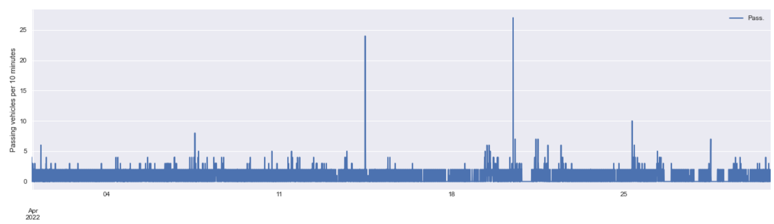

Figure 4.2: StreetSense sensor: The vehicle intensity per 10 minutes for the month April.

The resampled mmwave data and the StreetSense data are also plotted in one graph to see how they differ. The plots are shown in figure 4.3. The green line is the data of the mmwave data points and the blue line is the data of the StreetSense data points. As can be seen in the figure, the data points of the two different sensor differs a lot, as was expected from their plots in figure 4.1 and figure 4.2.

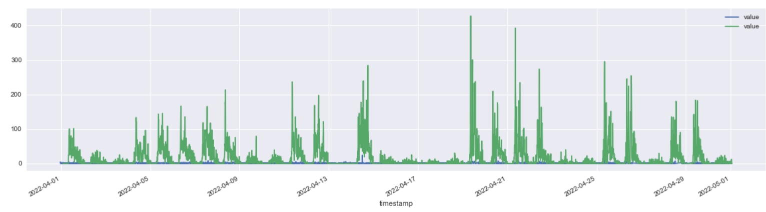

Figure 4.3: Mwave sensor (green) and StreetSense sensor (blue): The vehicle intensity per 10 minutes for the month April.

Cleaning

Deviating values can be detected by making use of box plots. If outliers cannot be explained, they are removed.

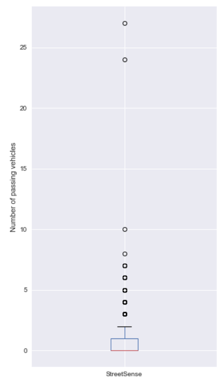

Figure 4.4: Boxplot for the vehicle intensity data of the StreetSense sensor

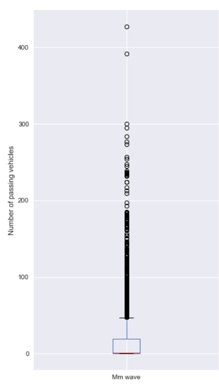

Figure 4.5: Boxplot for the vehicle intensity data of the mmwave sensor

As one can see in figure 4.4 and figure 4.5, both sensors have outliers for the vehicle counting. All outliers are checked on their significance and time of measuring, because not all outliers are false data. For example the most extreme value of the mm wave sensor has a value of 427 vehicles per 10 minutes at the time 15:50, which is practically possible. After checking all outliers for both sensors, the conclusion is to not delete any.

Bar plots
The blue line is barely notable in the graph of figure 4.3, making it appear that the StreetSense sensor does not deliver useful data. To check whether a certain pattern is present in the data points, the mean amount of tracked vehicles are plotted separately in bar plots. The bar plots for the mean amount of passing vehicles are shown in figures 4.6 and 4.7.

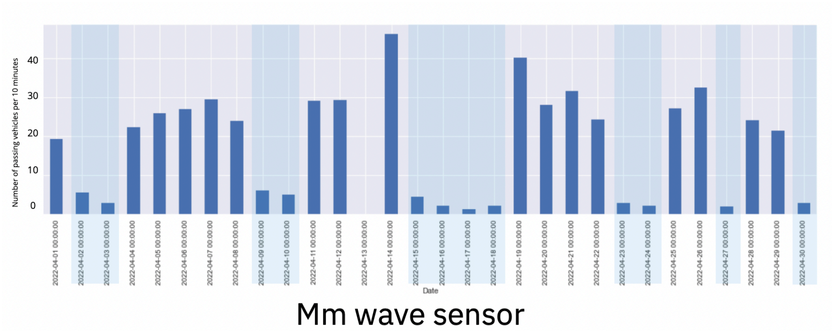

Figure 4.6: Mmwave sensor: The mean amount of passing vehicles per day for the month April

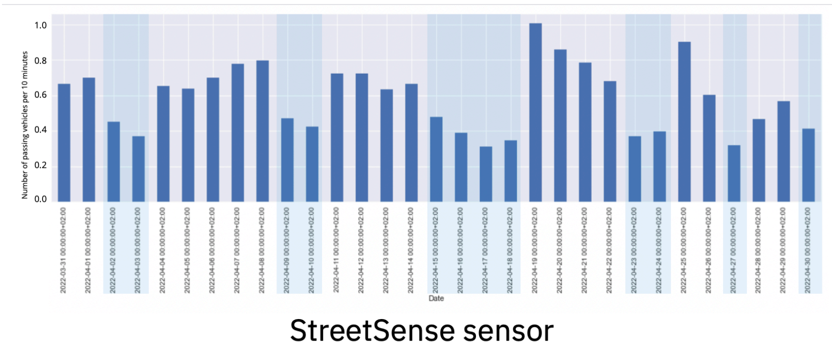

Figure 4.7: StreetSense sensor: The mean amount of passing vehicles per day for the month April

The striking thing about the above figures is that the values for the vehicle intensity of the different sensors are far apart, but that the pattern in the averages per day is somewhat similar, 4.6 and 4.7.
The weekend days and holidays are marked in light blue in the graphs. As with the mm wave data, a difference can now be seen in the weekdays and weekend days in the streetsense data as well. This difference indicates that the StreetSense sensor at least partly works, because most faculties are closed on weekend days. The patterns in the mean values is further investigated by making use of a statistical approach.

4.1.2. Statistical approach

The statistical approach is done by calculating and comparing the empirical cumulative distribution functions. An empirical cumulative distribution plots the data points from lowest to highest against their percentiles. The empirical cumulative distribution plots are shown in figures 4.8 and 4.9.

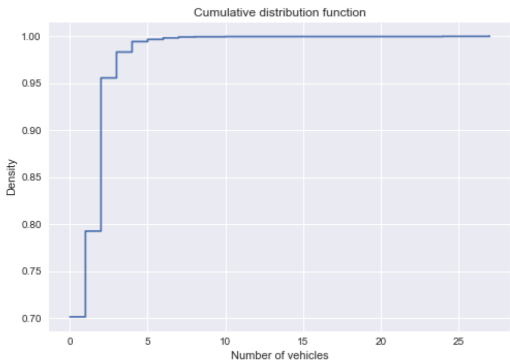

Figure 4.8: StreetSense sensor: empirical cumulative distribution

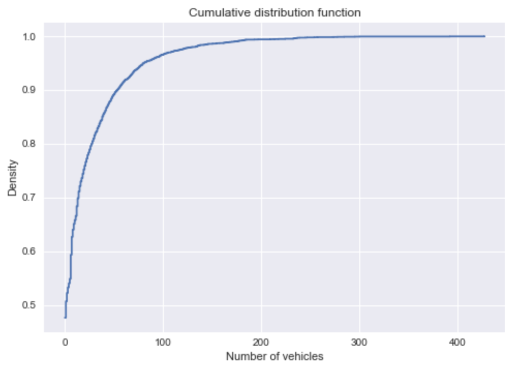

Figure 4.9: Mm wave sensor: empirical cumulative distribution

The values are, as mentioned before, of different sizes. Because the interest is now in only the distribution, the values are equalized by dividing the mm wave sensor values by the streetsense values and multpilying this value by the StreetSense values. The result is the plot in figure 4.10, in which the empirical cumulative distributions are shown for each sensor.

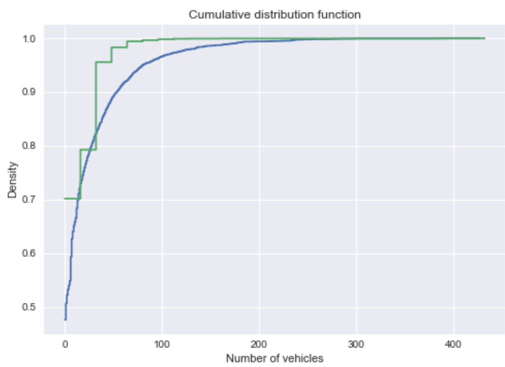

Figure 4.10: Equalized empirical cumulative distribution, StreetSense (green) and mm wave (blue)

Kolmogorov–Smirnov test

The distribution looks similar, but a statistical test has to prove this. This is done with the Kolmogorov–Smirnov (KS) test. The null hypothesis is that the samples are drawn from the same distribution. A confidence level of 95% is used, which means that the null hypothesis is rejected if the p-value is less

than 0.05. The results are a D statistic of 0.22523 and a p-value of 2.0659e-96. Because the p-value is much below 0.05, the null-hypothesis is rejected. This means that the data sets are not drawn from the same distribution.
From the analysis on the reliability of vehicle intensity measuring of the StreetSense sensor and the mmwave sensor, it appears that the mmwave sensor generates the most reliable data. The values for the StreetSense sensor are very low and are therefore not expected to be true. Therefore, in the next analysis, the mm wave data will be used instead of the StreetSense data.

4.2. Analysis on rain versus cycling volume

For this analysis two data sets are used: the rain rate data of the Davis weather station, and the vehicle counting data of the mm wave sensor, since this data is more reliable according to the former analysis. The analysis consists of a visual approach and assessing the changes in a macroscopic traffic model through the observation of the diagram describing relationship between vehicle intensity and rain.

4.2.1. Visual approach

For this analysis, both weather and cycling intensity data were collected in the first two weeks of April 2022.
The data first needs to be re sampled because the time intervals are unequal. For clear plots, the datasets are both re sampled to time intervals of 10 minutes.
For an intuitive impression the re sampled rain data is visualised, in figure 4.11.

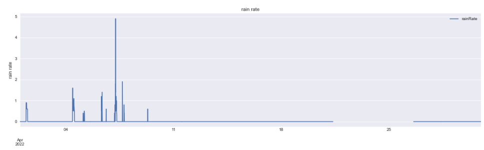

Figure 4.11: Rainrate per day in April

Cleaning

The vehicle intensity data is already cleaned in the former analysis. To confirm that the rain peaks are no errors, the peaks are compared to data of the KNMI weather station in Rotterdam [21]. All rain peaks did occur in Rotterdam as well, so no measurements are removed.

Visualising

The data from the Davis sensor, figure 4.11 shows that in these two weeks, three days can be considered rainy days: April 4, April 6 and April 7. As these days are all weekdays and no public holidays, the vehicle intensity data for these days is compared to similar week days, but under dry weather conditions. Due to a lack of data on rainy days, separation of the data according to the different rain intensities is not possible. For future research, this would be recommended for a more precise analysis.

The vehicle intensity versus rain rate for the rainy days are shown in figures 4.12, 4.13 and 4.14. The vehicle intensity decreases when it starts to rain during the day. As the rain rate decreases, the vehicle intensity increases again. During the night the vehicle intensity is as good as zero, so there is nothing useful to say about the night.

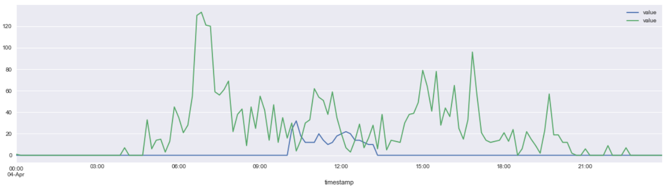

Figure 4.12: April 4. Vehicle intensity (green) versus rainrate (blue). Mean intensity: 22.3472 vehicles/10 minutes

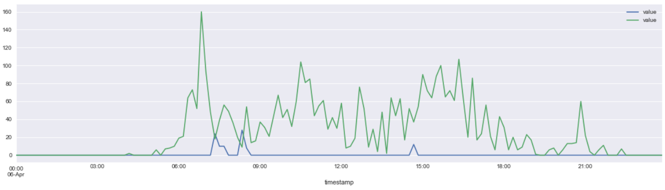

Figure 4.13: April 6. Vehicle intensity (green) versus rainrate (blue). Mean intensity: 26.2014 vehicles/10 minutes

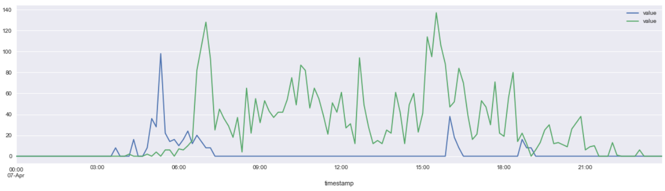

Figure 4.14: April 7. Vehicle intensity (green) versus rainrate (blue). Mean intensity: 27.4167 vehicles/10 minutes

4.2.2. Macroscopic traffic model

However, on the rainy days it did not rain all day long, so only the time windows in which it actually rained are considered for the rest of the analysis. The used time windows are:

Time window	Days with rain	Days without rain
10:00 - 14:00	April 4 (monday)	April 11
7:00 - 8:30	April 6 (Wednesday)	April 13
6:00 - 7:30	April 7 (Thursday)	April 14
16:00 - 16:30	April 7 (Thursday)	April 14
18:30 - 19:00	April 7 (Thursday)	April 14

The exact times with the rain rates are stated in figure A.13 in appendix A.

The vehicle intensity of the selected time windows are compared for the rainy days versus the non-rainy days, which is shown in the figures 4.15, 4.16 and 4.17. The vehicle intensities for the rainy days are shown green and the vehicle intensities for the non-rainy days are shown in blue. The selected time windows are marked in light blue. The decrease per time window is stated on the top of the time windows.

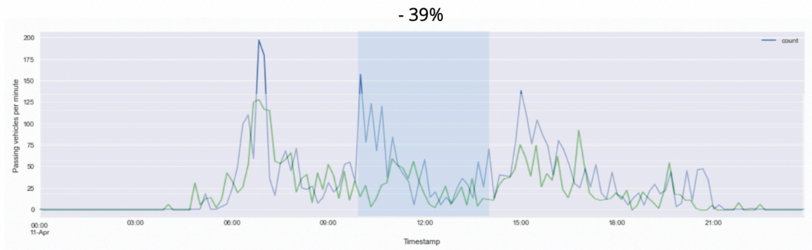

Figure 4.15: Rainrate for April 4 (rain) and April 11 (no rain)

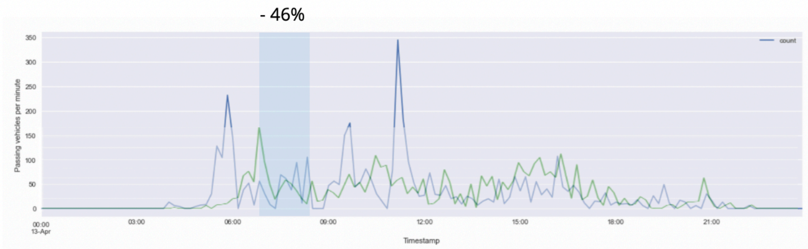

Figure 4.16: Rainrate for April 6 (rain) and April 13 (no rain)

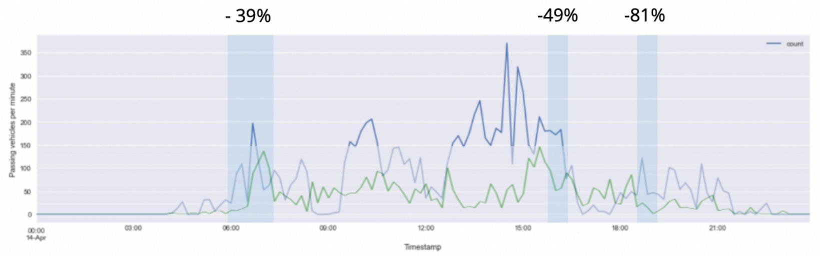

Figure 4.17: Rainrate for April 7 (rain) and April 14 (no rain)

An impact of rain on the counted vehicle intensity can be observed in the graphs above. An average decrease of 50.8% is noticed. On the other hand, this decrease cannot certainly be assigned to only rain. Other factors play a role as well, such as exam periods, number of the week in the education period and coincidence.

5 Conclusions and discussion

The conclusion from the data-driven research and an answer to the research question are discussed in this chapter.

The focus of this research was to answer the research question:

”*Do the sensors in the Plastic Road contribute to reliable traffic knowledge?*”

The main research question is divided into sub questions, which will be answered piece by piece in the bullet points below.

- *Which sensor technologies are applied at the Plastic Road and what do they measure?* The Plastic Road contains underground and above ground sensors. The underground sensors are from three different companies: Strain2data, Wavin and StreetSense. Whereas the above ground sensors are from the TU Delft itself. The purpose of the Strain2data sensors is to measure fatigue of the road, by making use of lvdt sensors, strain gauges, load cells and temperature sensors. The aim of Wavin is to measure the water/sludge level in the road, by making use of a sensor box. The aim of the StreetSense sensors is to measure mobility and slipperiness. Mobility is measured by a magnetometer.
  The above ground sensors exist of a camera with stereo vision, mm wave sensors, GPS / GNSS sensor, a Davis weather station and radar sensors. The purpose of these sensors differs from counting vehicles to measuring precipitation.

- *What is the reliability on vehicle counting of the underground sensors, in comparison to the above ground sensors?* To answer this question, an analysis is done on the reliability of vehicle counting of the underground StreetSense sensor, compared to the above ground mm wave sensor. When studying the results of the analysis, it can be concluded that the mm wave sensor is probably more reliable than the StreetSense sensor in the field of counting passing vehicles. The data values of the mm wave sensor seem plausible and the values of the StreetSense sensor do not, because they are very low. As can be seen in figure 4.2, according to the StreetSense sensor, there are almost as many road users at night as during the day at rush hour. That seems incorrect, because the university is closed at night.
  The generated data of the StreetSense sensor, does however show a plausible pattern when looking at the mean values per day. The mean values are lower on weekend days and on public holidays, which makes sense, as the faculty is closed then. To test whether the distributions of the two data sets are the same, the empirical distribution functions are calculated. The result is that the data sets have differing distributions as well.
  Although the measurements of the StreetSense sensor seem incorrect, it cannot be concluded that the StreetSense sensor is not reliable at all, because the difference in week- and weekend days makes sense. This could be further investigated.
  The reason for the deviating StreetSense data, could be the technology of the magnetometer

that is used for counting bikes. A magnetometer works with disturbances in the earth-magnetic field. The disadvantage of this technology is that individuals are hard to distinguish when they are cycling in a group. A group could be detected as one disturbance. Since the Plastic Road is quite a wide road and cyclists mostly pass the cycle path in groups, this could be the reason for the unreliable data.
Another reason for unreliable data of the StreetSense sensor could be the fact that not all bikes are made of ferrous materials, like carbon-fibre bikes. Non-ferrous bike will not disturb the earth-magnetic field so will not be detected by the magnetometer.

- *What is the effect of rain on the vehicle counting data of the sensors in the Plastic Road?* To answer this question, an analysis on the effect of rain on the vehicle counting data of the sensors is done. Based on the analysis performed, it cannot be stated with certainty that there is a relationship between rainfall and intensity. However, the results show that there could be a relationship. In the analysis, three rainy days in April were compared with three non-rainy days a week later. The analysis shows that there is a decrease of 50.8 % in counted vehicles on rainy days versus non-rainy days. However, not all differences can be attributed with certainty to the presence of rain. There may also be other factors that reduce traffic intensity, such as exams.
  What can be said with certainty is that the vehicle intensity decreases temporarily during most rain peaks and then increases slightly, see figures 4.12 to 4.14. This is particularly evident for April 6. This pattern could mean that cyclists wait to cycle during a rain peak, resulting in extra cyclists in the time window after the rain peak.

The main question of this paper cannot be answered for all sensors, because not all sensor data was available and there was not enough time to investigate all available sensors. Also, only vehicle counting and rain are investigated because the lack of time. However, the main question can be answered for the StreetSense sensor, mm wave sensor and Davis weather station. The StreetSense does not (yet) contribute to reliable traffic knowledge on vehicle counting. The mm wave sensor probably does, but cannot be confirmed due to the lack of ground truth data. The effect of rain can probably be read in the mm wave vehicle counting data, which is useful for further research into the relationship between weather conditions and cycling volume.

6 Recommendations

In this topic, recommendations are discussed for further research. The recommendations are stated separately per analysis.

Analysis on the cycling volume tracking reliability of the underground StreetSense sensor and the aboveground Mmwave sensor.

- When comparing two sensors for measuring the same variable, it is hard to say if they work well, because the measurements cannot be checked with measurements that are known to be correct. Now the conclusions are based on assumptions. For a more scientific conclusion ground truth research should be used to compare the data, which was not possible at this time.
- Data from more sensors can be used if ground truth data is not available. The data of other sensors was not available (in time) for this research. For further research, the data of other above ground sensors can be used for validation.
- A possible reason for the deviations in the StreetSense data could be that the magnetometer is not capable to detect distinguish multiple vehicles, when they are passing at the same moment. This could be further investigated by doing ground truth measurements with groups and individuals.

Analysis on the possibility to deduce a relationship between cycling volume and weather conditions based on the sensor data from the Plastic Road.

- The analysis is now done for only April. For a better analysis, it is useful to use data sets of more months. Also, April did not contain many rainy days, so the research is very limited. On top of that, the rainy days had only short rain peaks.
- Due to a lack of data on rainy days, separation of the data according to the different rain intensities is not possible. For future research, this would be recommended for a more precise analysis.
- For a more detailed analysis on the relationship between weather conditions and cycling behaviour, average speed could be of interest for further research. Average speed was not available at the moment.
- In this analysis, the rain rate is compared to data of the mm wave sensor, because that is the most reliable sensor according to the former analysis. However, this cannot be stated with certainty due to the lack of ground truth data. For further research, the data first needs to be compared with ground truth data before using it for the analysis on weather conditions versus cycling volume.

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A

Appendix A

```
: import json
import matplotlib.pyplot as plt
import pandas as pd


with open('/Users/katriendejong/Downloads/354444115341903.json') as f:
    data = [json.loads(line) for line in f]


df = pd.DataFrame(columns=["Date", "Pass.", "Avg speed", "Sign. strength", "Road surface temp.",
                           "Inner temp.", "Temp. module", "Air press. module", "Rel. humidity module",
                           "Cond.", "Cond. corr. with temp.","Magn.meter treshold for pass.",
                           "Magn.meter calibr. x", "Magn.meter calibr. y", "Magn.meter calibr. z"])

for i in range(0, len(data)):
    currentItem = data[i]
    df.loc[i]= [data[i]["ts"], data[i]["cnt"], data[i]["avgs"], data[i]["rssi"], data[i]['tmpt'],
               data[i]['tmpb'], data[i]['bmet'], data[i]['bmep'], data[i]['bmeh'], data[i]['ec'],
               data[i]['ec_cal'], data[i]['zthreshold'], data[i]['xCal'], data[i]['yCal'], data[i]['zCal']]
df
```

Figure A.1

```
### mmwave

path = '/Users/katriendejong/Downloads/April-Mei-Data/mmwavefiles/0402'
mmwave = pd.DataFrame()  # verzameling van alle data
for zip_filename in os.listdir(path):  # loop over de zipbestanden
    with zipfile.ZipFile(os.path.join(path, zip_filename)) as zf:  # open een zipbestand
        for file in zf.filelist:  # loop over de ingepakte bestanden
            data_new = pd.read_json(zf.read(file).decode('utf8')[2:-1], orient='index').T
            mmwave = pd.concat((mmwave, data_new))  # lees de nieuwe data en voeg samen
mmwave = mmwave.reset_index(drop=True)  # unieke index per bestand

mmwave['timestamp'] = pd.to_datetime(mmwave['timestamp'],unit='s')

mw_df = pd.DataFrame(mmwave, columns=["timestamp", "count"])
ss_df = pd.DataFrame(streetsense, columns=["timestamp", "Pass."])

plt.figure(figsize=(20,5))
plt.plot(mmwave['timestamp'], mmwave['count'], color='DeepSkyBlue')
# display(mmwave)

### resample!!

mw_df['timestamp']=pd.to_datetime(mw_df['timestamp'])
mw_df.set_index('timestamp',inplace=True)
new_df=mw_df.resample('10min').sum()

display(new_df)


new_df.plot(figsize=(20,5))
```

Figure A.2

```python
### mmwave

path = '/Users/katriendejong/Downloads/April-Mei-Data/mmwave-3/april'
mmwave = pd.DataFrame()  # verzameling van alle data

for zfile in os.listdir(path):
    if not zfile.startswith('.'):
        with zipfile.ZipFile(os.path.join(path, zfile), 'r') as unzipped:
            for file in unzipped.filelist:
                with unzipped.open(file) as f:
                    file = f.read().decode('utf-8')[2:-1]
                    data_new = pd.read_json(file, orient='index').T
                    mmwave = pd.concat([mmwave, data_new])


mmwave['timestamp'] = pd.to_datetime(mmwave['timestamp'], unit='s')
```

Figure A.3: StreetSense sensor: unfiltered vehicle count data

```python
with open('/Users/katriendejong/Downloads/streetsense2.json') as f:
    data = [json.loads(line) for line in f]


streetsense = pd.DataFrame(columns=["timestamp", "Pass.", "Avg speed", "Sign. strength", "Road surface temp.",
                           "Inner temp.", "Temp. module", "Air press. module", "Rel. humidity module",
                           "Cond.", "Cond. corr. with temp.","Magn.meter treshold for pass.",
                           "Magn.meter calibr. x", "Magn.meter calibr. y", "Magn.meter calibr. z"])

for i in range(0, len(data)):
    currentItem = data[i]
    streetsense.loc[i]= [data[i]["ts"], data[i]["cnt"], data[i]["avgs"], data[i]["rssi"], data[i]["tmpt"],
            data[i]["tmpb"], data[i]["bmet"], data[i]["bmep"], data[i]["bmeh"], data[i]["ec"],
            data[i]["ec_cal"], data[i]["zthreshold"], data[i]["xCal"], data[i]["yCal"], data[i]["zCal"]]

ss_df = pd.DataFrame(streetsense, columns=['timestamp', 'Pass.'])
# ss_df['timestamp']=pd.to_datetime(ss_df['timestamp'])
# ss_df.set_index('timestamp',inplace=True)

ss_df.plot(x='timestamp', y=['Pass.'], figsize=(20, 5))
plt.title('Streetsense vehicle count')
plt.xlabel('Timestamp')
plt.ylabel('Passing vehicles per 10 minutes')
```

Figure A.4

```python
path = '/Users/katriendejong/Downloads/April-Mei-Data/mmwave-3/april'
mmwave = pd.DataFrame()  # verzameling van alle data

for zfile in os.listdir(path):
    if not zfile.startswith('.'):
        with zipfile.ZipFile(os.path.join(path, zfile), 'r') as unzipped:
            for file in unzipped.filelist:
                with unzipped.open(file) as f:
                    file = f.read().decode('utf-8')[2:-1]
                    data_new = pd.read_json(file, orient='index').T
                    mmwave = pd.concat([mmwave, data_new])


mmwave['timestamp'] = pd.to_datetime(mmwave['timestamp'], unit='s')

plt.figure(figsize=(20,5))
plt.plot(mmwave['timestamp'], mmwave['count'])
plt.title('Mmwave vehicle count')
plt.xlabel('Timestamp')
plt.ylabel('Passing vehicles per 5 seconds')
display(mmwave)

### resample!!

new_df = mmwave.set_index('timestamp').resample('10 min').sum()

# display(mw_df)
# display(new_df)

new_df.plot(figsize=(20,5))
plt.title('Mmwave vehicle count')
plt.xlabel('Timestamp')
plt.ylabel('Passing vehicles per 10 minutes')
```

Figure A.5

```
rmm = mmwave.set_index('timestamp').resample('10 min').sum()
|

rmm['count'].resample('D').mean().plot(figsize=(20,5),kind='bar')
plt.savefig('mmmeanperday.png')
```

Figure A.6

```
ss = pd.DataFrame(streetsense, columns=['timestamp', 'Pass.'])
ss['timestamp'] = pd.to_datetime(ss['timestamp'])
rss = ss.set_index('timestamp').resample('10 min').sum()


rss['Pass.'].resample('D').mean().plot(figsize=(20,5),kind='bar')
plt.savefig('ssmeanperday.png')
```

Figure A.7

```
ss_df = pd.DataFrame(streetsense, columns=['timestamp', 'Pass.'])
ss_df['timestamp']=pd.to_datetime(ss_df['timestamp'])
ss_df.set_index('timestamp',inplace=True)
ss_df = ss_df.resample('10min').sum()
# ss_df['Pass.'] = ss_df['Pass.'] * 20
#display(ss_df)

mw_df = pd.DataFrame(mmwave, columns=["timestamp", "count"])
mw_df['timestamp']=pd.to_datetime(mw_df['timestamp'])
mw_df.set_index('timestamp',inplace=True)
new_df=mw_df.resample('10min').sum()
# display(new_df)

new_df["sensor"] = "mmwave"
new_df = new_df.rename(columns={"count":"value"})
ss_df["sensor"] = "streetsense"
ss_df = ss_df.rename(columns={"Pass.": "value"})
df_sensor = new_df.append(ss_df)

df_sensor_pivot = df_sensor.pivot(columns="sensor", values="value")
# display(df_sensor_pivot)

# Create subplots and plot
fig, (ax1, ax2) = plt.subplots(nrows=2, ncols=1, figsize=(20, 5))
ax1.plot(df_sensor_pivot["mmwave"], marker="o")
ax2.plot(df_sensor_pivot["streetsense"], marker="o")

ax1.set(ylabel="mmwave")
ax2.set(ylabel="streetsense")
plt.show()

ax = ss_df.plot(figsize=(20, 5), label='streetsense')
new_df.plot(ax=ax, label='mmwave')
plt.savefig('mmwavevsstreetsenseapril.png')
```

Figure A.8

```
with open('/Users/katriendejong/Downloads/streetsense2.json') as f:
    data = [json.loads(line) for line in f]


streetsense = pd.DataFrame(columns=["timestamp", "Pass.", "Avg speed", "rssi", "Road surface temp.",
                           "Inner temp.", "Temp. module", "Air press. module", "Rel. humidity module",
                           "Cond.", "Cond. corr. with temp.","Magn.meter treshold for pass.",
                           "Magn.meter calibr. x", "Magn.meter calibr. y", "Magn.meter calibr. z"])

for i in range(0, len(data)):
    currentItem = data[i]
    streetsense.loc[i]= [data[i]["ts"], data[i]["cnt"], data[i]["avgs"], data[i]["rssi"], data[i]["tmpt"],
                data[i]["tmpb"], data[i]["bmet"], data[i]["bmep"], data[i]["bmeh"], data[i]["ec"],
                data[i]["ec_cal"], data[i]["zthreshold"], data[i]["xCal"], data[i]["yCal"], data[i]["zCal"]]

rssi = pd.DataFrame(streetsense, columns=['timestamp', 'rssi'])

rssi.plot(x='timestamp', y=['rssi'], figsize=(20, 5))
plt.title('Streetsense rssi')
plt.xlabel('Timestamp')
plt.ylabel('rssi ')

poor_values = rssi['rssi'][rssi['rssi'] < -80]  # remove poor values
# ss_df = ss_df[ss_df['rssi'] != 0]

display(poor_values.index)
```

Figure A.9

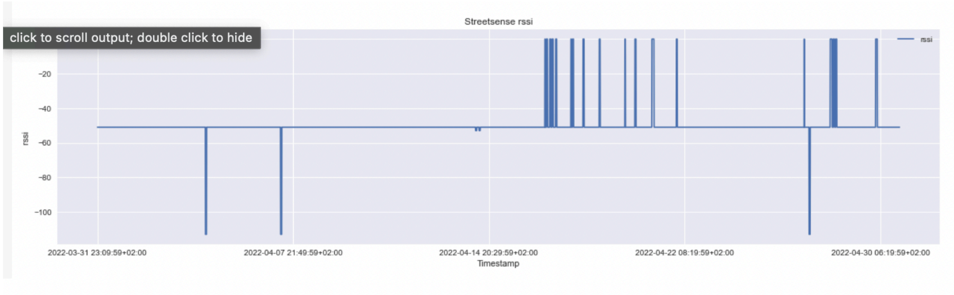

Figure A.10: Plot rssi streetsense sensor

```
new_df["sensor"] = "mmwave"
new_df = new_df.rename(columns={"count":"value"})
ss_df["sensor"] = "streetsense"
ss_df = ss_df.rename(columns={"Pass.": "value"})
df_sensor = new_df.append(ss_df)

df_sensor_pivot = df_sensor.pivot(columns="sensor", values="value")

display(df_sensor_pivot)

df_sensor_pivot.boxplot(figsize=(5,10))
```

Figure A.11

```
wdf4 = pd.DataFrame(weather4, columns=["dateTime", "rainRate"])
wdf4['dateTime']=pd.to_datetime(wdf4['dateTime'])
wdf4.set_index('dateTime',inplace=True)
wdf4_new=wdf4.resample('10min').last()
wdf4_new['rainRate'] = wdf4_new['rainRate']
# display(wdf4_new)

mw_df = pd.DataFrame(mmwave, columns=["timestamp", "count"])
mw_df['timestamp']=pd.to_datetime(mw_df['timestamp'])
mw_df.set_index('timestamp',inplace=True)
new_df=mw_df.resample('10min').sum()
# display(new_df)

new_df["sensor"] = "mmwave"
new_df = new_df.rename(columns={"count":"value"})
wdf4_new["sensor"] = "davis"
wdf4_new = wdf4_new.rename(columns={"rainRate": "value"})
df_sensor = new_df.append(wdf4_new)

df_sensor_pivot = df_sensor.pivot(columns="sensor", values="value")
# display(df_sensor_pivot)

# Create subplots and plot
fig, (ax1, ax2) = plt.subplots(nrows=2, ncols=1, figsize=(20, 5))
ax1.plot(df_sensor_pivot["mmwave"], marker="o")
ax2.plot(df_sensor_pivot["davis"], marker="o")
plt.savefig('rainandintensity0411.png')

ax1.set(ylabel="mmwave")
ax2.set(ylabel="davis")
plt.show()

ax = wdf4_new.plot(figsize=(20, 5), label='davis')
new_df.plot(ax=ax, label='mmwave')
plt.savefig('rainvsintensity04013.png')
```

Figure A.12

dateTime	rainRate
2022-04-04 10:10:00	3.6
2022-04-04 10:20:00	10.3
2022-04-04 10:30:00	6.7
2022-04-04 10:40:00	5.0
2022-04-04 10:50:00	4.8
2022-04-04 11:00:00	6.1
2022-04-04 11:10:00	6.0
2022-04-04 11:20:00	6.6
2022-04-04 11:30:00	4.8
2022-04-04 11:40:00	4.3
2022-04-04 11:50:00	6.6
2022-04-04 12:00:00	8.8
2022-04-04 12:10:00	7.4
2022-04-04 12:20:00	8.3
2022-04-04 12:30:00	6.3
2022-04-04 12:40:00	5.6
2022-04-04 12:50:00	4.8
2022-04-04 13:00:00	5.1
2022-04-04 13:10:00	4.8
2022-04-04 13:20:00	3.7
2022-04-04 13:30:00	1.2
2022-04-04 13:40:00	1.2
2022-04-04 13:50:00	1.2
2022-04-04 14:00:00	1.1

dateTime	rainRate
2022-04-06 07:20:00	8.2
2022-04-06 07:30:00	6.4
2022-04-06 07:40:00	3.5
2022-04-06 07:50:00	2.2
2022-04-06 08:20:00	7.4
2022-04-06 08:30:00	6.8
2022-04-06 14:40:00	5.4
2022-04-06 14:50:00	3.9

dateTime	rainRate
2022-04-07 03:40:00	4.0
2022-04-07 03:50:00	2.8
2022-04-07 04:20:00	6.4
2022-04-07 04:30:00	4.6
2022-04-07 05:00:00	9.6
2022-04-07 05:10:00	19.2
2022-04-07 05:20:00	44.9
2022-04-07 05:30:00	19.7
2022-04-07 05:40:00	9.3
2022-04-07 05:50:00	7.4
2022-04-07 06:00:00	6.6
2022-04-07 06:10:00	6.5
2022-04-07 06:20:00	8.3
2022-04-07 06:30:00	9.2
2022-04-07 06:40:00	8.4
2022-04-07 06:50:00	7.4
2022-04-07 07:00:00	5.2
2022-04-07 07:10:00	4.0
2022-04-07 07:20:00	2.0
2022-04-07 16:00:00	18.3
2022-04-07 16:10:00	12.5
2022-04-07 16:20:00	5.3
2022-04-07 18:40:00	16.5
2022-04-07 18:50:00	4.9
2022-04-07 19:00:00	4.0

Figure A.13: Rain rates per 10 minutes on the analysed rainy days (> 2.5 mm rain per day

B

Appendix B

Strain2data

Name	type	unity after conversion	conversion
‘str-xx’	strain sensors	incorrect data	incorrect data
‘lvdt-xx’	LVDT sensors	mm	n/a
‘ts-xx’	temperature strains	degrees Celsius	data[ts] / 100 + 11.7
‘lc-xx’	loadcells	kg	data[lc] * .66279188
‘acc-x’	accelerometer	g	(data[’acc-x’] - 12.180) * .9333
‘acc-y’	accelerometer	g	(data[’acc-y’] - 12.030) * .9430
‘acc-y’	accelerometer	g	(data[’acc-z’] - 12.146) * .9234

StreetSense

Attribute	name	unity
cnt	number of passages	
avgs	average speed	km/h
rssi	signal strength	dBm
tmpt	temperature road surface	°C
tmpb	temperature inside	°C
bmet	temperature module	°C
bmep	air pressure module	mBar
bmeh	relative humidity module	%
ec	conduction	S/m
ec_cal	conduction (corrected with temperature)	μS
zthreshold	magnetometer treshold value for passage	μT
xCal	magnetometer calibration value x	μT
yCal	magnetometer calibration value y	μT
zCal	magnetometer calibration value z	μT

Mmwave

Attribute	name	unity
sensor_id	Type of sensor	
count	number of passages	no. per 5 seconds
timestamp	Date and time	