Bachelor of Science Thesis in Civil Engineering

Optimizing of reaction time determination and its influence on bicycle flow during queue discharge process at a signalized intersection

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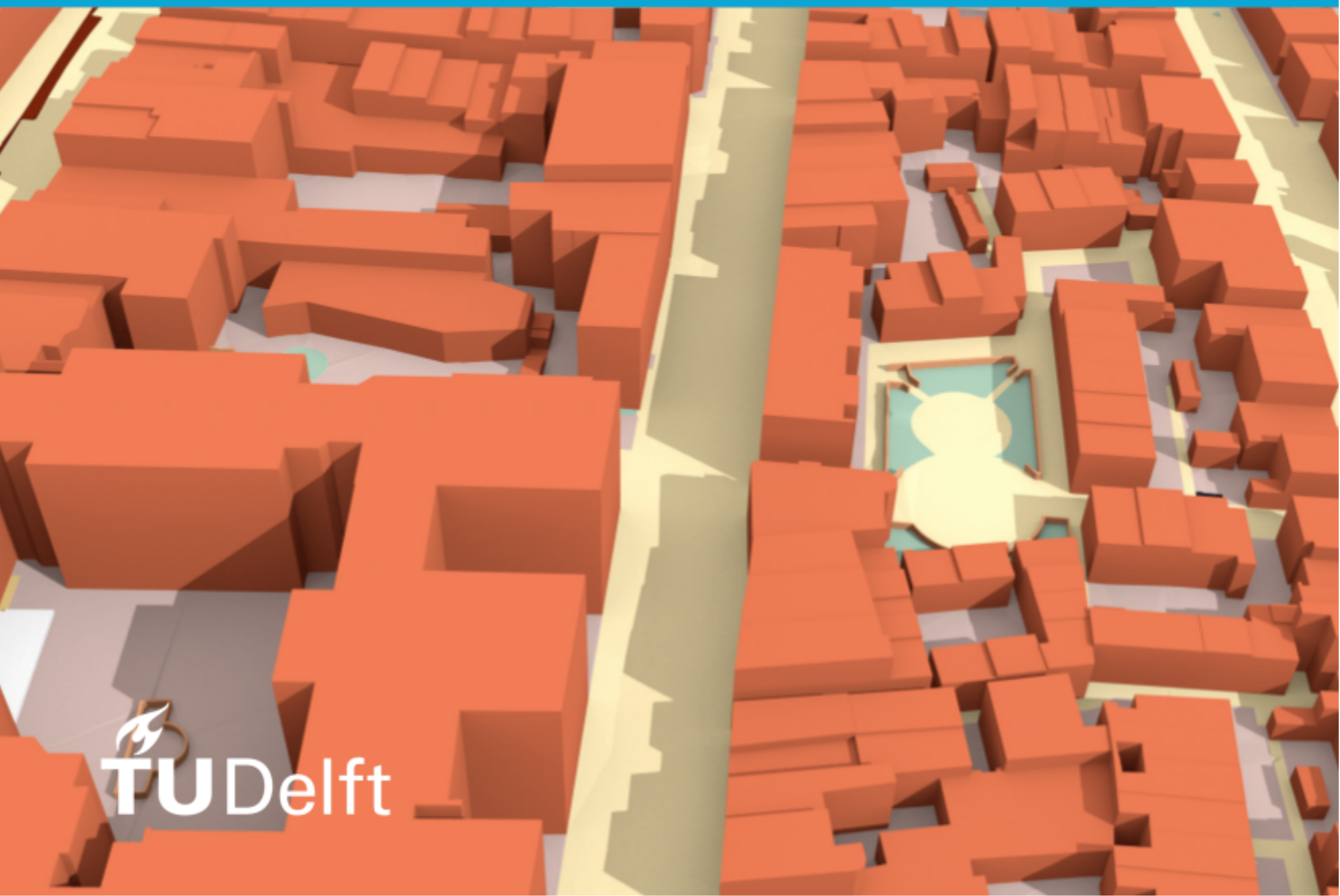

OPTIMIZING OF REACTION TIME DETERMINATION AND ITS INFLUENCE ON BICYCLE FLOW DURING QUEUE DISCHARGE PROCESS AT A SIGNALIZED INTERSECTION

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SUMMARY

This report aimed to gain more fundamental knowledge regarding reaction times and its influence on bicycle flow at a signalized intersection. Reaction times were computed using both the widely applied base method, and the virtual sub-lane method. The sub-lane method is preferred due to its improved way of assigning cyclists that are reacted to. A so called cyclist width is used within this method, and based on literature, a reasonable range from 0.5 to 1.5 meters was defined. Next, statistics on the reaction time results showed that this range was too wide, so it was narrowed down from 0.6 to 1.3 meters. Besides, the statistics showed that the virtual sub-lane method is indeed a better representation of reality than the base method.

In order to determine the influence of reaction time on bicycle flow, several bicycle flow characteristics were defined and used to test this relation. These flow characteristics are time headway, discharge flow, jam density and shock wave speed. Discharge flow is considered the most important of these characteristics, because this parameter best represents traffic capacity of through flow.

Using Pearson correlation coefficients, followed by simple linear regression and multiple regression analyses, the influence of reaction time on each of the flow characteristics was determined. These analyses provided more insight in the most reasonable range of cyclist widths that is implemented in the sub-lane method. This reasonable width was narrowed down to 0.7-1.3 meters. However, for this specific research, a width of specifically 0.8 meters returned the best results. This width was then used to present the influence of reaction time on the flow characteristics. The influence on time headway and shock wave speed is given by equations 0.1 and 0.3 respectively. The influence on jam density is given by equation 0.2, but this causal relation could better be reversed, so that jam density influences reaction time instead.

$$h = 0.907 * t_R + 2.62 \tag{0.1}$$

$$JD = 0.130 * t_R + 0.346 \tag{0.2}$$

$$SS = -1.991 + t_R + 5.635 \tag{0.3}$$

Finally, the influence of reaction time on discharge flow was analysed. This turned out not to be a one on one relation and could therefore not be expressed as an equation. However, the multiple regression analysis showed very clearly that a low reaction time in combination with a high jam density, causes a high discharge flow. This means that if the traffic capacity of through flow at a signalized intersection needs to be increased, the reaction time would have to be lowered and the jam density would have to be increased. A way to do that would be to install a countdown timer and use psychology to motivate cyclists to queue in a denser way.

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CONTENTS

1 INTRODUCTION

Car traffic flow is an extensively researched topic, where flow characteristics such as headway saturation flow and shock wave speed are widely known. However, for bicycle traffic flow, this is not the case. Extensive research in bicycle traffic flow is still lacking, and this is especially true for bicycle flow during a queue discharge process at a signalized intersection. Information on relations between different flow characteristics is scarce, while this can be of great value. This information may for example give insight in how to design the geometry of bicycle lanes and intersections. More knowledge in this topic might also allow for optimizations in traffic control schemes at signalized intersections.

Limanond et al. [2009] and Liu et al. [2012] showed that countdowns timers installed at signalized intersections significantly reduces start-up lost time for cars during queue discharge process. Start-up lost times were reduced by 0.6 to 2.25 seconds per cycle, depending on the direction of movement (left turn or straight through). This result shows that by using a countdown timer, a shorter reaction time is achieved by allowing the commuters to anticipate for the green light. Consequently, start-up lost time decreased. Although similar research in bicycle flow is missing, it might be expected that this relation also holds for bicycle flow, or might even be stronger due to the heterogeneous behaviour of cyclists. The fact that cyclists do not have to keep a lane and can overtake their predecessor easily, may contribute to a higher potential benefit that can be achieved by artificially lowering reaction times (for example by installing countdown timers). Proving the relation between a countdown timer and start-up lost time is, however, not part of this research, but is does show the importance of gaining knowledge in reaction time and its influence on traffic flow. Research papers that aim to compute reaction times and map its influence on bicycle traffic flow are lacking, which is why this research aims to do exactly this, using data retrieved from a cycling path at a signalized intersection in Amsterdam, the Netherlands. Through showing the importance of reaction time, this report aims to gain important fundamental knowledge in bicycle flow and to motivate other researchers to continue on this work.

Sharma et al. [2009] studied car traffic flow in India, which has a more heterogeneous character compared to car traffic flow in Western countries due to the problem of lacking lane discipline. The traffic flow in this research should therefore show more similarities with bicycle flow. Sharma et al. [2009] also showed that using countdown timers, a clear trend for reduced start-up lost time and end lost time could be observed. Furthermore, a significant relation was found with queue discharge characteristics, of which the headway distribution was the most important. Furthermore, Wenbo et al. [2013] showed that implementing countdown timers had a reduction of 5% on the saturation headway, creating a 5% increase in traffic capacity of through movement. These papers thus show us the importance of gaining fundamental knowledge in the effect of reaction time on traffic flow, and the potential increase in traffic capacity that can be obtained.

Traffic capacity of through movement at a signalized intersection may best be expressed by discharge flow, which is a macroscopic parameter indicating the amount of cyclists that cross the stop line (or any other fixed cross-section) during a given period of time. Discharge flow is thus expressed as the amount of cyclists that cross the stop line, per second. The term ”macroscopic” means that the parameter is determined over an entire discharge cycle. The term ”microscopic” on the other hand, indicates that a parameter is calculated with values of individual cyclists.

In order to gain insight in the effect of reaction time on bicycle flow, one essential relation to be considered is the one between reaction time and discharge flow. The hypothesis is that a quick response, and thus a lower reaction time, causes a higher discharge flow. Furthermore, Goñi-Ros et al. [2018] showed that discharge flow is strongly correlated with jam density and shock wave speed. These two macroscopic parameters were therefore also taken into account in the analysis, and a causal relationship was tested between reaction time and discharge flow through jam density and/or shock wave speed. After all, these three macroscopic variables are theoretically closely connected.

Jam density is defined as the density in which the cyclists are queuing, whilst having zero velocity, during a discharge cycle. Jam density is given as the number of cyclists per squared meter. When the traffic light changes to green, the cyclists in the queue will change their state from idle to accelerating. This change in state starts near the stop line and progresses backwards in the queue, which can be seen as a shock wave. The speed in which this happens is called the shock wave speed and is given in meters per second. Both the jam density and shock wave speed are also expected to have a one on one relationship with reaction time. It is hypothesized that a high jam density causes a high reaction time (slow response), because a high density of cyclists in the queue means that less space to overtake is available. The discharge process is less heterogeneous in this case, and as a consequence, cyclists in the queue have to wait for their predecessor (cyclist directly in front) to start accelerating, before they can start to move. The shock wave speed is also hypothesized to have a direct relationship with reaction time. When reaction times in a queue are low, this generally means that the commuters are changing their state from idle to accelerating in a short time period, thus yielding a high shock wave speed.

Another interesting relationship is the one between reaction time and time headway, since Sharma et al. [2009] showed that these variables are closely related. This relationship can be tested both on a microscopic and a macroscopic level, which helps to understand the difference between these analysis methodologies.

The single microscopic and three macroscopic flow variables mentioned above, are expected to have close relations with reaction time. In order to exactly find out about these relations and to link reaction time with discharge flow, a number of analyses were done: Pearson correlation coefficient, linear regression analysis and multiple regression analysis. These procedures are discussed in more detail in chapter 2. Although, before these relationships were tested, the reaction times had to be computed first.

The most basic and common way to compute reaction times at a signalized intersection during a queue discharge process, is by using the base method. This method numbers the cyclists from the front of the queue to the back and calculates the reaction times as the difference in time between a cyclist starting to move and his predecessor starting to move. The problem with this method is that it assigns a predecessor to a cyclist based only on the vertical y-axis (also see figure 2.1). The x-axis are in this case completely ignored. This causes incorrect assigning of predecessors, and so to an incorrect calculation of reaction time. This research uses both the base method and the virtual sub-lane method, which was used by Yuan et al. [2019] to determine headway. Computing reaction time with both these methodologies will give the opportunity to compare these procedures and to find an improved way to calculate reaction time. The virtual sub-lane method uses both the x- and y-coordinates to assign predecessors, by assuming a certain cyclist width (also see figure 2.2). The virtual sub-lane method is therefore expected to give more reasonable reaction times than the base method, depending on the implemented cyclist width. To define which reaction time results are reasonable and which are not, a statistical analysis on these results were done. By comparing this information with a predetermined set of criteria, the most reasonable reaction times could be defined. This also allowed for setting a more justifiable range of implemented cyclist widths. Next, the reaction times were compared to the bicycle flow parameters, which allowed for an even deeper analysis of reasonable results and reasonable widths. How these methodologies work exactly is described in chapter 2.

In summary, this research aims to first map the effects of different methods to calculate reaction time in bicycle flow at a signalized intersection. A base model is compared to the virtual sub-lane method, using a data set of 59 cycles of queue discharge processes at a signalized intersection in Amsterdam, the Netherlands. The second objective is to find the relations between reaction time and bicycle flow characteristics, as described above, so that reaction time can be calculated as accurate as possible and its influence on bicycle flow can be determined. This research was based on an empirical trajectory data set supplied by Yuan et al. [2019]. This data set was derived from snapshots that were taken by two cameras on a 10 meter high pole, their views of the 2 meter wide cycle path can be seen in figure 1.1. These two cameras together had a range of 20 meters upstream of the traffic light and they were recording between 12:45 and 19:00 on June 6, 2016. Furthermore, Yuan et al. [2019] used specific criteria to filter the discharge cycles so that only relevant cycles remained in the data set. For example, at least 7 bicycles need to stand still in the cycle path before the traffic light turns green, and no pedestrians can cross the cycle path during the discharge process. Other criteria can be found in Yuan et al. [2019]. The individual frames were converted to trajectory data in MatLab, and some preliminary results were computed. This research continues on these preliminary results. Yuan et al. [2019] supplied data for this research in the form of MatLab code containing trajectory data of each cyclist: their x- and y-coordinates at each moment in time where a frame was taken. The frame rate of this camera varies between 5 and 10 frames per second. Furthermore, the three macroscopic variables of discharge flow, jam density and shock wave speed were

Figure 1.1: The view of the cycle path from the two cameras at a height of 10 meters.

supplied for each discharge cycle.

The research goal can then be defined as follows: Comparing reaction time determination methods and exploring the influence of reaction time on bicycle flow during queue discharge process at a signalized intersection.

In order to successfully achieve this research goal, it was split into several sub-goals to make it more manageable. These sub-goals are given below:

1. Calculate reaction time using the base method.
2. Calculate reaction time using the virtual sub-lane method, with varying widths, after a justifiable range of widths has been determined.
3. Comparing the (statistical) outcomes of the different methods by matching them with a set of predetermined criteria. Followed by deriving a more reasonable range of cyclist widths.
4. Calculate the microscopic characteristic of time headway, and also convert it to a macroscopic interpretation.
5. Calculate the Pearson correlation coefficients between reaction time on one hand and the four flow characteristics on the other hand, and interpret the results.
6. Determine the linear relations between reaction time on one hand and the four flow characteristics on the other hand, using linear regression analysis. Interpret these results.
7. Determine relations between reaction time and some flow characteristics on one hand, and discharge flow on the other hand, using multiple regression analysis. Interpret these results.
8. Based on the results of the previous sub-goals, first compare the reaction time calculation methods, and then derive a model that explains the influence of reaction time on bicycle flow during queue discharge process at a signalized intersection.

The answers to these sub-goals collectively supply the answer to the main research goal. This main answer contributes to the fundamental knowledge in bicycle flow and motivates for further research in this topic. The knowledge gained in this research might lead to optimizations in geometric design of bicycle lanes and signalized intersections. By creating more understanding in the influence of reaction time on bicycle discharge flow, it might also help in the design of traffic control schemes, for example by implementing countdown timers where needed.

The results of each of the sub-goals are discussed in chapter 3, the methodology in which these results are obtained is discussed in chapter 2. Finally, chapter 4 gives the conclusion of this research and explains what might be interesting for future work.

2 METHOD

This chapter discusses how each of reaction times, characteristics and relations were calculated. Thereby, it shows exactly how the research sub-goals were achieved. This chapter is divided up into three sections. First, the reaction time calculation methods are explained, including how to compare them. Next, the calculation of the four flow characteristics are elaborated. The third section discusses how each of the relations were found, using the Pearson correlation coefficients, linear regression analysis and multiple regression analysis.

2.1 REACTION TIME CALCULATION

This section shows how the reaction times for both the base method and the virtual sub-lane method were calculated. Reaction time is here defined as the time difference between the initial movement of a cyclist and the initial movement of his predecessor (the person in front of him, also referred to as "leader"). When a bicyclist does not have a leader, the reaction time is defined as the time difference between the traffic light turning green and the time of initial movement of the cyclist. Equation 2.1 shows how the reaction time is calculated for both cases. The time of initial movement is based on the MatLab data set and occurs when the cyclist starts to move after standing still and waiting for the traffic light to turn green. In other words, the initial movement time is defined as the moment in time when the coordinates of the cyclist start change for the first time compared to his initial position.

$$\begin{cases} t_{R,i} = t_{IM,i} - t_{IM,i,pred} & \text{if } pred \neq NaN \\ t_{R,i} = t_{IM,i} - t_{green} & \text{if } pred = NaN \end{cases} \tag{2.1}$$

Where $t_{R,i}$ is the reaction time of cyclist i, $t_{IM,i}$ is the initial movement time of cyclist i, $t_{IM,i,pred}$ is the initial movement time of the predecessor of cyclist i, and t_{green} is the time moment when the traffic light turns green. NaN is an abbreviation for "Not a Number", and indicates that the cyclist does not have a predecessor.

As can be seen in equation 2.1, the reaction time for a certain cyclist i only depends on the initial movement times of cyclist i and of his predecessor, if cyclist i has a predecessor. Otherwise, the reaction time only depends on his initial movement time and the time moment that the traffic light turns green. This shows that the assigning of predecessor-successor pairs is an essential part of calculating reaction times. Both methods, the base method and the virtual sub-lane method, would actually generate the exact same reaction times if they would assign the exact same predecessor-successor pairs. This means that the base method and the sub-lane method both calculate the reaction time in the same way, but the essential difference between the methods is how the predecessor of a cyclist is determined.

2.1.1 Base method

The base method is widely applied although it may not be the most accurate way to calculate reaction times. However, in this research the base method is calculated regardless (sub-goal 1), so that it can be used as comparison material for the results of the virtual sub-lane method. Besides, the improvement of using the sub-lane method can then be quantified. Figure 2.1 shows a typical queue at a bicycle lane. Each black dot represents one bicyclist in the queue. With the base method, one general leader is assigned who is all the way at the front of the queue. This general leader has the highest y-coordinates of all cyclists in the discharge cycle and is therefore indicated with the number 1, which also means that he has no predecessor. The cyclist who is slightly behind number 1 in terms of y-coordinates (and thereby slightly further away from the stop line) is considered his follower (successor) and is indicated with number 2. The cyclist with the third highest y-coordinates is considered number 3 and so on. Cyclist number 3 is considered the follower of number 2, and number 2 is considered the leader of number 3. This way, each cyclist in a queue can be numbered according to their y-coordinates, and each cyclist can have a predecessor assigned. Hence, the predecessor of a cyclist i is cyclist $i-1$, where $i \leq N$, and with N as the number of cyclists in the queue. The only exception is for when $i = 1$, because in this case, the considered cyclist is the general leader, who has no predecessor ($pred = NaN$). The reaction time of each cyclist i can now determined with equation 2.1.

2.1.2 Virtual sub-lane method

The virtual sub-lane method is expected to deliver more reasonable and accurate reaction times, due to not assigning leader-follower pairs solely on y-coordinates, but also taking x-coordinates into account by considering a certain width w of the cyclists. Figure 2.2 shows the same cycle path, with the same cyclists and the same assigned numbers as in figure 2.1. However, the predecessors are now assigned in a different way. The red colored rectangle has a width w and represents the width of cyclist number 4. This width is a representation of the space that is required by a cyclist to move freely on the cycle path. Since the cyclist looks forward towards the stop line, the width is translated forward to create the red rectangle. This virtual red rectangle represents the virtual sub-lane of cyclist 4. The predecessor is now defined as the cyclist that is closest in terms of y-coordinates, but within this red square, which is in this case cyclist number 1. The process of assigning predecessors is therefore very similar as with the base method, but now with a certain limit in the x-coordinates. No longer is the entire cycle path considered, but rather only the part of the cycle path that is effectively used by the cyclist to queue. The big improvement of this method is that cyclists who could rather be considered "neighbours" (but with slight differences in y-coordinates) are now not falsely assigned as a predecessor-successor pair. For example, looking at cyclist 8, the base method would assign cyclist 7 as leader, and the sub-lane method would assign cyclist 6 as leader (depending on the implemented width). The assumption that cyclist

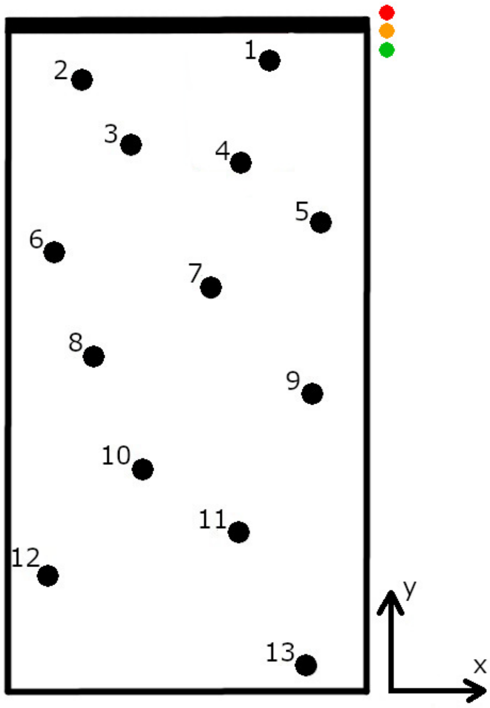

Figure 2.1: The base method: each black dot represents one bicyclist in the queue. These cyclists are numbered based on their y-coordinates, and a predecessor can be assigned to each cyclist based on these numbers.

8 reacts to cyclist 6 is much more reasonable than that he reacts to cyclist 7. Accordingly, should this method lead to more accurate reaction times. Once the predecessors are assigned for all cyclists with this virtual sub-lane method, the reaction times can again be calculated with equation 2.1.

One major difficulty using the sub-lane method is setting the correct cyclist width. As described in the research goals, this research aims to test a range of cyclist widths to find out what range is most reasonable (sub-goal 2). The statistical results obtained when comparing the base method with the sub-lane method, should provide useful information to define a reasonable range of widths. Afterwards, when more information is obtained regarding the relations part of this research, more criteria can be used to further narrow down this range. However, a wide initial range must be defined at the start to get reaction time results for the comparing of base method with sub-lane method. Previous research helps to set this initial range. In literature, many different sub-lanes have been proposed: Botma and Papendrecht [1991] suggested 0.78 meters (in the Netherlands), Brilon et al. [1994] suggested 1.00 meters and Allen et al. [1998] suggested 1.60 meters. Yuan et al. [2019] suggested a reasonable range between 1.00 and 1.40 meters, which was derived from the same data set as in this research. Based on this literature, the initial range of cyclist width, w, is set from 0.5 to 1.5 meters, with steps of 0.1 meters.

Notice that the virtual sub-lane method gives the exact same results as the base method as soon as the implemented width becomes large enough. Theoretically, this happens with a width of 4 meters, because any cyclist on one

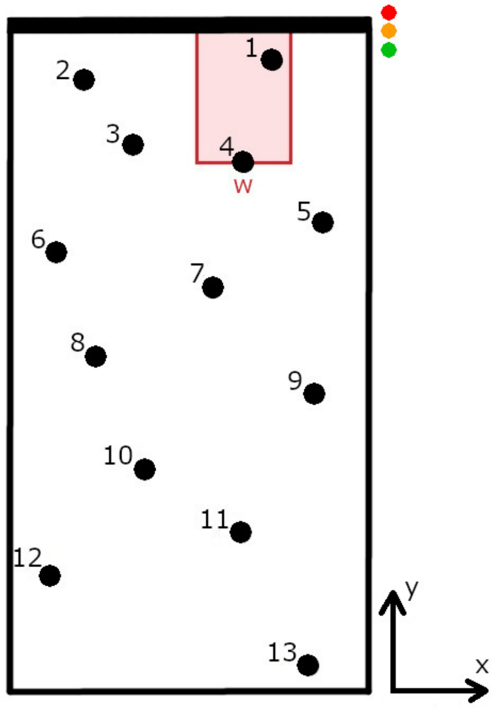

Figure 2.2: The virtual sub-lane method: each black dot represents one bicyclist facing the stop line (at the top), with each having x- and y- coordinates at a certain moment in time. The width is now essential is assigning leaders as a leader can only be withing this range of x-coordinates.

edge of the cycling path would still have two meters on either side, being exactly enough to reach the edge on the other side of the cycling path. However, the data contains several cyclists whose x-coordinates are slightly off the cycling path (see the figure in Appendix A for all initial positions). This means that in this data set, the virtual sub-lane method matches the base method exactly, when the implemented width is approximately 5 meters.

2.1.3 Comparing methods

Calculating the reaction times for the base method and for the virtual sub-lane method with widths ranging from 0.5 to 1.5 meters in steps of 0.1, gives 12 sets of reaction times. These results need to be converted to several statistical values in order to interpret the outcome, find the differences and make a fair comparison between methods (sub-goal 3).

The first comparison method that is used, is creating a histogram of each set of results in order to gain insight in the distribution of the computed reaction times. To visualize this distribution in an even better and smoother way, a kernel distribution function is derived. This is a non-parametric representation of the probability density function, and shows it in a smoothed curve. This kernel representation is determined according to equation 2.2, and is fitted in the histogram using the *fitdist* function in MatLab.

$$\hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{2.2}$$

Where n is the sample size, h is the bandwidth, K is the kernel smoothing function and x_i are random samples from an unknown distribution.

Next, to see which parametric distribution function best describes the results, several of them were tested in the plot and compared to the kernel function. Some example of these tested distributions are the normal, lognormal, logistic and t-location scale functions. Finding the closest fit compared with the kernel, reveals important information regarding the distribution of reaction times for each of the tested methods. These parametric distribution functions were also fitted using the $fitdist$ function in MatLab.

Furthermore, some relevant statistical properties are the mean value and the quantiles (of which the 0.50 quantile is the median) for each of the 12 sets of reaction times. These values are easily computed within MatLab and show the basic characteristics of a set of reaction times. One important criteria that is based on the mean value, is that the mean reaction time of the sub-lane method (for any width) cannot be lower than the mean reaction time of the base method. The reason for this criteria is the expectation that the base method has a too low mean reaction time, due to the incorrect assigning of predecessors. For instance, neighbours in a queue such as cyclists 8 and 7 in figure 2.2 are likely to have a similar initial movement time, and will thus result in a very low reaction time. However, this is an incorrect result as cyclist 8 most probably reacts to cyclist 6 instead of 7. This error is likely to occur a lot when applying the base method and this has a high impact on the mean reaction time. Therefore, when using the virtual sub-lane method, the implemented width is considered invalid when it yields a mean reaction time that is lower than the mean reaction time that is calculated with the base method.

Another interesting parameter is the percentage of reaction times that have a negative value. Like in the example of cyclists 6, 7 and 8 of figure 2.2 given in the paragraph above, the base method has a high chance of assigning incorrect predecessors. This method therefore tends to have very low reaction times, bringing the mean value down, but also increases the chance of measuring negative reaction times. For example, there is a considerable chance that cyclist 7 moves first, then 6 and followed by 8. Using the sub-lane method, this would not be a problem in most applied widths (which is the purpose of applying the sub-lane method), but the base method would measure cyclist 7 to have a negative reaction time. The percentage of negative reaction times is therefore expected to be higher with the base method or with high widths in the sub-lane method. Negative reaction times are physically speaking incorrect, but occur due to applying the model. They need to be prevented as much as possible though, to make the model represent reality in a better way. This leads to setting a criteria based on the percentage of negative reaction times. The approaches of calculating reaction times that yield a too high percentage of negative reaction times are considered unreasonable. The average amount of cyclists in a queue is 12. This research sets an upper limit of 2 cyclists per discharge cycle that are allowed to have negative reaction times, other researchers might set a different limit, but here 3 cyclists is considered too much. Thus, is 2 cyclists set as an upper limit, which leads to a percentage of 17%. When a method uses a very narrow width, this should yield a very low percentage of negative reactions, which is considered good. However, the mistake of a too narrow width cannot be made as this will generate many cyclists without a predecessor. Consequently, the majority of cyclists in a queue would be considered to react to the traffic light turning green, which is also not a realistic scenario. This leads to another interesting variable to use for comparing methods, which is the percentage of reaction times based on the traffic light rather than a predecessor.

The base method always has only one cyclist whose reaction time is based on the green light, regardless of the amount of cyclists in the queue. With an average size of 12 cyclists per discharge cycle, this should give a percentage of green light based reaction times of around 8%. However, based on a cycling path width of 2 meters and based on the initial positions given in the figure of Appendix A, a more realistic scenario is that at least 2 cyclists react to the traffic light (or 17%), these are the cyclists that are all the way at the front row and do not have a predecessor. As the width of the sub-lane method becomes narrower, this will lead to an increasing percentage of traffic light based reaction times. However, more than 4 out of 12 cyclists (or 33%) is not considered reasonable. Therefore, the reasonable range if implemented widths should yield traffic light based reaction times between 17% and 33%.

In summary, the results of the base method and sub-lane method, with widths between 0.5 and 1.5, are compared to a set of criteria. The base method already does not meet the requirements as the amount of traffic light based reaction times is below the minimum of 17%. Therefore, only the sub-lane method will be considered reasonable, but the range of widths is to be tested. Only if the results of an implemented width meet the criteria, will this width be considered reasonable. The criteria are as follows:

- The mean reaction time must be higher than the mean reaction time of the base method.
- The amount of negative reaction times must be lower than 17%.
- The amount of traffic light based reaction times must be between 17% and 33%.

These criteria help to narrow down the acceptable range of widths, which is again tested in the relations part of this research to even further narrow it down.

2.2 FLOW CHARACTERISTICS CALCULATION

Before the relations between reaction time and the flow characteristics can be determined, the flow characteristics themselves need to be defined first. Calculating time headway is part of this research and the procedure for doing this is given below. However, the macroscopic parameters discharge flow, jam density and shock wave speed are already calculated for this data set and are supplied by Yuan et al. [2019] and Goñi-Ros et al. [2018]. Calculating these three characteristics are therefore not part of this research. Since these parameters are extensively used, their calculation method will still be briefly discussed below. However, more details regarding these can be found in Yuan et al. [2019] and Goñi-Ros et al. [2018].

2.2.1 Time headway

The headway of a commuter can be calculated in different ways, for example based on time or based on distance. Since the goal in this research is to compare headway with reaction time, it makes sense to express headway in time (sub-goal 4). Besides, to make a fair comparison, the time headway is calculated in the same way as reaction time, meaning that the time headway of a cyclist is based on his predecessor or on the traffic light turning green. Equation 2.3 shows exactly the time headway was calculated.

$$\begin{cases} h_i = t_{ySL,i} - t_{green} & \text{if } pred = NaN \\ h_i = t_{yPred,i} - t_{SM,i,pred} & \text{if } pred \neq NaN \end{cases} \tag{2.3}$$

Where h_i is the time headway of cyclist i, $t_{ySL,i}$ is the time at which cyclist i reaches the y-coordinate of the stop line, t_{green} is the time at which the traffic light turns green, $t_{yPred,i}$ is the time at which cyclist i reaches the y-coordinate of the initial position of his predecessor, and $t_{SM,i,pred}$ is the time at which the predecessor of cyclist i starts to move. Due to the discrete y-coordinates and timestamps in the data set, the exact moment that a cyclist crosses a certain y-coordinate is hard to determine. To estimate this time moment as well as possible, linear interpolation is used to derive it. This is done according to equations 2.4 and 2.5 below, which describe these time moments for any cyclist i.

$$t_{ySL} = t_{cSL-1} + (y_{SL} - y_{cSL-1})\frac{t_{cSL} - t_{cSL-1}}{y_{cSL} - y_{cSL-1}} \tag{2.4}$$

$$t_{yPred} = t_{cPred-1} + (y_{pred} - y_{cPred-1})\frac{t_{cPred} - t_{cPred-1}}{y_{cPred} - y_{cPred-1}} \tag{2.5}$$

Where y_{SL} and y_{pred} are the y-coordinates of the stop line and the predecessor of cyclist i respectively. y_{cSL} and t_{cSL} are the y-coordinate and corresponding timestamp where the cyclist just crosses the stop line. y_{cSL-1} and t_{cSL-1} are the values of just one data point earlier and therefore indicate the y-coordinate and corresponding timestamp that the cyclist is just before the stop line. In the same way y_{cPred}, t_{cPred}, $y_{cPred-1}$ and $t_{cPred-1}$ show the y-coordinates and timestamps of the cyclist just before and just after crossing the y-coordinate of the initial position of his predecessor.

The time headway for each cyclist in the data set can be calculated using the equations above. The headway of each cyclist can then be compared with the reaction time of the same cyclist. This means that the derived time headway is a microscopic parameter and can be compared one on one with reaction time. In order to compare the microscopic and macroscopic approach, the time headway and reaction time should also be interpreted as a macroscopic variable. In order to do this, both the mean and the median value of both variables can be determined. These mean and median values are then a macroscopic representation of the microscopically calculated time headway and reaction time.

2.2.2 Discharge flow

The discharge flow (DF) is defined as the amount of cyclists that cross the stop line in a certain time period. Therefore, the discharge flow is expressed in number of cyclists per second. The supplied discharge flow (Yuan et al. [2019], Goñi-Ros et al. [2018]) in this research was calculated using a counting area instead of just the stop line. This area consists of the stop line and 0.4 meters further downstream, over the entire width of the cycle path. The discharge flow for any discharge cycle is then given by equation 2.6.

$$DF = q_d = \frac{\sum_{j=2}^{N} \chi_j}{\Delta y * \Delta t * W} \tag{2.6}$$

Where Δy is the length of the count area (so 0.4 meters), Δt is the time between the moments that cyclists $j = 1$ and $j = N$ cross line a, and χ_j is the distance that bicycle j travels through the count area during time period Δt.

2.2.3 Jam density

The jam density (JD) is a macroscopic characteristic that shows how densely packed the queue is. It is defined as the amount of cyclists per squared meter in the queue. When the cyclists are packed together closely, the jam density will have a higher value. It is calculated by Yuan et al. [2019] and Goñi-Ros et al. [2018], according to equation 2.7.

$$JD = k_j = \frac{N-1}{L * W} \tag{2.7}$$

Where N is the total amount of cyclists in the queue, W is the width of the cycle path, and L is given by equation 2.8.

$$L = d_N(t_0) - d_1(t_0) \tag{2.8}$$

Where $d_i(t_0)$ indicates the distance from the initial position of cyclist i to line a.

2.2.4 Shock wave speed

After the traffic light turns green, the cyclists in the queue change their state from standing still to accelerating. This change of state starts at the front of the queue and propagates as a wave backwards. The speed at which this wave travels is called the shock wave speed (SS) and is expressed in meters per second. It is supplied by Yuan et al. [2019] and Goñi-Ros et al. [2018] and is estimated by fitting a line (using linear regression) to the last point in the time-distance graph before bicycles $j = 1, ..., N$ start moving. The shock wave speed is then defined as the slope of this fitted regression line. For more information on the calculation method of the shock wave speed (or the discharge flow or jam density), refer to the sources.

2.3 FINDING RELATIONS

Finally, when the reaction times and bicycle flow characteristics are determined, the relations between them can be analysed. This is done for all the widths of the sub-lane method that are labeled reasonable, after the statistical comparison of methods (chapter 2.1.3). The analysis of relations consists of three steps. The first step is to use Pearson correlation coefficients to find out if reaction time on one hand, and the four bicycle flow characteristics on the other hand, have a significant relationship and how strong their correlation coefficient is. This gives a first impression of the relations between reaction time and the bicycle flow characteristics (sub-goal 5). Next, linear regression analysis shows how these relations exactly work. Equations can be derived to show how the variables are depending on each other. This should be enough information to analyse how reaction time influences bicycle flow characteristics one on one (sub-goal 6). Ultimately, to gain a more complete picture of how reaction time influences bicycle flow, a multiple regression analysis is executed. This shows how various characteristics may work together with reaction time to influence bicycle flow, and more specifically, how it influences discharge flow (sub-goal 7). After all, discharge flow is the most important flow characteristic in terms of traffic capacity of through movement, as was discussed in the introduction of this report. These three steps together gather enough information to derive a theory on how reaction time influences bicycle flow during queue discharge process at a signalized intersection (sub-goal 8 and accomplishing the main research goal).

2.3.1 Pearson correlation coefficient

The Pearson correlation coefficients between reaction time on one hand and the time headway, discharge flow, jam density and shock wave speed on the other hand are calculated using the $corrcoef$ function in MatLab. This function returns the correlation coefficient R and the p-value. The p-value is used for testing the hypothesis that there is no relationship between the variables (null hypothesis). If p is smaller than the significance level of 0.05, then the corresponding correlation coefficient R is considered significant. R can take any value between -1 and 1 and indicates how strongly correlated two variables are. A correlation coefficient of 1 indicates total positive linear correlation, -1 indicates total negative linear correlation and 0 means that there is no linear correlation at all. The Pearson correlation coefficient thus shows how linearly connected two variables are, and if this linear relationship is significant. This Pearson correlation method is based on equation 2.9 below.

$$\rho(A,B) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{\overline{A_i - \mu_A}}{\sigma_A}\right)\left(\frac{B_i - \mu_B}{\sigma_B}\right) \tag{2.9}$$

Where N is the number of data points, μ_A and σ_A are the mean and standard deviation of variable A (reaction time), and μ_B and σ_B are the mean and standard deviation of variable B (one of the four flow characteristics).

The p- and R-values are calculated between reaction time and the four flow characteristics, for the entire range of widths, with steps of 0.001. These values are then plotted on a graph to show how they vary over different implemented widths of the virtual sub-lane method. The p- and R-values are also calculated using the base method, for comparison purposes.

2.3.2 Linear regression analysis

The first step in the linear regression analysis is to plot the reaction times versus the four flow characteristics, using a scatter plot. Since (most) of the flow characteristics are macroscopic parameters, only one value per discharge cycle is available for analysis. This means that the microscopic reaction time (and time headway) need to be converted to a single value as well. As described in section 2.2.1, this is done by considering both the mean and median value per discharge cycle. Next, the scatter plots can be constructed and a linear relationship can generally already be observed (or not). However, just observing this is not enough. A closest estimate of the linear equation is also required to be able to do a proper analysis. This linear equation takes the form of equation 2.10 with β defined as in equation 2.11. α, the intercept, can be derived by filling in the equation for any known data point.

$$y = \alpha + \beta * x \tag{2.10}$$

$$\beta = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{2.11}$$

The linear regression lines are calculated and plotted using the $polyfit$ and $polyval$ functions in MatLab. An important aspect to pay attention to, is to make sure that reaction time is on the x-axis as the independent variable, and that the flow characteristic is on the y-axis as the dependent variable. This way the influence of reaction time on bicycle flow is tested and not the other way around.

2.3.3 Multiple regression analysis

Finally, to see how reaction time interacts with discharge flow and other flow characteristics, a multiple regression analysis is performed. The $curvefitting$ tool of MatLab is used to do so. The Lowess model within this tool makes sure that a smooth surface is fitted through the data points, by using locally weighted linear regression. The mean and standard deviation are both used to normalize the x- and y-data. In addition, the robustness setting is set to "bisquare" to minimize the effect of outliers. This method minimizes a weighted sum of squares, where the weight given to each data point depends on the distance between the point and the fitted line.

To test the goodness of fit of the fitted plane, four statistics can be derived: the Sum of Squares due to Error (equation 2.12), R-square (equation 2.13), Root Mean Squared Error (equation 2.16) and adjusted R-square (equation 2.15).

$$SSE = \sum_{i=1}^{n} w_i (y_i - \hat{y}_i)^2 \tag{2.12}$$

$$Rsquare = 1 - \frac{SSE}{SST} \tag{2.13}$$

Where SST is defined by equation 2.14.

$$SST = \sum_{i=1}^{n} w_i(y_i - \overline{y})^2 \tag{2.14}$$

For the SSE, a value closer to 0 is preferred as this indicates that the model has a small random error, and that the fit will therefore be more accurate and useful for prediction. The R-square can take any value between 0 and 1, but a value closer to 1 is preferred. However, the R-square is not always reliable which is why it is better to use the adjusted R-square as given in equation 2.15. This adjusted R-square is based on the residual degrees of freedom (v), which is defined as the number of response values n minus the number of fitted coefficients m estimated from the response values. So $v = n - m$. This allows for the calculation of the adjusted R-square and RMSE below.

$$adjustedRsquare = 1 - \frac{SSE(n-1)}{SST(v)} \tag{2.15}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{SSE}{v}} \tag{2.16}$$

The adjusted R-square can take any value less than or equal to 1, but a value closer to 1 is preferred, as this indicates a better fit of the plane. Just like with the SSE, a MSE value closer to 0 indicates a better fit and a regression model that is more useful for prediction.

3 RESULTS & DISCUSSION

This chapter discusses the results that were obtained in two separate sections. The first section shows the results of the comparison between the base method and varying widths of the virtual sub-lane method. Statistics are used to find a reasonable range of implemented widths. The second section discusses the results of finding relations. This section is divided up into three parts: the Pearson correlation coefficients, simple linear regression and multiple regression analysis. Finally, after all relations are obtained and interpreted, a revision is done on the range of reasonable widths. Furthermore, a final conclusion is drawn and the answer to the main research goal is given.

3.1 REACTION TIME CALCULATION

For both the base method and virtual sub-lane method, the reaction times were calculated. These reaction times were used to construct a histogram and to fit several distribution functions. Figure 3.1 shows such a histogram, for the virtual sub-lane method with a cyclist width of 1.4 meters. The histograms and fitted distributions for the other widths and for the base method are given in Appendix B. As can be seen in these histograms, the logistic and t-location scale distributions seem to be well fitting estimations, which have a somewhat similar shape as the normal distribution, but they are known for having heavier tails. This means that the data set might have a lot of outliers.

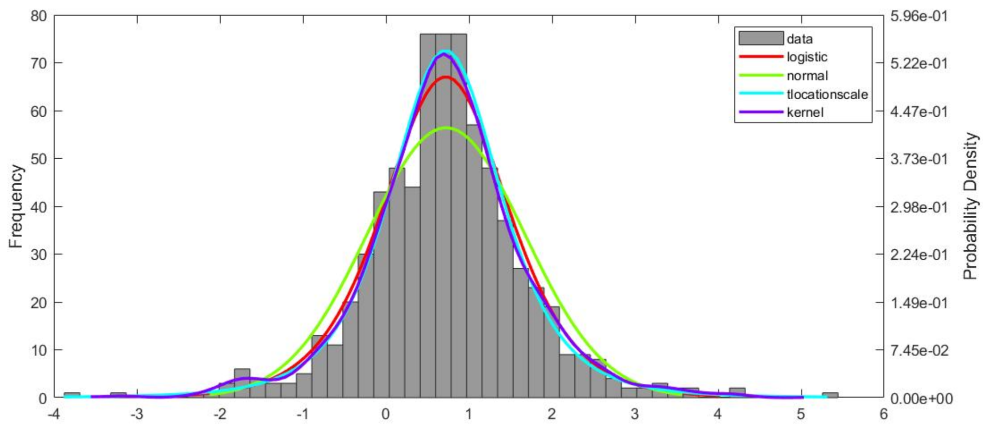

Figure 3.1: The histogram of reaction times for the sub-lane method with a implemented width of 1.0 meters. The kernel distribution function is fitted, along with the normal, logistic and t-location scale distribution functions.

Method		Mean reaction time [s]	Amount of negative reaction times [%]	Amount of traffic light based reaction times [%]	Quantiles				
					0.025	0.25	0.50	0.75	0.975
Base method		0.3104	29.64	8.17	-1.804	-0.191	0.337	0.862	2.255
Sub-lane method	**w=0.5**	1.1173	11.63	37.53	-1.025	440.1	0.968	1.688	4.081
	w=0.6	1.0046	12.19	32.27	-1.053	0.368	0.891	1.573	3.648
	w=0.7	0.8939	13.30	27.70	-1.156	0.305	0.811	1.407	3.025
	w=0.8	0.8382	13.85	26.18	-1.245	0.263	0.787	1.366	2.874
	w=0.9	0.7665	14.82	23.55	-1.303	0.210	0.749	1.285	2.742
	w=1.0	0.7231	15.51	22.30	-1.366	0.188	0.708	1.213	2.659
	w=1.1	0.6866	15.93	20.36	-1.446	0.177	0.675	1.192	2.659
	w=1.2	0.6569	16.48	19.53	-1.366	0.166	0.646	1.155	2.581
	w=1.3	0.6341	17.04	18.70	-1.446	0.153	0.623	1.133	2.581
	w=1.4	0.6006	17.45	18.01	-1.312	0.122	0.595	1.088	2.558
	w=1.5	0.5823	17.87	17.31	-1.312	0.024	0.584	1.073	2.515

Table 3.1: Statistical characteristics of the results of the different reaction time calculation methods.

Next, several statistical properties were derived from these reaction times and an overview of these statistics is given in table 3.1. The table shows the mean reaction times, percentage of reaction times that have a value lower than zero, the percentage of reaction times that were based on the traffic light turning green and several quantiles. These results are also presented in figure 3.2, with the implemented width on the x-axis, varying from 0.5 to 1.5 with steps of 0.01.

Table 3.1 and figure 3.2 show that the mean reaction time seems to drop exponentially with increasing implemented width. This makes sense, as an increasing width means that less of the reaction times are based on the traffic light (which are generally slow reactions), and more of the reaction times are based on cyclists to the side (”neighbours”) who should actually not be considered predecessors. The base method has the lowest mean reaction time of all, as was expected. With an increasing width, the amount of negative reaction times increases linearly and the amount of traffic light based reaction times decreases exponentially. This can be seen clearly in the figure (3.2), and the big difference between the base method and virtual sub-lane method is also noticeable. In fact, all implemented widths show a lower percentage of negative values than the base method. This is considered an improvement, because negative reaction times are theoretically incorrect. The virtual sub-lane method however still contains negative values. This can be explained by the fact that followers are not only reacting to their respective leader, but can also react to a group of cyclists, the traffic light changing to green, or a combination of those. This tells us that the virtual sub-lane method is not perfect, but it certainly is a big improvement compared to the base method.

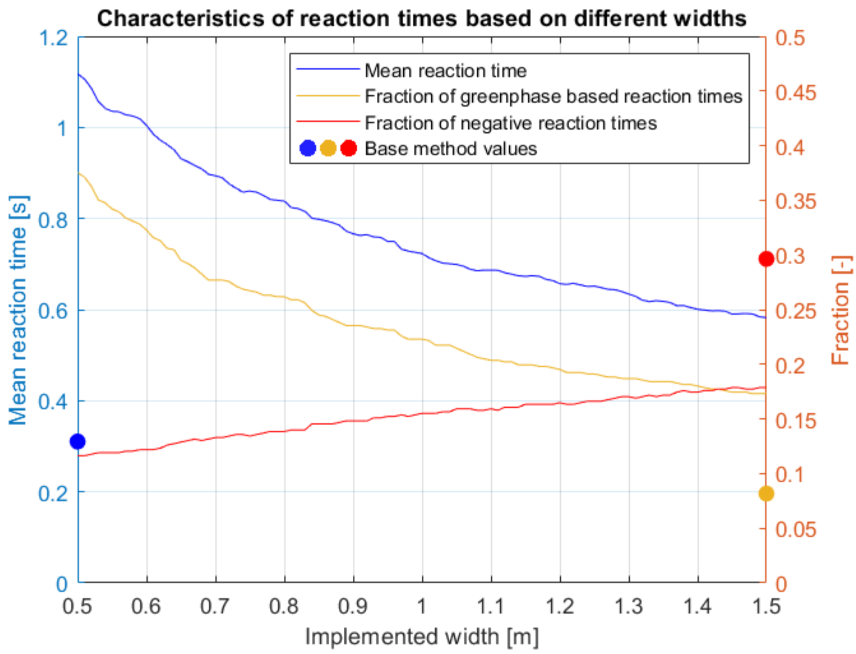

Figure 3.2: The mean reaction time, fraction of greenphase based reaction times and the fraction of negative reaction times based on different widths for the virtual sub-lane method. These values are also given for the base method, indicated by the colored circle on the y-axes.

The results of the statistical values are as expected, and they indeed behave like was described in chapter 2.1.3. With these results, the range of cyclist widths can be reviewed, using the predetermined set of criteria. The first criteria was that the mean reaction time of all implemented widths should be lower than the mean reaction time of the base method, all widths seem to meet this first criteria. The second rule was that the amount of negative reaction times has to be lower than 17%. After rounding off, this means that the upper limit of the reasonable range changes from 1.5 meters to 1.3 meters. Finally, the third criteria, saying that the amount of traffic light based reaction times must be between 17% and 33%, changes the lower limit of the range to 0.6 meters.

The reasonable interval of cyclist widths has therefore changed to 0.6-1.3 meters. This new range will thus be used in the further analysis of this research. This interval can be narrowed down more after the relations with bicycle flow characteristics become clear and more information is learned.

Another interesting result that was noticed in some of the analysis graphs, was that reaction times close to zero are barely present, while reaction times of exactly zero are very common. After several attempts to try and explain this behaviour, the reason was brought down to a combination of how reaction time is calculated and of the varying frame rate of the cameras. A proof and explanation of this phenomena is given in Appendix C.

Figure 3.3: The p-values derived with the Pearson correlation coefficient method. This plot shows the p-values for each relation between reaction time and the flow characteristics. The p-values are given on the y-axis and the implemented virtual sub lane widths are given on the x-axis, ranging from 0.6 to 1.3 with steps of 0.001. The marked circles on the right y-axis represent the values for the base method.

3.2 RELATIONS

This section discusses the influence and interaction between reaction time and bicycle flow characteristics. These relations are discussed in three different sections. First, the Pearson correlation coefficients are shown, next the linear regression analysis is examined, and finally the multiple regression analysis is discussed.

3.2.1 Pearson correlation

The Pearson correlation coefficients give an initial insight in the relations between reaction time and the four bicycle flow characteristics. These coefficients were computed for widths between 0.6 and 1.3 meters with steps of 0.001 meter, to make sure that the graphs are sufficiently smooth and accurate. Figure 3.3 shows the p-values for each of the tested relations, varying over the cyclist width. Some of these p-values range quite widely between 0 and 1, while the significance value is only 0.05. Figure 3.4 shows the same plot once more, but now with a limit on the y-axis so that the p-values within the significance range can be taken a closer look at. Lastly, the correlation coefficients, indicated by R, are shown in figure 3.5.

The first thing that can be derived from these figures, is that using the median for converting the microscopic parameters to a macroscopic inter-

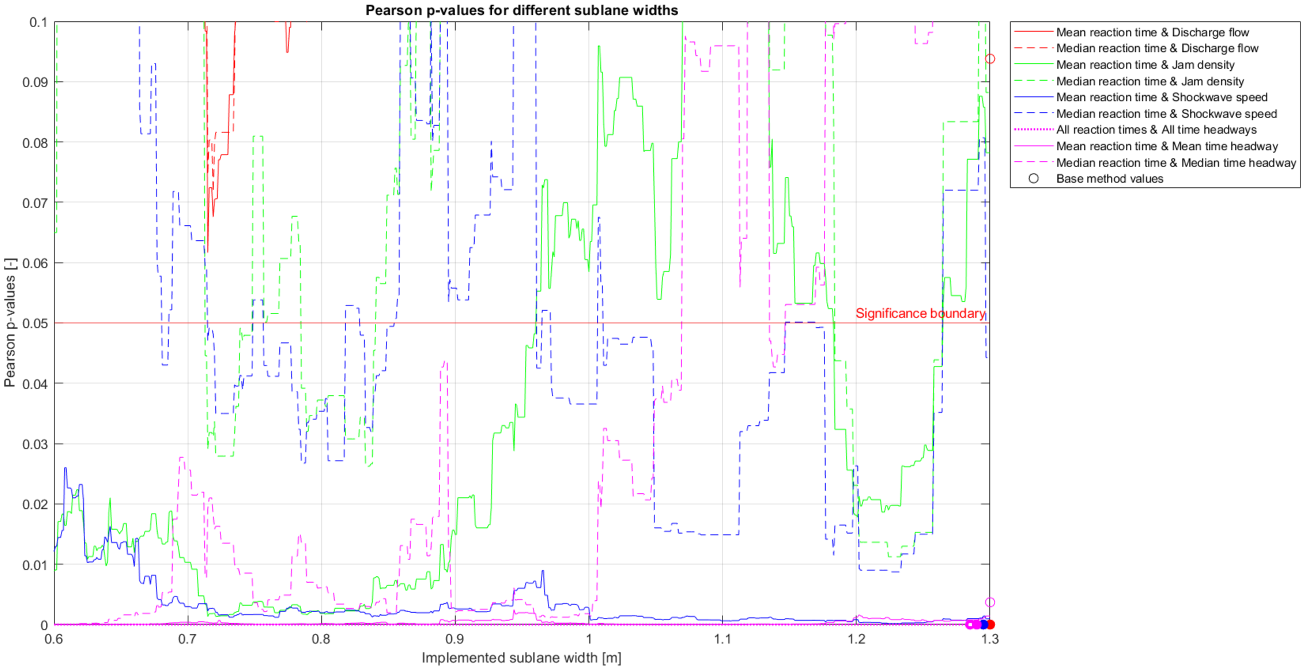

Figure 3.4: The same plot of the p-values once more, but now with a y-limit of 0.1.

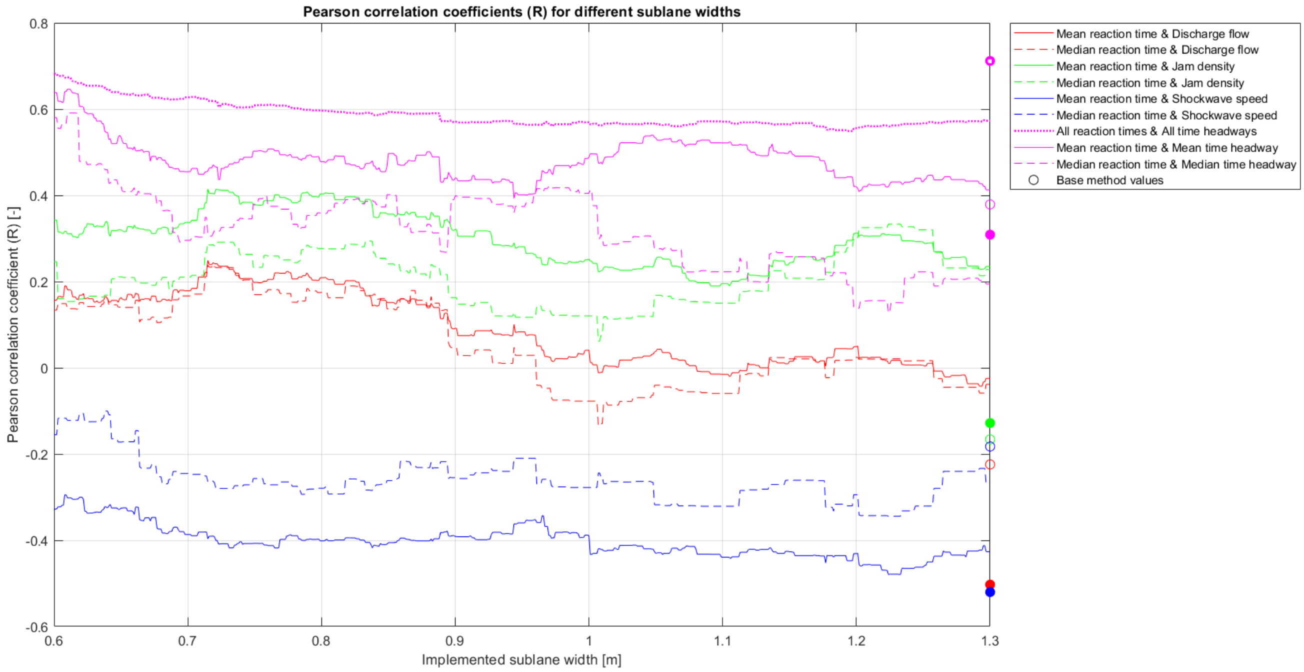

Figure 3.5: The correlation coefficients derived with the Pearson correlation coefficient method. This plot shows the R-values for each relation between reaction time and the flow characteristics. The R-values are given on the y-axis and the implemented virtual sub lane widths are given on the x-axis, ranging from 0.6 to 1.3 with steps of 0.001. The marked circles on the right y-axis represent the correlation coefficients for the base method.

pretation is not the best way. Both the p-values and R-values for almost any relationship calculated with the median, is fluctuating drastically and considered very unstable. Especially when looking at the p-value of the median of reaction time on one hand and jam density, shock wave speed or time headway on the other hand, can it be seen that this approach is indeed fluctuating a lot. Therefore, is it better not to use this median approach to derive results from, and is it better to use the mean value instead. This mean value approach is much more stable and yields more significant relationships than the median one. Thus, will the median no longer be used to convert a microscopic variable to a macroscopic one. Only the mean value will be used to derive relationships, from here on. The reason for this big difference might be explained by that the mean is a weighted average of all the values in a discharge cycle, and might represent the discharge cycle in a better way than the median, which is just a single data point that can be very different in every discharge cycle.

Now looking at the mean results, another thing that can be noticed right away is that, surprisingly enough, the p-value between reaction time and discharge flow is very high. Apparently, reaction time and discharge flow do not have a significant one on one linear relationship, for any of the widths at all. The corresponding R-value is also very low (0.2) and decreases even further down to zero as a larger width is applied. This indicates that reaction time and discharge flow do not have a linear one on one relationship. However, there could still be a nonlinear relationship, or a multiple regression analysis could also give somewhat different results.

The relation between reaction time and jam density is significant for most of the implemented widths. Only between widths 0.96 and 1.18, is the p-value slightly above the significance boundary. Also for widths of 1.27 meters and up is the p-value greater than 0.05. The p-value of the base method seems to be a lot higher and shows that a large cyclist width does not give good results. The correlation coefficient R, fluctuates a bit around +0.3. This means that jam density and reaction time are slightly linearly correlated, but there is also still a lot of variation.

The relation between reaction time and shock wave speed is significant for all the range of widths and is even significant when applying the base method. The correlation coefficient shows weak negative correlation (around -0.4), meaning that when reactions are quick (and thus have low values), that the shock wave speed tends to be large. This result makes sense, because having a quick mean reaction means that the cyclists in the queue will change quickly from standing still to accelerating and thus would the shock wave speed be high. For the correlation between reaction time and shock wave speed it does not seem to matter which width or method is applied to calculate reaction times, because the p- and R-values are practically constant over the entire range of widths and even for the base method.

The most significant relation turns out to be the one between reaction time and time headway. The correlation is considered significant over the entire range of widths and also with the base method. This is true for both the microscopic and the macroscopic (mean) approach. The correlation is also relatively strong with values between 0.4 and 0.7, meaning that with a quick reaction, the time headway will generally also be shorter. This is a promising result, because it could indicate that reaction time plays an important role in the traffic capacity of through flow. However, further analysis needs to be done before conclusions can be drawn.

Looking at the relationship between reaction time and time headway, there is another thing that can be noticed. The microscopic approach seems to give much better results than the macroscopic approach. This is true for both the p-value and the R-value. This could be explained by that the microscopic approach compares each cyclist's reaction time and headway one on one. With a macroscopic approach, the mean value of both variables is compared. This might give certain problems, for example outliers can change the mean value greatly and therefore have a big impact on the correlation coefficient. Considering that a logistic and t-location scale distribution were found when constructing the histograms, outliers might be present in relative large numbers. Thus, when possible, it would be better to use the microscopic approach rather than the macroscopic approach to find relationships.

A final remark on the results of the Pearson correlation coefficients, is that the best results regarding the p- and R-values, lie between a width of 0.7 and 0.9 meters. The p-values seem to be lowest in this region and the R-values seem to be highest. This does not necessarily mean that this is the best range of widths, but it is a promising result. Further analysis would need to make clear whether this is indeed the range that could be considered the most reasonable, or at least yield the best results when relating reaction time with bicycle flow.

3.2.2 Linear regression analysis

The linear regression discusses several plots. Each one of these plots shows the results of the linear regression analysis with reaction time on the x-axis and one of the four bicycle flow characteristics on the y-axis. Notice that in agreement with the discussion of the Pearson correlation results, the macroscopic representation of reaction time is now only based on the mean value and not on the median.

Figures 3.6 and 3.7 show the linear regression results of the microscopic and macroscopic approach respectively, between reaction time and time headway. The high correlation that was found before between these variables, can now indeed be confirmed. The scatter plots both show a clear linear pattern and the fitted lines for each of the widths all show a similar relation. An increase of 1 second in mean reaction time would generate an increase of time headway approximately between 0.7 and 1.1 seconds. This of course depends on the width that is implemented as can be seen in the linear regression equations (in the top left corner of the figures). These results seem reasonable, and they also agree with the results of the Pearson correlation analysis.

The correlation coefficients clearly showed that a linear one on one relationship between reaction time and discharge flow is non existent. The linear regression plot of figure 3.8 only confirms this result. The regression lines do not seem to agree on a certain linear pattern, and the data points of the scatter plot itself also reveal that a linear relationship does not exist between

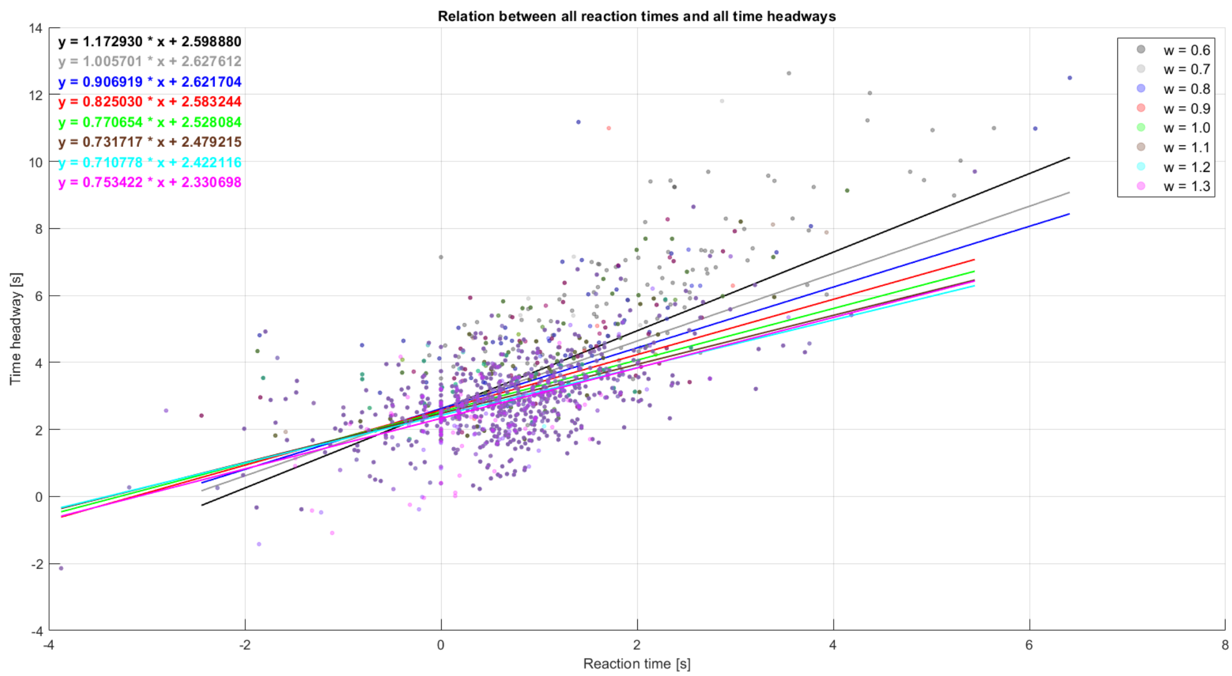

Figure 3.6

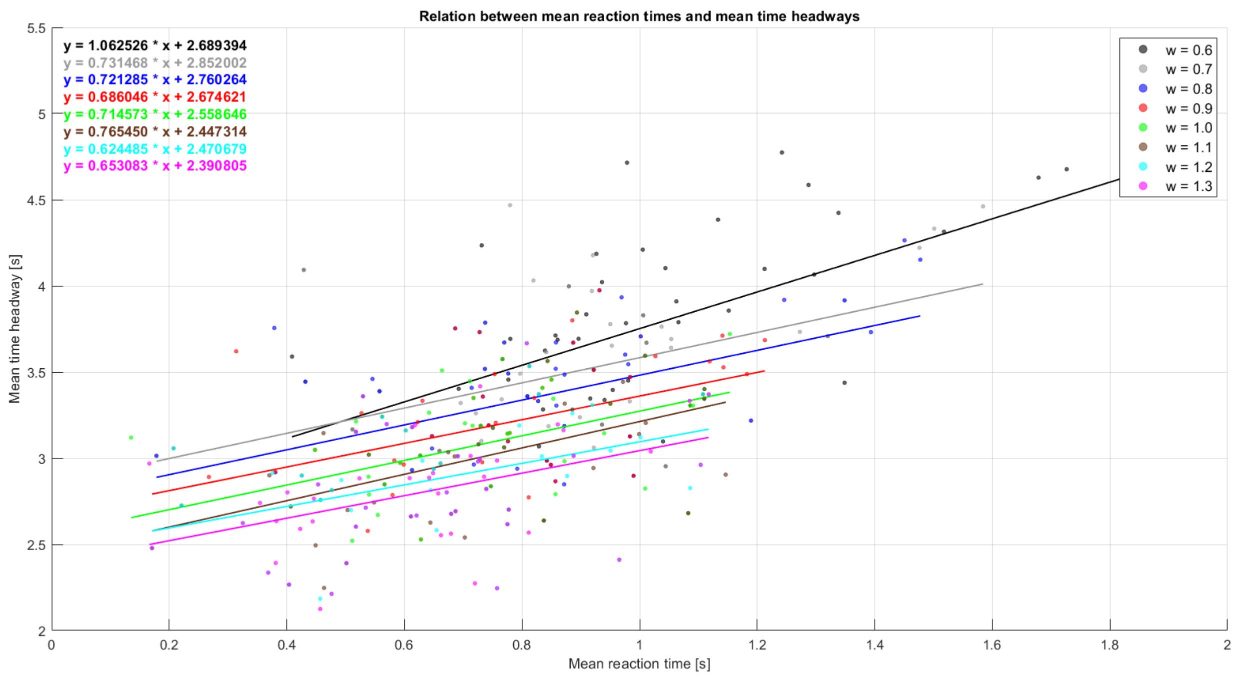

Figure 3.7

these variables. Which leaves only the multiple regression analysis to find any relation between reaction time and discharge flow.

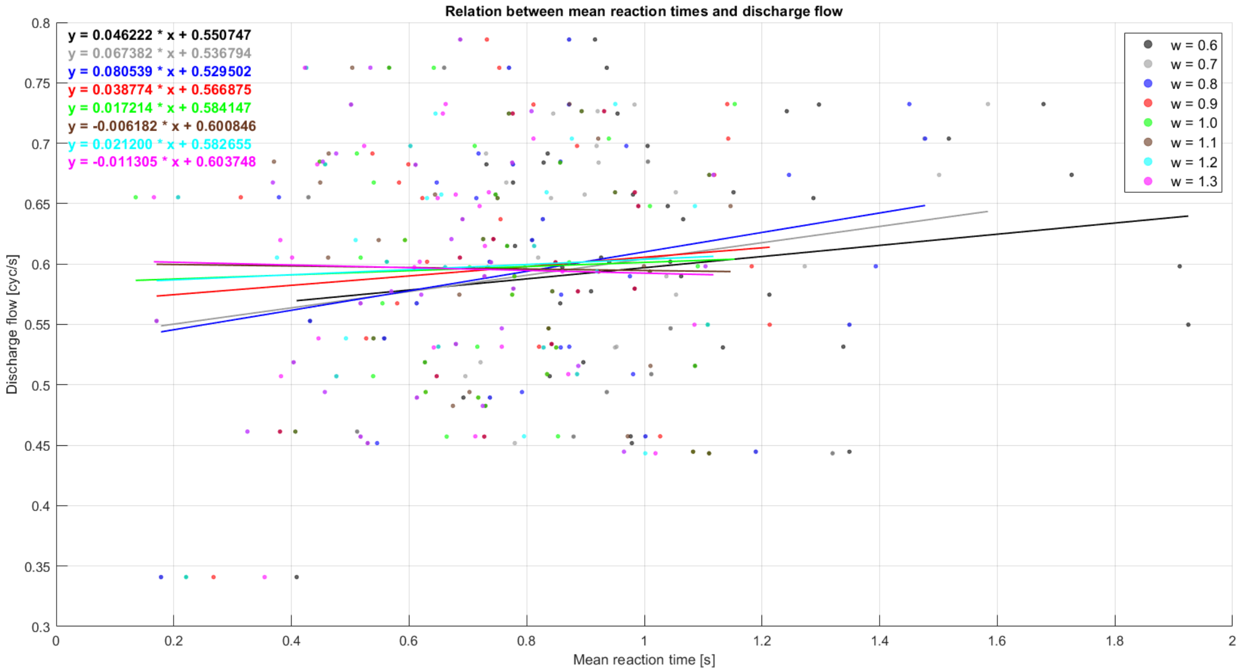

Figure 3.8

The results of the linear regression analysis between reaction time and jam density are given in figure 3.9. A linear relation cannot clearly be seen just based on the data points of the scatter plot, this can however also be caused by the mix of data points of the different implemented widths. The regression lines for all widths do however agree in a positive relationship, which is also in agreement with the Pearson correlation coefficients. An increase of 1 second in mean reaction time would approximately cause an increase of 0.07 to 0.12 cyclists per squared meter in jam density. However, this interpretation does not make sense, as jam density is already defined before cyclists can even have a reaction at all. The causal order between these variables could also be the other way around. A higher jam density could also be the reason for reaction times to become larger. A very busy cycling path would leave less space for a cyclist to overtake after the traffic light turns green. This would force the cyclist to wait until there is enough space to move, and delay his reaction time. The causal order in this relation thus makes more sense the other way around.

Finally, figure 3.10 shows the plot with the results of the linear regression analysis between reaction time and the shock wave speed. These results also agree with the results of the correlation coefficients, and show a clear negative relation between reaction time and shock wave speed. The equations show that an increase of 1 second in mean reaction time would yield a decrease in shock wave speed of approximately 1.8 to 2.4 meters per seconds. This makes sense because the reaction time of every cyclist in a queue would increase by 1 second and this can easily cause a decrease of about 2 meters per second in shock wave speed.

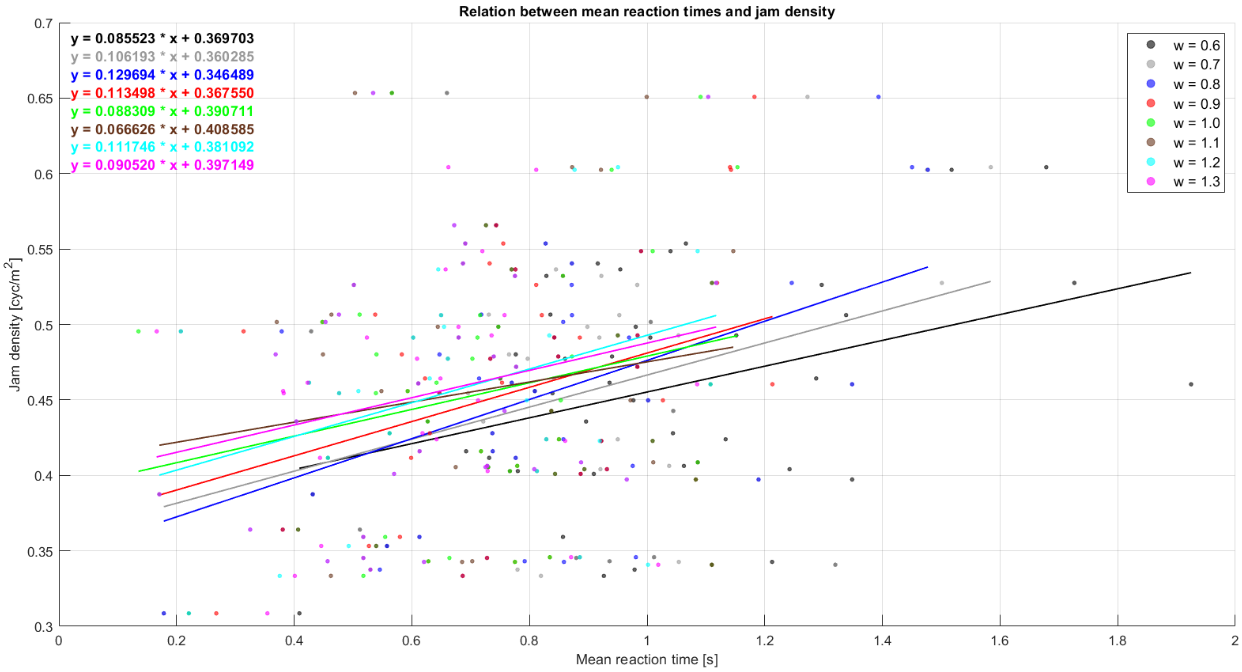

Figure 3.9

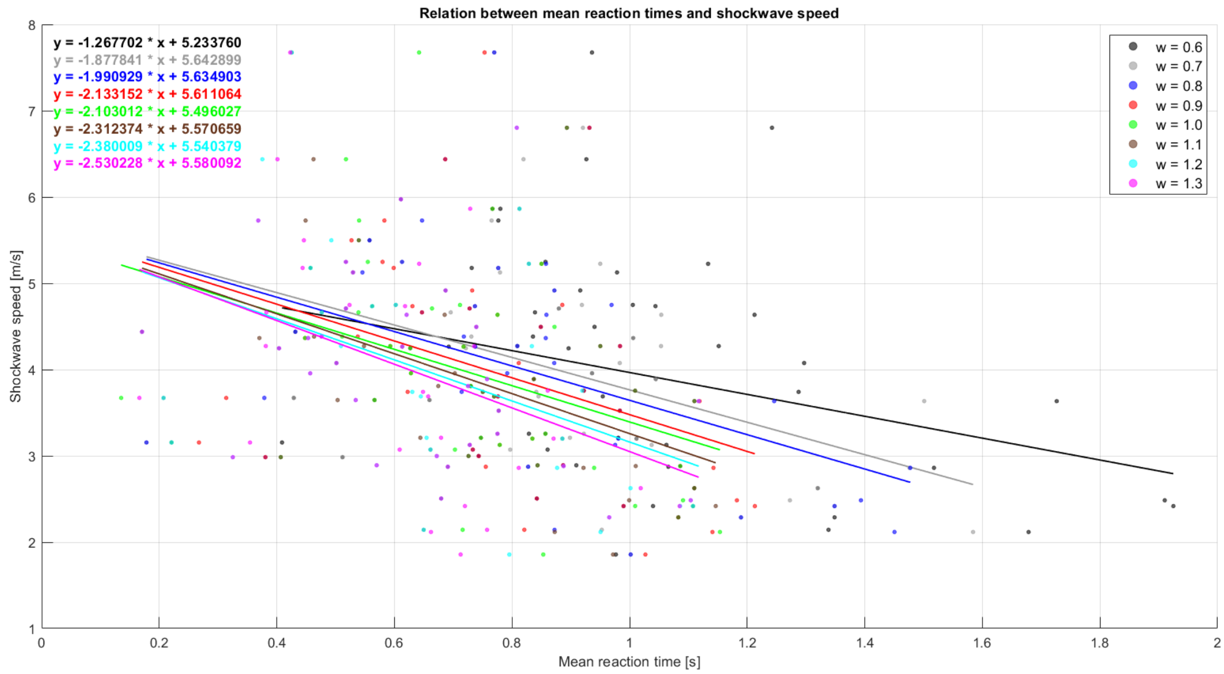

Figure 3.10

One thing that can be noticed in almost all of the figures above is that generally speaking, widths of 0.7 and 0.8 meters yield almost the same results in every comparison. Widths between 0.9 and 1.3 meters also seem to form a group that show very similar results. This is an interesting observation considering that the width between 0.7 and 0.9 meters showed the best results in the Pearson correlation analysis.

Another thing that can be noticed in all of the figures above, is that the width of 0.6 meters seems be very off with the rest of the results. The regression line based on a width of 0.6 meters seems to yield very different results than the rest of the widths. This is probably caused by a higher amount of outliers. These outliers tend to be reaction times with large values, which is most probably caused by the high percentage of reaction times that are based on the traffic light turning green. This regression analysis therefore shows that a width of 0.6 meters does not give the best results. The lower limit of the range of reasonable widths is therefore change from 0.6 meters to 0.7 meters from this point onward.

3.2.3 Multiple regression analysis

The last analysis of this research is the multiple regression analysis. The reaction time has been combined with each of the characteristics time headway, jam density and shock wave speed to find if any of these combinations have a relation with the discharge flow. However, the combinations of reaction time on one hand with time headway and shock wave speed on the other hand, did not yield any results of interest. But the combination of reaction time and jam density did show some very clear relation with discharge flow. The 3D scatter plots for reaction time on the x-axis, jam density on the y-axis and discharge flow on the z-axis were computed for each of the widths varying between 0.7 and 1.3 meters. Next, the fitting planes according to the method described in chapter 2.3.3 were plotted. Finally, the goodness of fit results were computed for each relevant width, they are given in table 3.2. As can be seen from this table, the RMSE is very close to 0 and the adjusted R-square is also approaching 1, which means that fitted plane describes the relation between these variables quite well, for all cyclist widths. The width of 0.8 meters does seem to be the best fit, this result is given in figure 3.11. The plots of all other widths are given in Appendix D.

Width	SSE	R-square	RMSE	Adj R-square
0.7	0.1862	0.6492	0.0627	0.5855
0.8	0.1707	0.6784	0.0600	0.6201
0.9	0.2008	0.6217	0.0651	0.5531
1.0	0.1824	0.6564	0.0620	0.5941
1.1	0.2082	0.6078	0.0663	0.5366
1.2	0.2156	0.5939	0.0674	0.5202
1.3	0.2014	0.6206	0.0652	0.5518

Table 3.2: The goodness of fit results for each reasonable width in the multiple regression analysis of reaction time and jam density vs. discharge flow.

The relations between reaction time on one hand and three of the four bicycle flow characteristics on the other hand were already identified with the Pearson correlation coefficients and simple linear regression analysis. These relations are all significant, and they are all one on one relations. Such a linear relationship between reaction time and discharge flow could not be found. The multiple regression analysis however, shows that a combination

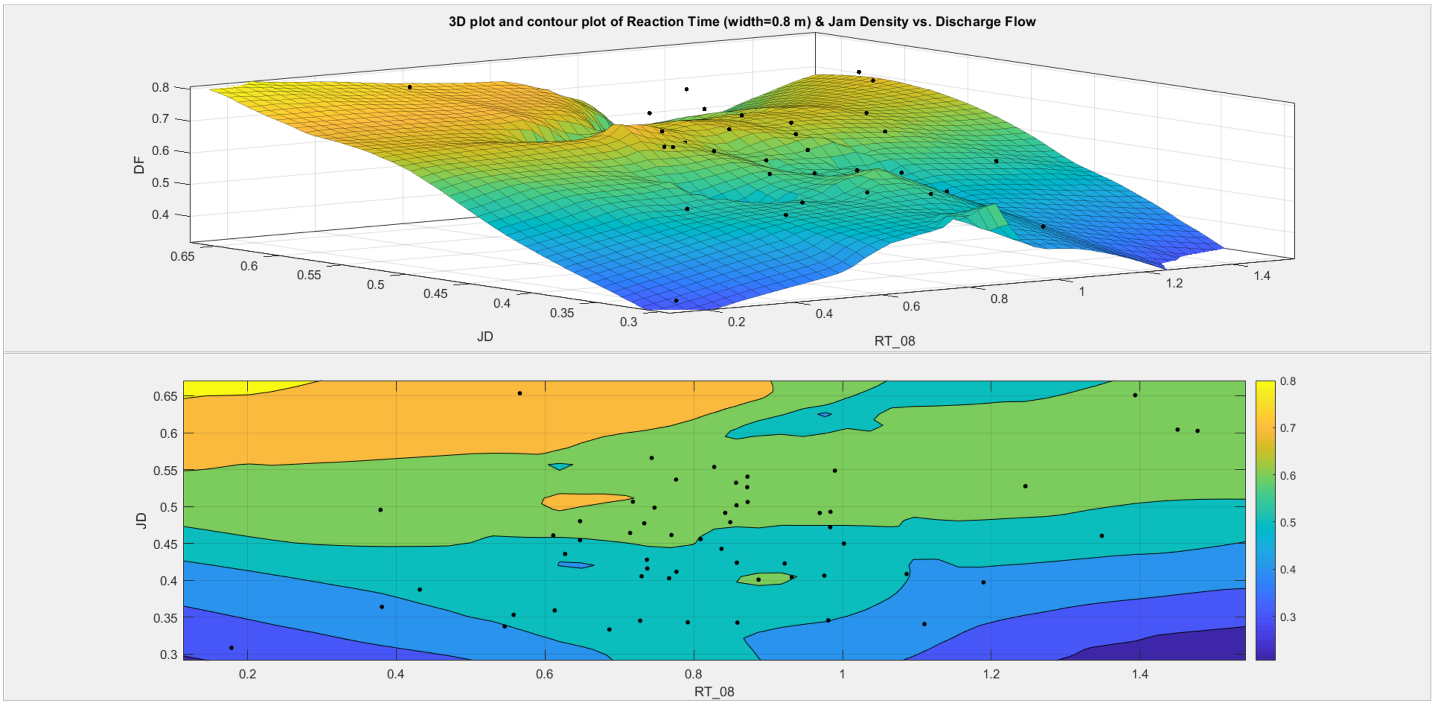

Figure 3.11

of a low reaction time and a high jam density, together cause a high discharge flow (as can be seen in figure 3.11. This means that a discharge cycle with a high jam density and a low mean reaction time, causes the cyclists in the queue to discharge quickly. This also means that encouraging cyclists on a cycle path to queue in a dense manner and to find a way to decrease their reaction time, can increase the traffic capacity of through flow.

4 CONCLUSION

The aim of this research consisted of two parts. The first part was to compare reaction time calculation methods and to find the most reasonable range of widths for the implementation of the virtual sub-lane method. The second part was to map the influence of reaction time on bicycle flow. Bicycle flow was then expressed as four flow characteristics: time headway, discharge flow, jam density and shock wave speed. Discharge flow was considered the most important of these characteristics, because this is the best variable to describe the traffic capacity of through flow. Now that all these analyses are finished and all information is gathered, a conclusion can be drawn on both parts of the aim of this research.

A reasonable range of widths started off with 0.5 to 1.5 meters, based on statistics was it brought down to 0.6 to 1.3 meters. Next, the Pearson correlation method helped to narrow it down slightly more to 0.7 to 1.3 meters. What was also noticed in the results of the Pearson correlation analysis, was that the widths between 0.7 and 0.9 meters yielded the best results. Later, during the multiple regression analysis, the width of 0.8 meters gave the best fitted plane. For these reasons, 0.8 meters is defined as the "ideal" width to calculate reaction times with the virtual sub-lane method. This does not mean that 0.8 meters should always blindly be used for every situation. Any width between 0.7 and 1.3 meters is considered reasonable and the "ideal" width depends on the purpose and calculation method. However, for this research, 0.8 meters is defined as the most reasonable width to calculate reaction times with the sub-lane model.

Now that the width of 0.8 meters has been defined as the ideal width for this research, it can be used to express the influence of reaction time specifically on each of the flow characteristics that define bicycle flow. Equation 4.1 shows how reaction time influences time headway, equation 4.2 shows how reaction time influences jam density and equation 4.3 shows how reaction time influences shock wave speed. The causal relation between reaction time and jam density can however better be reversed, as is discussed in section 2.3.3.

$$h = 0.907 * t_R + 2.62 \tag{4.1}$$

$$JD = 0.130 * t_R + 0.346 \tag{4.2}$$

$$SS = -1.991 + t_R + 5.635 \tag{4.3}$$

Finally, the influence of reaction time on discharge flow cannot be expressed with an equation. However, the multiple regression analyses clearly showed that a lower reaction time causes a higher discharge flow, when combined with a high jam density. This means that if the traffic capacity of through flow of a bicycle path at an intersection needs to be increased, the recommendation would be to install countdown timers, so that cyclists can anticipate on the green light and decrease their reaction time. When this measure is combined with psychological tricks to motivate cyclists to queue in a denser way, this would indeed increase the traffic capacity of through flow.

Furthermore, the recommendation for further research would be to develop a new method that determines reaction times in an even more accurate way. Although, the virtual sub-lane method is a big improvement over the base method, it is still not ideal as it still generates a significant amount of negative reaction times, which is physically speaking incorrect. An improved method could be based not on one single predecessor, but perhaps on a group of predecessors which each have a certain weight, based on the distance and based on how much the predecessor is directly in front or more to the side (x-coordinates). The traffic light could also be taken into account in this method, where the weight could be based on the distance from the stop line. A triangular shaped area to define predecessors could also be used rather then a sub-lane, to simulate the field of view. In case a complete new data set is created for new research, my recommendation would be to use a camera with a constant and high amount of frames per second. Furthermore, I would also recommend to collect more data and use a microscopic approach to find relations rather than a macroscopic one.

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Appendices

A APPENDIX 1: ALL INITIAL POSITIONS

The figure below shows the initial positions of all the cyclists from all the discharge cycles. As can be seen, a number of cyclists queue just next to the cycle path, which explains why the x-coordinates vary slightly more than 2 meters. The horizontal black line at $y = 28.7m$ indicates the stop line.

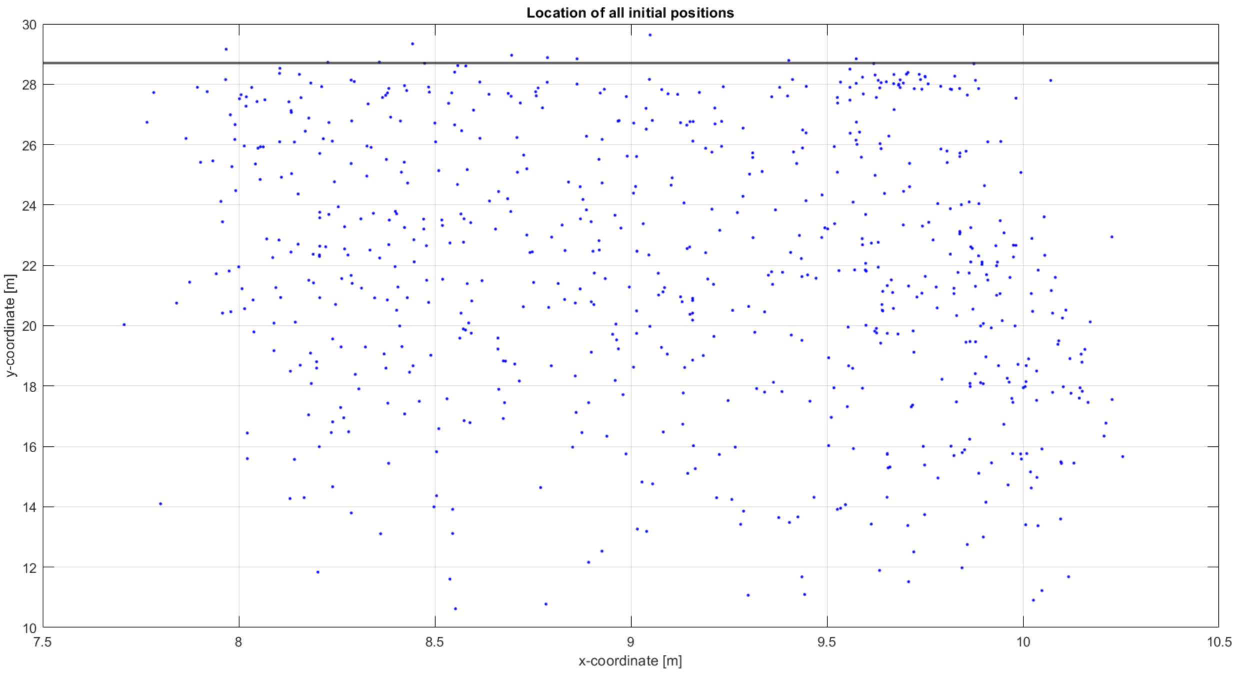

Figure A.1: The initial positions of all cyclists in terms of x- and y-coordinates.

B APPENDIX 2: ALL HISTOGRAMS OF REACTION TIMES

The histograms below show the distributions of reaction times for the different applied methodologies.

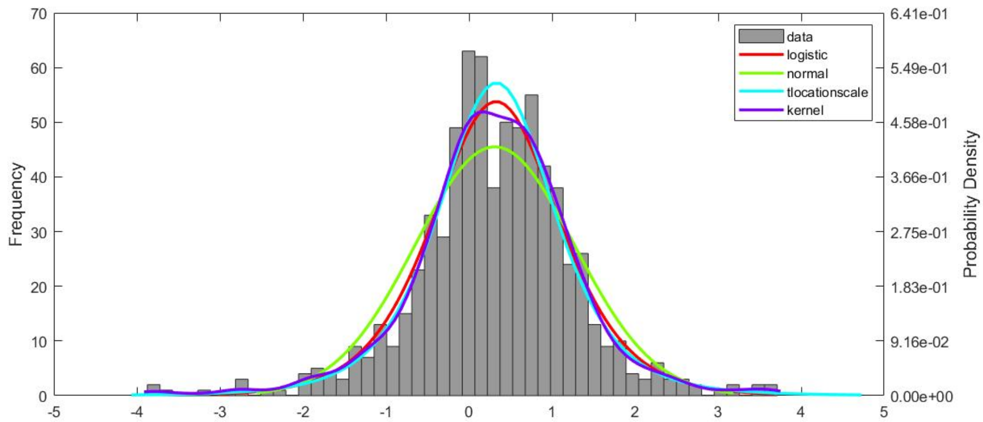

Figure B.1: The histogram of reaction times for the base method.

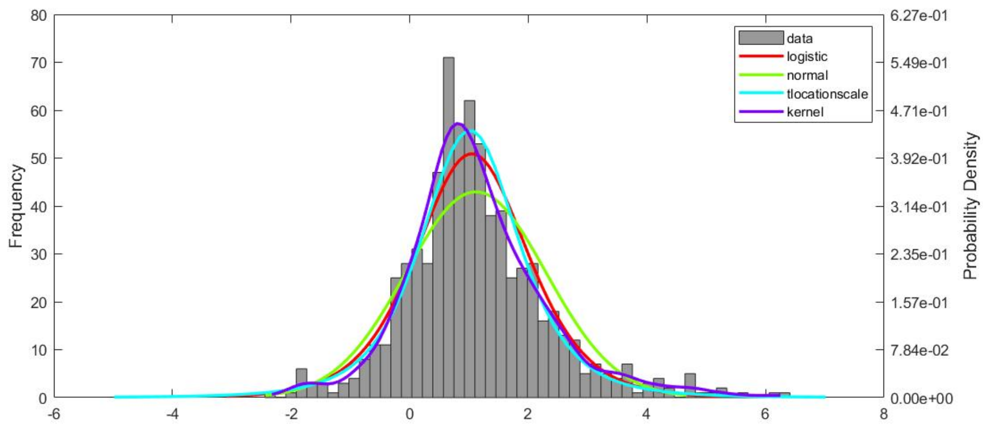

Figure B.2: The histogram of reaction times for the sub-lane method with a implemented width of 0.5 meters.

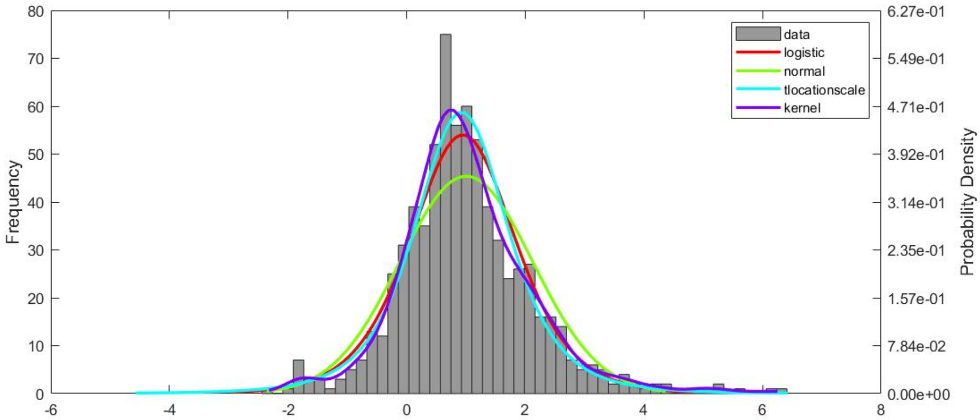

Figure B.3: The histogram of reaction times for the sub-lane method with a implemented width of 0.6 meters.

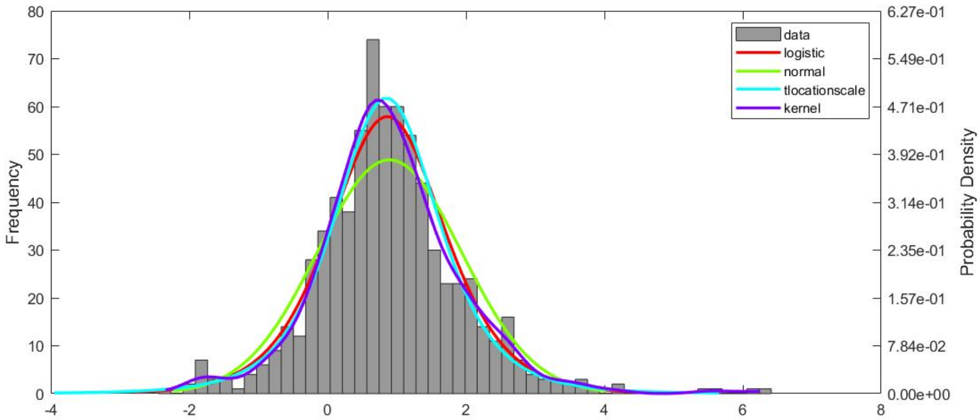

Figure B.4: The histogram of reaction times for the sub-lane method with a implemented width of 0.7 meters.

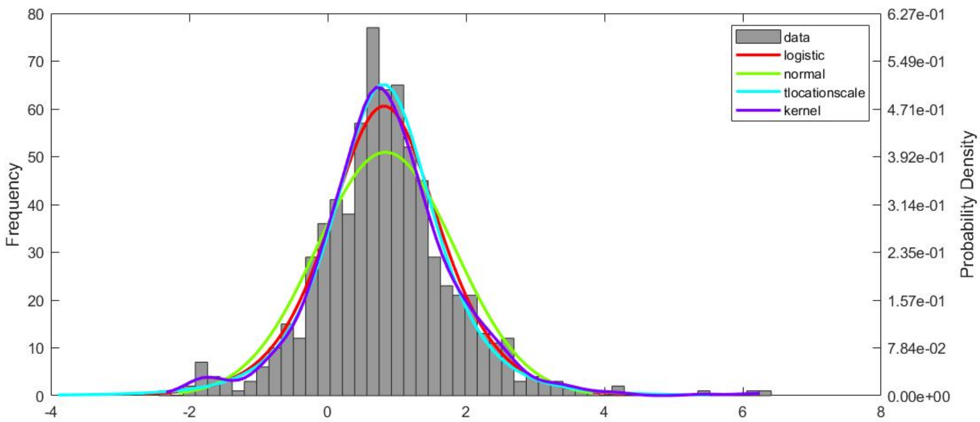

Figure B.5: The histogram of reaction times for the sub-lane method with a implemented width of 0.8 meters.

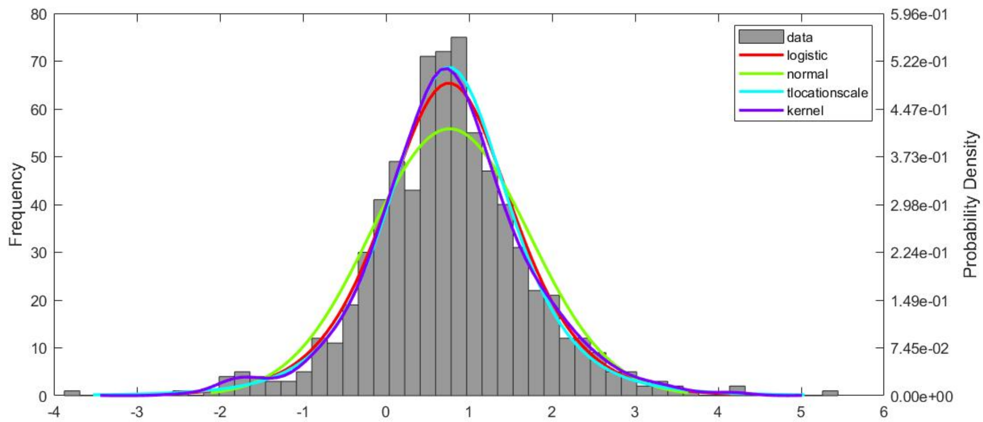

Figure B.6: The histogram of reaction times for the sub-lane method with a implemented width of 0.9 meters.

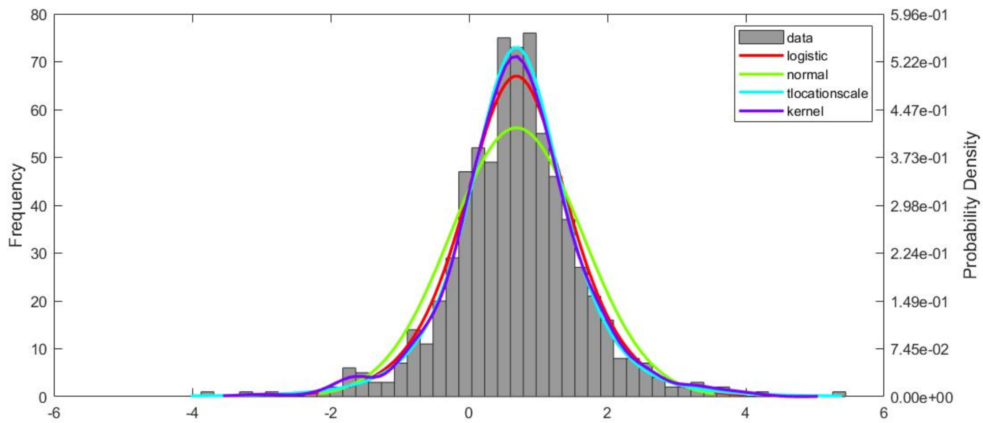

Figure B.7: The histogram of reaction times for the sub-lane method with a implemented width of 1.1 meters.

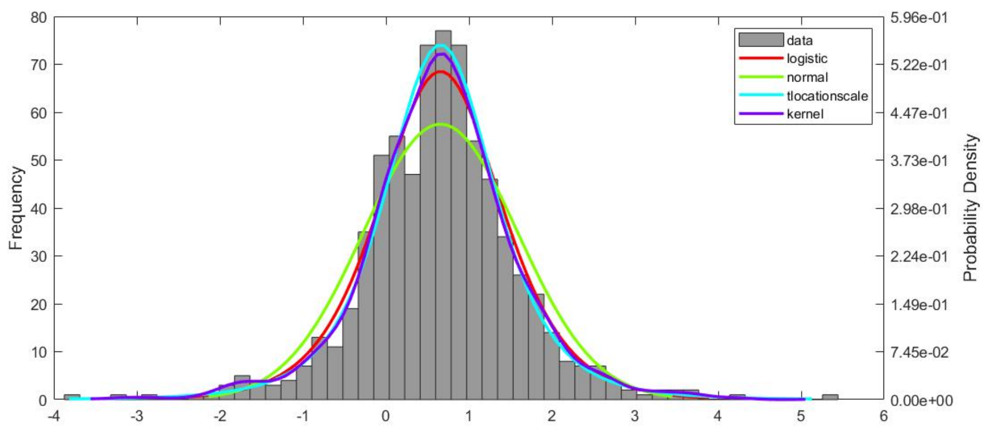

Figure B.8: The histogram of reaction times for the sub-lane method with a implemented width of 1.2 meters.

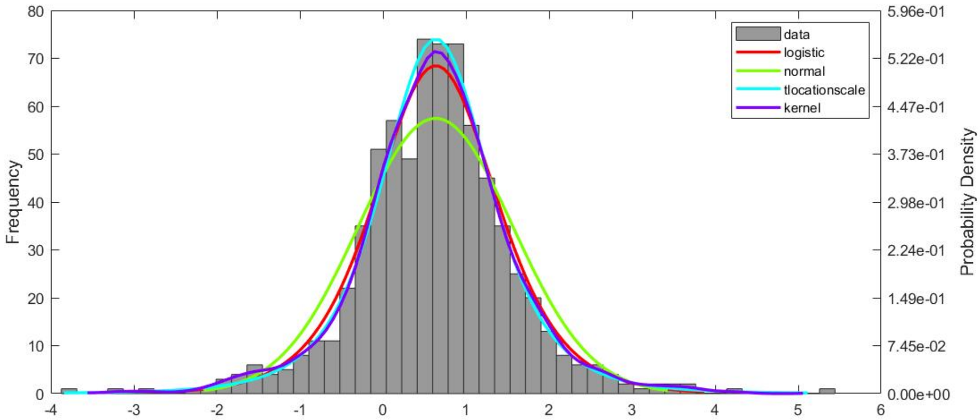

Figure B.9: The histogram of reaction times for the sub-lane method with a implemented width of 1.3 meters.

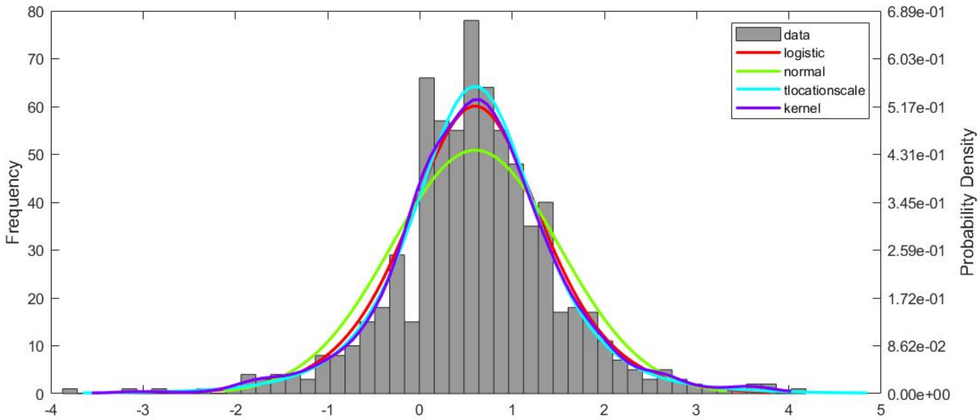

Figure B.10: The histogram of reaction times for the sub-lane method with a implemented width of 1.4 meters.

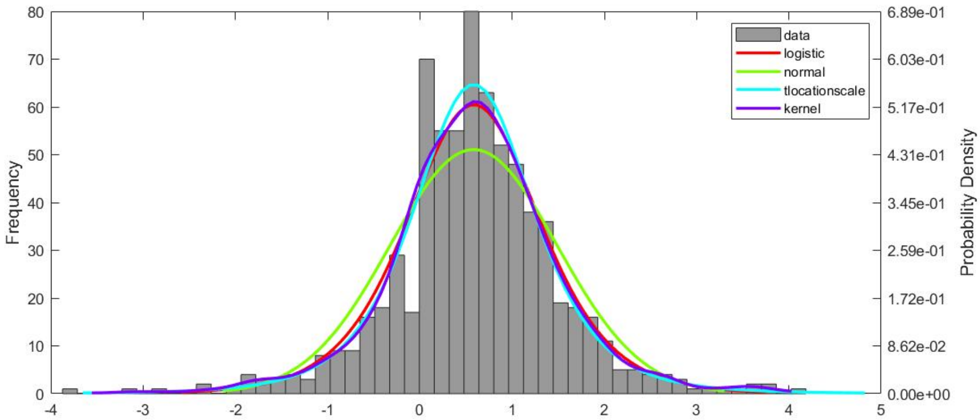

Figure B.11: The histogram of reaction times for the sub-lane method with a implemented width of 1.5 meters.

C APPENDIX 3: EXPLANATION OF BEHAVIOUR OF REACTION TIME VALUES NEAR ZERO

As can be seen in figure 3.6, reaction times are often exactly zero, but only in a few cases is reaction time a very small value near zero. This seems like strange behaviour and looks like some mistake. However, after several attempts to find out why this happens, it was discovered that this behaviour is the result of an inconsistent frame rate of the cameras. The figure below shows the decimal values of the starting to move times of all cyclists. The cyan coloured dots represent the timestamps that give a non-zero reaction time and the red dots show the timestamps that lead to reaction times of exactly zero.

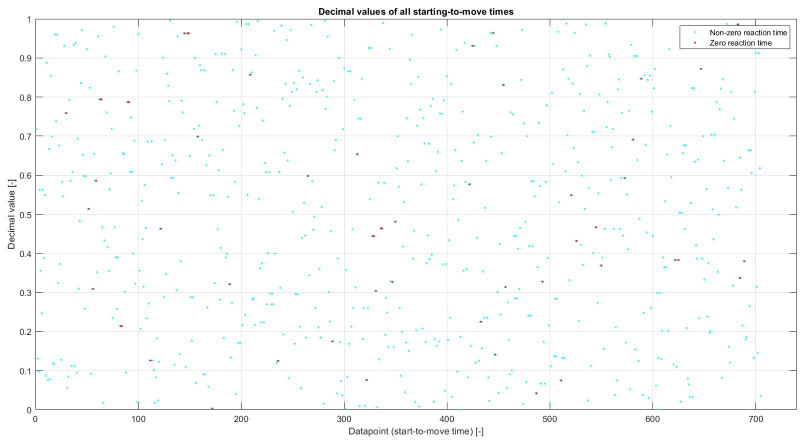

Figure C.1: A plot showing the decimals of the starting to move times of each cyclist.

When looking closer at the graph, several small clusters of dots can be noticed. Every single red dot is also located in one of these clusters. When we take a closer look at the x- and y-coordinates and the timestamps of the corresponding data points, one thing stands out: the timestamps of these data points are more "isolated". In other words, the frame rate of the camera is temporarily lower, which causes bigger differences between the timestamps of data points. This causes a local loss in accuracy and when the traffic light turns green around this time, there is a higher chance that two (or more) cyclists are observed as starting to move at the exact same time. In reality, they might not be starting to move at the same time, and when the camera has a higher frame rate, this might also not be the case. But due to the slower frame rate for a few snapshots, are the timestamps further away from each other, which increases the chance of two cyclists to start to move at exactly the same timestamp. This phenomena increases the chance that a reaction time is calculated as exactly zero and lowers the chance that the reaction time is very low and close to zero. The reaction times basically shift from very low to zero due to this temporarily change in frame rate.

D APPENDIX 4: ALL MULTIPLE REGRESSION PLOTS

The 3D and contour plots for all widths in the range between 0.6 and 1.3 are given below, with exception for the width of 0.8. This includes 7 plots where reaction time and jam density are compared versus the discharge flow, and 1 plot where shock wave speed and jam density are compared versus discharge flow.

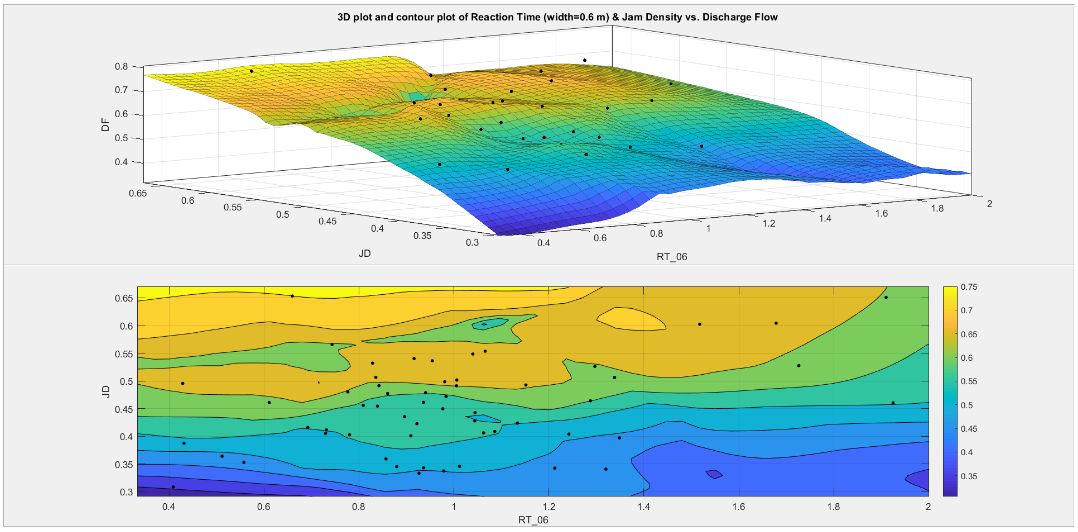

Figure D.1: 3D and contour plot of reaction time (width=0.6 m) and jam density vs. discharge flow

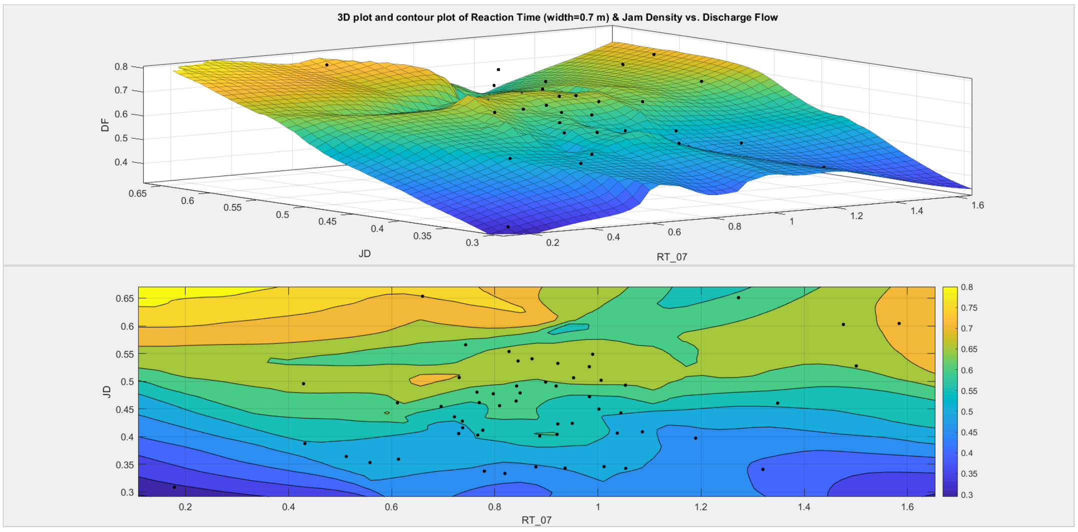

Figure D.2: 3D and contour plot of reaction time (width=0.7 m) and jam density vs. discharge flow

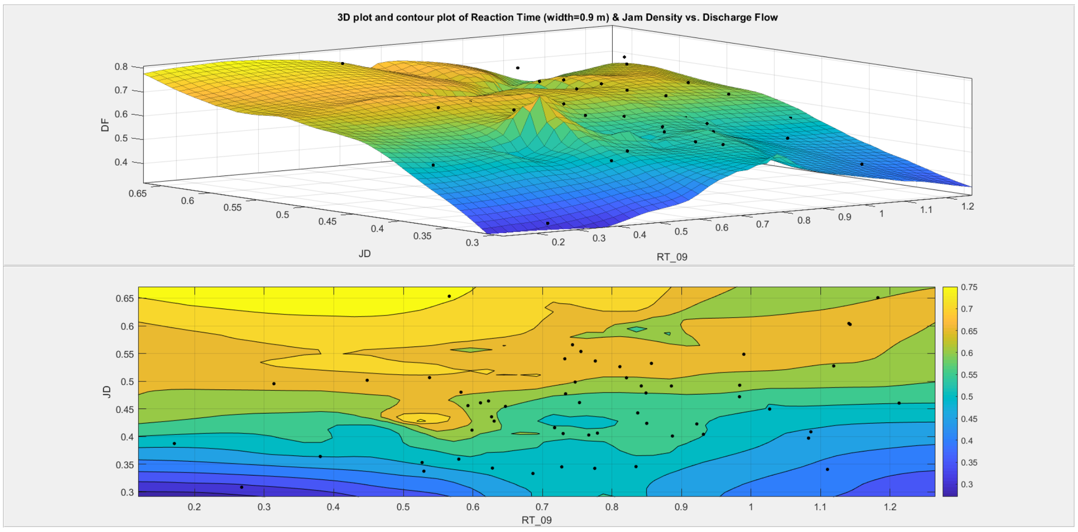

Figure D.3: 3D and contour plot of reaction time (width=0.9 m) and jam density vs. discharge flow

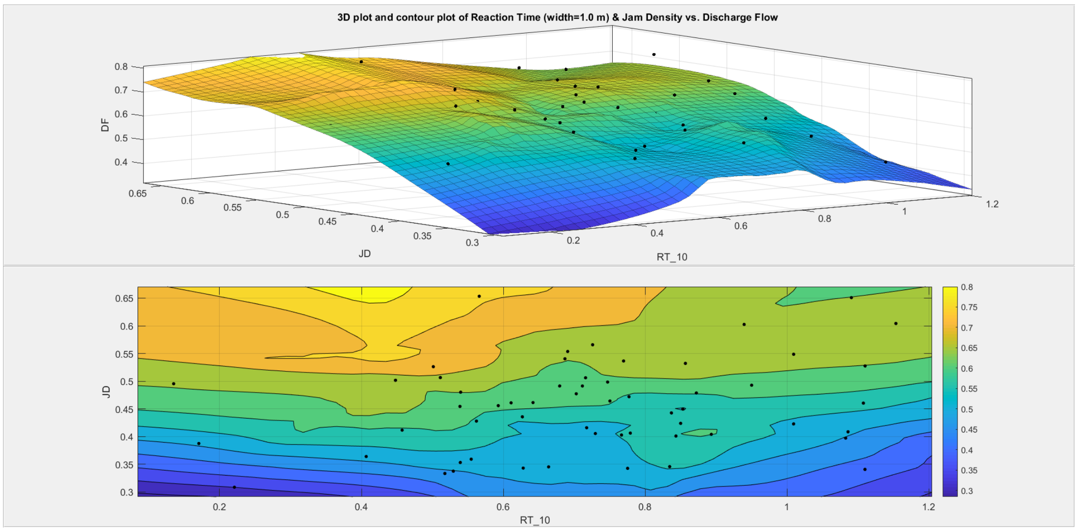

Figure D.4: 3D and contour plot of reaction time (width=1.0 m) and jam density vs. discharge flow

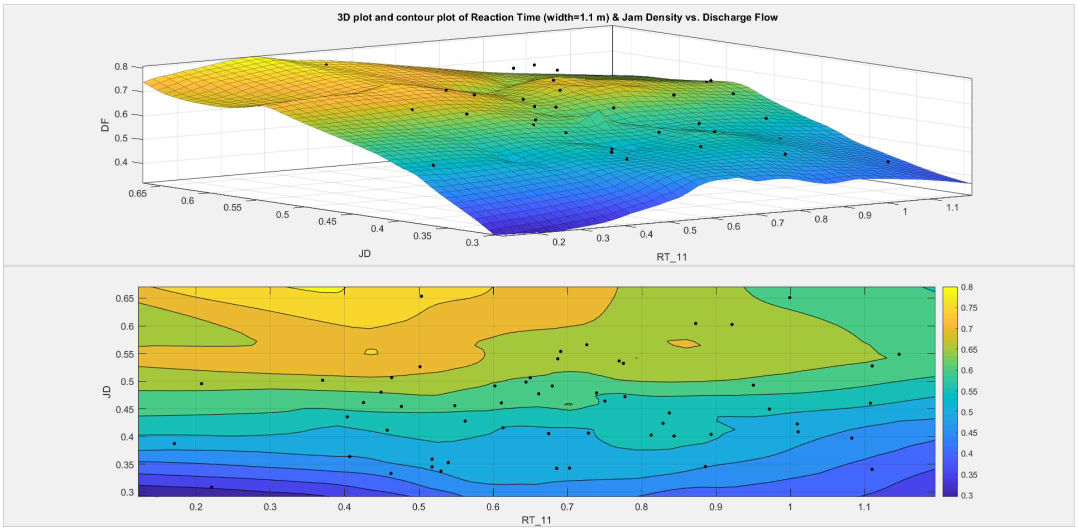

Figure D.5: 3D and contour plot of reaction time (width=1.1 m) and jam density vs. discharge flow

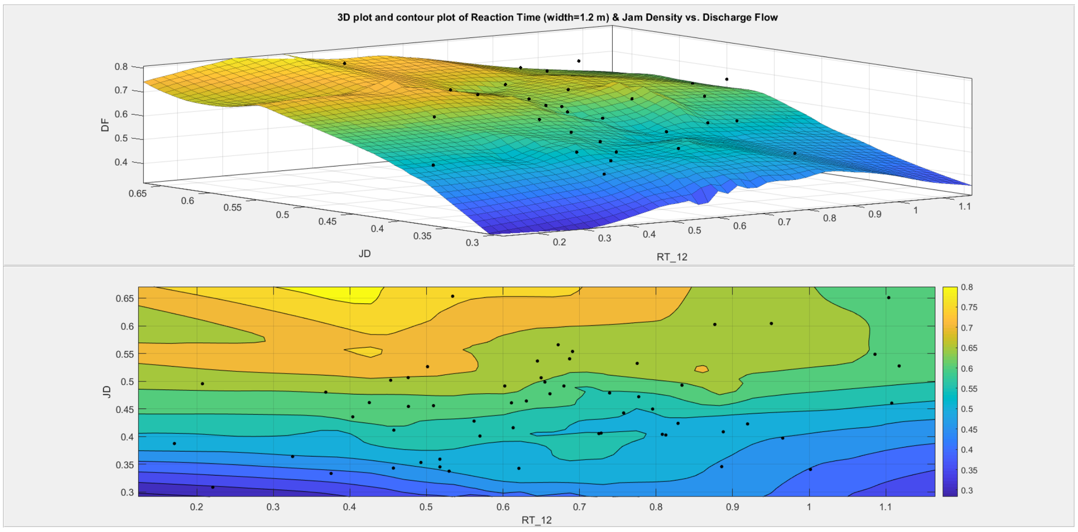

Figure D.6: 3D and contour plot of reaction time (width=1.2 m) and jam density vs. discharge flow

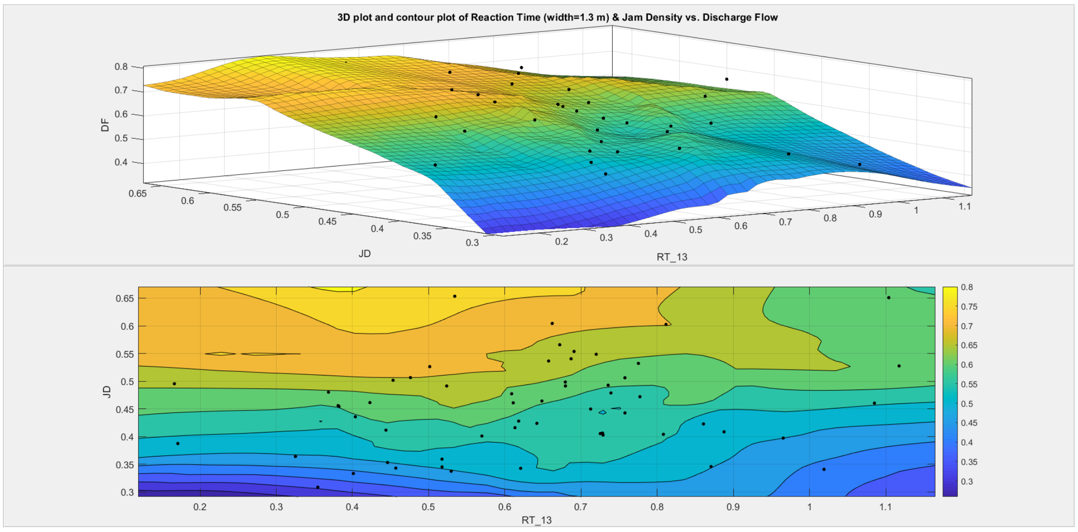

Figure D.7: 3D and contour plot of reaction time (width=1.3 m) and jam density vs. discharge flow

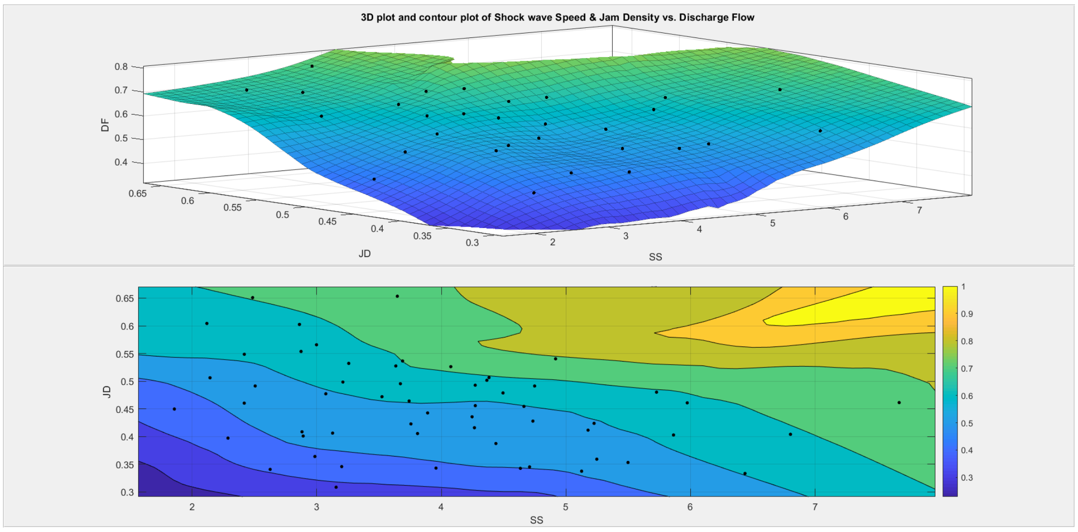

Figure D.8: 3D and contour plot of shock wave speed and jam density vs. discharge flow

COLOPHON

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