# Analysing the influence of a cyclist's position and the local density on bicycle queues

## A BACHELOR THESIS IN TRANSPORT AND PLANNING

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# Preface

With great fulfilment I can present my bachelor thesis to you, the reader of this thesis. After a quarter of hard work, reading papers, programming several lines of code and after mashing the keys of my keyboard, I can present this thesis. This bachelor thesis has been written to complete the Bachelor end project for the Bachelor of Civil Engineering at the TU Delft. The thesis has been carried out at the section of transport and planning under the supervision of two researchers from the section. This thesis is mainly written to contribute to existing research in the field of bicycle studies. Therefore the target audience has been focused on researchers but people with an interest in the subject can always read the thesis.

I want to thank my supervisors Yufei Yuan and Dorine Duives for their valuable feedback and the fellow students of our BEP-group for their feedback during this quarter.

*Jochem van Dijk*

*Delft, June 2022*

## Summary

Research into the behaviour of cyclists around intersections is still quite new. Previous research has mainly focused on the discharge process of cyclists and the quantification of this data. Little is still known about how cyclists create a queue in front of a traffic light. Therefore, this thesis will research the influence of the cyclist's position and the queue density on the discharge rate. The research will mainly look at bicycle queue configurations of the cyclists. The arrival and discharge behaviour won't be researched in detail but the general discharge characteristics will be used in the analysis. A dataset has been provided with 57 discharge periods of cyclists before a traffic light. This dataset can be used to look at the queue configurations of cyclists. The research consists of two parts. The first part looks at the positioning of the cyclists in the queue. Cyclists can position themselves in pairs with other cyclists or a cyclist can choose to join the end of a queue. A model has been created to define why cyclists position in a certain way and the model quantifies this data per queue. These positioning types are: Single cyclist, cyclists in pairs, cyclists in threes and cyclists which are positioned staggered. With this data, combinations of positioning types were made to represent queue patterns in the data. These queue patterns were analysed on the discharge rate and other flow variables. This showed that the positioning of cyclists does have an influence on the discharge rate. Queues with a high number of staggered cyclists would for example deliver higher discharge rates than queues with a lower number of staggered cyclists. The results of the model have also been compared with existing literature. It was found that cyclists can queue up much closer than they do already as this could also enhance the discharge process of a queue. The second part of the research looks at the local density that characterizes the bicycle queues. Bicycle queues have an overall density for the entire queue but the local density can show differences in the queue configuration. The local density has been visualized for several queues to investigate how the local density changes. No direct relation was found between distributions of the local density and the discharge rate. For this thesis, the local density can also act as a good measure to investigate queue configurations in a different manner.

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# 1. Introduction

Bicycles are a popular means of transport in the Netherlands, and they can be seen everywhere. Cycling in the cities is especially favourable because of the great cycling infrastructure and it's connection to the public transport network. Cyclists usually have a dedicated lane on the road, this creates a safe space but it also requires different intersection design and it can create new problems. Bicycle jams can form up before a signalized intersection and this can create bottlenecks or delays for the cyclists. In recent years, more and more cities are banning cars from city centres so people have to choose another mode of transport to get to their destination (Nieuwenhuijsen & Krheis, 2016). Therefore, it is important to have a bicycle infrastructure which can handle large amounts of cyclists. There are several ways to realize a robust network, for example by providing plenty of alternative routes. This can only solve a part of the problem as delays can still form around busy intersections. If an intersection can handle bicycle traffic more efficiently, there is no need for extra infrastructure but the network can be enhanced with small changes. This thesis will investigate the behaviour of cyclists before an intersection to research if these traffic jams can be prevented. The next section will already give a brief introduction into the field of bicycle studies, to give information for the research question of this thesis.

## 1.1 Background information

Research into the behaviour of cyclists around intersections is still quite new. Previous transport research has always been focused on cars so there is quite a bit of knowledge on that subject. Due to the problem sketched in the introduction, it is important to understand the behaviour of cyclists, to determine capacities for an intersection and to set up traffic lights. The behaviour of cyclists is different from cars because there is no designated place for cyclists on a bicycle path to wait on the green signal and the behaviour around intersections is less structured than for cars because each cyclist has a different destination and preference.

Around an intersection, it is possible to collect data on the position of the cyclist to know where the cyclist stops, how fast the cyclist accelerates etc. This individual behaviour of a cyclist is the microscopic characteristic of the cyclist. If the position and movement of an entire group of cyclists is considered, the characteristics that can be derived are macroscopic and they give insights into the overall flow around the intersection. Both characteristics are important, but the macroscopic characteristics can be used to generalize the problem and derive the capacity of an intersection.

Empirical analysis has been done to research these macroscopic flow characteristics like: jam density, wave speed and discharge flow. Existing research showed that there is a link between these variables. The behaviour of cyclists is complex and can vary a lot depending on the cyclist itself (Goñi-Ros et al. 2018). This research has been carried out with the same dataset that will be used in this thesis. Further research has been done on the same dataset by Yuan et al., (2019) to discover capacities in practice and to compare them with theoretical values for capacities. This showed that more research is needed into the width of the cycle path and the space that a cyclist uses because this behaviour is highly stochastic. Due to this behaviour, capacity calculations become less accurate (Yuan et al., 2019).

Not only the queue discharge process has an influence on the discharge rate, but the queue formation is especially important for the discharge speed. The queue formation process is based on the individual choices of the cyclists and thus requires a model to depict the outcome of these choices. Gavriilidou et al. (2019) have created such a model which consists of the mental and the physical tasks that a cyclist does. This model has been used to reconstruct the queue formation process and it was validated against a dataset with cyclist trajectories. This model provides insights into the queuing process and the choices that are made by the cyclists. This can help to make small changes to the infrastructure which can eventually enhance the queue formation. A better queue formation will discharge more efficiently or faster, which can eventually enhance the performance the network.

Theoretical research has been done to investigate ideal queue configurations at which the discharge rate is high (Wierbos et al., 2021). Comparing this research with a realistic dataset could help to further understand the queue formation of cyclists and the corresponding flow characteristics.

## 1.2 Research Question

In this Bachelor thesis the formation of bicycle queues and it's influence on macroscopic flow characteristics is investigated. The queue configuration can be seen as the process which leads to the creation of the queue or the positioning of the cyclists in the queue. This thesis will focus on the positioning of the cyclists in the queue and not on the arrival of the cyclists before the queue is created. By researching the queue configuration of cyclists, it is possible to gain insights into cyclists behaviour and this knowledge can be applied to come up with solutions for real-world applications. The general research question for this thesis is:

*What is the influence of the cyclist's position and the queue density on the queue discharge rate?*

To answer this research question, several sub-questions will be used. These are shown below and explained in the following paragraph.

*Does the relative position from cyclists to each other impact the queue discharge rate?*

*What positioning patterns can be found in the queue configuration?*

*How do these patterns compare to existing research and how do they impact macroscopic flow variables?*

*How does the local density vary over the queue and how does it impact the queue discharge rate?*

For this project a dataset will be used which consists of 57 discharge periods. The data set has been recorded in Amsterdam in 2016 and a detailed description of the experiment setup can be found in Goñi-Ros et al.,(2018) and section 3.1. The dataset can be used to construct a methodology for the main research question. The methodology will be split into two parts. The first part will try to answer the first three sub-questions by focusing on the positioning of the cyclist. A model will be constructed to define positioning patterns in which the relative position of the cyclist will be captured. The model can then be applied on the dataset to generate results. The results can be used to investigate the patterns which can also be linked to existing research from Wierbos et al., (2021). The second part of the methodology will focus on the other sub-question. The methodology will define how the local density can be calculated and how the dataset can be used to generate results for the local density. Together, these sub-questions will provide information to answer the main research question.

## 1.3 Research relevance

The aim of this research is to provide more understanding of cyclist's behaviour around an intersection. This is done by working out two subjects. The results from these subjects can be used to understand cyclists positioning around an intersection and in what patterns cyclists will queue. With this new knowledge, the thesis contributes to existing research into bicycle flow but the results can also act as a basis for future research into how the discharge process of cyclists can be influenced. In this way, bicycle jams can be prevented or shortened. Bicycle jams can have a negative impact on the cycling experience so it's best to minimize this, as cycling has multiple positive impacts for the environment and the cyclist itself (Doorley, Pakrashi, & Ghosh, 2017).

## 1.4 Reading Map

The structure of the report is as follows. Chapter 2 will give more background information on traffic flow theory and queue behaviour. The methodology will be defined in Chapter 3. This will be done in two parts for the different subjects. Chapter 4 shows the results of the data and chapter 5 contains the discussion of the results, recommendations for future research and it provides a link between the results and literature. The report will then close off with the conclusion. An interested reader can still go through the appendix to view more figures.

# 2. Literature

Analysis of macroscopic flow variables requires knowledge about them. Section 2.1 will introduce general traffic flow theory while section 2.2 will provide the definitions for the discharge and the density. These variables will be used throughout the thesis so a basic understanding is needed. Section 2.3 will then introduce relevant literature about queue behaviour and queue formation which is relevant for the methodology of this thesis.

## 2.1 General traffic flow theory

To get a better understanding of traffic flow theory. General traffic theory and important variables are discussed first.

Traffic flow can be expressed in multiple variables. The basis for traffic flow theory is the trajectory that a vehicle or cyclist has used to get to their destination. The trajectory describes the position of the cyclist over time along the lane (Hoogendoorn & Knoop, 2012). Information described in the trajectory are the longitudinal position ($x_i(t)$), the lateral position ($y_i(t)$) and the time ($t$) where $i$ represents the cyclist in the order. In traffic flow, it is interesting to look at the flow of the entire group. To do this, headway models can be used to plot the trajectory data of multiple cyclists. An example of this can be seen in figure 1. At a given point along the trajectory, the headway, or the time between two cyclists, can be expressed with $h_i$. The time is usually calculated between a specific point like the head of the cyclist because this is a recognizable point. The distance between the two cyclists is expressed with $s_i$. The headway gives valuable information about the discharge process because it indicates the distance that cyclists keep from each other, but cyclists also discharge cycling next to each other. Still, a cyclist needs its own place on the road when accelerating from an intersection. In modelling theory this is called a virtual sublane and this concept is used to predict how cyclists use the space of a cycle path.

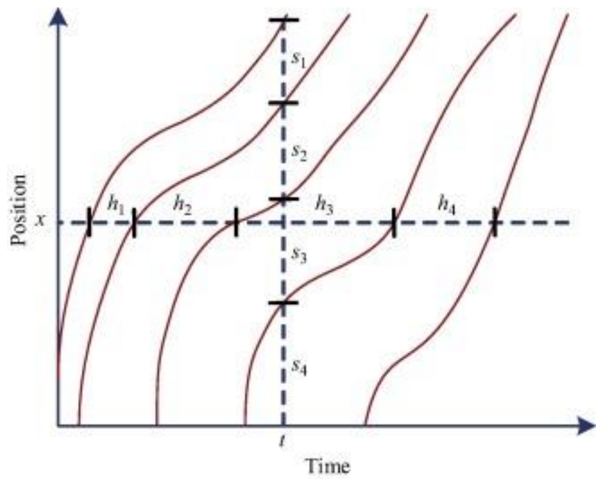



*Figure 1: Example of cyclist trajectories in a headway model. (Li & Chen, 2017)*

The headway thus looks at the differences between the individual cyclists. This makes it a microscopic variable. Macroscopic flow variables will be introduced in section 2.2, these variables say something about the entire group of cyclists and that's why these are called macroscopic. It is important to remember the difference between microscopic and macroscopic flow variables as they both represent different properties.

## 2.2 Flow and density,

With the headway defined, the flow of the entire group can be defined. Generally, flow is defined as: 'The average number of vehicles ($n$) that pass a cross-section during a unit of time ($T$)' (Hoogendoorn & Knoop, 2012). In formula form:

$$q = \frac{n}{T} = \frac{n}{\sum_{i=1}^{n} h_i} = \frac{1}{\bar{h}}, (1)$$

Because the headway also represents the time difference, the average headway can be used to calculate the discharge flow. Another macroscopic flow variable is the density $k$ or: 'The number of vehicles per distance unit' (Hoogendoorn & Knoop, 2012).

$$k = \frac{n}{X} = \frac{n}{\sum_{i=1}^{n} s_i} = \frac{1}{\bar{s}}, (2)$$

Here $X$ is defined as the length over which the cyclists are scattered and $\bar{s}$ is the average distance between the cyclists when they pass a specific point. The density can't be computed by looking at a single point along a road. All the cyclists must be captured in a single instant on the lane. Capturing this data therefore requires extensive observations above a road.

In Goñi-Ros et al.,(2018) these variables are defined slightly differently. Because traffic flow theory has usually focused on cars for its research, the variables are of course not similair. Cars discharge from a traffic light in an organized manner because they have a dedicated lane. Cyclists are free to choose their queue position and they have more freedom in the discharge process. Especially the first cyclist in a queue has an influence on the discharge time as this cyclists has to respond to the traffic light. This reaction time can greatly vary between cyclists so it has a direct impact on the average discharge of the group of cyclists. To filter out this deviation, the first cyclist is not incorporated in the calculation of the macroscopic flow variables (Goñi-Ros et al.,2018). The formula for density now becomes:

$$k = \frac{N-1}{L * W}, (3)$$

Here $N$ denotes the total number of cyclists in the queue. $W$ is the width of the cycle path in meters and $L$ is defined in the following formula:

$$L = d_N(t_0) - d_1(t_0), (4)$$

$L$ is defined as the distance between the first and the last cyclist in the queue, where $d_i$ is the distance from a reference line to the cyclist. The reference line, or line $a$, is situated $0.4$ meter from the stop line, in the discharge direction of the cyclists. Because not all cyclists stop before the stop line, the stop line itself can't be used as a measurement point for the average discharge. That's why a reference line is introduced. The area between the reference line and the stop line now acts as the count area. By looking at the time that it takes for every cyclist to pass through the count area, the discharge can be calculated. The order in which the cyclists pass the stop line is defined by index $j$ as the cyclists start overtaking each other from $t_0$, index $i$ can't be used. An overview of this scenario can be seen in figure 2.

Usually, the headway distance is used to calculate the discharge, as is done in *eq. (2)*. In *eq. (3)* the density is not defined with the headway model, so the same is done for the average discharge:

$$q = \frac{\sum_{j=2}^{N} X_j}{\Delta x * \Delta t * W}, (5)$$

Here $X_i$ is the distance that bicycle $i$ travels through the count area, $\Delta x$ is the distance between the reference line and the stop line, $\Delta t$ is the time when cyclist $j = 1$ and $j = N$ cross the reference line and $W$ is the width of the cycle lane.

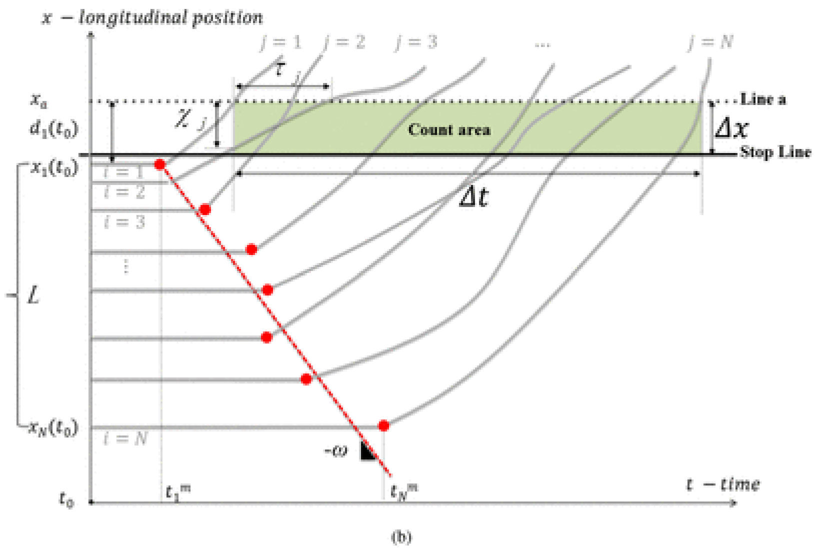



*Figure 2: Sketch of the count area that is used to calcualte the discharges.*

This thesis will use these macroscopic flow variables as defined in *eq. (3)* and *eq. (5)*. The discharge can also be defined differently by including virtual sublanes in the calculation which has been done in (Yuan et al., 2019), but this requires a different approach which would increase the complexity of the calculations.

## 2.3 Relevant Literature

This section will discuss relevant literature for queue behaviour and formation. First, some general statements about queue behaviour will be made in paragraph 2.3.1. Then paragraph 2.3.2 will respectively discuss research about behaviour during the queue formation, earlier queue formation research in practice and lastly a paper is discussed in which the queue formation was studied in a controlled experiment.

### 2.3.1 Queueing Behaviour

Cyclists have the freedom to queue at any place on a bicycle lane when they stop for a red light. In the queueing process, each cyclist has their own preference. One cyclist may choose to stop on the right side of the lane, to rest their foot on the sidewalk. A different cyclist might be in a hurry, and they can queue up on a free spot on the left side of the lane where they can easily overtake the rest. The queue position thus depends on personal preference of the cyclist but also on the available space in the lane.

Another observation that can be made about queueing, is that people will queue differently in different situations (Kneidl, 2016). Kneidl has summarized several types of queueing for pedestrians, but similarities can be spotted for cyclists. For example, queueing in front of a traffic light is a simple process, as the area is demarcated by the sidewalks or the car lane. This queueing process is comparable with pedestrians but not in all situations. A different phenomenon arises when people queue in front of a train, a very dense and organised queue forms (Davidich et al,, 2013). For cyclists, this same behaviour can be observed when people queue for a ferry, or a bridge that has opened. The queue becomes very dense but the discharge process is still somewhat organized. Research on these dense queueing situations hasn't been done for cyclists but it is interesting how these situations differ from the behaviour around a signalized intersection. Somehow, cyclists don't feel the need to queue up closely in front of an intersection. This could be related to the lower waiting time that cyclist's have at an intersection or the total number of cyclists that queue up is lower. This thesis might provide some insights into dense queueing behaviour and the knowledge on general queueing theory is relevant for this subject.

Kneidl ( 2016) also notes: Social groups of people will influence the queue formation. These groups will move as a group in the queue and they will prefer to queue together. Group behaviour is an interesting subject which is relatively hard to study because the groups have to be correctly identified. Future research can focus on this but for this thesis it is important to realize that group behaviour has an effect on the queue configuration itself.

### 2.3.2 Queue formation

As mentioned in the introduction, the queue behaviour of cyclists has been understudied but existing research projects can act as a basis for this research. The contents of some papers will be discussed shortly and summarized. This will provide information and act as a theoretical basis for the current research.

Participating in traffic, can be seen as a complex task. Drivers must perform different tasks which require different decisions. Gavriilidou et al., (2019) have created a model with two layers which captures the decisions that cyclists make in the queue formation proces. This model is a discrete-choice model which is based on an operational mental and physical layer. The different layers in the model make choices for different tasks such as steering and route choice. The layers contain different attributes to describe the choices that a cyclist makes. As the model is a simplification of a cyclists behaviour in the real world, the model was validated with the same dataset that is used for this research. Results from this research showed that cyclists prefer to queue up next to the curb of the sidewalk instead of creating a dense queue at the front of the cycle lane.

Research by (Kucharski et al., 2019) also focused on the queue formation process. Their research recorded cyclists which were forming queues in front of a traffic light and they specifically looked at multichannel queue behaviour. The data consisted of 50 queues of cyclists with a queue size varying between two and seven cyclists. Althougth these are small queues, it is interesting to see when cyclists decide to form another sublane or when they join an existing one. Still, Kucharski et al., (2019) noted that the queue formation process is highly stochastic and non-deterministic, so it's difficult to predict the queue formation process. Due to the larger queue sizes in the dataset for this project. The variability of the process can already be recognized. Cyclists don't queue up perfectly in channels because they leave a larger gap than necessary or they queue up, alternating between pairs and threes. For this thesis, a similair model could be constructed with a few improvements to account for the differences in the data.

Next to empirical research, a real-life experiment was set up by (Wierbos et al., 2021) to measure jam densities for queue configurations which haven't been recorded in practice. In a controlled situation, the bicycle queues could be configured in a much denser way. This showed that the discharge rate increased with the jam density and values for the jam density could be reached which were far higher than seen in practice. The research was done on a lane which was two meters wide, so the setup is comparable with this thesis because the data was also gathered on a cycle path of two meters wide.

The queue configurations and their theoretical densities that were tested can be seen in figure 3. For this dataset it will be difficult to find similar queues, so the research will have to be more detailed about the queue configurations.  An interesting insight from the research by Wierbos et al., (2021) was that a three-two-three configuration delivered the highest discharge rates. The density that could be achieved with this configuration was higher than expected and it thus also delivered a higher discharge rate. For this research the bicycle queue configurations can be used as a template to compare queue configurations from the dataset.

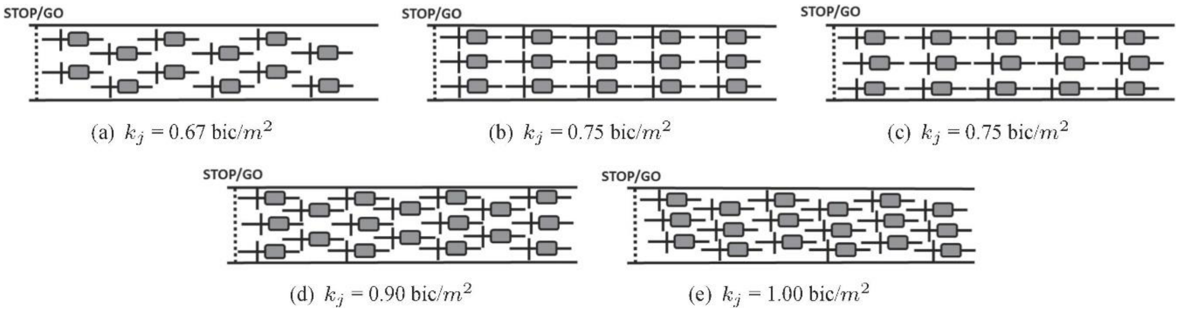



*Figure 3 Queue configurations with theoretical jam densities. (Wierbos et al., 2021) (a) in pairs, staggered, (b) In Threes and side by side, (c) In threes and v-shape where the middle cyclist is placed slightly backwards, (d) Alternating in pairs and in threes, (e) In threes with a shift.*

# 3. Methodology

In the methodology the basis for this research is defined. Section 3.1 will shortly discuss the dataset which will be analysed. Section 3.2 will be about the cyclists positioning model and section 3.3 will define the methodology for the local density.

## 3.1 Dataset

As discussed in the introduction, this thesis will use a dataset with bicycle trajectories which were captured on a cycle path that leads to a signalized intersection in Amsterdam. The cycle path is two meters wide and consists of a pedestrian crossing before the stop line of the cycle lane. Images were captured with two cameras which were mounted on a pole next to the cycle lane. The camera views can be seen in figure 4. Together, the cameras cover 20 meter of the cycle path. The images where then processed to retrieve trajectory data which can be used for analysis. This process has resulted in 57 useful discharge periods which have around 7 to 15 cyclists in each discharge period. Not all recorded discharge periods are present in the dataset because of a few criteria. These criteria focus on for example the number of scooters in a dataset. If there were more than two scooters in the queue, the data is not used, because the research is aimed at the behaviour of cyclists. Other criteria focused on the behaviour of the cyclists. If a cyclist ignored normal traffic rules, the data is not usable because this delivers irregular data for the macroscopic flow variables. Further explanation on the dataset and on the criteria that have been used, can be found in research done by Goñi-Ros et al. (2018).

*Figure 4: View of the two cameras that were used to record the dataset.*

## 3.2. Cyclist's positioning

In this section, the methodology for the cyclists positioning model is defined. Section 3.2.1. will describe how the average dimensions of a cyclist are defined to use the data in the dataset. Section 3.2.2. will then describe the theoretical basis of the model. The results that the model generates will then be explained and shown in section 3.2.3. Lastly groups are defined in section 3.2.4. These groups will be used to analyse the results of the model on queue patterns.

### 3.2.1 Cyclist's dimensions

To calculate the respective positioning of cyclists. A clear definition is needed for the analysis. The data in the dataset has been recorded as point data. In other words, only one point on a cyclist has been tracked to measure the trajectory of the cyclists. This means that the full position of the bicycle is not known so average measurements have to be used to analyse the data. According to research done by (Gavriilidou, et al., 2019), an estimation can be made of the bicycle dimensions. The average bicycle length is 180 cm, and the handlebar length is 60 cm. The point on the cyclist that has been used to track the cyclist is on its head. The position of the cyclist's head can vary on the bike depending on the type of bicycle and the person cycling on it. Previous research with trajectory data done by Gavriilidou

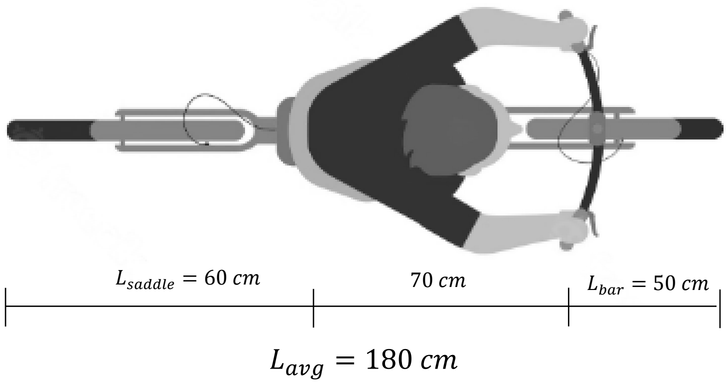



*Figure 5: Bicycle and cyclist's dimensions. Sketch not to scale.*

et al. (2019) has just used the head as a reference point but in this thesis it is necessary to know the position of the bike under the cyclist. Because there is no standard geometry for a bicycle a standard Dutch city bicycle was measured. A figure of it can be seen in appendix A. The bicycle had a length of 182 cm., the saddle was positioned at 60 cm. from the edge of the rear wheel and the handlebars were located at around 50 cm. from the front wheel. This leaves a space of around 70 cm. in which the head of a cyclist can be during the riding Every cyclist will assume a different position on the bike depending on the position of the handlebars and therefore it is not possible to use a standard definition for the location of the bicycle under the cyclist. The assumed bicycle dimensions have been sketched in figure 5.

It is assumed that the head of the cyclist will be halfway above the bicycle for the average cyclist. So at 90 cm. from each wheel edge. This is a simplification for the model but without a general definition this is sufficient for the current research.

### 3.2.2 Cyclist's positioning model

In this section, the cyclists positioning model is defined. First, attributes will be defined which are based on the preferences of cyclists queuing positions. With these attributes, positioning types can be defined, which the model will use to come up with the results for each queue. Lastly the limitations of this model will be discussed shortly.

**Attributes for path choice**

Gavriilidou et al., (2019) defined three attributes for the Queue positioning in a model on operational cycling behaviour. Operational behaviour describes the tasks that a cyclist has to perform on the bike. This behaviour is split in two layers, the operational mental layer, which focuses on decisions like path choice or where to stop. The operational physical layer of a cyclist focuses on the execution of the tasks which were provided by the operational mental layer. So if a cyclists wants to overtake another cyclist, the operational physical layer will execute the task by pedalling and steering but the decision has been provided by the mental layer. This model is a simplification of cyclists behaviour but the operational mental layer that has been constructed for this model provides a basis to understand how cyclists choose their queue position. In the operational mental layer, three attributes have been defined which describe this behaviour. These attributes are:

- *Distance to nearest bicycle(s):* The cyclist chooses a spot with a big enough gap towards the cyclist in front which feels comfortable. Depending on the circumstances this could be very close. This gap will influence the ability of the cyclist to take off.
- *Distance to stop line:* Depending on the cyclist, the cyclist will position itself closer to the stop line to influence it's discharge time. For some cyclists this is a key attribute and they will pay less attention to the other attributes such as *distance to the sidewalk or lateral distance to the nearest cyclist.*
- *Distance to sidewalk*: A cyclist might want to stop next to the sidewalk to use it as a foot rest.

A new attribute that isn't defined by Gavriilidou et al., but which helps to describe the path choice is:

- *Lateral distance(s) to the nearest cyclist(s):* When choosing a queuing position the lateral distance could be of importance because cyclists show swaying behaviour when they start to accelerate (Wierbos et al., 2021). This swaying requires extra space so a cyclist might choose to queue behind other cyclists, to guarantee that their is enough space. On the other hand, this attribute also depends upon the queue position of the other cyclists so it's not completely up to the cyclist itself. Some cyclists might feel more confident to take off without a lot of swaying so they might choose a spot in between two cyclists.

These four attributes will influence the path choice of cyclists towards their queuing positions. Other assumptions could add to these attributes such as social conventions, group behaviour or other personal factors which influence the desired queuing position, but these will not be discussed in this paper.

**Positioning types**

When the queue starts to form, the position for the first cyclist is easy. The cyclist has to stop near the button of the traffic light to report that a cyclist is waiting. The other cyclists will then have to choose their position based on the remaining space. A cyclist can do this in four ways. These ways will be introduced and an explanation is given why a cyclist will queue this way, based on the attributes.

- *Single cyclists*: The cyclist has no other cyclists positioned to his side and the wheels of cyclists behind or in front do not overlap with the wheels of the cyclist. A single cyclist wants to keep enough *Distance to the nearest bicycle* or bicycles behind chose not to queue up next to the cyclist. The cyclist can also have a preference for the *Distance to the sidewalk* for a more comfortable queue spot.

- *In pairs*: The cyclist is positioned in the queue with one other cyclist on it's side. The other cyclist is only $0.9\ m$ meter in front or behind in such a way that they are roughly positioned on the same lateral line. The cyclist can have a preference for the *sidewalk* but a position *to the stop line* is more important than queuing up as a single cyclist.

- *In threes*: The cyclist has two cyclists on it's side or on either side such that the other cyclists are only $0.9\ m$ in front or behind the cyclist and they are roughly positioned on the same lateral line. A comparison can be made for the cyclists queuing in pairs with the addition of *the lateral distance to the nearest cyclist.* Cyclists queuing in threes don't have a problem with this and are focused on other attributes.

- *Staggered*: The cyclist is positioned in the queue such that the cyclist in front or behind is positioned $0.9\ m$ till $1.8\ m$ meter away from the cyclist. The cyclist's body does not overlap with the bicycle besides his, therefore this positioning is defined as staggered. Depending on the position of the cyclist. The cyclist can be positioned staggered to a cyclist in front but positioned in pairs with another cyclist. Cyclists which are positioned staggered don't have a preference for a large *distance to the nearest bicycle.* Queuing up closely helps them to move closer *to the stop line* when there is no more available space in front.

These attributes cannot fully clarify the positioning of a cyclist for each cyclist. For example: The first cyclist in a pair didn't choose to queue up as a pair. The attributes only help to clarify the path choice of individual cyclists. The current model aims to count the positioning types of the cyclists and the attributes help to define these types.

**Position distance and definition limitations**

The basis for the positioning model is the distance between the cyclists. In table 1, an overview is given of these distances. As mentioned in section 3.2.1, the reference point of the cyclist is taken at the half of an average bicycle's length which is the head of the cyclist in the data. Cyclists are defined as in pairs or as in threes when their reference points are not further away than 0.9 meter. Staggered cyclists are defined differently because their heads are not on the same lateral line as the other cyclists bicycle. These zones can be seen in figure 6, a reference cyclist is shown and the other cyclists are positioned at the limit of the zone. To be in the zone itself the cyclists have to be positioned slightly to the left.

*Table 1: Distances used in cyclist's positioning model*

| Type | Distance to cyclist in front or cyclist behind [*in meters]* |
|---|---|
| Single | $x > 1.8$ |
| In Pairs | $0 < x \leq 0.9$ |
| In Threes | $0 < x \leq 0.9$ |
| Staggered | $0.9 < x \leq 1.8$ |

The positioning types have not been directly used from (Wierbos et al., 2021). Wierbos also defined other types such as cyclists positioned with a shift or cyclists in a v-shape, as can be seen in figure 3. Adding this as a positioning type would make the analysis more complex and the positioning for this counts on a highly regulated queue configuration which is not realistic in practice.

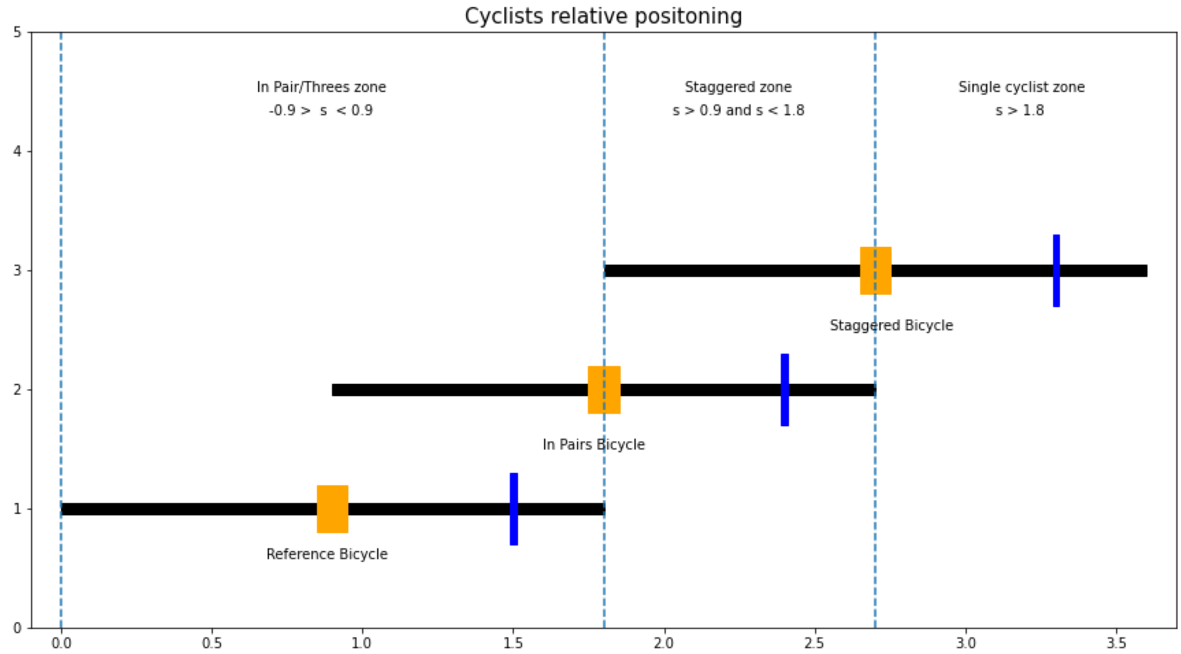



*Figure 6 Sketch of the defined positioning types. The orange block represents the head of the cyclist which is defined halfway at the bicycle. The blue bar represent the handle bars. The cyclists are positioned at the limit of the zone, to be in the zone, the cyclists have to be moved to the left slightly.*

Another limitation of this definition of the positioning types is that cyclists which are defined as in pairs are not really next to each other, although the name suggests otherwise. A different positioning type could have been added to account for the difference in distance between staggered cyclists and cyclists in pairs. This was not done to stick to the defined attributes. This positioning type would have to be based on social factors or other preferences of persons to be correctly defined as it's difficult to make a differentiation for this positioning type with the existing attributes. As a result of that, the other positioning types would also have to be based on these factors to complete the model but it is not the aim of this thesis to construct such a model.

### 3.2.3 Model simulation

To retrieve the desired results, a model was constructed in python. The model runs through the initial positions of the cyclists to retrieve the distances between the cyclists. If a distance falls in a defined positioning zone, the model adds this to the right positioning type. This is all added up and after the simulation the macroscopic flow variables are added for analysis. The data that was generated through the model will be shown here shortly. In figure 7, a queue configuration can be seen and the positioning distribution can be seen in table 2.

*Table 2: Cyclists positioning model results of a single queue,*

| Single cyclist | In Pair | In Threes | Staggered | Queue size |
|---|---|---|---|---|
| 0 | 12 | 3 | 12 | 16 |

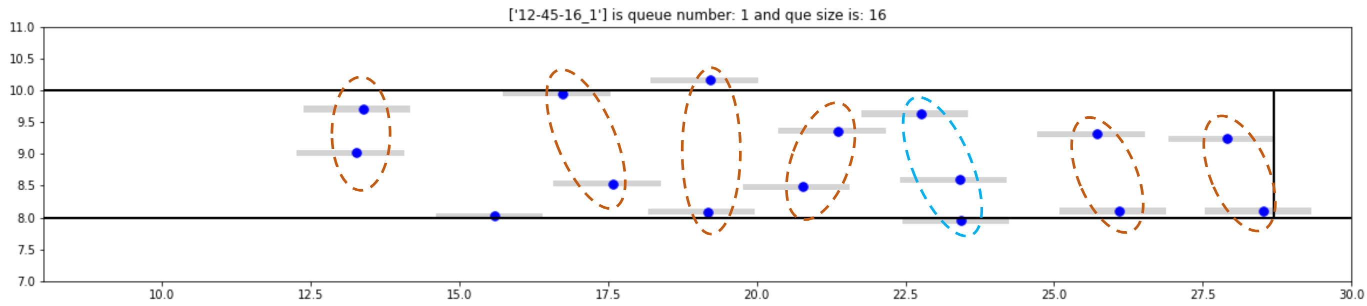



*Figure 7: Sketch of  cyclist's positioning for a single queue.*

In this queue the pairs are indicated by the orange lines and the Threes are indicated by the blue lines. In this queue 12 cyclists are positioned in pairs, 3 cyclists in Threes and 12 were positioned staggered.

In the model, pairs are counted as pairs, so a pair is two cyclists. An exception can occur where one cyclist is part of 2 pairs. This happens in figure 8, in the purple circle, indicated with the black arrows. The cyclist at the top forms two pairs with both cyclists at the bottom but the bottom cyclists are only positioned staggered so they won't form a Threes. The result for the pairs is still counted but not as a two full pairs, which would give a value of four, but a value of three is given. To be completely precise, the cyclist should be counted as a 'double paired' cyclist. This is something that could be done in a future model. The same situation also applies for staggered cyclists. If a cyclist is positioned 'double staggered', a value of three is added to the result instead of a value of four. This can also be seen in figure 8. The red arrows represent the Staggered cyclists and the green arrow represents a cyclists which is positioned as 'double staggered'.

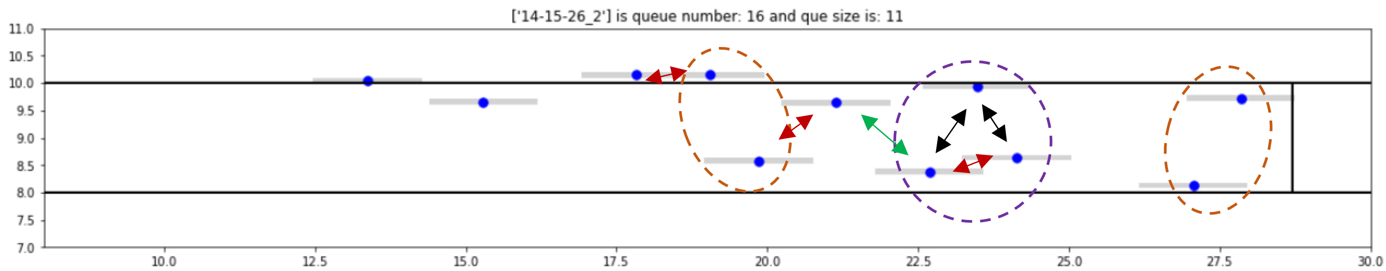



*Figure 8: Sketch of cyclist's positioning for a single queue.*

The result for the queue shown in figure 8 can be found in table 3.

*Table 3: Cyclists positioning model results for a single queue.*

| Single cyclist | In Pair | In Threes | Staggered | Queue Size |
|---|---|---|---|---|
| 2 | 7 | 0 | 7 | 11 |

**Total model results**

The total results of the model can be seen in table 4. The results of the positioning model will be discussed shortly because the results are used in the next part of the methodology when the queue patterns will be defined.

*Table 4: Total results of the cyclists positioning model.*

| Single cyclist | In Pair | In Threes | Staggered | Total cyclists |
|---|---|---|---|---|
| 44 | 417 | 105 | 749 | 703 |

The number of single cyclists is low in the dataset, just as the cyclists positioned in Threes. Cyclists positioned in pairs make up more than half of the total cyclists and there are more cyclists positioned staggered than there are cyclists in total. Cyclists are thus likely to have more than one positioning attribute. This is logical as there can be multiple cyclists in front or behind a cyclist which can all be positioned in different ways. The model does not count separately if a cyclist is positioned 'double staggered' or even 'triple staggered'. The same holds for cyclists which are positioned as 'double paired', these cyclists still fall in the group of cyclists positioned in pairs, although this should be a lower amount in the dataset as cyclists can also be positioned in threes.

### 3.2.4 Queue patterns

To analyze the data of the model, this section will describe groups in which the data will be placed, based on queue patterns.

First, the data will be ordered based on certain patterns. Wierbos et al., (2021) has done research in a controlled environment to discover jam densities of certain queue configurations. One highlight of that study was that higher jam densities were reached which weren't seen in practice before. By defining similar queue configurations with the help of the positioning model. The data can show if these queue configurations are realistic and secondly how they perform. An overview of the groups is given in table 5. An explanation of the different groups is given below the table.

*Table 5: Overview of the groups with the different queue patterns.*

| Number | Percentage of queue size | | N ≥ Que size |
|---|---|---|---|
| 1 | 50 % In pairs | | - |
| 2 | 30 % In threes | | - |
| 3 | - | | N Staggered |
| 4 | - | | 1.5 * N Staggered |
| 5 | 50 % In pairs | + | N Staggered |
| 6 | 50 % In pairs | + | 1.5 * N Staggered |
| 7 | 30 % In threes | + | N Staggered |
| 8 | 30 % In threes | + | 1.5 * N Staggered |
| 9 | 80 % In pairs and In threes | | - |

- 50 % or more of the cyclists in a queue is *In Pairs*: This group will look at the impact of a high number of cyclists which are positioned in pairs. Because the number of cyclists that are positioned in pairs is distributed quite evenly in the dataset. A value of 50 % was chosen.

- 30 % or more of the cyclists in a queue is *In Threes*. This group will look at the impact of a high number of cyclists which are positioned in threes. Due to the low number of cyclists which are positioned in threes a value of 30 % was chosen. For a higher percentage there wouldn't be any queue where the cyclists in threes represent a big group of the queue. A lower percentage would return more queues but that will also lower the number of cyclists positioned in threes in the queue.

- The number of *Staggered* cyclists is larger or equal than the queue size. This group will look at the impact of staggered cyclists in a queue. The number of staggered cyclists is very high in the dataset so the queues in this group will only contain a number of staggered cyclists which is higher or equal to the queue size.

- The number of *Staggered* cyclists is 1.5 times larger than the queue size. This group will look at the impact of a high number of staggered cyclists in a queue. The difference with the previous group is that it is expected that this group will have a very dense configuration in the queue.

- 50 % or more is *In Pairs* and the number of *Staggered* cyclists is larger than the queue size. This group will be a combination of these positioning types, to check if the combination of queuing in pairs and staggered cyclists delivers different results. It is expected that a denser queue will form if cyclists queue up like this.

- 50 % or more is In pairs and the number of *Staggered* cyclists is 1.5 times larger than the queue size.

- 30 % or more is *In Threes* and the number of *Staggered* cyclists is larger than the queue size. This group will be a combination of these positioning types, to check if the combination of queuing in threes and staggered cyclists delivers different results. It is expected that a denser queue will form if cyclists queue up like this.

- 30 % or more is *In Threes* and the number of *Staggered* cyclists is 1.5 larger than the queue size.

- 80 % of the cyclists is *In Pairs* or *In Threes*. This group will recreate a three-two-three queue configuration by setting a high value for the summated percentage. This is different from the previous groups were the positioning type would had to have a certain value. To make sure that not only queues with pairs are in this group, a minimum is set that 15% of the cyclists should be in threes. This criteria is lower than 30 % percent because this group should help to analyse the combination of pairs and threes in a queue. Not a high percentage of cyclists positioned in threes.

For each group, the following variables will be reported in the results section.

$k_{j,avg}$, Average queue Jam Density in bicycle per squared meter.

$k_{j,med}$, Median value of the Jam Density.

$q_{avg}$, Average queue discharge in bicycle/second/meter.

$q_{med}$, Median value of the discharge

$N_{avg}$, Average number of cyclists or average queue size.

$L_{avg}$, Average queue length in meters.

$S$, Number of phases or sample size.

With these variables the data can be analysed and the impact of the different queue patterns can be compared. In the discussion the results will be compared with existing research by Wierbos et al., (2021). To compare how the queue patterns perform.

## 3.3 Local density

The second subject for this thesis is the density of the queues. The Jam density (*eq. 3*) describes the density of the whole queue but this variable looks at the entire bicycle lane. This section will first describe how the local density can be calculated. With this definition, groups will be defined which will be used for the analysis of the data.

First, the outline of the model has to be set. The stop line of the traffic light is situated at $x = 28.7\ m$. Cyclists can queue on or over the stop line so the stop line can't be taken as the start line of the model. The start line represents the line from which the calculation will be started. This line is set at $x = 30\ m$. The data showed that most cyclists will stop before $x = 29.1\ m$. The extra 0.9 meter is to account for the space of the bicycle. By using a set start line instead of the first cyclist for the analysis, the model will show differences in queuing behaviour in the first few meters. As it is expected that the local density will also vary at the front of the queue.

Now that the start line of the model is defined, the rest can be defined. The model will start from the start line and will create intervals of $\Delta x_d$ meters until the end of the analysis zone is reached. Which is about 20 meters. The density will be calculated for each interval and this data can be used for analysis. $\Delta x_d$ can also vary in length to check how the local density varies for different lengths of $\Delta x_d$. These lengths will be a multiple of the average bicycle length of 1.8 meter. Now an interval is just as long as the average bicycle and the interval can scale with the average bicycle length. The unit which is normally used for the jam density is bicycle per squared meter. This unit will be used as well, the downside of this definition is that bicycles which are positioned in two intervals, will only be counted in one interval but using a different variable would mean that the results aren't comparable to the jam density. An overview of the intervals and the model can be seen in figure 9. Note that the stop line is the line for the traffic light, not the model stop line and the intervals are an example. The number of intervals can vary for the chosen $\Delta x_d$.

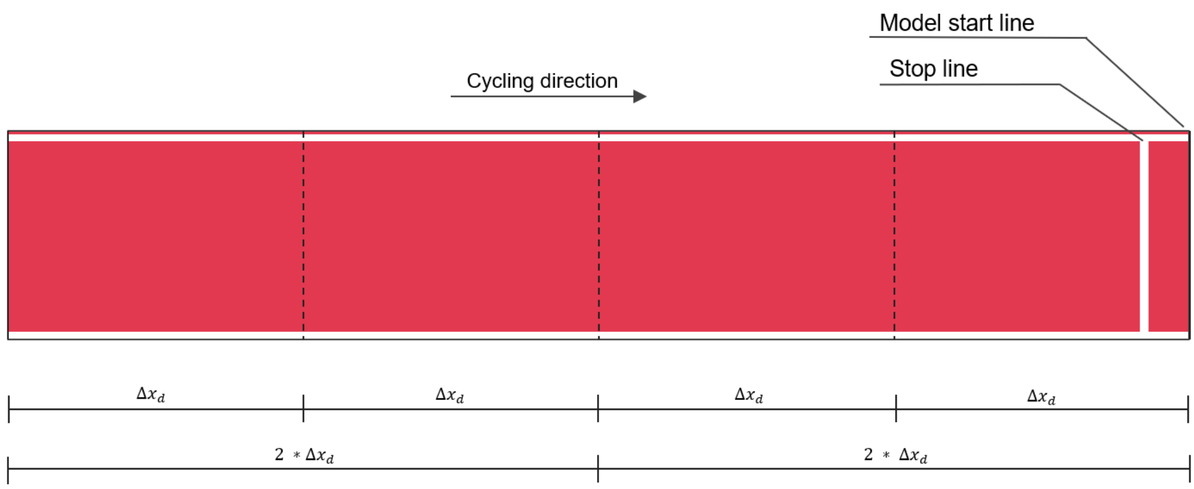



*Figure 9: Overview of how the local density will be calculated along the cycle path.*

**Define groups**

Jam density and especially the local density is depending on the queue size of the group of cyclists. For bigger queue sizes, the queues will be longer and thus have different density values along the intervals. In table 6, an overview can be found of the queue sizes that are present in the dataset and their respective sample sizes. The sample size is the number of times that a queue size is represented in the dataset. As can be seen in table 6, not all queue sizes have a large sample size and there was no queue with a queue size of eight cyclists.

*Table 6: Overview of the different queue sizes in the dataset and their sample size.*

| Queue size [Number of cyclists] | 6 | 7 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample size [Number of phases] | 1 | 1 | 7 | 5 | 13 | 4 | 11 | 5 | 2 | 1 | 1 | 1 | 2 | 2 |

For a descriptive analysis of the data, the queue sizes will be grouped in the following order, which can be seen in table 7. With this order, all queue sizes are represented and by taking the average of the group, the data is somewhat smoother than the data per queue. These groups will not be used for the statistical analysis as there is a big difference in sample size between the groups. The descriptive analysis of the data will look at trends and the variation of the local density in the data.

*Table 7: Overview of the groups for the descriptive analysis.*

| Group number | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Queue size [Number of cyclists] | 6,7 | 9,10 | 11,12 | 13,14 | 15,16,17 | 18,19,20 |
| Sample size [Number of phases] | 2 | 12 | 17 | 16 | 4 | 5 |

For the statistical analysis of the local density, the groups in table 8 will be used. A sample size larger than 10 is deemed to be a sufficient sample size as this takes up one-sixth of the dataset. In Wierbos et al., (2021) a sample size of three is used to calculate density values from the queue formations. That research was a controlled experiment so the data should be less variable than the current dataset. Therefore the sample size is also chosen to be larger than Wierbos et al.'s definition to account for the high variability in the dataset.

*Table 8: Overview of the groups for the statistical analysis.*

| Group number | 1 | 2 | 3 |
|---|---|---|---|
| Queue size [Number of cyclists] | 9,10 | 11,12 | 13,14 |
| Sample size [Number of phases] | 12 | 17 | 16 |

The statistical analysis will look at the variation of the local density along the bicycle path. To do this, the mean local density will be plotted for each group. Around the mean, the variance of a group can be plotted to investigate how the local density changes along the bicyle path. The variance demonstrates the spread of the data around the mean (Dekking et al., 2005). By taking the root of the variance, the standard deviation can be taken for each point of local density and plotted above and under the mean of the data.

# 4. Results

The results of the models will be presented in this chapter. Section 4.1 will show the results of the cyclists position model and section 4.2 will show the results for the local density.

## 4.1 Cyclists position Results

The total results of the model and the description of the model can be seen in section 3.2.3, as a reminder, the total results of the model can be seen in table 9. For each queue, the model has delivered a list with the number of cyclists that are positioned in a certain way. The model has been validated manually for queues with interesting data.

*Table 9: Total model results of the cyclist's positioning model.*

| Single cyclist | In Pair | In Threes | Staggered | Total cyclists |
|---|---|---|---|---|
| 44 | 417 | 105 | 749 | 703 |

These results alone, don't tell a lot about queue patterns or queue configurations. In table 10 and table 11, the average flow characteristics of the groups defined in the methodology are shown. In the table, the first group is the average of all the data while the other groups show the average flow variables of the defined queue patterns. The flow variables and queue characteristics that are shown in the tables are briefly explained below. An explanation of the different groups can be found in section 3.2.4.

$k_{j,avg}$, Average queue Jam Density in bicycle per squared meter.

$k_{j,med}$, Median value of the Jam Density.

$q_{avg}$, Average queue discharge in bicycle/second/meter.

$q_{med}$, Median value of the discharge

$N_{avg}$, Average number of cyclists or average queue size.

$L_{avg}$, Average queue length in meters.

$S$, Number of phases or sample size.

*Table 10: Results per group.*

| Group | Total | 50 % pairs | 30 % Threes | N Staggered | 1.5 * N Staggered |
|---|---|---|---|---|---|
| $k_{j,avg}[bic/m^2]$ | 0.474 | 0.462 | 0.522 | 0.505 | 0.550 |
| $k_{j,med}$ $[bic/m^2]$ | 0.478 | 0.452 | 0.502 | 0.511 | 0.546 |
| $q_{avg}[bic/s/\text{m}]$ | 0.557 | 0.556 | 0.558 | 0.583 | 0.620 |
| $q_{med}[bic/s/\text{m}]$ | 0.552 | 0.545 | 0.554 | 0.597 | 0.687 |
| $N_{avg}$ | 12.1 | 12.3 | 10.9 | 12.9 | 13.4 |
| $L_{avg}[m]$ | 12.5 | 12.9 | 10 | 12.5 | 11.6 |
| $S$ | 57 | 41 | 12 | 32 | 10 |

Before all the different groups are analysed, it is practical to tell something about the sample size $S$. The total dataset that was analysed for the cyclists positions consisted of 57 queues or samples. Each group has a different sample size because of the presence of that group in the dataset. As can be seen in the table, these values range from 2 to 41. For the analysis of the cyclists position a sample size larger than five is deemed sufficient. This definition is different from the sample size that was chosen for the local density. The local density depends on the queue size and can vary a lot over the queue. Therefore more samples are needed to provide good data for the analysis. Queue patterns rely on the relative positioning of the cyclists itself and not on the queue size. Therefore a sample size larger than five is used. The group with 30 % threes and N staggered cyclists will not be used in the analysis because of this. The sample size is too low, to compare the group with the other groups.

*Table 11: Results per group.*

| Group | Total | 50 % pairs + N Staggered | 50 % pairs + 1.5 * N Staggered | 30 % threes + N Staggered | 30 % Threes + 1.5 * N Staggered | 80 % pairs and Threes |
|---|---|---|---|---|---|---|
| $k_{j,avg}[bic/m\text{^}2]$ | 0.474 | 0.496 | 0.549 | 0.577 | 0.562 | 0.521 |
| $k_{j,med}$[bic/m^2] | 0.478 | 0.511 | 0.552 | 0.562 | 0.562 | 0.510 |
| $q_{avg}[bic/s/\text{m}]$ | 0.557 | 0.586 | 0.622 | 0.591 | 0.624 | 0.586 |
| $q_{med}[bic/s/\text{m}]$ | 0.552 | 0.607 | 0.657 | 0.605 | 0.624 | 0.621 |
| $N_{avg}$ | 12.1 | 13.2 | 14.1 | 12.2 | 12 | 13 |
| $L_{avg}[m]$ | 12.5 | 12.9 | 12.3 | 10.3 | 10 | 11.8 |
| $S$ | 58 | 21 | 7 | 6 | 2 | 13 |

Now onto the analysis of the groups. Not every group will be discussed in detail. The groups which are discussed are: 1.5 * N Staggered, 50 % Pairs and 1.5 * N Staggered, 30 % In Threes and N Staggered, 80 % Pairs and Threes. For these groups a boxplot will be shown, the other groups will be compared with each other based on their flow variables. Boxplots of the other groups can be found in appendix B. Some notes that can be made from the groups that aren't discussed in detail are:

- The group with 50 % Pairs has a lower density and comparable discharge value when compared with the total dataset. More cyclists in pairs will thus not directly affect the flow variables.

- The 30 % Threes group has a higher density value and a comparable discharge value when compared with the total dataset. With more cyclists in Threes, denser queues can be formed but this doesn't have a direct impact on the discharge.

- The N Staggered group has a higher density value when compared with the total dataset: More staggered cyclists in a queue can thus create denser queues.

- The average queue length and size don't change much for each group: Formation of queue patterns will thus not depend on queue length and size.

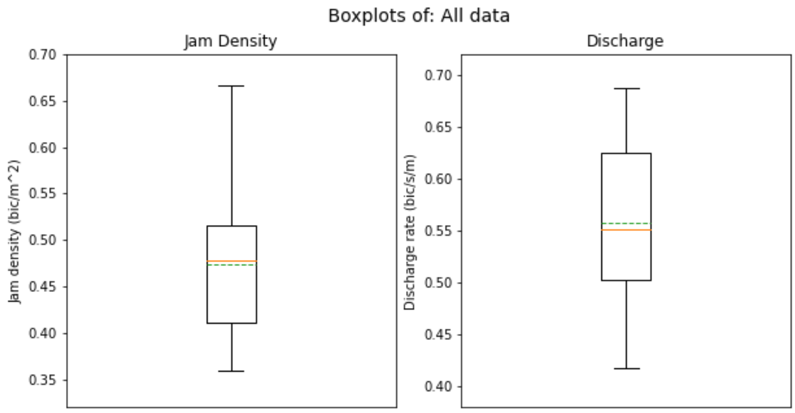



*Figure 10: Boxplots of total data.*

The boxplots in figure 10 show the Jam Density and the Discharge data of all the queues in the dataset. The mean of the data is represented by the green dotted line in the boxplot and the median is represented by the orange line. The median is the value in the middle of the dataset. Half of the dataset is below the median and another half is above the median. The median is less sensitive for outliers in the dataset and can therefore represent the data in a different way. The boxplot consists of a box and two outgoing lines. The borders of the box are represented by values at 25 and 75 percent of the dataset. Meaning that under the box, 25 % of the data is present and above it is the remaining 25 percent. This data is represented by the outgoing lines around the box. The horizontal lines at the end of these outgoing lines are the maximum and minimum value of the data.

For the total data, The Jam Density has a smaller box than the discharge. This means that the density data is less variable but the data has a lot of outliers, because the extremes are far away from the boxplot. The Discharge has a wider box which means that the data is more variable.

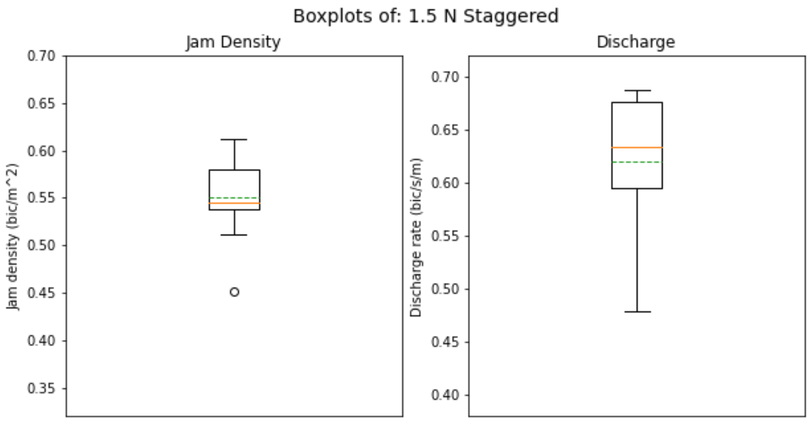



*Figure 11: Boxplots of group with high number of staggered cyclists.*

Figure 11. shows the boxplot for the group of queues with a high amount of staggered cyclists. The jam density and discharge are high for this group. Both average values are high (*0.55 bic/m^2 and 0.62 bic/s/m*) when compared with the other groups. The boxplot for the jam density also shows that the spread of the density is low. Apparently, a lot of staggered cyclists in a queue will create a dense queue and the discharge process is efficient because of the dense queue. The sample size of this group is 10 queues.

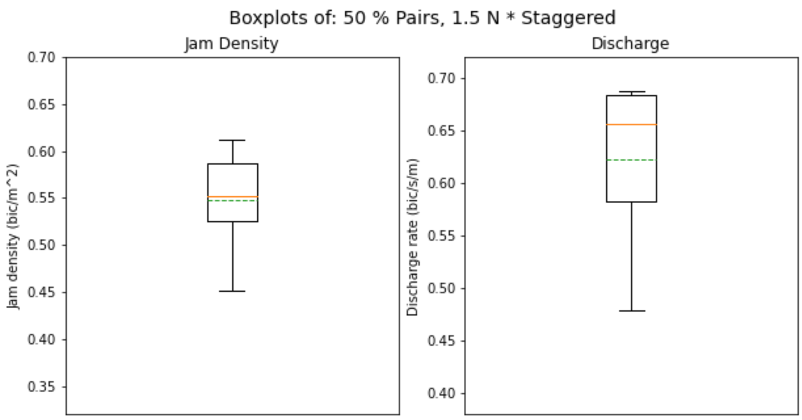



*Figure 12: Boxplots of group with high number of staggered cyclists and cyclists in Pairs.*

The group with a 50 percent cyclists in pairs and a high amount of staggered cyclists is even smaller with 7 queues. Average density and discharge values are comparable with the previous group (*0.549* *bic/m^2 and 0.622 bic/s/m)* but the median of the discharge is a lot higher. The sample set of this queue is comparable with the previous group so the queues with a discharge value lower than the median were probably filtered out. A high number of pairs in a queue will thus positively affect the discharge rate if there is a high number of staggered cyclists in the queue.

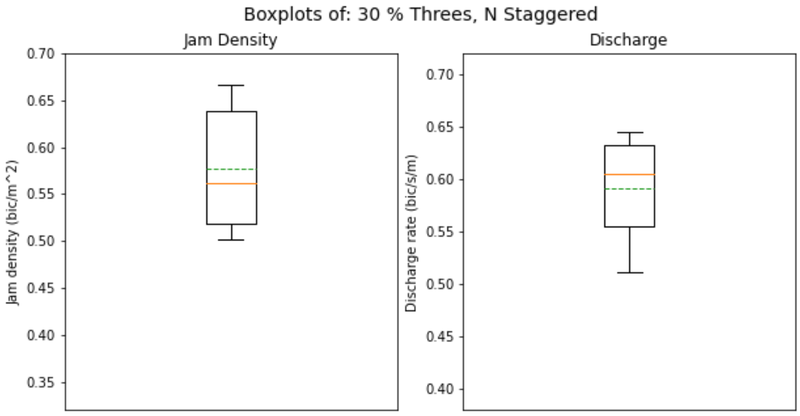



*Figure 13: Boxplots of group with cyclists in threes and normal number of staggered cyclists.*

The group with cyclists in threes and a normal amount of staggered cyclists also show comparable data with the previous two groups. The average density is a bit higher (*0.577 bic/m^2*), while the average discharge value is a bit lower (*0.591 bic/s/m*) than the two previous groups. The higher value for the density can be explained by the cyclists positioned in threes. This will create denser queues because the space on the cycle path is used efficiently. The maximum value of the discharge is also lower for this group, the positioning in threes can thus have an impact on the discharge rate

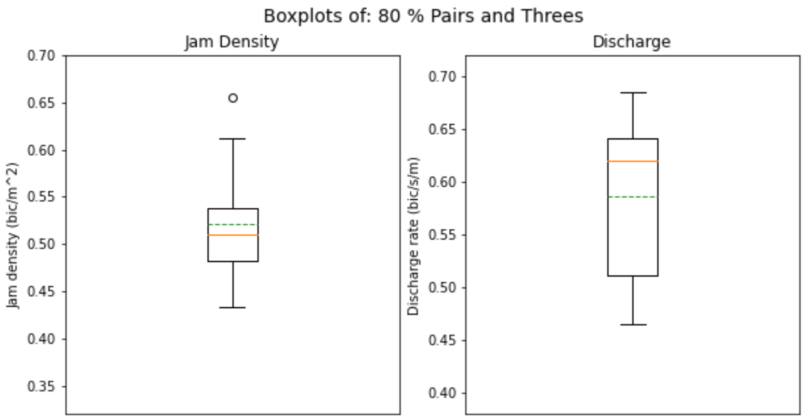



*Figure 14: Boxplots of group with cyclists in pairs and in threes.*

The last group for analysis is the group with a lot of pairs and threes. Of all the previous groups, this group has the lowest average density *(0.521 bic/m^2*) and the lowest average discharge (*0.586 bic/s/m).* If the data is compared with the rest of the groups, the discharge data is still high, especially the median value of the discharge. When looking at the boxplot of the jam density, The box of the jam density is very small but the outliers around the box go quite far. This shows that this queue type doesn’t necessarily deliver very dense queues, although this would be expected as a lot of cyclists queue up in pairs or in threes. This group has the largest sample size of the groups that were analysed, 13 queues are in this sample set, so that can explain why the data shows more variability. For slightly different criteria, the results could already be different.

**Summary**

The results in this section show the influence of different queue patterns on the macroscopic flow variables. The groups that were discussed in this results section all show high values for the density and discharge data in comparison with the total dataset. Each group has their own characteristic which is reflected in the result of the group. The results in the groups still vary highly per queue but the average flow variables show how these groups perform. The results of the groups that weren't discussed are also shown. These results didn't show much difference in regard to the total dataset, so it was difficult to asses the performance of their characteristics.

## 4.2 Local Density

The other part of the methodology has focused on the local density of the cyclists. In this section the results of the local density will be shown. In 4.2.1, the data is visualized and the effect of the interval size $\Delta x_d$ discussed. Section 4.2.2 then describes the descriptive analysis of the data and section 4.2.3 covers the statistical analysis of the data. At the end of section 4.2.3, a summary is provided.

### 4.2.1. Visualization and interval size.

Once the data has been divided into the groups for the analysis. Plots with the data could be made to visualize the data. This can be seen in figure 15. Here two queues can be seen with a similar queue size. The stop line of the cycle path is defined at 28.7 meter, so this is also the place where the cyclists queue up in the graph. The traffic light is thus on the right side of the graph. This could also be derived from the graph itself as the local density is higher on the right side and becomes zero on the left side. The queues also show that the local density can vary over the queue. Some graphs show several high and low peaks while other show a more even distribution.

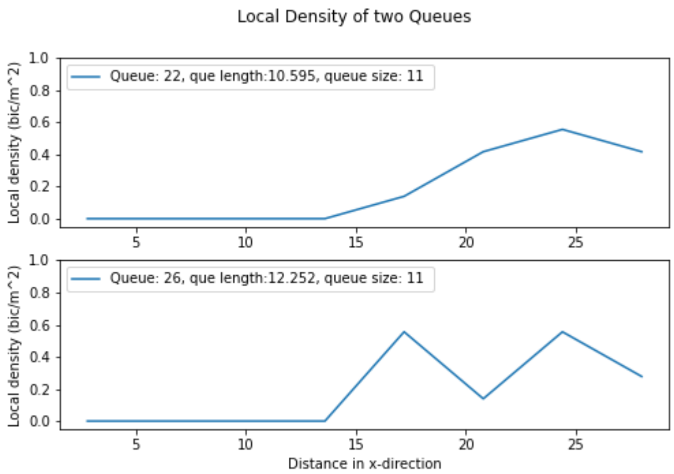



*Figure 15: Behaviour of the local density of two different queues.*

Before the rest of the analysis, the impact of the interval size $\Delta x_d$ is discussed. The interval is important for the number of cyclists that are counted in the interval. In a small interval, less cyclists can be counted. If there are a lot of cyclists in the interval, this will result in a high value for the local density but the next interval can have a much lower value for the local density. This is because sometimes cyclists are counted which are on the limit of the interval. For bigger interval sizes this is less of a problem. The density varies less over the x-axis for a $\Delta x_d$ of 3.6 and 5.4. As can be seen in figure 16. The local density is plotted for one queue with 20 cyclists but the value for $\Delta x_d$ varies each time.

The first graph with a $\Delta x_d$ of 1.8 shows a spiky graph where the local density varies a lot over the graph. The second graph shows a line which still changes abruptly but not as much as the first graph. The third graph shows little variation in the local density and doesn't really provide a good image of the density in the queue. The interval is too big to see a variation in the density. The first and second graph show variation which can be useful for analysis. To show how the local density relates to the actual queue configuration, figure 17 has been plotted with the interval lines when $\Delta x_d$ is 1.8 meters. The difference in local density can easily be seen as the density changes when the number of cyclists change. The downside of this small interval is that it's harder to see how the local density develops over the entire queue.

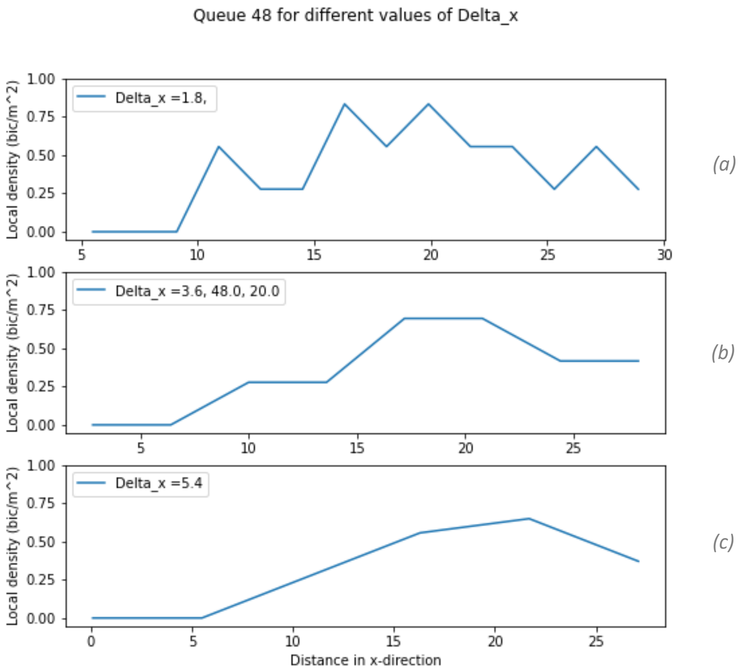



*Figure 16: Behaviour of the local density for three different values of delta_x: 1.8 (a), 3.6 (b), 5.4 (c).*

When figure 17, is observed, it is expected that the local density is at it's peak between 17 and 21 meters, at an average value from meters 21 to 28 and the value lowers between 10 and 15 meters. Due to the peaks in the data, this is harder to see in the first graph of figure 16(a), but figure 16(b) can represent the data in a better way. Because the interval size is also larger, the chance that a cyclist is situated in between two intervals is lower. This will provide more accurate results for the density as more cyclists will be counted in an interval in which they are positioned.

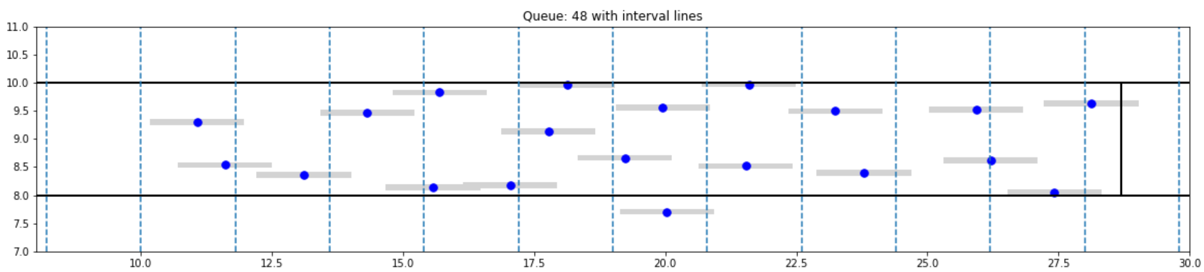



*Figure 17: Visualization of a single queue with interval lines of 1.8 meters.*

Other values for $\Delta x_d$ such as $\Delta x_d = 2.7$ and $\Delta x_d = 4.5$ have also been considered for the analysis but they were excluded in the end. These interval sizes represent 1.5 and 2.5 times the bicycle length and could have provided slightly different results. This was not the case as the data resembled a combination of the adjacent interval sizes and didn't provide a clear difference. For the rest of this section, the results are shown for a value of $\Delta x_d = 3.6$. This provides the best representation of the local density. Other results for a different value of $\Delta x_d$ will be shown in appendix B.

### 4.2.2 Descriptive analysis

With the groups defined for the descriptive analysis in the methodology. The average local density has been calculated for each group and plotted in figure 18. The figure shows nicely how the local density behaves differently for different queue sizes. The two groups, number five and six, with the largest queue sizes have longer queues due to the higher number of cyclists but the local density is also higher for the larger queues. The groups with smaller queue sizes, number one and two, have a shorter queue length but the queue length doesn't double in size when the queue size doubles. This can indicate that cyclists have the tendency to queue closer when a large queue is forming.

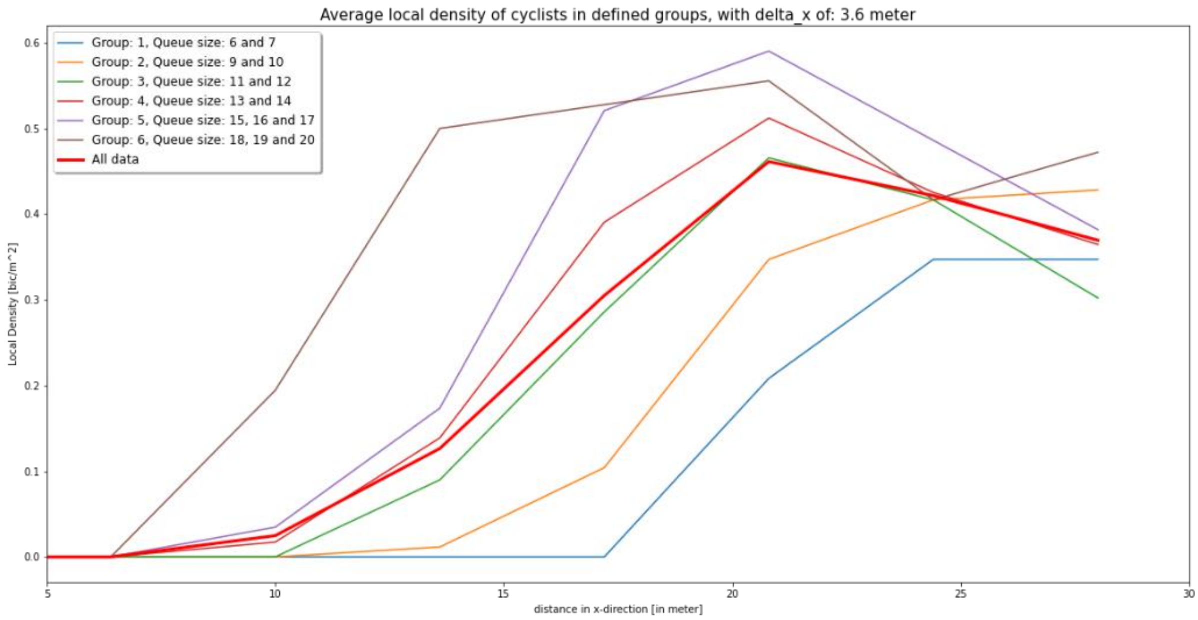



*Figure 18: Average local densities for descriptive groups with delta_x is 3.6 meters.*

Groups five and six also behave differently with respect to each other. Group six has a lower maximum density than group five while the local density stays at a higher value for longer and it eventually lowers at around the same angle. The difference in queue size isn't that big, so it would be expected that group five would also drop of at a later point. Instead, the local density moves back to the line of group four. This difference in behaviour could be explained by assuming that cyclists stop to form a dense queue until a certain queue size. Once the queue has reached a certain size, cyclists will queue up less dense at the back of the queue because queuing up densely will not have a big impact on their ability to discharge quickly from the intersection. Because there are no bigger queue sizes in the dataset, this assumption cannot be tested. Also, group five and six have small sample sizes so the local density can actually behave differently for these queue sizes.

Lastly it is interesting to see that for each group the local density lowers to zero at roughly the same angle. Not every cyclist has the preference to queue up closely so the end of the queue has a lower local density. An advantage of this behaviour is that a cyclist which wants to queue up to the front of the lane can always move to the dense part of the queue.

### 4.2.3 Statistic analysis

For the statistic analysis, different groups have been defined with a larger sample size. The explanation of this definition can be found in section 3.3. The groups have been plotted with their average local density in figure 19. In the figure, the average local density of all the queues has also been plotted.

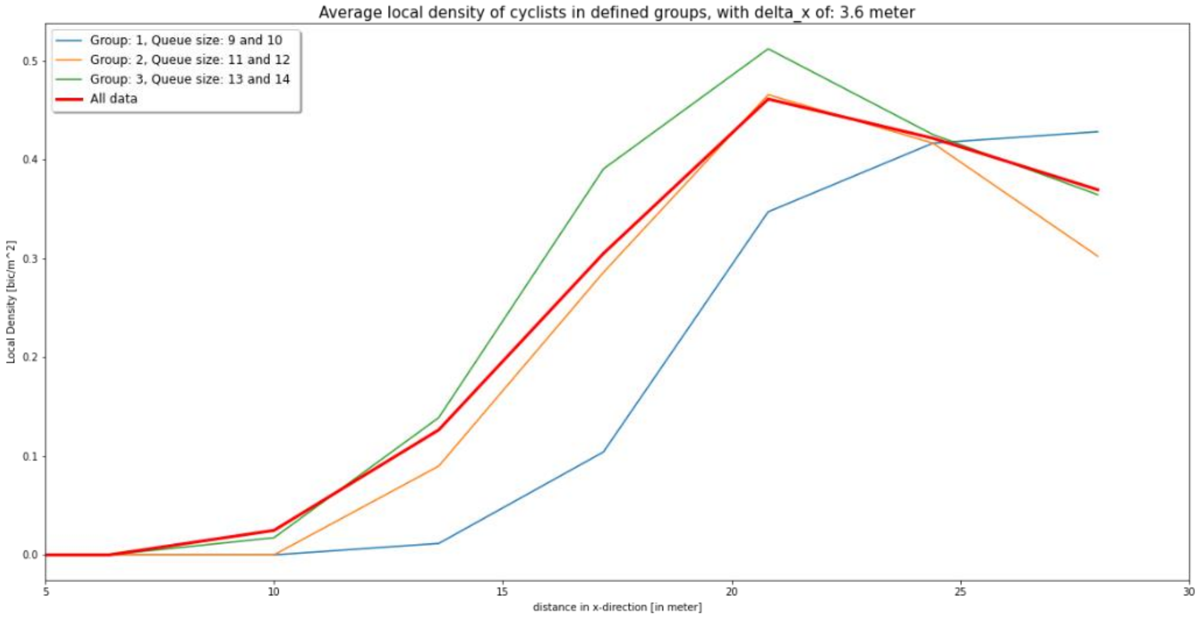



*Figure 19: Average local density of statistical groups with delta_x is 3.6 meters.*

Just as the groups which were defined for the statistical analysis, the groups with a larger queue size have a higher local density. Interestingly, the behaviour of the local density is different at the first interval, around x = 28 meters. Group one has the highest local density of the three groups at this interval but this is also the largest value for the local density of group one. The other groups reach their maximum value at a later point. This behaviour is unexpected as it would be expected that cyclists want to queue closely to the traffic light. The difference in the first interval is expected because the interval starts before the stop line. This is done to account for cyclists which cross the stop line. Generally speaking, this is not normal cyclists behaviour so it's not strange that the first interval would have a lower value for the local density because of the measurement method. The second interval would then have to have a higher local density as cyclists would queue up there behind the first cyclist, but cyclists choose to queue up densely at a later point.

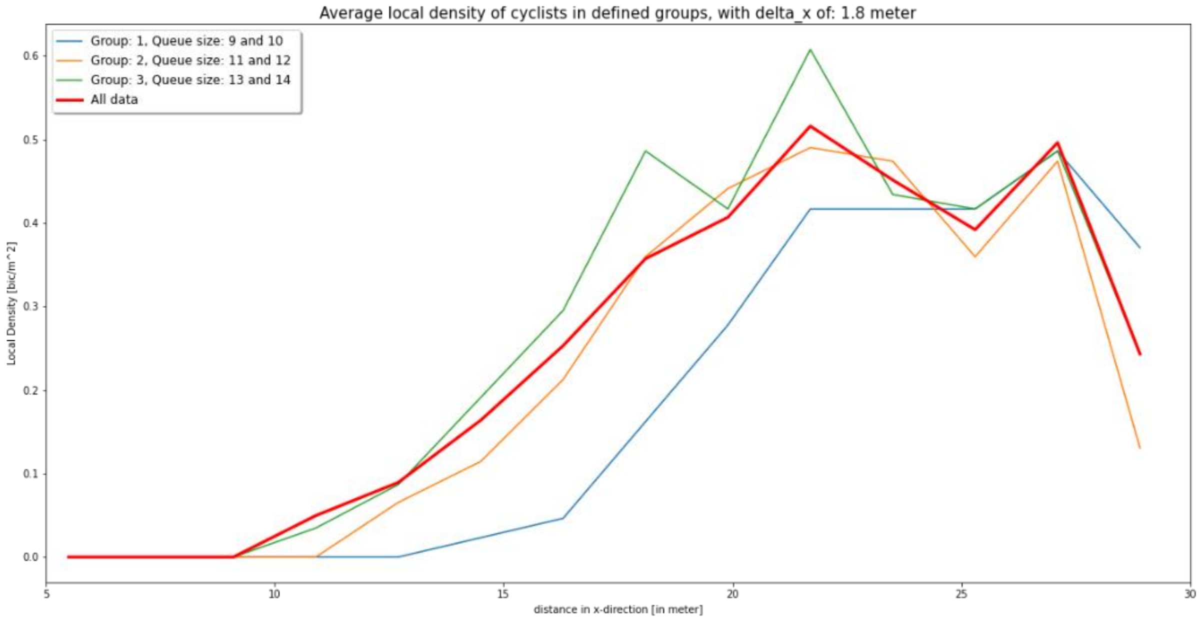
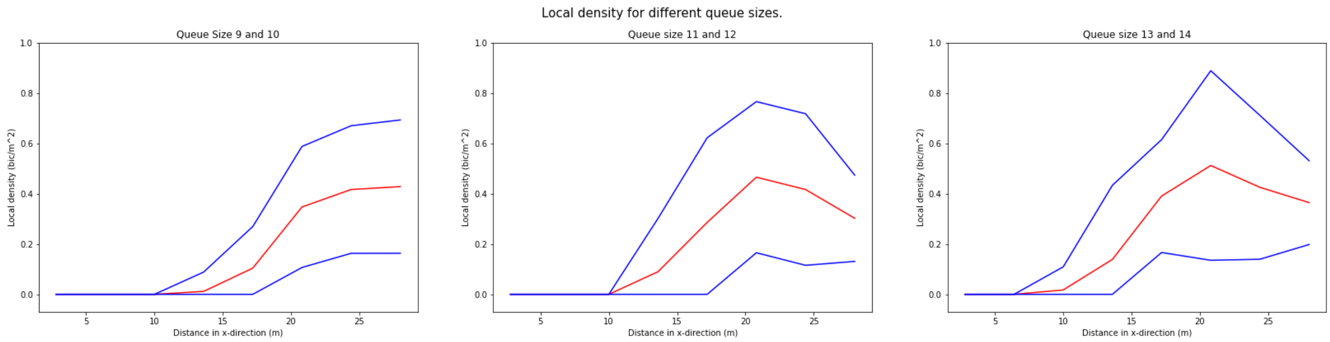



*Figure 20: Average local density of statistical groups for delta_x is 1.8 meters.*

Figure 20 shows the same data but with a lower value for $\Delta x_d$. This figure shows that the local density can vary a lot, even for average data. In this figure, the local density is even lower in the first interval but a peak is observed in the second interval. This is not the maximum for the local density as this occurs in a different interval for group two and three.

A better way to show the variation of the local density along the bicycle path is to plot the variance around the data. This is done in figure 21. The red lines represent the average of the group and the blue lines show the variance which is two standard deviations away from the mean. If the blue lines are closer to the red line, the variance is lower so the spread of the data around this point is lower. Consecutively, if the blue lines are further away from the red line, the spread of the local density is larger. Negative values for the standard deviation have been changed into zero in the data, as the local density can't become negative.




*(a)* *(b)* *(c)*

*Figure 21: Average local density plotted with the upper and lower values of two standard deviations for queue size: 9 and 10(a), 11 and 12 (b), 13 and 14 (c).*

If the spread of the data around a point is large, this means that the behaviour of that data can change a lot. Interestingly, the largest variance occurs at the maximum value for the local density of each group. Apparently the distribution of cyclists can change a lot around this point. This can be due to groups in the queue or different queue configurations can form around this point. This can be seen in figure 15. The local density varies less at the back of the queue as the blue lines are closer to the red line there, this was also observed in the descriptive analysis but the variance now shows that this is the case. For group two and three the local density also varies less at the front of the queue. Apparently cyclists don't feel the need to queue closer to the front or they don't have a preference for this, otherwise the local density would vary more, but this is not the case.

**Summary**

The results in this section provide an insight into the behaviour of the local density along the bicycle path. The local density depends largely on the queue size, larger queue sizes will reach higher values of the local density as these queues will be denser. The behaviour is also highly variable per queue. Some queues contain high and low peaks of the local density while others show a more even distribution of the local density. Cyclists also don't have the tendency to queue up close to a traffic light. The local density shows higher peaks later on the bicycle path then close to the beginning of the bicycle lane. After the peak value of the local density has been reached, the local density will gradually return to zero which shows that queuing behaviour is less structured at the end of a queue. If different distributions of the local density can impact the discharge rate can not be concluded from this analysis. To do this, the analysis would have to focus on these different distributions but this behaviour is also greatly variable per queue.

# 5. Discussion

In this chapter the results of both subjects will be discussed and recommendations are given for future research. First the cyclists positioning model will be discussed. Then the results of this model will be discussed and the results will be compared with existing research. Lastly, the local density is discussed.

**Cyclist's positioning model**

In this section the cyclists positioning model will be discussed. The model has been created to count the way in which cyclists are positioned with respect to each other. The model has been based on the preferences of the queuing position of a cyclist. These preferences have been described in certain attributes. With the attributes, the different positions in which cyclists can queue were described and these were then used to build the model.

As described in the methodology itself the model doesn't make a distinction between cyclists which are positioned staggered or 'double staggered'. A future model could use a more extensive definition or this model could define more types. This would of course depend on the research goal of this model. If this model wants to capture all the possible positioning types that exist, it will be useful to define all these scenarios. This will especially be useful for larger queue sizes. In these queues, a single cyclist can be surrounded by 4 or more other cyclists. The current model would keep adding all these cyclists as staggered or as pairs, while the cyclists is actually positioned 'triple staggered' or 'double paired'. This is just an example to show that the current model can not properly define the positioning types for larger queues. The outcome of the model still makes sense but it is a simplification if all these other types would be included.

The goal of this research was to make a simple distinction between these positioning types and the model delivers this. A model with more positioning types would be harder to analyse and it probably won't have any practical applications. A cyclist won't care how it's positioned in the queue and it would be hard to explain to cyclists which don't measure the discharge rate of a bicycle queue on a regular basis what their positioning type or preference is.

**Queue patterns and a comparison with literature**

The groups were discussed in chapter 4.1 all had combinations of queue patterns which resulted in high values for the jam density and discharge rate. The queue patterns consisted of a high number of staggered cyclists, cyclists in pairs and in threes and a combination of these positioning types. In the literature a positive relation between the jam density and the discharge exists (Goñi-Ros et al., 2018). Other research from Wierbos et al., (2021) has also focused on the queue configuration of cyclists but then in an experiment setup. Different queue configuations were tested, these can be seen in figure 3. The research done by Wierbos et al., (2021) discovered jam densitites that haven't been measured in practice before.

Now that the queues from this dataset have been characterized in a queue pattern. The results can be compared, some of the groups in this dataset show resemblance with the groups found in Wierbos et al, (2021). These groups have been listed next to each other in table 12. A general comment that should be made first is that the jam densities and discharge rates differ greatly. The aim of this short analyis is to look at the relative difference between groups. In other words, what differences arise in the dataset from Wierbos et al., (2021) and can these differences be found in the current dataset? The average flow variables are listed in table 12 but the differences in the groups that were discussed in chapter 4.2 are also important to remember.

*Table 12: Group results from Wierbos et al.,(2021) and the current research.*

| Wierbos et al., (2021) | | | Current research | | |
|---|---|---|---|---|---|
| Groups | $k_{j,avg}[bic/m\text{^}2]$ | $q_{avg}[bic/s/\mathrm{m}]$ | Groups | $k_{j,avg}[bic/m\text{^}2]$ | $q_{avg}[bic/s/\mathrm{m}]$ |
| In pairs | 0.71 | 0.64 | 50 % In pairs | 0.46 | 0.56 |
| Side by side in threes | 0.83 | 0.68 | 30 % In threes | 0.52 | 0.56 |
| Three-Two-Three | 1.07 | 0.75 | 80 % in pairs and in threes | 0.52 | 0.59 |
| - | - | - | 50 % Pairs, 1.5 N Staggered | 0.55 | 0.62 |
| In threes with a shift | 0.99 | 0.69 | 30 % Threes, N Staggered | 0.58 | 0.59 |
| No queue instructions | 0.66 | 0.56 | All data | 0.47 | 0.56 |

The in pairs and side by side in threes group can be compared with the queues with 50 % in pairs and 30 % threes. The jam densities differ greatly but the difference in discharge rates is somewhat comparable. When the actual queue configurations are compared with eachother visually. One difference is that the cyclists are queued wheel to wheel with eachother. This can be seen in figure 22. Compare this with figure 7, which has a lot of cyclists in pairs and in threes, and there is a lot more space between the cyclists in a normal queue. This observation can also clarify the high jam densities that were found.

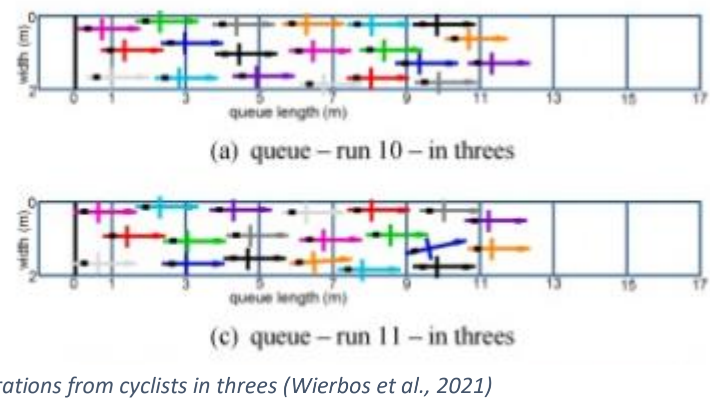



*Figure 22: Queue configurations from cyclists in threes (Wierbos et al., 2021)*

The three-two-three group delivered the highest jam densities and discharge rates. In the current dataset the 50 % pairs, 1.5 N Staggered group delivered the highest results but the queue configuration is more comparable with the 80 % in pairs and in threes group. It should be mentioned that the three-two-three configuration in Wierbos et al., (2021) showed that the cyclists would also queue up staggered or very close to each other. That’s why such high jam densities were used and a group with a high number of staggered cyclists is also comparable with this group.

The in threes with a shift group can be compared with the 30 % threes, N staggered group. The shift which is defined by Wierbos et al., (2021) can be seen as a cyclist which is positioned staggered. Both groups reach high values for the jam density and the discharge is higher than average.

Interestingly the discharge rate of a queue when no instructions were given is equal to the average discharge behaviour of the total dataset. Of course, the average value of a dataset is not comparable with the data from four queues. The dataset contains lots of differences in queue size, density, discharge and so on but the observation is interesting because the other discharge rates reported in Wierbos et al., are all a lot higher.

It is interesting to see that the groups defined in this research show a bit of resemblance with the groups defined in Wierbos et al., (2021). What does this tell about the queue characteristics in practice? First of all, dense queue configurations can occur in practice but their density value is lower. Cyclists choose to keep more distance from each other and because of the different preferences of cyclists. They don’t have a common goal to discharge from the traffic light as fast as possible, future research can focus on creating denser queue patterns in practice for cyclists by giving instructions or by assisting with road signs. Secondly, a high number of staggered cyclists in combination with cyclists in pairs and threes can create dense configurations. Cyclists in threes don’t appear as often in the dataset, to assume that it’s regular behaviour for cyclists to queue up in threes. If there was a threes in a queue this would be three or six cyclists. Queues with a higher number of cyclist were rare. The threes that were found could be due to group behaviour, but this is hard to prove. A two meter wide bicycle path could be too small to queue in threes comfortably. Cyclists might have more preferences for queuing up in pairs or staggered so it’s better to focus on these positioning types if cyclists are encouraged to position in a certain way.

**Local density along the bicycle path and it’s applications**

This thesis mainly showed how the local density can vary along the bicycle path. This information is useful to determine if the design of bicycle paths can be improved before an intersection. Based on the behaviour of the local density, bicycle paths could be changed according to the maximum value that occurs. Based on figure 18, the bicycle path could be widened from the stop line towards x = 15 meters. This would come down to around 13 meters of bicycle path that can be adjusted to give the cyclists more space. The capacity and thus the discharge rate depends on the width of the bicycle path (Wierbos et al., 2019) so an increase in the width can increase the discharge but there is also more space for cyclists to queue. If this solution works depends largely on the situation in which it is applied but more research is needed to asses this.

Through this dataset a lot is known about the number of cyclists that pass this specific intersection. For other intersections this information is not available or this data has to be acquired first. Therefore it is also difficult to know if this solution will work for other intersections. The bicycle path on this intersection is a one-way bicycle path while others have two-way bicycle traffic. The shape of an intersection can also differ and sometimes there is just no space to create enough space for queing. The solution might thus not be widely applicable but the takeaway from this should be that by widening a small bit of the bicycle path of an intersection, traffic flow might be improved.

In future studies, the relation of the local density and other macroscopic flow variables can be investigated, to find differences in the distribution of the local density.

# 6. Conclusion

This thesis has tried to answer the main research question: What is the influence of the cyclists position and the queue density on the queue discharge rate? This was done by looking at the positioning of cyclists in the queue. A model has been created to quantify how cyclists are positioned in the queue with respect to each other. This model is based on the preferences of cyclists to choose their queue position. With the outcome of the model, groups were created to analyse how different combinations of positioning types would influence the discharge rate. These combinations showed that a high number of staggered cyclists or a high number of cyclists in pairs can create dense queues with high discharge values.

The results of these groups have been compared with existing research into queue configurations. This showed that the defined queue combinations could be compared with queue combinations from a controlled experiment. This comparison showed differences between the groups. Cyclists can queue up closer than they do in practice and queue patterns from the experiment can be found in actual queue configurations. The positioning of cyclists will thus impact the discharge rate as different queue patterns deliver different results for the discharge rate.

The queue density has been researched by calculating the local density over the entire queue. This analysis provided insights into the behaviour of the local density. The local density can vary greatly per queue size but also per queue as the configuration of a queue is variable. Large queue sizes, show larger values for the local density and their longer queue lengths can be recognized in the local density. A relation between distributions of the local density and the discharge rate couldn't be found. Nevertheless, the local density can act as a good measure for infrastructure design because it provides insights into the distribution of bicycle queues.

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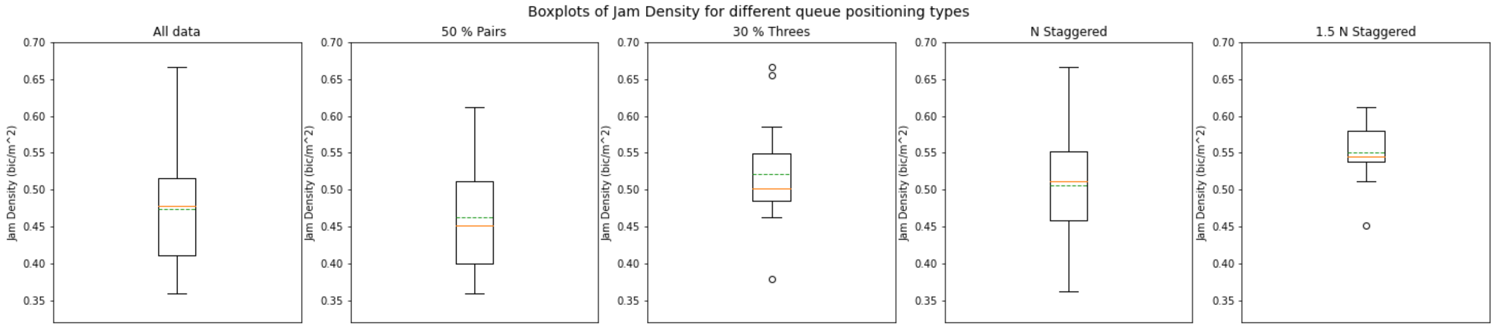
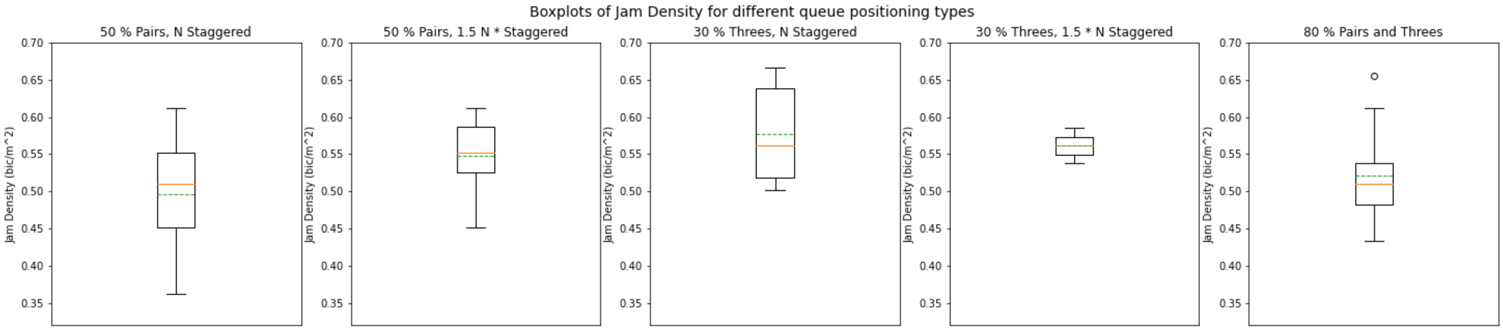
# Appendix A: Bicycle dimensions

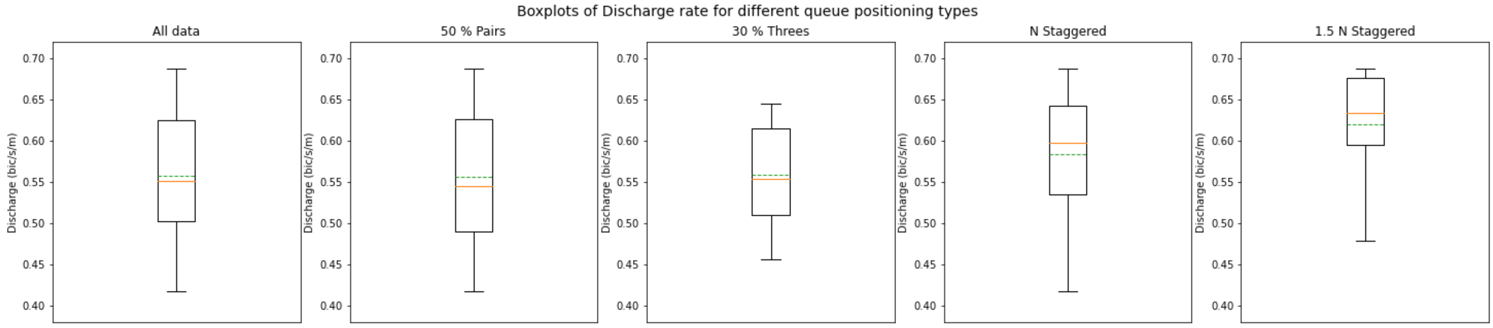

My bicycle was 182 cm in length from the outer edges of the wheels and the centre of the saddle is positioned at around 60 cm. from the edge of the rear wheel.

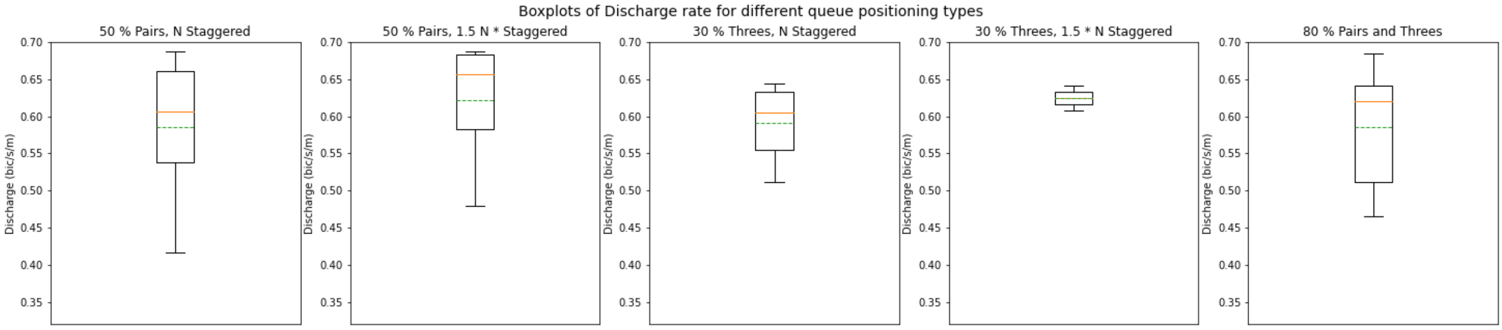
# Appendix B: Results

Cyclist's positioning model results.

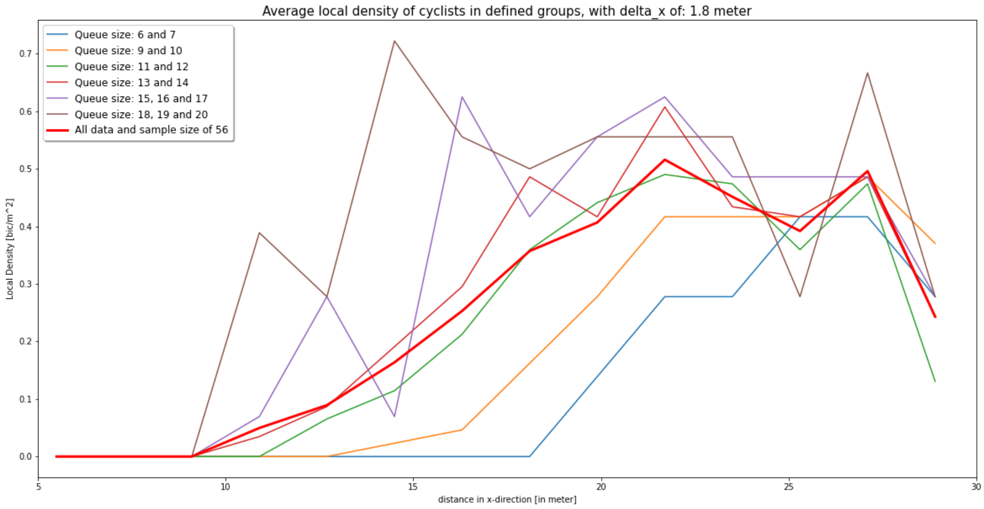


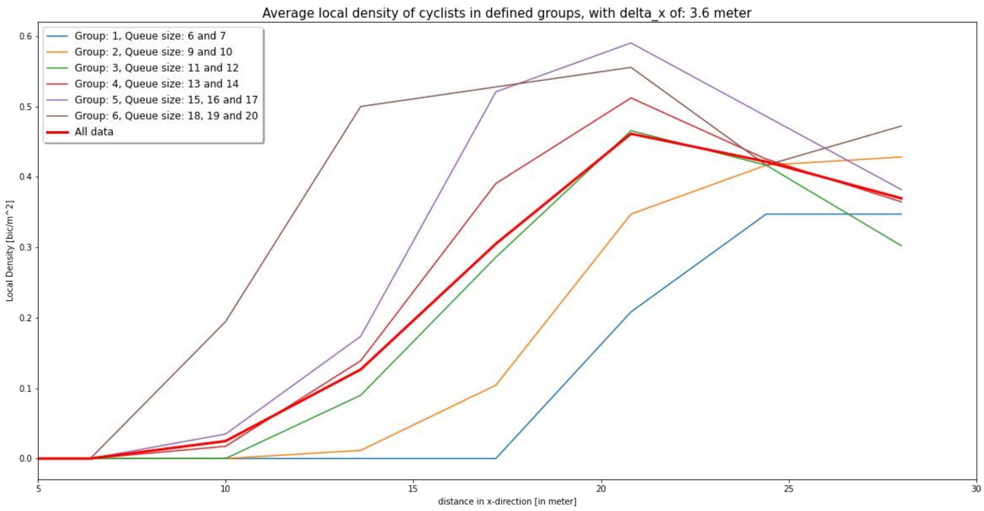



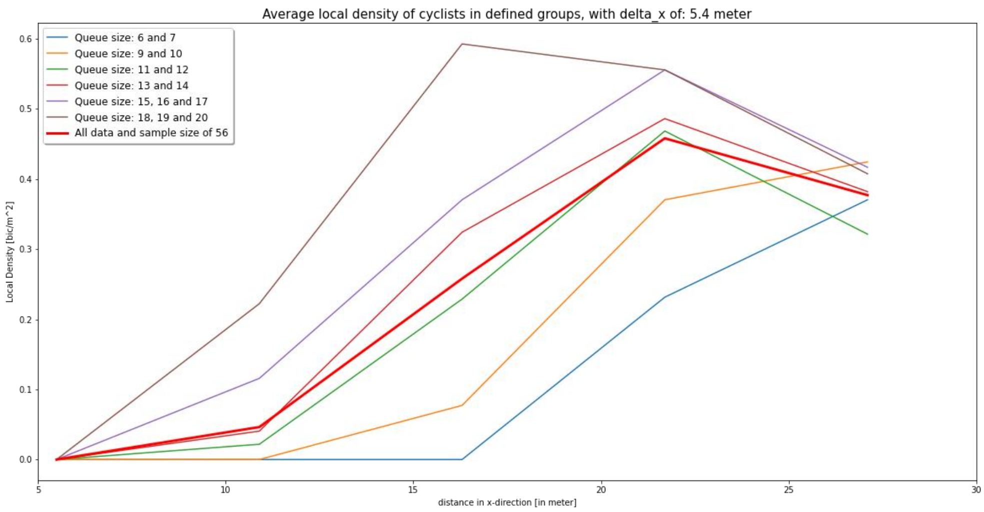



**Local density, descriptive groups.**



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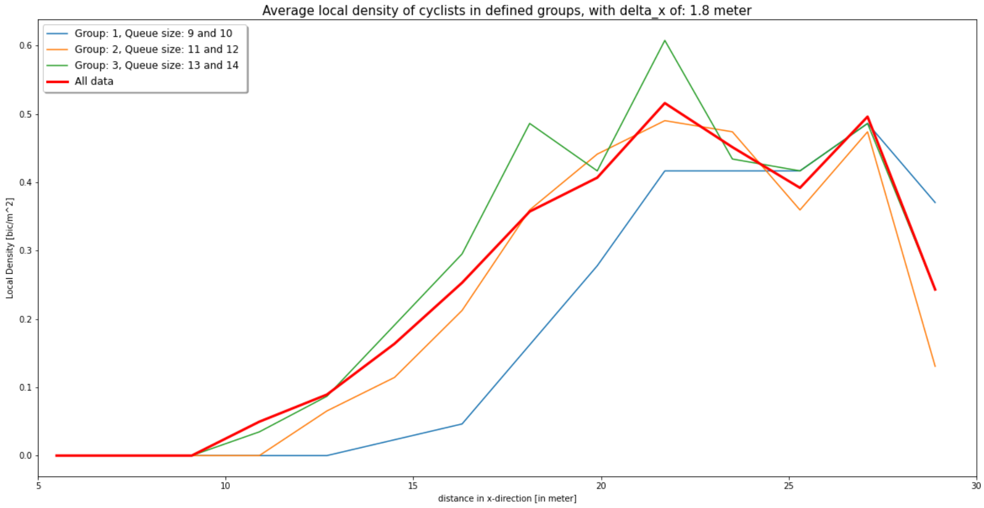


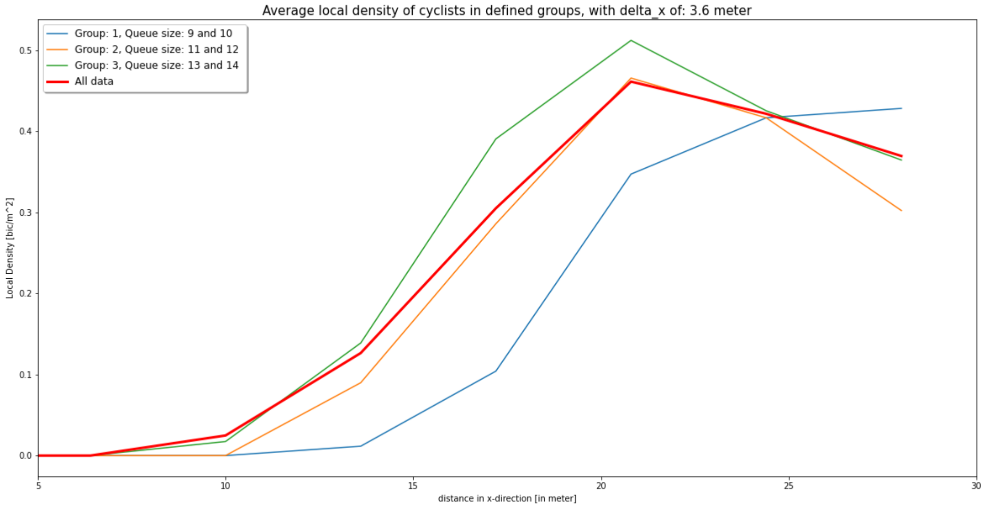


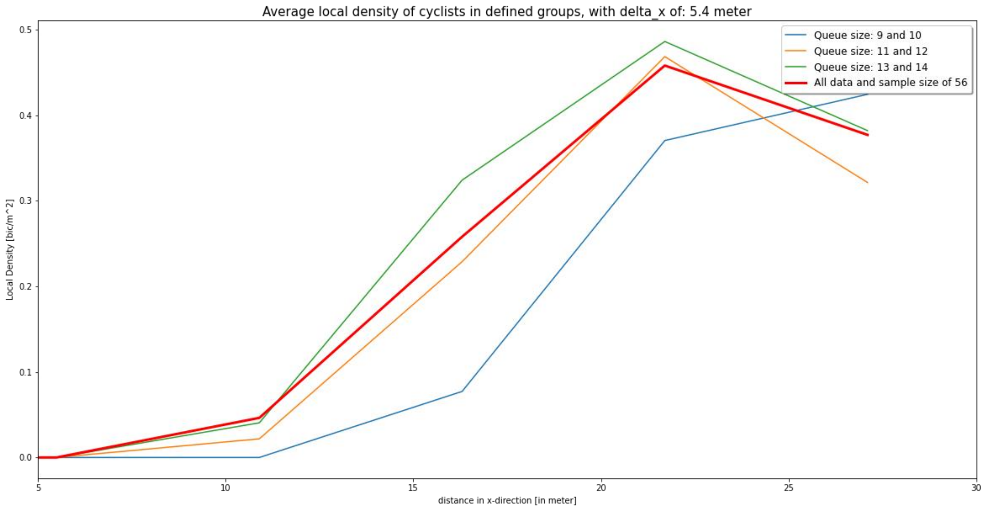

## Local density, with variance for delta_x = 1.8, 3.6, 5.4