Simulating cyclist behaviour

An examination of what we know about this subject and how we should go further

MSc Metropolitan Analysis, Design & Engineering

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Preface

I am pleased to present this master's thesis, which finalizes my time at the MADE (Metropolitan Analysis, Design & Engineering) programme. The process of writing this thesis has been an insightful and mostly fun experience for me. I am grateful that my supervisors gave me the space to figure out what I want to research and how I want to do it. This gave me a true feeling of ownership. I want to thank my supervisors, Jan Anne Annema and Haneen Farah, for their thorough and attentive feedback which showed that they had my best interest at heart.

I would also like to thank my friends and family for their constant support and interest in my research, even when they would not understand what I was talking about. I would like to thank a few individuals in particular. The contributions of Maarten and Kiki have lifted the quality of this report through proofreading and discussing my thoughts with me. I would also like to thank Leon for the insightful discussions during our coffee breaks.

Lastly, I would like to express my gratitude for the professionals that made time for my thesis. Thanks to Zoë Peters from the municipality who provided data and made time to talk with me on multiple occasions. I am also thankful for the help of Maria Salomons, who sat with me to figure out any Vissim related issue. And I would like to the various professionals from companies and knowledge institutes that spoke with me about my thesis and the broader cycling academic landscape.

I hope you enjoy reading my thesis.

Executive summary

Cycling as a mode of transport is getting increasingly more attention from academics and governments around the world. It improves the physical and mental well being of citizens, it is efficient in terms of space and it provides economic benefits. However, traffic engineers and urban planners of these cities currently lack the means to quantitatively test their bicycle infrastructure designs. Simulation models have become an important tool for the transport planner as it is cheap and effective. But simulation models of cyclist behaviour are an understudied subject.

This is not only an issue for cities that attempt to transform there mobility landscape to a more bicycle-friendly one, but also for established cycling cities that face new challenges because of the introduction of new vehicle types (e.g., e-bike, e-step) and new mobility business models (e.g., shared mobility, flash delivery). The academic world is also affected by the fact that cyclist simulation is understudied. The literature review of this thesis reveals that the academic landscape on this subject is foggy and unclear. The most popular model in academia is the Social Force Model (SFM). However, just the SFM leads to unsatisfactory behaviour, as is confirmed in the case study of this thesis. Thus, the academics propose a hybrid model. Herein, the SFM is constrained by additional rules, regimes or decision making processes. However, these propositions are tailored to cycling in a specific context and they are created in unmentioned software, using unmentioned programming languages. This hampers the possibility to replicate and verify their study.

The primary conclusion is that academics and simulation software developers should work towards a standardised behavioural model for cyclists, similar to the SFM for pedestrians and the car-following model for motorised traffic. An example of a leading principle for cycling behaviour could be a model where cyclists move along predetermined trajectories rather than being led by a force. This seems to solve the challenges researchers face regarding the operational behaviour of the cyclists.

It is also advised in future research to discuss the semantics of cyclist behaviour simulation. Literature that used this principle of predetermined trajectories still referred to their model as a model based on the SFM. This understates the fundamental criticism of these researchers on the SFM.

Lastly, commercial software companies are advised to actively partake in this process of creating a standardised model for cyclist simulation. With pro-cycling policy becoming more popular in cities all over the world, it is expected that municipalities and research institutes will show interest in a standardised model for cyclist behaviour when offered by a simulation software company. Moreover, such a standardised model incorporated in an applied simulation software should improve the verifiability and replicability of academic research. As a properly calibrated model for cyclist behaviour, would mean that less academics are inclined to create their own custom model for their research.

If these proposed developments come to fruition, other research subjects and applications become possible or more accessible. It should allow peer reviewers to test a researcher's simulation model more easily. It enables urban planners and traffic engineers of local governments to quantitatively test their infrastructure designs and it enables academics to study the rapidly changing urban mobility landscape. For instance, it provides a possibility to experiment with infrastructure designs, aiming to tackle the contemporary challenges of established cycling cities.

Abbreviations

API	Application Programming Interface
CA	Cellular Automata (model)
CB	Conventional Bicycle
EB	Electric Bicycle
PDM	Particle Dispersion Model
PET	Post-Encroachment-Time
PPFM	Physiological Psychological Force Model
SFM	Social Force Model
SUMO	Simulation of Urban MObility
TTC	Time-To-Collision
UDA	User Defined Attribute

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1. Introduction

Cycling as a mode of transport is getting increasingly more attention from academics and governments around the world. Metropoles such as London and New York have stated the ambition to encourage cycling as a mode of transport (Osowski & Waterson, 2016). Metropoles like Paris and Bogotá have put their money where their mouth is and are successfully transforming the urban mobility landscape to encourage cycling (Masliy, 2023). This is rightly so, as cycling brings many benefits across several categories. Commuters on the bicycle do not only gain benefits in terms of physical health, but also prove to have a reduced risk of mental illness (Berrie et al., 2024). Moreover, cycling is better for the environment as the CO2 emissions are negligible in respect to cars and bicycles do not pollute the air whatsoever (de Guerre et al., 2018). Cycling also provides economic benefits for two reasons. First of all, research shows that bicycle infrastructure is cheaper than car infrastructure in terms of construction as well as maintenance (Schroten et al., 2014). Second, a recent study of Movares (2024) found that pedestrians and cyclists spend 25% more money in their local economy than travellers by car. Lastly, the bicycle and its infrastructure is much more efficient in terms of space, arguably the most valuable resource a city has.

A popular tool for academics and municipalities to test and analyse infrastructure designs is simulation modelling. Simulation models have become an important tool for the transport planner as it has become a standard expectation of the planning process for highway motor traffic or pedestrian spaces (Osowski & Waterson, 2016). The main reason for this is that simulation models can be a cheap and effective method for the analysis of infrastructure, provided that the movements and interactions of the road users are accurate and realistic (Twaddle et al., 2014). This condition does not seem to be self-evident for the simulation of cyclists. Traffic simulation software does not offer standardized behavioural models for cyclists as it does for cars or pedestrians and academic literature does not describe a general consensus on how cyclists should be modelled. This is a missed opportunity for previously described cities that want to encourage cycling or even make cycling an integral part of their urban mobility system. Traffic engineers and urban planners of these cities currently lack the means to quantitatively test their infrastructure designs.

The lack of means to properly simulate cyclists is not only an issue for municipalities that want to encourage cyclists, but also for established cycling cities such as Copenhagen, Munich or any city in the Netherlands. Namely, these cities are faced with new challenges that arise due to the introduction of new vehicle types such as the e-bike and the introduction of new business models such as shared mobility and flash delivery of groceries. Moreover, Statistics Netherlands recently reported a peak of cycling traffic deaths (CBS, 2023). The municipality of Amsterdam has put one and one together and suspects the surge of e-bikes are related to the increase of traffic accidents, and attempt to combat this trend through policy measures (NOS, 2023; Niemantsverdriet, 2023). Academic research on the impact of E-bikes on traffic conflicts is yet to be conducted, therefore the policy measures of Amsterdam are not (yet) backed by research. However, any regular user of the Dutch urban cycling infrastructure will confirm that the mobility landscape is rapidly changing. It might be that this new reality requires not policy makers but urban planners and traffic engineers to come with innovative solutions to these issues. For instance, how would a fast lane on the bicycle path impact the behaviour, flow and safety of the bicycle path? Or could e-bikes be seduced to circumvent the city centre if there were a ring way with minimal traffic lights? If only there were a cheap and effective way to quantitively test these ideas.

1.1 Knowledge gap

The introduction of this report highlights the potential of cyclist simulation for cities around the world to either promote cycling policy or to research effective methods for dealing with the changing urban mobility landscape. First one must understand the behaviour of a cyclist in order to simulate it (Twaddle et al., 2014). But unfortunately, examinations of cyclist behaviour is an understudied subject in academia (Gavriilidou et al., 2019). Furthermore, the landscape of cyclist simulation is diffuse and all methods reveal shortcomings in terms of behaviour (Twaddle et al., 2014). Compared to other modes of transport, there is no widely adopted method for simulating cyclists. Car traffic simulation is usually simulated through the car-following model and pedestrian simulation is usually simulated through the Social Force Model (SFM) (Barceló, 2010). Such a specific method has not been widely adopted in the world of cyclist simulation yet.

Therefore, this thesis aims to make a relevant contribution to the simulation of cyclist behaviour. As I would argue that cyclists deserve a more dominant spot in the world of simulation, just as cyclists are claiming a more dominant spot in urban areas around the world.

1.2 Research questions

In order to make a contribution to the described knowledge gap, within the timeframe of a master's thesis, the following research questions have been formulated. The main research question that shall be answered is as follows:

How to improve cyclist behaviour simulation?

Then, three subquestions have been formulated. First of all, an examination of the current academic landscape shall be conducted through the following question:

What is the state of the academic research on simulating cyclist behaviour

Second, the gained insights shall be put to use by creating a simulation model myself. To give the simulation model a purpose, a small case study will be performed. Insights and learned lessons during the creation of the case study shall be described by answering the following questions*:*

What can be learned about cyclist behaviour simulation by applying current simulation insights/tools and knowledge in a specific case?

Third, the created case study shall examine the correlation between speed, speed difference and conflict. The examined vehicle types are conventional bicycles (CBs) and electric bicycles (EBs). EBs have a higher average speed than CBs, allowing for the examination of the relation between speed, speed difference and conflict. This correlation is partly chosen for its current relevance in the Netherlands. But the measurement of conflicts shall be primarily used as a way to validate the created simulation model. Therefore, the third subquestion is formulated as follows:

To what extent can the calibrated model for the case study be validated through the measurement of conflicts between different vehicle types on the bicycle path?

2. Methodology

This section describes the applied methods that are used in order to answer the research questions posed in section 1.1. The first two subsections will describe more practical research choices, namely the choice of simulation software and the choice of location and vehicle types for the case study. The following subsections describe more specifically the methods that are applied in order to answer the posed subquestions.

2.1 Software choice

As will be explained in section 2.2, the focus of this thesis will be on microscopic modelling. Therefore, simulation software that solely focuses on mesoscopic or macroscopic simulation (e.g., PTV Visum) will not be taken into account in this section. For this thesis, Aimsun, SUMO and Vissim were considered. These will be shortly described:

Aimsun

AIMSUN is an acronym for Advanced Interactive Mocroscopic Simulator for Urban and non-urban Networks. It originated from a research program of the University of Catalonia and does not solely specialize in microscopic simulation anymore as the software now also provides possibilities for mesoscopic and macroscopic simulation (Barceló, 2010). Barceló writes in their chapter dedicated to Aimsun that its development focuses on integration, modularity, scalability and interoperability. This is reflected on the website of Aimsun, where the newest features include hybrid meso-micro models and macro-meso models (Aimsun, 2023).

In the study of Thijsen (2021), Aimsun is described as a software with the capability to create models with a high level of detail, but it requires heavy coding. Aimsun's website also provides a page on implementing cyclists in a simulation model. Cyclists can be integrated with car traffic or get a separate bike-lane. The web page also describes the ability to allow for non-lane-based behaviour. However, a description of what the behaviour is then based on is not given and the subsequent settings if you toggle this behaviour on are limited. Also the moving images on the webpage display stiff and car-like movements of the cyclists (Hayman, 2020).

SUMO

SUMO (Simulation of Urban Mobility) is an open source software that is primarily developed by the German Aerospace Centre (DLR) in collaboration with other knowledge institutes. In *Fundamentals of traffic simulation*, Barceló states that SUMO is created as an open source software for two reasons (Barceló, 2010, p. 269):

1. In the academic field, many different simulations were developed as tools within diploma or doctoral theses, in order to evaluate the objective that was the thesis' real topic. These simulation models would not be made public after the thesis had finished. In other words, its aim is for academics to not have to reinvent the wheel.
2. The second reason is that these simulations Barceló speaks of were often incomplete and contained many problems. Moreover, since every researcher would make their own model, the models would be hard to compare. According to Barceló, the creators of SUMO argue that this hampers scientific development.

Unfortunately, section 4 of this report will reveal that the issues SUMO is meant to tackle by being open source have not disappeared. Although the philosophy of this software is similar to the aim of this thesis, it lacks practical usability for the simulation of cyclists within the timeframe of this thesis. The documentation on their website formulate that the simulation of bicycles is still in development phase. It also explicitly states that no specific behavioural model is used for the simulation of cyclists

(Sumo, 2023). Thijsen (2021) describes in his report that the use of SUMO usually requires additional imported or manually written algorithms.

PTV Vissim

Perhaps the most frequently mentioned traffic simulation software is PTV Vissim. Twaddle et al. (2014) state that traffic simulation software primarily focus on motorized traffic, but that Vissim is the main exception to this rule. Barceló also state that Vissim stands out for its ability to simulate multimodal traffic. Motorized traffic, public transport and pedestrians can all be simulated on the microscopic level in this software. One of the reasons for this is the VisWalk package which is part of the Vissim software. This package, designed for the simulation of pedestrians, follows a different behavioural model. Cars are modelled for what Twaddle et al. describe as 'longitudinal continuous models' and pedestrians are modelled after the Social Force Model (SFM). Cyclists can be modelled within Vissim from either of these behavioural models. Longitudinal continuous models is an overarching term that is typically utilizes a specific type of car-following model. Twaddle et al. critique this type of model for cyclists, as the lateral movement is constricted through lanes. This would not be a problem in the SFM. However, the SFM in the VisWalk package is specifically designed for pedestrians and PTV provides no guides or tutorials on how to use this model for cyclists.

Conclusion

Given the timeframe of this project, it is preferable to use a software that is widely adopted and user friendly. Moreover, it is important that the model is able to simulate fine-grained movements of the cyclists. Therefore, the simulation software that will be used for this study is Vissim. This is largely because of two reasons. Firstly, there is a case study of Thijsen (2021) that experimented with the modelling of cyclists in Vissim. This acts as reference to what is possible in this software and allows me to build upon his work. Secondly, a license as well as guidance is made available by the TU Delft for this software. The municipality of Rotterdam has also stated that they use Vissim for mobility analysis, and are willing to offer guidance as well. This combination of compatibility to the municipality of Rotterdam as well as the TU Delft plus the references that show the possibility of getting the right results from the simulation make Vissim the most suitable software for this research.

2.2 Case study

Several demands and wishes need to be considered in order to choose a suitable case for my thesis. The most important thing is that the road in question has to be a bicycle path rather than a bicycle lane (i.e., separated from car traffic). Moreover, it is preferable that the street has a relatively high density of cyclists. This is of importance because the number of cyclists that use the cycling path will act as a baseline scenario for the simulation. Conflicts should already occur to a certain degree in this scenario, in order to be able to measure if speed and speed differences affect it significantly. Another requirement that is implied here, is that there is actual data on cyclists on the case path.

The municipality of Rotterdam has provided me with a dataset of cyclists at 27 different locations across the city. In addition to the dataset, the mobility data department of the municipality provided me with expert judgement which led to useful insights on finding a suitable case. The dataset consists of hourly cyclist counts in the month October 2022. Each location contained 744 entries (24 hours x 31 days) of how many cyclists passed in each direction during a given hour. For my case study, I will look at relatively busy bicycle paths. Thus, I chose the ten locations with the highest mean cycling counts during rush hour (08:00 – 09:00 & 17:00 – 18:00) after removing error values from the dataset. This left the following locations as depicted in figure 1.

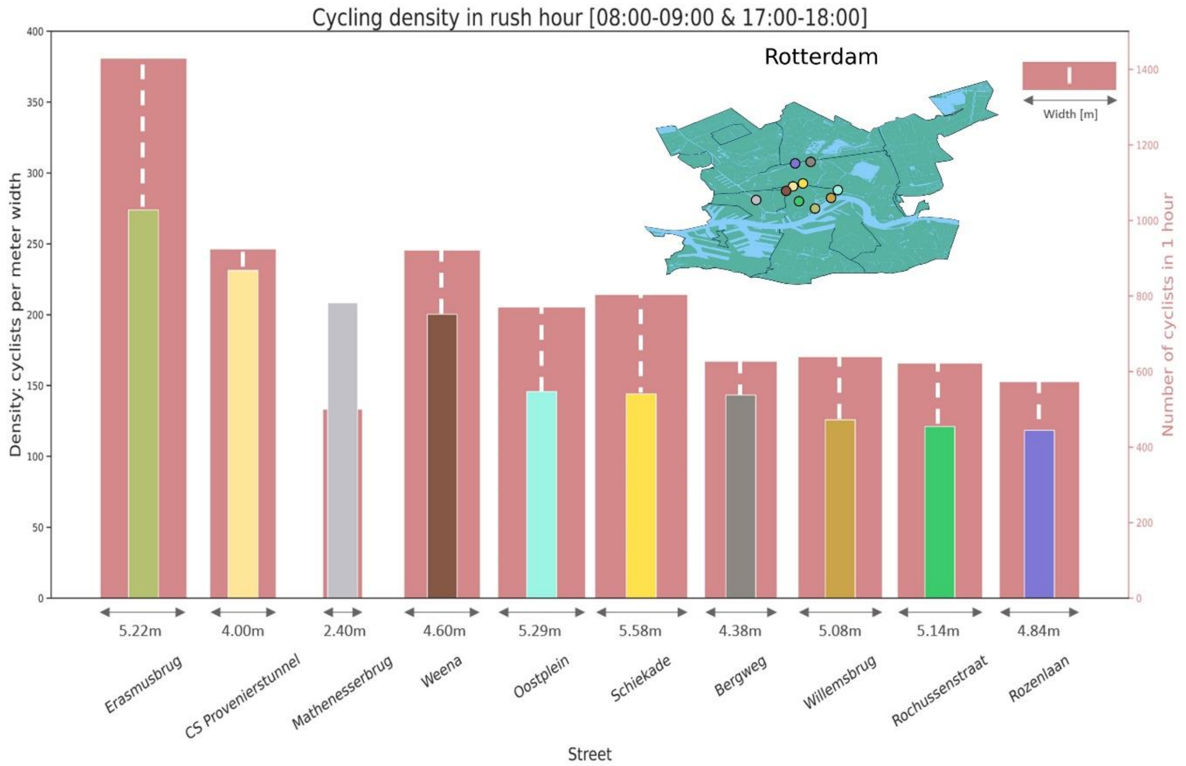

Figure 1, Double bar graph depicting the cycling density of ten locations in Rotterdam (Veraart, 2024)

Of these locations, the following bar graph is created (figure 1). This graph depicts the density in cyclists per hour per meter width of cycling path on the left y-axis, and the actual number of cyclists during rush hour on the right y-axis. This figure shows that the highest density of cyclists can be found at the Erasmusbrug, followed by the Provenierstunnel at Rotterdam Central Station. The x-axis highlights that the width of the second bar corresponds to the actual width of the bicycle path in question.

Note that, except for the path at the Mathenesserbrug and CS Provenierstunnel, the depicted width is actually the sum of two cycling paths (one on either side of the road). This is essential information for the choice of the case study, as it is preferable that the simulation model is of one bicycle path that allows cyclists from both directions. This is important for the measurement of conflicts, as will be further explained in section 3.2. Therefore, the CS Provenierstunnel is the most suitable choice for the case-study. As the cyclist density is relatively high and it contains a two-way cycling path.

Digital twin

The Provenierstunnel in Rotterdam is a tunnel that goes underneath the train tracks of Rotterdam's central station. The full bicycle path is roughly 300m long and connect the Proveniersplein of Rotterdam north to Weena in central district (see figure 2). The bicycle path is a two-way street with a total width of 4 metres. On both sides, the path ends in a crossroads in which the cyclist can go in three directions.

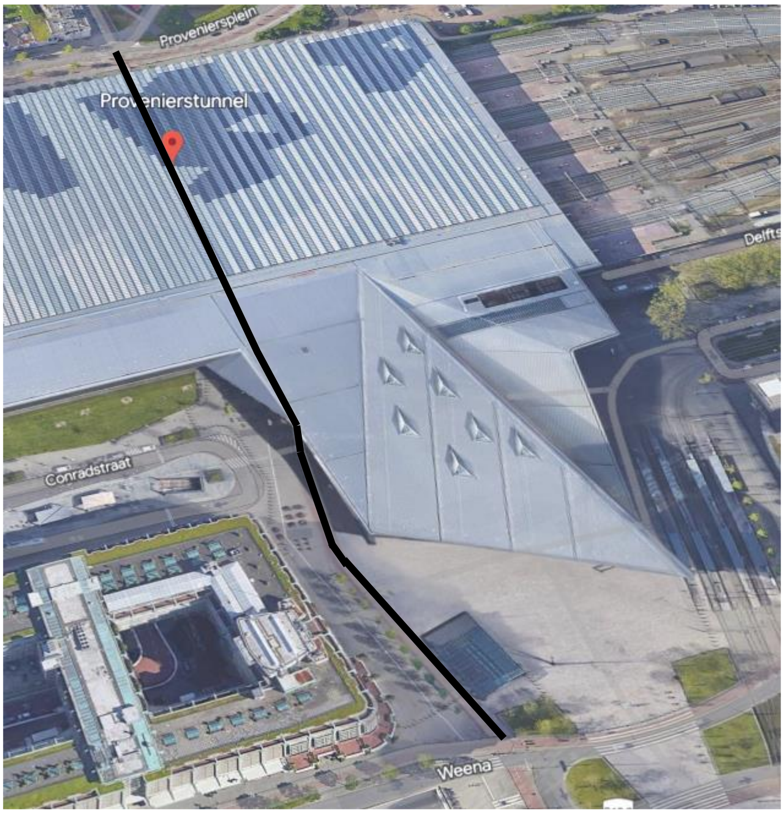

Figure 2, Birds-eye view on the Provenierstunnel at Rotterdam central station. Adapted from (Google, n.d.)

The aim is to make a digital twin of this traffic situation. This entails that the simulated environment will be a direct copy of its physical counterpart to the highest extent possible within the timeframe of this project.

Vehicle types

E-bikes are a broadly used term that can refer to a variety of vehicles. For instance, some Chinese studies refer to e-bikes for vehicles that reach a speed up to 45 km/h and have rudimentary pedals (Schleinitz et al., 2017), which would be commonly referred to as electric scooters in the Netherlands. In order to make a useful distinction between vehicles in the Netherlands, this study will adopt the chart of ANWB, which separates vehicles by speed and weight class (figure 3). ANWB states that this is a relevant distinction, as it is advised to design infrastructure for vehicles within its own category because it should lead to more safety (ANWB, 2020).

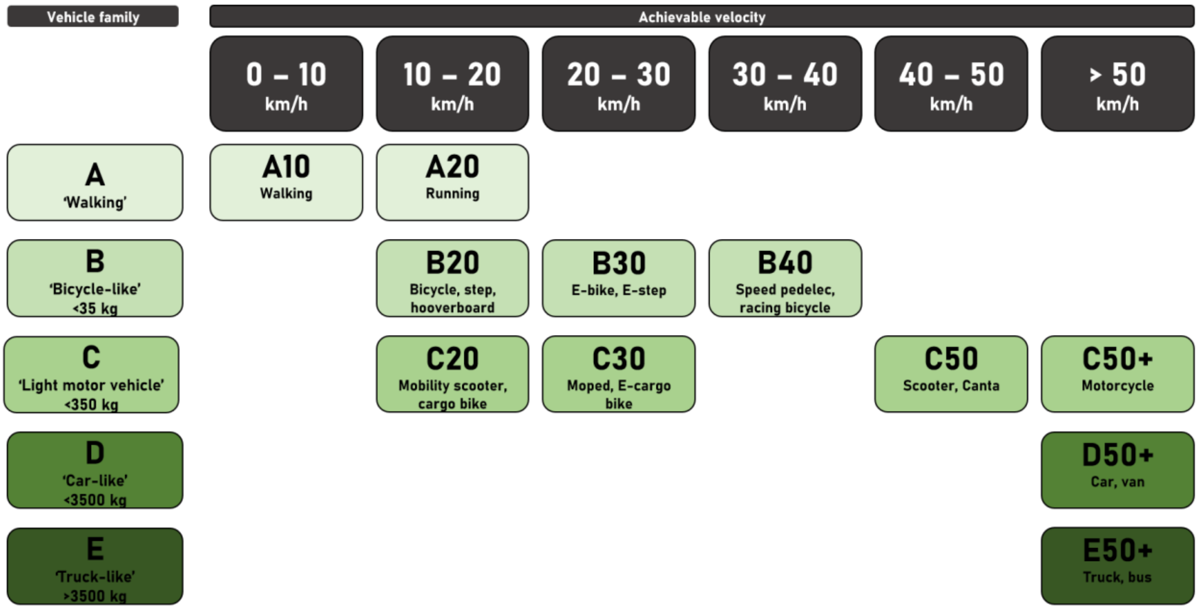

Figure 3, Distinction of vehicle types based on weight and velocity. Adapted from ANWB (2020)

This chart exemplifies the recent diversification of the urban bicycle path, as it shows 13 vehicles among 5 categories (B20, B30, B40, C20 and C30) that could be using the bicycle path. However, this study will focus on the distinction between Conventional Bicycle (CB, 'bicycle') of the B20 category and the Electric Bicycle (EB, 'e-bike') of the B30 category. The main reason for this is that these vehicles are similar in use and design with the average speed as biggest difference. This makes for a suitable pair for this case study.

2.3 Desk review

A desk review has been conducted in the orientation phase of this project. The scope of this review was fairly wide and the aim was to converge towards a suitable knowledge gap that could be solved within the timeframe of this thesis. The most relevant concepts and literature of this review are described in section 3.

Several strategies have been employed in order to find other researches that are relevant for this study. Google scholar, Scopus and the online library of Wageningen University & Research have been used as search engines for academic studies. A grasp of the search terms that were prompted in these engines were as follows: "risks of the electric bicycle in infrastructure"; "risks of the electric bicycle in infrastructure the Netherlands"; "cycling speed"; "cycling speed electric bicycle"; "electric bicycle safety"; "perceived safety cycling"; "perceived safety electric bicycle"; "cycling safety Rotterdam"; "simulation bicycle traffic"; "microsimulation of cycling"; "cycling behaviour the Netherlands". A few of the used literature has been sent to me or brought to my attention by my supervisor or one of my peers. The remaining literature has been found through references of the literature that was already at hand. Whenever a relevant statement was accompanied with a source, this study would be directly searched using the DOI from the reference list. This strategy has led to the bulk of the sources that were eventually used.

Lastly, the non-academic sources have been found through searches on Google and Ecosia. This was relevant as it appears that research on cycling in the Netherlands occurs more outside of academia than within. Research institutes such as TNO and Fietsberaad, as well as consultancies, regularly conduct a range of studies related to cycling. Several of these institutes were invited to an unstructured interview. This helped me to gain a better understanding of relevant research topics and policies within the Netherlands. Moreover, some of the interviewees generously shared additional literature that could be useful for this thesis. This was especially the case for the research on conflicts on the bicycle path.

2.4 Literature review

From the desk review, it became apparent that the academic landscape of the simulation of cyclist behaviour is diffuse and unsettled. Therefore, this specific topic required a more in-depth literature review. The literature review of section 4 is based on other literature reviews that were found through the desk review. Twaddle et al. (2014) provide a comprehensive overview of different methods that can be applied for cyclist simulation. While Thijsen (2021) describes in-depth how the Social Force Model (SFM) has been developed for cyclists over time. These two works formed the basis from which other works were examined through the references of each newly discovered work. In addition, academic search engines were used with the aim to cover potential blind spots and to find more recent research within this field. This led me to the study of Li et al. (2021), which again provided a comprehensive literature review of the SFM. This cycle of searching and examining bibliographies was repeated until unknown sources in a literature review were hardly found.

2.5 Simulating cyclist behaviour

Section 5 describes the configuration and calibration of the simulation model that is used for the case study. The aim of this section is to gain insights on modelling cyclist behaviour by doing it. Configuring the simulation model mainly required knowledge of the chosen software. This required knowledge is obtained through webinars, online tutorials, the documentation provided by the software company and online fora. Whenever these resources were insufficient, I was able to meet with an expert on the simulation software from the TU Delft.

The calibration of the simulation model has been realised through three different methods. First of all, previously used sources as well as the documentation from the software company were used to gain a theoretical understanding of the parameters that define the behaviour of the cyclist. Parameter values could then be logically derived from this theoretical understanding. Secondly, a comparative analysis has been performed to the described literature in section 4. This analysis provided insight on the alignment or misalignment of academics on certain aspects of the calibration. Lastly, simulation model has been calibrated through extensive experimentation. Through a trial and error process, parameter values were repeatedly changed in order to observe its effects. This does not lead to a fine grained calibration, but it allows for more radical interpretations of certain parameters.

2.6 Simulation results

Section 6 reveals the results of the simulation model. The aim of this section is to complete the case study research cycle. This might give more insight on the simulation of cyclist behaviour, as it enables a discussion on the validation of the simulation model. In addition, the case study will test a hypothesis on the correlation between conflicts, speed and speed differences on the bicycle path. This hypothesis shall be tested through the simulation of three scenarios. There is a baseline scenario in which the current real life situation is simulated. The other two scenarios simulate the same number of cyclists, but with higher speed differences and higher speed respectively.

Each scenario simulates 18 days (18x24 hours). The hourly data is processed and analysed using a python code. This code can be found in appendix II.

3. Literature review

This section describes the three main aspects of this research. First of all, research on the behaviour of cyclists shall be described. The aim of this description is to provide context on how cyclists are studied in general, as well as to provide a useful framework to examine cyclist behaviour. Secondly, traffic simulation modelling is discussed. This is a description of the methods that have historically been used to simulate different types of traffic. Lastly, a definition will be given on how conflict will be measured in the simulation of the case study.

3.1 Cyclist behaviour

This subsection will attempt to illustrate the behaviour of cyclists on the bicycle path. This is required knowledge in order to model cyclists, since a simulation model should represent reality. However, researchers find this subject to be in short supply (Twaddle et al., 2014; Gavriilidou et al., 2019). A cyclist's behaviour cannot be compared to the behaviour of cars as the cyclist enjoys certain degrees of freedom, while the behaviour of cars is strictly constrained by rules. With this freedom comes a more complex behaviour pattern in respect to cars. As Twaddle and their colleagues put it (2014, p. 145): *'As bicyclists are much more flexible than car drivers, the question why they behave in the ways they do becomes at least as important as how they behave.'*.

Theurrentt landscape of cycling research seem to have a strong focus on the effects of cycling rather than the cycling itself. For instance the safety is studied (Schepers et al., 2014; Schepers et al., 2018; de Guerre et al., 2018), by quantitively analysing the number of bicycle related accidents and injuries. Also the economic and health costs and benefits of cyclists are examined (Rich et al., 2021). Research that does focus on the cycling itself is primarily interested in how cycling is experienced and how safety is perceived by the cyclists (Petzoldt et al., 2017; Schleinitz et al., 2017; de Winter, 2020). These studies are conducted through surveys, interviews or naturalistic observation studies. Then there are studies that focus on how the infrastructure design affects safety and the cycling experience (Olsson & Ellder, 2023; Hull & O'Holleran, 2014; Schepers et al., 2015).

Another facet of cycling research, especially in the Netherlands, is research carried out by knowledge institutes and consultancies. These studies are usually commissioned by a national or local government, or by an organisation that pushes cycling policy on the political agenda. For instance, 'Fietsberaad' is a Dutch organization that studies, examines and promotes cycling policy. They conducted a study that examined the perceived busyness and the experienced stress of cyclists on the bicycle path. They found three factors that come into play for the perceived busyness on the bicycle path (CROW, 2017).

- Physical factors
  The physical environment in which people use space. Available infrastructure and the number of users in an area are part of this.
- Social factors
  This is about the behaviour of those around you. If the behaviour of others do not match with your norms and values, it can lead to frustration.
- Individual factors
  This regards the motivations and expectations of the individual user. Also experiences from the past play a part here, as they influence expectations.

A projection of future mobility predicts a rapid growth of e-bikes in the coming years (KiM, 2022). Moreover, emerging mobility concepts such as shared mobility and new vehicles such as the 'fatbike' and the e-step are creating a dynamic urban mobility landscape. This impacts the social and individual factors of the road users. Consequently, the physical factors might not suit the changed social and individual factors anymore. This provides an opportunity for simulation modelling. Provided that the behaviour of the road users can be accurately predicted (i.e., modelled), simulation models can prove to be a relatively cheap method to experiment with the effectiveness of different infrastructure designs.

Dutch professor te Brömmelstroet (2014) poses a critique on the infrastructure design, implying that the physical factors do not suit the needs of cyclists to begin with. In his study, he examined several busy cycling crossroads with his students in order to observe the behaviour of the cyclists. He argues that the physical factors are not designed to suit the cyclists' needs. With a sense of flair, te Brömmelstroet compares Dutch cyclists navigating a crossroads to a swarm of sparrows displaying complex patterns in the evening sun. It is argued that this comparison is fitting as the sum of all movements in this 'flock' reveals complex patterns, however each individual navigates on the basis of simple rules. However, te Brömmelstroet states that the infrastructure (i.e., physical factors) is designed as if it was for geese, who travel in straight lines rather than as swarming flocks. The study also concludes that the cyclists seem to be used to the chaos of these crossings in rush hour, as they display a large amount of situational awareness. However, respondents of interviews also indicated that it leads to frustration and stress.

This situational awareness is especially displayed by cyclists that are named 'momentumists'. These are cyclists who deviate from the designed path, without creating dangerous situations for others. Examples of this are taking shortcuts over the sidewalk or using an 'olifantenpaadje' (desire path). Te Brömmelstroet praises this behaviour not only for their displayed skill and awareness, but also because they improve traffic flow and they highlight design flaws of the infrastructure (te Brömmelstroet, 2014). From a traffic simulation perspective, this 'momentumist' behaviour highlights two other points of discussion. First, te Brömmelstroets notion of enhanced situational awareness implies that there is a variance among cyclists in their ability to observe and register their surroundings. Incorporating this variance into a simulation model is complex as simulation models tend to generalize behaviour. Second, it has been observed that about 13% of the cyclists break the rules (7% 'momentumists' and 6% 'recklists'). This is complicated for simulation because it adds the question 'when does one decide to break the rules?'.

Gavriilidou et al. (2019) provide a useful framework for examining the behaviour of cyclists in their study. The question raised by the rulebreakers of te Brömmelstroet can become more specific using the framework below, as it becomes a matter of operational mental behaviour of cyclists. Gavriilidou et al. start their abstract with the statement that cyclist behaviour is a greatly understudied subject. Gavriilidou and their colleagues attempt to contribute to cyclist behaviour by building upon the conceptual framework of Michon (1985) and Hoogendoorn & Bovy (2004) which describes car and pedestrian behaviour respectively. This framework proposes three levels of behaviour, which is described for cyclists as follows:

1) <u>Strategic</u>
   Departure time and activity pattern choice
2) <u>Tactical</u>
   Activity scheduling, activity area and route choice
3) <u>Operational</u>
   a. <u>Operational mental</u>
      Path choice within route
   b. <u>Operational physical</u>
      Pedalling and steering

This framework, specifically the operational behaviour, shall be used for the examination of cyclist behaviour in the simulation models of other literature. This will be further explained in section 4.1.

3.2 Conflicts

According to Petzoldt et al. (2017, p. 480), a conflict is defined as follows:

"Following the definition, a certain situation qualified as a conflict if there either was an actual collision, or if one or more parties involved had to brake or change direction to avoid such a collision"

This definition shows a striking resemblance to the description of the Time-To-Collision (TTC) metric. Both speak of a need to initiate action at a certain point in order to avoid collision. This implies that this definition of Petzoldt et al. might be transferrable to simulation modelling.

The TTC metric is developed by Hayward (1972) who aimed to quantify near-misses in traffic. This metric is used to this day, for instance by knowledge institutes such as TNO. One particular study of TNO regards conflicts on bicycle paths in the Netherlands (de Goede et al., 2013). This study utilizes the variables Time-To-Collision (TTC) and Post-Encroachment-Time (PET). TTC is a metric that calculates the time for two cyclists that are on course to collide, how much time it will take if neither of the cyclists takes action to prevent the collision (i.e., braking or steering). TNO describes a characteristic curve for TTC when a collision is impending (figure 4). The interesting part of this curve is when the TTC is at its lowest point. This is the moment where one or both of the cyclists avert the collision. When the TTC reaches a certain low value threshold, one could speak of a dangerous situation or at least an uncomfortable encounter.

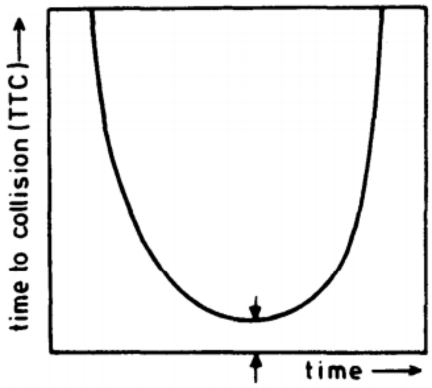

Figure 4, Characteristic graph of Time-To-Collision (TTC) (de Goede et al., 2013)

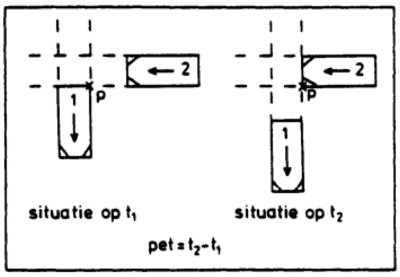

Figure 5, Definition of Post-Encroachment Time (PET) (de Goede et al., 2013)

For PET, there is no theoretical collision course for the cyclists. As the cyclists are calculated to just miss each other by a (small) margin. However, when one or both cyclists changes direction or speed, a collision could still occur. As you can see in figure 5, PET is calculated by subtracting the moment where the first cyclist leaves a location (t_2) by the moment the second cyclist enters that location (t_1). As a result you have the PET which is simply the margin by which the two cyclists missed each other. Note that this measurement is specifically for situations where the cyclists are not going in the same direction. Again TNO does not mention any critical values for this measurement of conflict situations.

Lastly, TNO defines a conflict between two cyclists by simply measuring the lateral distance between them. The report states that there should be a minimal distance of 25cm between the outlines of the cyclists. Thus, assuming a bicycle width of 75 cm, the two cyclists should have a 'heart-to-heart distance' of 100cm (de Goede et al., 2013).

These three methods of measuring conflicts are part of the DOCTOR method that TNO developed in this study. The described methods are used to estimate the probability of an accident happening. The other aspect of the DOCTOR method estimates the severity of the accident, if it were to happen. A study of Adjenughwure et al. (2023) applied the DOCTOR method in their study. They used the DOCTOR classification as is described in table 1. This table is described by Adjenughwure and their colleagues as a generalized classification for traffic in the Netherlands (i.e., for all vehicle types). Presumably, it assumes that the reaction time of a person is the same regardless of the vehicle they use. Moreover, the used vehicle highly impact the extent of consequences, as consequences are much higher with heavier and faster vehicles.

Table 1, DOCTOR Classification of Conflicts With a Severity Score 1–5 (1: light, 5: severe). Adapted from Adjenughwure et al. (2023)

	Probability of collision								
Extent of consequences	TTC (s)						PET (s)		
	No	>2.0	2.0-1.5	1.5-1.0	1.0-0.5	0.5-0	>1.0	1.0-0.5	0.5-0
0 (Very small)	Na	Na	Na	1	1	2	Na	Na	1
1 (Small)	Na	Na	1	2	2-3	3	Na	1	2
2 (Reasonably large)	Na	1	2	2-3	3	4	1	2	3
3 (Large)	1	2	2-3	3	4	5	2	3	4-5

The simulation model of this thesis will measure conflicts in two ways. First of all, collisions between two cyclists will be measured. This is essentially a TTC of zero seconds. Secondly, conflict will be measured using the TTC variable. Similar to Adjenughwure et al., the TTC values will be measured up to 2 seconds, with intervals of 0.5 seconds. The PET variable will not be used, as it requires a sharp corner in the bicycle infrastructure to occur. The case study will examine a single, rather straight bicycle path. Therefore, conflicts with PET will not occur. Also the consequences of a possible accident will not be taken into account for the measurement of conflict.

3.3 Cycling simulation models

This subsection shall describe different methods to simulate cyclists. First, a description shall be given of three different branches of simulation. Afterwards, different model types will be described through the work of Twaddle et al. (2014), which reviews different methods for modelling bicycle behaviour.

Macroscopic, microscopic and mesoscopic simulation

In the family of traffic simulation modelling, there are three large branches named macroscopic modelling, microscopic modelling and mesoscopic modelling. Macroscopic modelling is based on the 'continuum traffic flow theory', where a flow is analysed through three characteristic variables: volume $q(x, t)$, speed $u(x, t)$, and density $k(x, t)$, which are assumed to be defined at every instant in time t and every point in space x (Barceló, 2010, p.15). Although the key elements of speed and density are fairly relevant to my research question, macroscopic modelling does not analyse individual road users.

Microscopic modelling analyses the motion of individual road users in traffic. This includes modelling the actions of vehicles such as acceleration, deceleration and overtaking manoeuvres. Central to this type of modelling is that decisions of individual road users is dependant on its surroundings. This seems to be a better fit for the purpose of this research, as bicycle conflicts are essentially an interaction between two individual road users. In the wider field of simulation modelling, this type of modelling is also referred to as agent based modelling. Herein, each bicyclist is treated as a self-determined agent (Liang et al., 2018).

Lastly, mesoscopic modelling is a branch that falls in between the former two. According to Barceló, mesoscopic modelling captures the essentials of traffic dynamics in a simplified manner. Therefore, mesoscopic models are generally less data demanding and more efficient than microscopic models. The simplification with respect to microscopic modelling lies either in the grouping of vehicles into packages or platoons (i.e., not simulating individual road users anymore), or the simplification lies in the dynamics and mathematics of the vehicles' movement.

The aim of this thesis is to contribute to the behaviour of individual cyclists in simulation models. It is therefore evident that the remainder of this report will focus on microscopic modelling.

Car-following models

Barceló (2010) describes in their book *Fundamentals of traffic simulation* that the development of microsimulation started in the 1950's. In this period, pioneers Reuschel and Pipes came up with the car-following theory. This theory assumes that every road user, car in their case, positions themselves at a reasonably safe distance from the car in front of it. According to Pipes, this was roughly a car's distance for every 10 miles per hour of speed. Further development of this theory led to a general equation to describe the behaviour of individuals in the simulation:

$$Response\ (t+T) = Sensitivity\ \times Stimulus\ (t)$$

For the car-following theory, the stimulus is caused by the car in front ('the leader'). According to the discussions in the second half of the twentieth century on this model, a road user can take one of two actions: one can accelerate or decelerate. Thus, simply put, if the leading car accelerates, the following car accelerates as a response and vice versa for deceleration. This changed in 1981, when Gipps proposed to include more behavioural aspects into the model. For instance, a desired speed of individual road users. This idea changes the nature of one's choices to accelerate or decelerate. According to Gipps, a car accelerates until it reaches their desired speed on which it wants to cruise on the road. And a car only decelerates when it is somehow constrained and thus forced to not drive at their desired speed. These constraints are usually imposed by the preceding car, the leader. (Barceló, 2010)

This type of model is rarely used for microscopic simulation of cyclists. Twaddle et al. (2014), who describe this model as a type of longitudinally continuous model, critiques this behaviour for cyclists because of its limitations in the lateral direction. The only lateral movement that exists in these models are lane switches, which does not reflect cyclists, argue Twaddle et al. There is one study that takes the car-following model as a basis and adds more freedom by creating a multitude of lanes on the bicycle path (Pérez Castro, 2020). However, Pérez Castro concludes that there are aspects that can be improved in this approach. Other studies that use this approach have not been found.

Cellular Automata models

Cellular Automata (CA) models are time- and space-discrete models (Twaddle et al., 2014). Discrete models are the counterpart of continuous models. In space-continuous models, you can draw areas and shapes however you like (e.g. a rectangle of 1.345 x 2.5) and simulate within that space. While in space-discrete models, one makes use of a grid with cells of size 1x1, and objects such as vehicles occupy a number of those cells at a time, but it's not possible to occupy half of a cell. It works the same way for time. In continuous models, you can set the model to simulate in seconds, or microseconds or hours and the model will continuously measure during simulation. While discrete models make use of timesteps and measure only at the instance of each timestep. (Ossimitz & Mrotzek, 2008)

CA models, as a time- and space discrete model, is a simplified model that has fast simulation and efficiency as primary perks. Twaddle et al. (2014) describes a history of this model type as being suitable for simulating mixed traffic, where cyclists would occupy 3x1 cells and cars would occupy 5x3 cells for instance. The purpose of these models are primarily to analyse traffic flow and density. Therefore, even though individual road users are simulated, the purpose of this model type is more similar to macroscopic models. It is also not suitable for this thesis, as the analysis of fine grained movements are not a strength of this type of model because it is space-discrete. Although CA models are regularly mentioned as alternative in academic literature, no study has been found that utilizes this model type.

Social Force Models

Another common model for traffic simulation is the Social Force Model (SFM) (Thijsen, 2021). This model disregards the longitudinal and lateral axis of a road or path, but rather it describes a plane on which a road user wants to move from A to B as quickly as possible. This is called the driving force of the road user, which drives it directly to a destination and accelerates until the desired speed is realised. Other forces cause the road user to deviate from this direct path or desired speed, these are called repulsive forces and attractive forces (Helbing & Molnár, 1995).

According to Helbing and Molnár, the movement of pedestrians can be described by a driving force which moves the pedestrian to their destination and a set of repulsive and attractive forces which can disrupt the driving force. Figure 6 below displays a simple form of the SFM, which shows the driving force and two repulsive forces. The two repulsive forces, F_social and F_obstacle, are meant to avoid pedestrian i from colliding with the other pedestrian or the wall respectively. The size of both forces is largely determined by the distance between the other person or the obstacle. More complex versions of the SFM also contain attractive forces, for instance because pedestrians know each other, or are attracted to street artists or window displays of stores. However, the remainder of this study does not consider these attractive forces.

The reasoning behind these repulsive and attractive forces are that the surroundings of a pedestrian influence its decision-making. Obstacles, traffic and other pedestrians do not only hinder a pedestrians' route physically, but also psychologically as a pedestrian alters its route before it bumps into an obstacle or someone else.

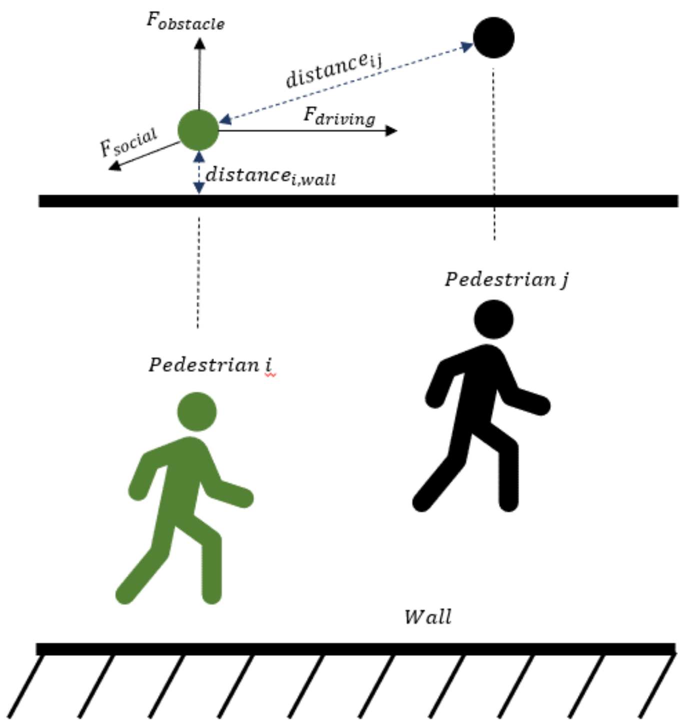

Figure 6, Simplified schematic of the Social Force Model. (Veraart, 2024)

Helbing & Molnár designed this model for simulation of pedestrians. However, this model type is also used by many researchers to simulate bicycle traffic (Twaddle et al. 2014). These researchers use the SFM as a foundation for simulating cyclists. Therefore, the SFM will be the model of choice for the case study of this thesis as it has been the most used model type by other researchers that were found during the desk research. Moreover, the chosen software of PTV Vissim offers a version of the SFM in a package called PTV VisWalk. However, it appears the SFM as it is designed for pedestrians is inadequate for cyclists on its own. Therefore, the researchers often add rules or decision making processes in order to simulate cyclist behaviour more accurately. These related studies for cyclists are further discussed in section 4.

Logic models

Twaddle et al. (2014) also describe the logic model in their paper. According to Twaddle et al., it is an adaptation to the SFM in which the 'tactical behaviour' is also taken into account. Presumably, the definition of 'tactical behaviour' of Twaddle et al. is similar to the definition of 'operational mental behaviour' of Gavriilidou et al. (2019), as Twaddle et al. describe the behaviour of positioning and making choices on how to avoid conflict. Twaddle et al. describe three sub models of this 'tactical behaviour' that makes a logic model distinctive from the SFM:

- Situation detection model
  Cyclists measure the location, speed and direction of all surrounding road users and subsequently calculates possible conflicts.
- Path sketching model
  Possible trajectories are drawn out using the given information from the situation detection model.
- Reactive path generation model
  The chosen trajectory from the path sketching model is carried out while the situation detection model is continually active.

An interesting note to this model is that it has not been found in other literature. Even the model described by Twaddle et al. as a logic model, from Schönauer et al. (2011) does not speak of the logic model. It is merely described as an adaptation of the SFM. The same applies to the model of Rinke et al. (2017), which will be discussed in the following section. The model of Rinke et al. strongly resembles the description of Twaddle and their colleagues, however Rinke et al. too speak of an adaptation to the SFM. Therefore, it appears that the logic model is not yet recognized as an established model type.

In conclusion, the logic model is sooner regarded in academia as an adaptation of the SFM than stand-alone model. However, adaptations of the SFM are not always done in the same way as the logic model. Therefore, the literature review in the following section will regard the SFM as a whole and different adaptations of it.

4. Literature review on the SFM

The following subsections discuss the current status of cyclist simulation in the academic world. It is concluded from the previous section that the SFM is the most frequently used model for the microsimulation of cyclists, as well as the most usable for this study since it allows for fine grained movements of the cyclists. Therefore, this model type will be further examined in this section. A general approach to assessing cyclist behaviour is first described. Afterwards there will be a description of the scientific development of the SFM for cyclists, what its challenges are and how the researchers propose to tackle them. Lastly, the replicability and verifiability of the reviewed studies are described.

4.1 Cyclist behaviour framework

As described in section 3.1, the framework to examine cyclist behaviour is that of Gavriilidou et al. (2019). This study attempts to contribute to cyclist behaviour by building upon the conceptual framework of Michon (1985) and Hoogendoorn & Bovy (2004) which describes car and pedestrian behaviour respectively. This framework proposes three levels of behaviour: 1) strategic, 2) tactical and 3) operational (see table 2).

For this study, the operational behaviour of cyclists is most relevant, which was also the case for the study of Gavriilidou and their colleagues. It is more relevant, as the strategic behaviour is best studied through macroscopic simulation rather than microscopic simulation. Tactical behaviour can be relevant in a microscopic simulation research, however it is not necessarily so, as route choice can also be predetermined in simulation models. Moreover, variations of routes are largely dependent on the available infrastructure and its users at the location of the study. Thus, improving tactical behaviour is location dependent and does not contribute to a better model of cyclist behaviour in general. Therefore, the modelling of cyclist behaviour in this thesis only regards the operational behaviour of the cyclist.

Table 2, Framework of cyclist behaviour. Adapted from Gavriilidou et al. (2019)

	Car (Michon, 1985)	*Pedestrian (Hoogendoorn and Bovy, 2004)*	*Cyclist (Gavriilidou et al., 2019)*
Strategic	General plans: Trip goals, route and mode choice	Departure time and activity pattern choice	Departure time and activity pattern choice
Tactical	Controlled action patterns (Manoeuvres)	Activity scheduling, activity area and route choice	Activity scheduling, activity area and route choice
Operational	Automatic action patterns (split-second control)	Walking behaviour	<u>Operational mental</u>: Path choice within route <u>Operational physical</u>: Pedalling and steering

The study of Gavriilidou et al. suggest that the behaviour of cyclists is similar to pedestrians on the strategic and tactical level. However, they propose that the behaviour on the operational level for cyclists is more complex than it is for pedestrians. According to this study, operational behaviour can be split into two categories, mental and physical. The physical side describes the pedalling and steering of a cyclist, in other words the physical operations a cyclist performs while cycling. The mental side describes the path choice within the route, in other words the positioning of a cyclist and the choices a cyclist makes during the route. For instance, the decision of a cyclist to overtake another cyclist is part of the operational mental behaviour, while the steering and incidental acceleration a part is of the operational physical behaviour. The operational mental behaviour and operational physical behaviour will be relevant indicators for the accuracy of cyclist behaviour in the following (sub)sections.

4.2 Academic research on the SFM for cyclists

Many researchers were inspired by the work of Helbing and Molnár (section 3.3) and started exploring the possibility of using the SFM for the simulation of cyclists. According to Osowski and Waterson (2016), the SFM is an established and validated model for pedestrian simulation. Therefore, they argue, it could form the basis for a valid model to simulate cyclists. However, Osowski and Waterson do not completely copy the SFM. Their study examines ten fundamental parts of the SFM in order to conclude whether or not it is useful for the simulation of cyclist behaviour. Final judgement: Osowski and Waterson accept three of those fundamental parts, five are rejected and two are partially accepted (see table 3). This table illustrates that the SFM contains underlying assumptions that may work well or is acceptable for pedestrians but less so for cyclists.

Table 3, Comparison acceptance and rejection of underlying properties of the pedestrian SFM. Adapted from Osowski & Waterson (2016)

Acceptance	*Principle*
Accept	Agents move through, and due to, a socially generated force field
Accept	Agents can be attracted to one another (e.g., family / friend groups)
Accept	Agent speeds are bound at a maximum
Partial accept	Agents are attracted to a waypoint/destination
Partial accept	Agent perception is variable with angle of view
Reject	Force field is vectoral
Reject	Social force spatial profiles are “near-future” distributions of possible location
Reject	Agents are compressible
Reject	Agent speeds vary continuously down to zero
Reject	Agent speeds “relax” to their desired velocity

Xiao et al. (2012) denote the same lack of valid models for cyclist behaviour. They point out in their study that no contemporary models accurately describe bicycle behaviour on the individual level, including the SFM. Xiao et al. state that the SFM can work sufficiently in terms of acceleration, deceleration and steering (i.e., the physical operational behaviour) but not in terms of decision making and positioning (i.e., the mental operational behaviour). Dias et al. (2018) concurs this observation, stating that the SFM can be calibrated to sufficiently simulate evading manoeuvres of cyclists as well as segways and pedestrians (i.e., operational physical behaviour). However, Dias and their colleagues conclude that more complex behaviour patterns of these road users require more research. According to Xiao et al., the SFM treats the cyclist as particles on which social forces apply, which does not represent the complexity of a cyclists’ thoughts and psychological behaviour. This criticism is shared among many researchers that try to mimic cyclists in their simulation (Liang et al., 2018; Rinke et al., 2017; Li et al., 2021; Osowski and Waterson, 2016). However, there seems to be no consensus on how to properly tackle this issue.

Huang et al. (2017) propose a different solution. They created a simulation model of an unsignalized intersection with heterogeneous traffic (i.e., cars, cyclists and pedestrians). In their modified SFM, the driving force drives the cyclist along a predetermined path, rather than straight to the destination. This predetermined path is examined by the cyclist, prior to entering the intersection. If conflict areas are predicted, then an alternative pathway is calculated which subverts the conflict area. This alternative pathway is followed and social forces are applied if this pathway still leads to conflicting situations with other road users. Thus, Huang et al. propose an alternative for the operational mental behaviour, whilst keeping the operational physical behaviour of the SFM in conflict situations. Their model is created in FLOWSIM, and calibrated and validated through the analysis of video footage of intersections in Beijing and Guangzhou, China.

In the same year, Qu et al. (2017) published a paper in which mixed traffic is simulated. They observe in Zhengzhou, China, that electric bicycles (EBs) tend to form their own lane in mixed traffic infrastructure. Thus, the modified SFM of Qu et al. makes use of a virtual lane for EBs. In this lane, the cyclist either follows the preceding cyclist, or decides to overtake by switching lanes to where the cars drive. Thus, Qu et al. created two different regimes for EBs. When they have switched lanes towards the cars, a car-following force is activated that keeps the cyclist in the car traffic flow with minimal interactions with other road users. On the bicycle path, the regular forces of the SFM are applied. In other words, Qu et al. designed two behavioural models. One for when EBs travelled among cyclists and the other for when EBs travelled among cars. Their model is also calibrated and validated through the extraction of video footage of real-life traffic in China, this time in Zhengzhou. The simulation software Qu et al. used is not mentioned. Their proposal does not describe a generalized model for cyclist behaviour, as the paper studies a specific behaviour of electric bicyclists at a specific type of (Chinese) infrastructure.

Similarly, Yang et al. (2018) propose that different forces apply according to certain decisions of the cyclist, such as a following force and a passable gap force. Their study also specifically examines EBs crossing a mixed traffic intersection. In this case the intersection is signalized. Yang et al. also observed a tendency of EBs to position themselves on a motor-vehicle lane (i.e., in between cars). The following force ensures that the vehicle obeys the general traffic flow in terms of direction and velocity. The passable-gap force is applied in so-called ‘shuttling behaviour’. This is essentially a check for a vehicle that desires to overtake (by switching lanes), that there is enough space to do so. If there is enough space, the gap is passable, and the vehicle can switch lanes. Just like Qu et al., different behavioural models are applied depending on the infrastructure type the cyclist uses. However, Yang and their colleagues added an additional behavioural model for the transition between the two infrastructure and behavioural types. Similarly to Huang et al. (2018), Yang and their colleagues implicitly propose to change the operational mental behaviour rather than the operational physical behaviour within the SFM. As the proposed behavioural models do not necessarily alter physical operations of the cyclist such as acceleration, deceleration and steering. Rather, they aim to change the behaviour in positioning and path choice within the route with their proposed model. Yang et al. calibrated their model using data from one intersection site, and validated it through data of another site. It is not mentioned which software or programming language is used.

Liu et al. (2019) observe a dispersion behaviour of cyclists that go straight on a crossroad. They compared this behaviour to charged particles in an electric field, creating force fields around the cyclists rather than forces that act upon the cyclist. Liu et al. argue that cyclists tend to distribute themselves evenly on a space, just like gas particles would do in a sealed tank for instance. Accordingly, they name their model the Particle Dispersion Model (PDM). This proposal addresses the operational mental behaviour by describing a behaviour of positioning on the bicycle path, as well as operational physical behaviour, since they use a different natural phenomenon to describe the movement and behaviour of cyclists. This study too is calibrated through extracted trajectories of cyclists from video footage of two intersections in China. Some programming tools are described, however the used software for simulation is not mentioned. As a seasoned Dutch urban cyclist, I do not recognize the described dispersion behaviour. Therefore, this dispersion behaviour might be a regional, cultural phenomenon or a consequence of different infrastructure design. Hence, the validity of the Particle Dispersion Model should require more research to study its general applicability for cyclist behaviour.

Li et al. (2021) propose a dynamic boundary of the path in order to adjust the boundary force accordingly to the current density on the bicycle path. Moreover, Li and their colleagues propose an additional behavioural model in which a cyclist behaves according to one of three regimes: freely moving, following and overtaking. These regimes add a layer of decision making which the SFM lacks according to the researchers. This proposal also mainly addresses improvements on the operational mental behaviour of simulated cyclists. But similar to Liu et al (2019), it is meant to describe a specific behaviour of cyclists crossing a mixed traffic intersection. Li et al. (2021) do not mention used software for simulation. Their calibrated values for the simulation were found through a genetic algorithm, created in Matlab.

Thijsen (2021) explored in their thesis the limits and possibilities for the simulation of cyclists, similar to the aim of this thesis. Their case study in Utrecht covers a large area in which the cyclists do not only interact with each other, but also with pedestrians and cars. Another similarity is the choice to model in PTV Vissim. Ultimately, Thijsen opted for two different solutions in his simulation model. Most of the infrastructure was created as a lane-based model where the rules of the car-following model apply. And the shared space ('woonerf'), where pedestrians, cyclists and cars share the same infrastructure, was modelled after the SFM. Thijsen states that more use of the SFM for other infrastructure than shared space was ill advised, as it led to unrealistic behaviour at high densities. According to Thijsen, two-way bicycle paths with >500 cyclists per hour per direction leads to too many collisions in his configuration. These collisions occur when cyclists attempt to overtake by using the lane in the opposite direction. This seems to be a fallacy of the operational mental behaviour, although it is not explicitly mentioned. In their report, Thijsen elaborately describes how their model is calibrated and configured in PTV Vissim.

Other studies propose a Physiological, Psychological Force Model (PPFM) (Xiao et al., 2012 ; Liang et al., 2018). The PPFM differs from the SFM in two aspects. Firstly, they propose a more elaborate system of forces in order to describe the movements of cyclists more accurately. Secondly, their proposed model defines two different spaces in which forces occur (see figure 7). The forces act up when a cyclist sees an obstacle or other cyclist in their perceptive or reactive space respectively. The reactive space has a short range (up to 6 meters ahead) and is seen as the personal space of a cyclist, which provokes an instinctive reaction when the space is invaded. In other words, if something or someone is in the reactive space, the cyclist finds it either dangerous or uncomfortable. The perceptive space has a range that is assumed to be double that of the reactive space and is seen as the space that a cyclist observes, anticipates and avoids conflict. In other words, the perceptive space is used by the cyclist to manage its general position and prevent any conflict and the reactive space is used in urgent situations to prevent actual collisions.

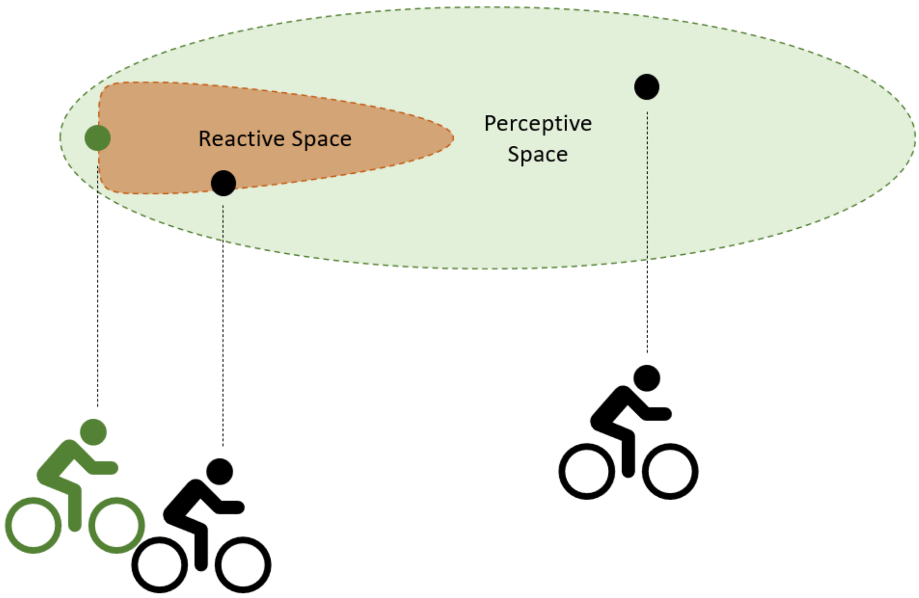

Figure 7, Diagram of the reactive space and perceptive space of a cyclist. Adapted from Liang et al. (2018)

Some academics pose additional critiques to the use of SFM for cyclists. As is described at the start of this subsection, Osowski & Waterson (2016) do not accept several fundamental properties of the SFM. For instance, they argue that the SFM does not represent two physical characteristics of cycling. They state that the required steering movements of the bicycle to stabilize it at low speeds are not part of the SFM and that the 'relaxation time' is not representative of how cyclists actually accelerate and brake. The study of Rinke et al. (2017) agrees that the SFM does not represent the operational physical behaviour of cyclists either. Although both studies of Osowski & Waterson and Rinke et al. still use parts of the SFM, they propose more radical alterations to the model in order to make it suitable for cyclists. It seems that they agree that forces are a fitting representation for movement, but disagree with several fundamental aspects of the SFM.

Unlike the previously described studies, Osowski & Waterson and Rinke et al. both critically examine the whole SFM, rather than creating additional rules on top of the SFM. Osowski & Waterson focused on how the perception of cyclists should be modelled. Rinke et al. propose a multi-layer approach with a free flow layer and a conflict layer above the SFM. Here, a cyclist only takes action when it detects an impending conflict using TTC, rather than always taking action when another road user is near.

Moreover, Rinke and their colleagues studied the way that cyclists tend to avoid conflict. They found that cyclists tend to prefer changing direction to braking. However, if a change of direction does not resolve the conflict, the cyclist will brake. This decision making process makes use of trajectories that each cyclist plans to follow. When conflict is imminent, the cyclist will calculate alternative trajectories. This reminds of the logic model described by Twaddle et al. (2014) in section 3.3. However, Rinke et al. do not mention the term logic model in their study. Rinkes model of calculating trajectories is different from the SFM, where such a decision is only emulated by the forces that act upon the cyclist. A cyclist in the SFM moves away from other cyclists because a force acts upon them, rather than that they anticipate conflict and make a decision to change course. Through this, Rinke et al. show two improvements in respect to the SFM. First of all, the more complex decisions and behaviour of cyclists is better described in this manner. Just as Twaddle et al. (2014) state, the question why cyclists behave the way they do is just as important as how they behave. Therefore, more 'sentient' agents better represent the complex behaviour of cyclists. This complexity of cyclist behaviour is confirmed in a study of te Brömmelstroet (2014). He observed complex movement patterns and a high level of situational awareness of cyclists at a busy intersection in Amsterdam. Second, the cyclists have a trajectory. This should improve the routing of cyclists. For instance, the trajectories can be set to have a preference to cycle on the right side of the bicycle path. This trajectory should also improve the anticipation of cyclists. This is an improvement of the operational mental behaviour of the cyclists.

4.3 Replicability and verifiability

The overview of microsimulation academic research on cyclist behaviour, as described in the previous subsection, reveals a lack of information to be able to replicate the cited journal articles in this specific field. The methodology sections of these studies often describe the mathematics that underly their simulation model. Although mathematics are essential for behavioural models and the backbone of simulation software, just the mathematical equations do not enable me to create a replica of their simulation model. Relevant information such as the used software or programming language remain undiscussed. The table below depicts the values of three core parameters of the SFM by each of the described studies (that use a form of SFM). Subsection 5.3 shall elaborate on the meaning of these values, simply put: *A* describes the power of the social force, *B* describes the range of the social force and a low value of *Tau* means a strong driving force. The table exemplifies the lack of consensus on how cyclists should be modelled within the SFM framework.

Table 4, Parameter values of the SFM of other studies, as well as the simulation software they used, whether they propose a change to the operational mental behaviour or the operational physical behaviour and how they calibrated their model.

	Dias et al. (2018)	*Huang et al. (2017)*	*Qu et al. (2017)*	*Yang et al. (2018)*	*Liu et al. (2019)*	*Li et al. (2021)*	*Thijsen (2021) Isotropic*	*Thijsen (2021) Mean*
A	1.38	2.33	1.7	6.3	0.61	0.42	5	3
B	1.93	0.18	3.25	2.9	0.841	8.04	0.4	1.1
Tau	1.35	1.61	0.6	1.1	13.03	9.03	1.3	1.3
Software	-	FLOWSIM	-	-	-	-	VisWalk	VisWalk
Calibration method	Experiment	Video	Video	Video	Video	Algorithm	Experiment	Experiment

Of the studies that used the basic parameters of SFM, as described in table 4, only the study of Thijsen (2021) could be replicated. The model validation section, on the contrary, is often extensively discussed in these papers. For example, the validation section describes the location of the video camera that is used, which software is used for video extraction and analysis and a description of the algorithm that translates the video footage into parameter values. But the usefulness of such a paper is limited when there is no knowledge of how the model is built and the assumptions behind it. The simulation models in these studies are often tailored to a specific case and propose an altered version of the SFM. This altered version cannot be replicated in an applied traffic simulation software like PTV Vissim, as this software does not provide flexibility on how the SFM is applied. Hence, it is suspected that their simulation model is programmed from the ground up using a more flexible programming language such as Python, Matlab or C++. However, custom made simulations will inevitably contain assumptions and design choices. Therefore, it is relevant to discuss in the methodology section which software are used and how the simulation model is designed.

Moreover, it is interesting to point out that many of the researchers use the same calibration method but land on different values. This could be due to cultural differences or different infrastructure designs that invite different behaviour, or it could be related to the different alterations that each researcher proposes to the original SFM.

This hampers scientific development in two ways. First of all, I am not able to verify their work. A reader of their study simply has to trust that their findings are correct. Second, I am not able to build upon their work. It appears that this is not a new issue in traffic simulation, as the open source software SUMO (section 2.1) mentions these exact issues for the simulation of motorized traffic. Section 5 will reveal that I get unsatisfactory cyclist behaviour when I use the calibrated parameter values of their custom model in my generalized, user friendly PTV model. For instance, it leads to the cyclists 'bouncing' off each other in a rather unnatural way.

4.4 Subconclusion

In summary, the described studies seem to agree for the most part that the SFM, as used for pedestrian modelling, could form a foundation for the modelling of cyclists. However, just the SFM does not seem to be accurate enough. The criticism of most of the researchers are on the operational mental behaviour of cyclists. Only Rinke et al. (2017) and Osowski and Waterson (2016) also formulate criticism on the operational physical behaviour of the cyclists in the SFM.

However, the described studies lack a cohesive academic debate on how to properly simulate the behaviour of cyclists. Some create a model with additional rules or decision making processes that are tailored to the situation and infrastructure of their case study. Others propose a new type of model without describing how this model can be created and configured. As a researcher, I am not able to verify these models without knowing how the researchers programmed their model and what software they used. This is exemplified in table 4, in the row of used software for simulation. This is a shame as it does not propel the development of cyclist simulation forward, while all researchers seem to agree that this is an understudied subject that deserves more attention.

5. Simulating cyclists in PTV Vissim

This section describes the calibration and configuration of the simulation model for the case study. The aim of this section is twofold. First of all, there is a learning-by-doing aspect that is described. Throughout the description of how the model is configured, there are useful notes on what is advised and what is not advised when other researchers want to create a similar model. Secondly, this section enables the reader to replicate the created model in order to test my findings.

The structure of this section is split into the configuration and the calibration of the final simulation model. Prior to these two steps, the choice of model type for the simulation is described, which impacts both the configuration and the calibration of the simulation model. The configuration subsection describes how the model is set up and arranged so that it operates correctly. The calibration subsection describes how the model parameters are optimized towards realistic cycling behaviour.

5.1 Cyclists as cars or cyclists as pedestrians?

The challenge for simulating the behaviour of cyclists lies in its freedom of movement. Cyclists can move more freely than cars, whose movements are constrained by rules and lane-based infrastructure. Car traffic models generally separates the infrastructure into lanes, and creates a separate but related one dimensional model for each lane (Osowski & Waterson, 2016). This lane-based structure seems unsuitable for cyclists. However, cyclists do not move as freely as pedestrians either. Pedestrians can take a step backwards or sideways at any moment and are not obligated to walk on a certain side of the road. The behaviour of cyclists seems to fall in between the pedestrian and car behaviour in this respect. However, cyclist behaviour in PTV Vissim must be based on either cars or pedestrians, depending on how the infrastructure network is drawn.

The creation of a simulation model in PTV Vissim generally starts with the infrastructure network. In the PTV Vissim 2023 software package, there are two general streams of simulating mobility. The regular Vissim package allows you to simulate cars, cyclists and public transport through a network of links and connectors. The behavioural basis for this package is the car-following model.

The VisWalk package allows you to simulate pedestrians navigating areas rather than links and connectors. These pedestrians spawn in an origin area and are destined for a specific destination area. The basis of their behaviour is the Social Force Model. This software is largely used to model pedestrians, but research shows that it could also be suitable for the microsimulation of cyclists (Thijsen, 2021; Pérez Castro, 2020).

This choice impacts many other settings and configurations, as well as the calibration of the cyclist's behaviour. As can be seen in the Vissim toolbar in figure 8, there is a distinction between functions that work with links and functions that work with areas. Because of this distinction, it is not possible in PTV Vissim to create a hybrid model in which agents move

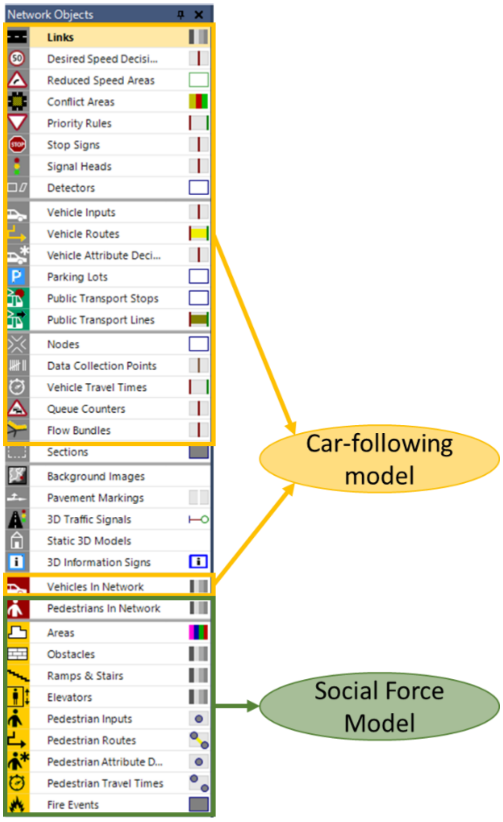

Figure 8, Toolbar of Vissim

according to the SFM, but also make decisions like in the car-following model.

So, when one desires to simulate cyclists, the choice needs to be made if the cyclists should behave more like cars on a freeway or highway, or more like pedestrians on the sidewalk or in a building. In general, the cyclists should be simulated as cars for macroscopic analysis, for instance to analyse the flow or density of a bicycle path. In other words, when the accuracy of the movement of cyclists is not as relevant for one's study, the car following model is a suitable choice for the simulation (Pérez Castro, 2020). But for simulating the behaviour of cyclists, it is advised to simulate the cyclists as pedestrians, as the SFM displays more fine grained movement of the cyclists. Thus, the model for this thesis shall be using the SFM. However, do note that this approach in this software does not lead to ideal cyclist behaviour. This will be elaborated on in following subsections, as well as in the discussion in section 7.

5.2 Model configuration

This subsection describes how the simulation model is set up. It regards the creation of the bicycle path network, creating cyclist types with separate speed distributions and setting the cyclist volumes.

5.2.1 Network

As stated in section 5.1, the model follows the force-based approach. Therefore, the network is drawn using the 'Areas' function. Although it is called a 'network', the model only consists of the single case study bicycle path: the Provenierstunnel in Rotterdam. Earlier iterations also contained intersecting bicycle paths on the north and south side of the Provenierstunnel, but these were removed due to calibration issues (see section 5.4 Lessons learned).

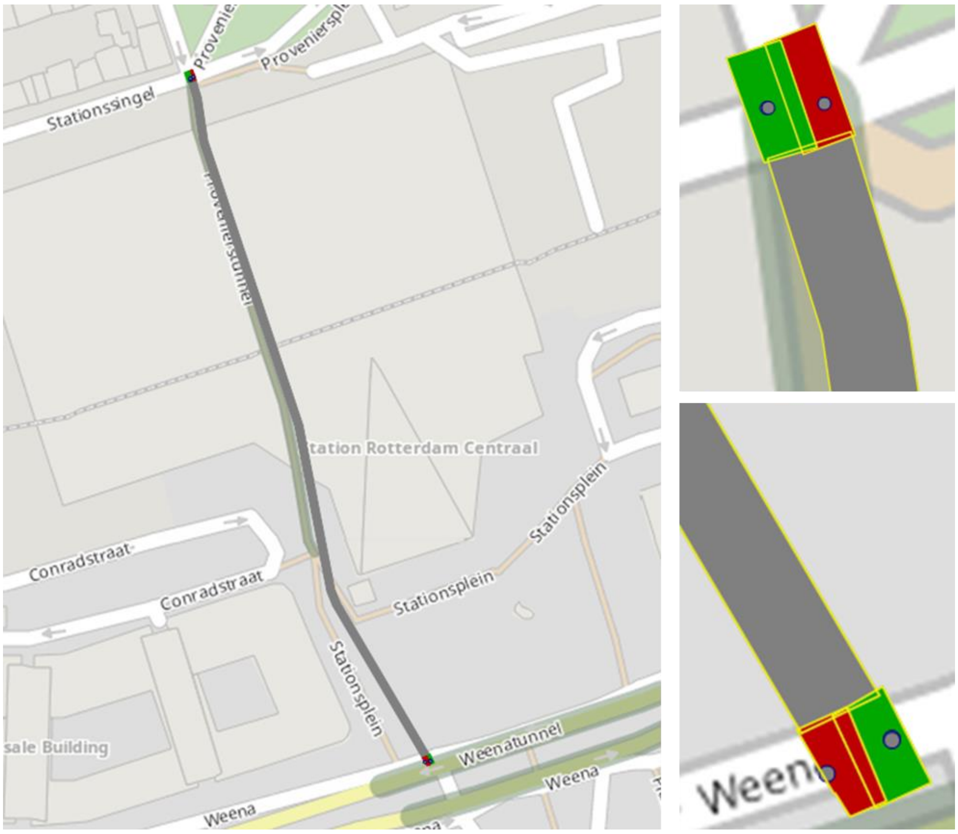

Figure 9, Overview of the definitive simulation network

Figure 9 depicts the final lay out of the simulation network. The background map is the world map of PTV Vissim which is the background by default. The two small green areas are defined as 'Origin areas', which are designated areas in which the cyclists are created. Similarly, the red areas are defined as 'Destination areas', which are designated areas in which the cyclists will disappear. The exact shape of the bicycle path has been measured from the PDOK viewer database (*PDOK viewer, n.d.*), which reveals that the background map of PTV Vissim is not completely accurate.

The bicycle path itself consists of one large polygon. The path is 4 metres wide. Earlier versions of the network experimented using multiple polygons to create a network with the aim to improve cycling behaviour or for more accurate dimensions of the bicycle path. However, this did not lead to satisfactory results. See Section 5.4 Lessons learned for a more elaborate explanation. Therefore, the most important takeaway from the use of areas in PTV Vissim, is that it is advised to create large polygons for the network instead of short sections. As it is my experience that conflicts tend to occur on the intersection of areas, as if the cyclists do not perceive or anticipate other road users that are in a different area.

5.2.2 COM API

An Application Programming Interface (API) is used to enable two computer programs to communicate. PTV Vissim uses the COM API, with which one can link a programming software (e.g., Matlab or Visual Studio) to the simulation model. In this case, a Python code is created in Spyder for several configurations and inputs of the simulation model. This code can be found in appendix II.

5.2.3 Inputs

Besides the learning-by-doing aspect of configuring a simulation model of cyclists, the aim of the case study is to research the effect of speed differences on conflicts on the bicycle path. Specifically, the speed differences that occur due to the recent surge of electric bicycles (EBs) on the Dutch bicycle path. Therefore, two types are created in the simulation model. One type for conventional bicycles (CBs) and one for electric bicycles (EBs). Then, one can set the desired speed distribution for each type. The desired speed is the speed that cyclists maintain in free flow condition, when they are undisturbed by obstacles or other road users. For this model, a normal distribution is assumed (see figure 10). The mean and standard deviation values are taken from the study of Twisk et al. (2021). Twisk et al. conducted a study on the speed characteristics of conventional bicycles (CBs), pedelecs (EBs) and speed pedelecs in urban and rural areas in the Netherlands. The numbers shown in table 5 show the total mean speed and standard deviation of that study for CBs and EBs.

Table 5, Observed mean speed and standard deviation of CBs and EBs. Adapted from Twisk et al. (2021)

	Mean speed	*Standard deviation*
Conventional Bicycle	17.6	2.63
Electric Bicycle	21.0	3.27

A similar speed distribution has been created for EBs, using their respective mean speed and standard deviation. These speed distributions are then assigned to the two bicycle types so that there is one type classified as CBs and one as EBs.

Then, the relative flows for each type are configured (i.e., the percentage of CBs and EBs in the simulation), using the COM API in a python code. The list in Vissim that shows the relative flows of the different types is called 'Pedestrian Compositions'. This list couples the 'Pedestrian types' (i.e., bicycle types) with the speed distribution and relative flow. The relative flow can be easily changed using the COM API in Python, which is beneficial for scenario simulations. The Python code can be found in appendix II.

Figure 10, Speed distribution of CBs configured in the simulation model

Note that besides 'pedestrian types', there are also 'pedestrian classes' in PTV Viswalk. These classes are not used for configurations such as speed distribution or relative flow, but they can be used for altering the visual appearance of the agents in your model. For instance, the dimensions, clothing or gender can be set in this list.

Lastly, the cyclist volumes need to be set. This is the number of cyclists that use the bicycle path per time interval. This is based on real life data, received from the municipality of Rotterdam of the month October in 2022. This month is chosen by the municipality to make available to me and has not been chosen for a specific reason. Each simulation will simulate one day, with time intervals of one hour. Again, the COM API is used in a Python code to set the transfer of the cyclist volumes from a .csv datafile to the simulation model (see appendix II).

5.2.4 Output generation

This subsection describes the settings with regard to running the simulation itself and the undertaken steps to create the desired output to answer the last subquestion of this research.

Simulation settings

The simulation settings for this model regard the length of the simulation in seconds and the step interval of each simulation second. A choice has been made to do simulations of 24 hours. The first reason for this choice is that it suits the hourly data of cyclist volumes that the municipality provided for this study. Secondly, it can provide interesting insights on the results as the volume of cyclists on the bicycle path changes throughout the day. It allows for quicker recognition of critical volumes when conflicts occur. Or when an unlikely number of conflicts occur at low volumes, for instance in the night, it says something about the calibrated cyclist behaviour.

The step interval is set to 20 time steps per simulation second. This setting essentially describes the resolution of the movement of the cyclists or pedestrians in the model. The step interval, like several other settings, should be balanced on the quality of the simulation model and the time it takes to run one simulation. Many steps per simulation second leads to more accurate simulation but requires more simulation time. The setting for 20 time steps per simulation second led to satisfactory behaviour and measurements of conflicts. The simulation time is also still feasible.

Lastly, the simulation model needs to be configured in such a way that the right output data can be found after running the simulation. This is not self-evident in PTV Vissim, as there are many options and attributes that can be created as output for analysis. The User Defined Attributes that are described in the next subsection can be generated as output by checking the following box at *'Evaluation'>'Configuration'>'Direct Output'>'Pedestrian record'*. Then, click on 'more' next to 'Pedestrian record' to set the time step resolution of the generated output. In this case it is set to 5, meaning that every 5 time steps is recorded in the output. In other words, every 0.25 seconds of the simulation is recorded and generated as output. The generated output can then be found as a Perl Source File (.pp).

$$\frac{1\ [simulation\ second]}{20\ [time\ steps]} * 5\ [resolution] = 0.25\ [seconds\ per\ measurement]$$

User Defined Attributes

Conflicts are measured through the Time-To-Collision metric, as described in section 3.2. TTC is not a preprogrammed function of the PTV Viswalk software. Thus, it must be manually created via so called 'User Defined Attributes' (UDA's). These UDA's are designed to give the user as much freedom as possible to create their desired function within PTV Vissim or Viswalk. The created output data can take on many different forms and it can be based on existing data or a formula.

When a formula is chosen for the UDA, one gets access to other attributes of Viswalk. Which attributes you can access depends on the location of your UDA. The location of your UDA is the 'list' in which you create it. 'Lists' are tables within PTV Vissim in which you can set your settings and configurations. For instance the list 'Areas' governs in my case the location and shapes of my cycling network, as described in section 5.2.1, and the list 'Pedestrian Inputs' governs the cyclist volumes per hour, as described in section 5.2.3.

The UDA for TTC is created in the list 'Pedestrians in Network'. This list is only active during simulation and describes live information of all the cyclists that are active in the network. This list is necessary as location for my UDA as it enables access to existing attributes such as the location and speed of each cyclist for each moment (or time step) in the simulation. This has been used for the creation of the UDA's in the model. There is a different UDA for TTC for each step of 0.5 seconds (i.e. 'TTC_1/2Sec', 'TTC_1Sec', 'TTC_3/2Sec' and 'TTC_2Sec'). These TTC UDA's give a Boolean value as output, meaning that it is either 0 or 1. The value of 1 is given when a cyclist and its nearest neighbour have the same location in X-seconds, if neither cyclist adjusts speed or direction. This extrapolation of a cyclist's location in X-seconds is calculated through other UDA's.

Figure 11 shows examples of how these UDA's are programmed in the 'Pedestrians in Network' list. The left UDA in figure 11 shows the UDA that calculates the X-Coordinate of a cyclist in 1 second time. To calculate this, the current X-Coordinate of the cyclist ('COORDCENTX'), the orientation angle in degrees ('ORIENTATIONANGLE') and the speed in km/h ('SPEED') are used. The latter two had to be converted to radians and m/s respectively. For calculating the Y-Coordinate in 1 second time, the only difference is that the Sine of the orientation angle is used instead of the Cosine.

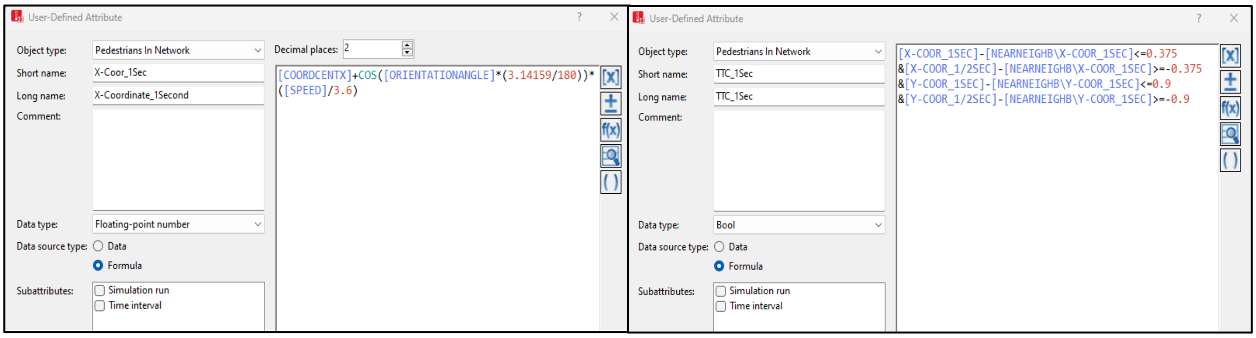

Figure 11, Created UDA's in the simulation model. The left figure shows a UDA for the predicted X-Coordinate in 1 second. The right figure shows the calculation for TTC in 1 second.

Note that this implies that the orientation angle is zero degrees when the cyclist travels to the east, which is found out through experimentation in the software. Also note that this implies that the coordinate system that the software creates for the network is in metres, which is a convenient bonus as no conversion calculation is required. The right UDA in figure 11 calculates if a collision should occur in 1 second time if neither cyclist changes speed or direction. This reveals another convenient function of PTV Vissim, as the coordinate UDA's can be used for the cyclist in question as well as its nearest neighbour. These UDA's of the cyclist are subtracted from the same UDA of the nearest neighbour, the result shows the distance in X or Y direction between the two cyclists. Cyclists generally are 75 cm wide and 180 cm long (Thijsen, 2021). Thus, if the distance between the two cyclists in X seconds is between -0.375m and 0.375m in X direction and between -0.9m and 0.9m in Y direction, a collision is imminent and the TTC UDA gives a 1 as output. Through this way, four TTC values are calculated: TTC in 0.5 seconds ('TTC_1/2Sec'), TTC in 1 second ('TTC_1Sec'), TTC in 1.5 seconds ('TTC_3/2Sec') and TTC in 2 seconds ('TTC_2Sec'). Then there is a UDA called 'Collision' which gives a 1 as output when the current coordinates of a cyclist and its nearest neighbour are within the same ranges as for the TTC calculation. There is also an 'Opposite Direction' UDA, which checks if the nearest neighbour travels in the opposite direction or in the same direction. This is to provide extra information on the nature of the conflict.

Lastly, the reader should note that the calculation for TTC in this fashion essentially draws a box around the cyclist of 75 cm by 180 cm (see figure 12). This box is drawn using the X and Y coordinates of the cyclist, thus the box does not change its angle along with the angle of the cyclist. This issue might be solvable in a Python script using COM, or with more complex UDA's. But unfortunately, I did not manage to resolve this issue within PTV Vissim.

The cyclist shown in figure 12 is travelling the sharpest segment of the bicycle path. In other words, the angle misalignment of the drawn box will not be bigger than is displayed in figure 12. Therefore, this way of calculating TTC is more or less acceptable for this network, as each cyclist is generally cycling on the north-south axis. However, when a larger network with perpendicular bicycle path is used, a way should be found to move the angle of the 'drawn box' along with the orientation angle of the cyclist.

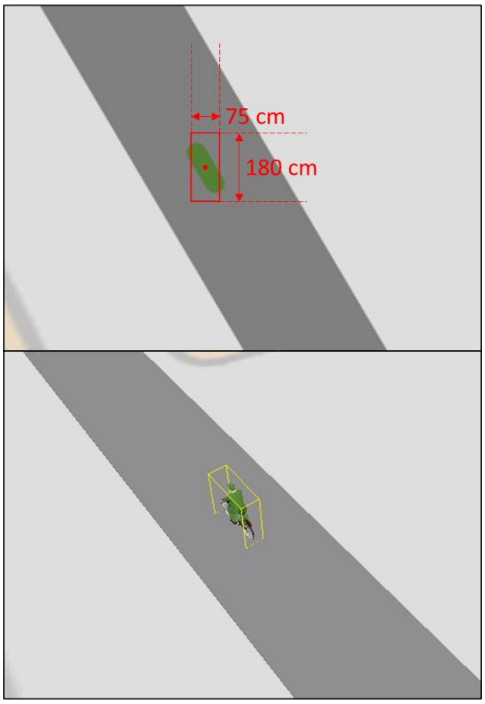

Figure 12, display of 'box' drawn around cyclist for TTC calculation in the top figure and what the drawn box ideally looks like in the bottom figure.

5.3 Model calibration

The parameters of the simulation model for this thesis are calibrated through theoretical reasoning and a trial and error process of examining the behaviour of cyclists in the model. I refer to this process as the test phase. The examination of cyclist behaviour is compared to my personal experience as a seasoned urban cyclist and to my observations of the cyclists on the case bicycle path at Rotterdam central station.

5.3.1 Parameters of VisWalk

Table 6 below shows the description from PTV documentation of the parameters which define the 'walking behaviour' (in this case cycling behaviour) within PTV VisWalk.

Table 6, Description of each behaviour parameter from PTV Vissim adapted from PTV Group (n.d.-a)

Name	*Symbol*	*Description*
Relaxation time	τ (Tau)	The driving force sets a systematic movement into the direction of the desired velocity v0. It is the smaller, the smaller the difference between the desired and the current velocity v is. And it is the smaller, the larger Tau is. Tau has the dimension of time. It can therefore be interpreted as reaction or inertia time.
ReactToN		During calculation of the total force for a pedestrian, considers only the influence exerted by the n closest pedestrians.
ASocIso	A_{iso}	A social isotropic governs the strength (A) of the social force between two pedestrians.
BSocIso	B_{iso}	B social isotropic governs the range (B) of the social force between two pedestrians.
Lambda	λ	Lambda governs the degree of anisotropy of the forces.
ASocMean	A_m	A social mean governs the strength (A) of the social force between two pedestrians.
BSocMean	B_m	B social mean governs the range (B) of the social force between two pedestrians.
VD	VD	Parameter VD in seconds. Documentation states that increasing VD makes opposing pedestrians evade more. The social mean force calculates the expected distance between two pedestrians on the basis of VD in seconds, if both pedestrians keep their speed.
Noise		The greater this value, the stronger the random force that is added to the systematically calculated forces if a pedestrian remains below his desired speed for a certain time. Noise is set to 0 for pedestrians waiting in front of a red signal head. This allows for realistic passing of approaching pedestrians and calm waiting behaviour of pedestrians in stationary state. As soon as the signal head turns green, Noise is reset to the default value.
Side Preference		Specifies whether opposing pedestrian flows prefer using the right or the left side when passing each other.

For the simulation model of this thesis, there are several parameters that have the biggest impact on the cycling behaviour. Those are the parameters that impact the driving force, the social mean force and the social isotropic force. These three forces are the main forces that act upon the cyclist. The resultant force, which ultimately defines the movement of the cyclist, is the sum of these forces. Therefore, these forces need to be in balance with each other. The parameters related to these forces are discussed in the following subsection. Then, the other parameters are discussed. Lastly, the grid size of the model is described, which is not a parameter of behaviour that is described on the website of PTV (PTV Group, n.d.-a), but greatly impacts the behaviour of the cyclists in the model.

5.3.2 Driving force, social mean force and social isotropic force

Table 7 below reveals the parameter values of the studies described in section 4.3 that use SFM as a basis. In this table, the final values for the calibration of this simulation model have been added. The SFM in its simplest form uses three parameters to describe cyclist behaviour. These three parameters determine the shape of two forces, the driving force and the social (isotropic) force.

Table 7, Comparison of parameter values of the basic SFM between other studies and my configuration

	Dias et al. (2018)	Huang et al. (2017)	Qu et al. (2017)	Yang et al. (2018)	Liu et al. (2019)	Li et al. (2021)	Thijsen (2021) Isotropic	Thijsen (2021) Mean	My configuration Isotropic	My configuration Mean
A	1.38	2.33	1.7	6.3	0.61	0.42	5	3	0.6	0.6
B	1.93	0.18	3.25	2.9	0.841	8.04	0.4	1.1	2	25
Tau	1.35	1.61	0.6	1.1	13.03	9.03	1.3	1.3	1.0	1.0

Driving force

The relaxation time (Tau) is the denominator in the formula for the driving force. The driving force is the force in this system that moves the agent from origin to destination. Its formula looks as follows:

$$\vec{F}_{driving} = \frac{\vec{v}_0 - \vec{v}}{\tau}$$

In which:

$\vec{v}_0$ is the desired velocity in which the agent wants to move

$\vec{v}$ is the velocity in which the agent is moving

τ is the relaxation time in seconds

As you can see in the plot on the next page (figure 13), the value of Tau determines the slope of the driving force. A higher value results in a lower driving force when the cyclist is going slower than its desired velocity. However, the exact meaning of relaxation time remains contested. According to Liang et al. (2018), creators of the PPFM, relaxation time is the time it takes for cyclists to accelerate to the desired speed from 0 m/s. In their experiment, that takes the cyclist 4.3 seconds on average (N.B. this is not included in table 7, as their PPFM does not make use of parameters A and B in the same way). However, according to Huang et al. (2017), the relaxation time is the time it takes for a cyclist to recover to its desired speed once it is hindered by an obstacle or other cyclist, similar to PTV documentation who describe it as a form of reaction time (table 6). Thus, their experiments to measure Tau led to a much lower value (1.61), as the difference in velocity that the cyclists need to overcome is much smaller.

Looking at the application of the driving force in the simulation software, the definition of Huang et al. (2017) seems to fit better. Because, in PTV Viswalk the acceleration of the cyclists is also capped in the settings (at 1 m/s^2). Thus, the driving force does not truly dictate how quickly the cyclist reaches their desired speed from 0 m/s. Moreover, the PTV documentation states that increasing the value does not only decrease acceleration, but also decreases density on the bicycle path and it increases the turning radius of cyclists PTV Group (n.d.-a). Especially the decreased density is of importance in my case study. A higher Tau led to slow and indecisive agents in my simulation model. The driving force is generally the dominant force in the system of forces in the SFM, which needs to be challenged by the repulsive forces. Thus, a high Tau (i.e., a low driving force) leads to a more sensitive system of forces.

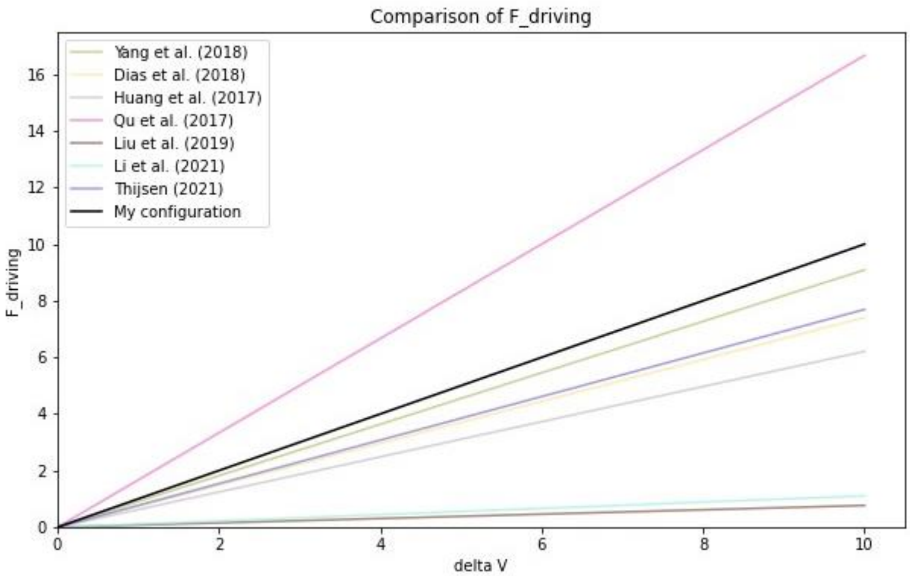

Figure 13, Plot that compares the driving force between different configurations (Veraart, 2024)

Social isotropic force and social mean force

Parameters A and B refer to the social force. In the basic SFM, the social force is one force which acts as a repulsive force between two cyclists. However, in PTV Viswalk the social force consists of two parts, the social isotropic force and the social mean force. The social isotropic force is the same as the regular social force used in other studies. This is because other studies only use one repulsive force in their version of the SFM, simply described as the social force. The social mean force is a bit more complicated as it also takes the relative speed into account. This section shall elaborate more on these two components. But for the figure below, it is important to take note that the social force in my configuration and that of Thijsen (2021) are the sum of the social mean force and social isotropic force.

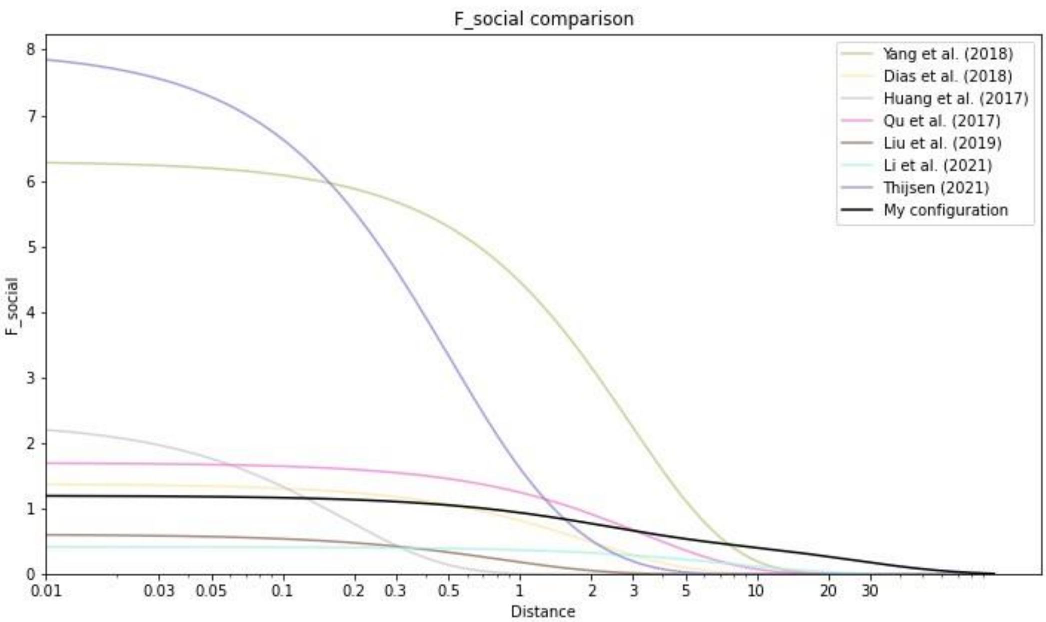

Figure 14, Comparison of the repulsive force between my configuration and that of other studies. (Veraart, 2024)

The formula for the social force, or the social isotropic force when PTV VisWalk is used, is as follows:

$$\vec{F}_{soc,iso} = A_{iso} * e^{-\frac{\overrightarrow{d_{ij}}}{B_{iso}}}$$

In which:

A_{iso} Is social isotropic parameter A

B_{iso} is social isotropic parameter B

$\overrightarrow{d_{ij}}$ is the distance between the two road users i and j (body surface to body surface)

The parameter A determines the base strength of this force. If the value of A doubles, the resulting force also doubles. The effect of B is more complicated. It affects how the distance between the two road users is weighed. A and B are often referred to as the power and range of the social force respectively. Note that the value of the social force approaches the value of A (or the sum of A's for my configuration and that of Thijsen (2021)), when the distance approaches 0.

The graph above reveals that my configuration is different in a two ways with respect to other studies. First of all, the social force starts gaining significance when the distance between two cyclists is still tens of metres. My configuration is built this way, because when a cyclist has a velocity of about 5 m/s (=18 km/h), they anticipate other cyclists (or pedestrians) several seconds in advance. Therefore, they should start acting on other cyclists that are 20 to 30 metres away. The study of Osowski and Waterson (2016) assumes that each cyclist 'plans' 5.0 seconds ahead. At the previously described velocity, this translates to roughly 25 metres. Other studies, where the social force kicks off up to 5 metres (i.e., about 1 second), might have additional rules or decision making processes in their model in order to simulate this anticipation at larger ranges. It might also be that the behaviour of cyclists is significantly different in other countries, for instance in China.

Secondly, the curve of my configuration stands out because of its shape. As is said before, the social force in PTV Viswalk consists of two parts, rather than only the social isotropic force described above which is used in most other studies. The other component is called the social mean force, which has a similar formula, but emphasizes the relative speed of the two cyclists. My configuration uses the two different forces in such a way, that a generally uniform slope is created (see figures14 and 15). Because as the distance gradually gets closer between two cyclists, it gradually becomes more urgent to undertake action. In contrast to the configuration of other studies, where a cyclist suddenly takes action when they are too close. This leads to 'panicky' and 'bouncy' behaviour of the cyclists during my test phase. Again, the researches might have tackled this issue through rules or decision making processes in their custom model. But testing just their parameter values did not lead to realistic behaviour for my case of a two-way bicycle path in Rotterdam, the Netherlands, simulated in PTV VisWalk.

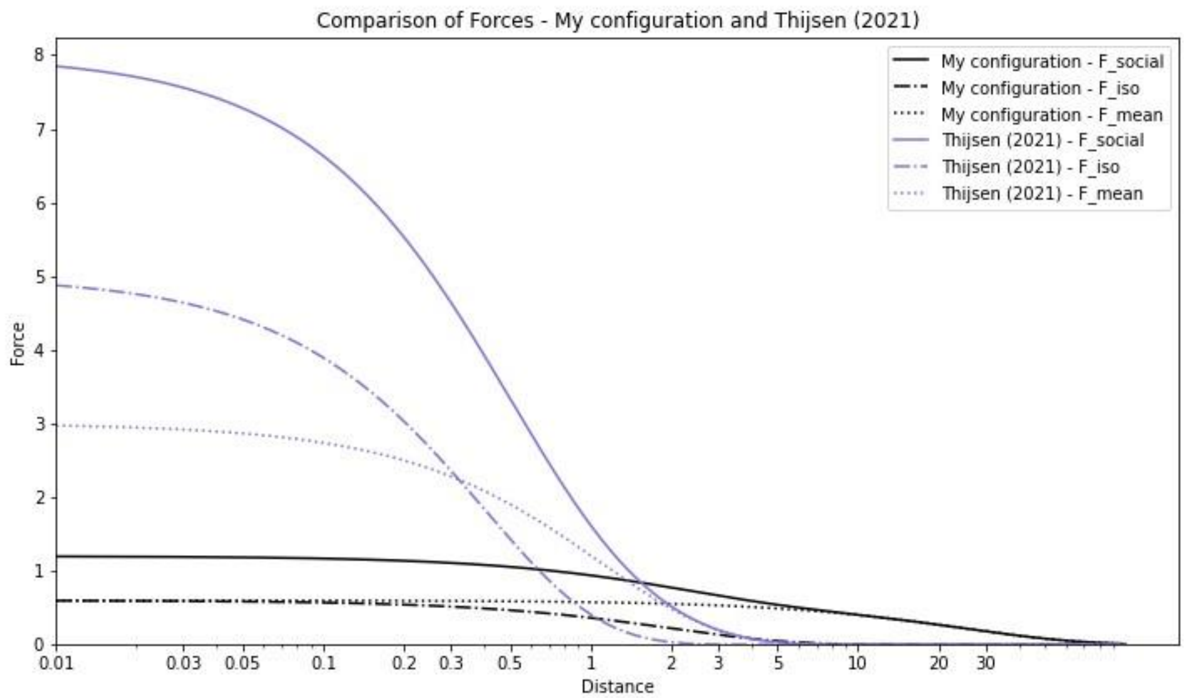

Figure 15, Comparison of social isotropic and social mean force to Thijsen (2021). (Veraart, 2024)

The figure above shows how the sum of the isotropic force and the mean force leads to the social force for my configuration and that of Thijsen (2021), the only other study that uses PTV VisWalk and/or shares the value of these additional parameters of the social mean force. Note that a simplified version of the social mean force is used for this graph, in which VD is assumed to be 0. This is because the calculation of the social mean force becomes significantly more complicated which requires specific hypothetical situations and vector calculations. This is further explained in appendix I.

However, the simplified version does depict the interaction of the social isotropic force and social mean force in relation to the distance between two cyclists. In contrast to the exponential curves of other configurations, my configuration resembles the idea of the PPFM of Liang et al. (2018). In their study, Liang and their colleagues describe a perceptive space, in which the cyclist anticipate other cyclists and makes timely adjustments to prevent conflicts. In addition, there is a reactive space, which is a close ranged space in front of the cyclist that is regarded as their 'safe space'. If someone or something enters this space, the cyclist will steer or brake in order to avoid conflict. In my configuration, the mean force can be seen as the perceptive space in which a cyclist acts from long range. And the isotropic force can be seen as the reactive range which acts up when other cyclists get uncomfortably close.

Lastly, there is the parameter VD which influences the social mean force. However, this parameter is not included in the analysis based on the graphs of figure 14 and 15. This has to do with the simplification of the graphs, which does not take the direction of vectors into account. Further explanation of the vectors of the social mean force can be found in appendix I, in which a hand calculation is done to explore the effect of the vectors in the calculation. Unfortunately, the hand calculation did not provide much more insight on how the parameter affects behaviour. Hence, the statement in PTV documentation that the social mean force calculates the distance between two pedestrians on the basis of VD in seconds is used to estimate a value for this parameter.

Table 8, Final parameter values related to the driving force, the social isotropic force and the social mean force.

Parameter	Value	Explanation
τ	1	Most of the studied researches seemed to land on similar values for the relaxation time, between 0.6 and 1.61. During the test phase of my configuration, a value of 1 led to satisfactory results. A much higher value creates slow and indecisive cyclists that also tend to clog the bicycle path at high densities, while a lower value affected the force balance with the social forces, requiring higher values for A which in turn had other effects on the behaviour of the cyclists.
A_{iso}	0.6	As said, the value of A should balance out the value of the relaxation time as they determine the strength of their respective forces. In this model, a value of 0.6 for the short range repulsive force resulted in satisfactory behaviour. A lower value resulted in insufficient action to avoid collision (i.e., cyclists going through each other or just past each other), while a higher value creates 'force fields' around the cyclists that results in unnatural looking behaviour when two cyclists are near each other (i.e., cyclists bouncing off each other).
B_{iso}	2	The 'range' of the social isotropic force is interpreted quite literally as the personal space of a cyclist as described in the PPFM of Liang et al. (2018). This space is estimated to be 'a few metres', and further observation while testing the model led to the conclusion that a value of 2 results in satisfactory collision avoidance behaviour.
A_{mean}	0.6	The value for this parameter is calibrated with similar argumentation as the value for A isotropic. However, it is noteworthy that a large value for this A has a bigger (negative) impact on the cyclist flow on the bicycle path, due to the larger range of this force.
B_{mean}	25	Again, the value for B has been literally interpreted as a range in metres. This time the range of the perceptive space according to the PPFM of Liang et al. (2018), which begs the question: how many metres do cyclists perceive or 'look around'? Osowski and Waterson (2016) assumed a 'planning time', which plays a similar role as a perceptive space, of 5.0 seconds. At a velocity of 5 m/s, this roughly translates to a perceptive space of 25 metres. Slight adjustments of this value in the simulation model (e.g., 20 or 30) led to no significant differences in the behaviour of the cyclists.
VD	5	In the social mean force formula, the expected distance between the two cyclists in [VD] seconds time is calculated. This is also interpreted as the assumed 'planning time' of Osowski and Waterson. Since this is also a parameter with the dimension time in seconds, the same value of 5 seconds is adopted for my simulation model. Slight adjustments of this value (e.g., 3 or 7) does not lead to significant differences. Extremely low values (e.g., 0.5) leads to very late overtaking (i.e., wheels touching before overtaking) and extremely high values (e.g., 50) leads to the opposite (i.e., cyclists starting their overtaking manoeuvre tens of metres in advance.

In conclusion, the parameters that are mathematically related to the driving force, the social isotropic force and social mean force are calibrated through theoretical interpretation and through my personal judgement while testing the effects in PTV Viswalk. This calibration method has led to rough values with low precision, unlike some of the described studies in section 4 which are calibrated up to two decimals by analysing video footage. However, it has led to radical differences in respect to other studies. Specifically, such a high value of the B parameter (B mean in my case) has not been used in any other study to my knowledge. Another interesting approach to this calibration, is to use the two different social forces of PTV Viswalk to mimic the PPFM model of Liang et al. (2018), in which a distinction has been made between long range anticipation and short range conflict evasion. Lastly, it should again be emphasized that the graphs of figure 14 and 15 show a simplified version of the forces. As the mathematical formulae for the social forces include vectors, where relative angles and directions are taken into account. The graphs just assume the distance and speed as a scalar number, without direction.

5.3.3 Other parameters

This subsection discusses the parameters that are not calibrated through comparison with other studies or theoretical reasoning and interpretation. During the test phase, these parameters either had no significant effect on the behaviour when the value of it changed, or the parameter clearly had a preferable value without any trade-offs or considerations to choose anything different.

React to N

The parameter 'React to N' refers to the maximum number of other cyclists in a cyclist's environment that are taken into account for the calculation of the social force. For instance, if this parameter is set to 1, the social forces are only calculated from their nearest neighbour. When set to 2, the two nearest neighbours will affect the cyclist and so forth. The default setting for this parameter is 8, which is the same for the simulation model of this thesis. Essentially, there is a composition of ‘N’ cyclists that affect the cyclist in question. If this composition changes (i.e., one cyclist overtakes another, or a cyclist from the opposite direction gets close), the net resultant force changes. If the value for ‘React to N’ is low, a change of composition has more impact on the resultant force, as the resultant force is composed by less parts. Therefore, having a low value for this parameter is undesirable, as it could lead to unstable behaviour when the composition changes often for a cyclist. If the value of this parameter is high and the composition changes, the cyclists that switch are the furthest away from the cyclist in question and thus they play a small part in the net resultant force. To put it shortly, a higher value for ‘React to N’ leads to more stable behaviour.

However, it should be noted that a higher value leads to more complex calculation that the software needs to perform for each pedestrian or cyclist that is active in the model. Therefore, a high value of this parameter in combination with a large simulation model could lead to a long simulation time. Moreover, in the case of this simulation model a stable behaviour, as far as the naked eye could see, was reached at relatively low values. Increasing the value did not lead to significant changes. Therefore, the value of ‘React to N’ is kept at its default value, for lack of reason to change it.

Lambda

The parameter Lambda can only have a value between 0 and 1. When the value is 1, a cyclist is equally affected by each surrounding other cyclist, regardless of their respective positions. When the value of Lambda is 0, other cyclists directly behind our cyclist have no effect on it (see figure 16). Its effect on the cyclist gradually increases when the other cyclist positions itself to the front of our cyclist. When a cyclist affects the cyclist in front of it (i.e., when lambda has a non-zero value), the social force acts as a push on the cyclist in front of it. This leads to unnatural behaviour where cyclists regularly go faster than their desired speed, for instance when followed by a fast EB. Therefore, this value is set to 0 in my configuration.

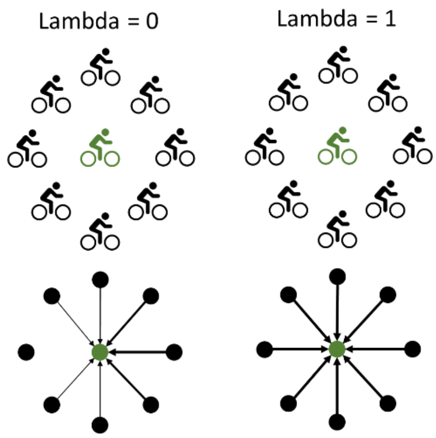

Figure 16, diagram that illustrates lambda, adapted from PTV Group (n.d.-a)

Noise

Noise is another force that PTV VisWalk added to their version of the SFM. Thus, noise has the unit m/s^2, just as the driving force, the social mean force and the social isotropic force. Noise is a random force that acts up when a cyclist systematically cycles slower than its desired speed. Essentially, this parameter is added as a way to solve gridlocks in the network. When a situation is created that a group of agents are stuck in a narrow path for instance, the random ‘noise’ force can force movements in the crowd which allows the agents to eventually go past each other. However, it is a functional requirement of this model that no gridlocks can occur during simulation as the cyclist behaviour would then be too far from realistic. Therefore, the parameter ‘Noise’ is set to 0.

Side Preference

This parameter has three options: ‘None’, ‘Left’, or ‘Right’. It determines the preference of a cyclist, when it approaches another cyclist that is going the opposite direction. When ‘None’ is chosen, it is completely left up to the social forces to determine which side the two cyclists pass each other. ‘Right’ has been the chosen option for my model, as we cycle and drive on the right side of the road in the Netherlands. Note that a cyclist only choses to go right when another cyclist from the opposite direction approaches, otherwise, it will prefer to cycle in the middle of the area. Therefore, it is no solution to the issue that the agents refuse to keep one side of the path when navigating the network.

5.3.4 Grid size

Depending on where you look in PTV documentation, the grid size is or is not a behavioural parameter of the SFM. It cannot be found in the list of 'Walking behaviour', where all the other parameters that are described in the previous subsections can be set (PTV Group, n.d.-a). For clearance, it can be found at *'Base Data'>'Network Settings'>'Pedestrian Behavior'*. However, the grid size greatly influences the behaviour of cyclists.

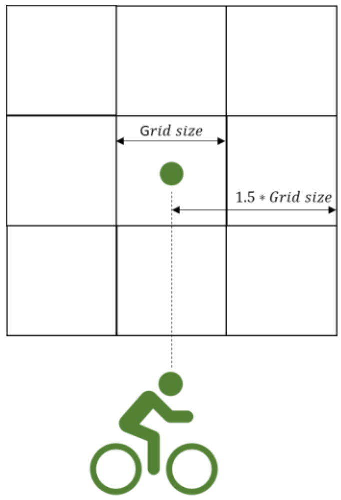

Figure 17, illustration of the Grid size adapted from PTV Group (n.d.-a)

To explain the grid size, one should imagine that the weather in the simulation network is extremely foggy. As the grid size determines how far each cyclist can 'see', or in other words it determines the thickness of the fog. As you can see in figure 17, a grid is drawn in the simulation network, with squares (or cells) with the length of the value for Grid size. Every cyclist can 'see' only in its own square, and all the squares around it.

The default value for this setting is a grid size of 5 metres. Thus, every cyclist can only 'see' 7.5 metres in front on average (or when it is at the centre of a grid cell). This might be sufficient for pedestrians, but not for cyclists as they travel with a much higher speed. Just as is explained for the parameter B Mean, cyclists anticipates obstacles and other cyclists several seconds, or tens of metres, in advance. When the grid size would be kept at the default setting, the social forces would come into effect when another cyclist is already within ten metres close. This undermines the long range of the social mean force in this calibration, which is meant to have cyclists anticipate other cyclists and make timely adjustments to avoid conflict. A note from PTV (PTV Group (n.d.-a)) about the grid size, is that a high value increases the required computational power for a simulation and can therefore largely impact the runtime of one simulation. However, because the network of this simulation model is rather small, the larger runtime has not been significant. Therefore, the grid size has been set to 50 metres as it makes sure that it does not limit the social forces in the SFM whatsoever.

5.4 Lessons learned

This section will highlight all lessons that are learned in the process of configuring and calibrating the simulation model for this research. Some of which are already discussed in the previous sections, and others are new as they are not part of the final simulation model.

5.4.1 Configuration

Network definition

First of all, the way the areas are drawn is important. When the drawn network in the software consists of multiple segments that are stitched together, it creates some issues. Although it is not for certain, the cyclists seem to disregard other cyclists that are on another segment. Therefore, cyclists around the corner for instance are poorly anticipated.

An earlier version of the network had the bicycle path split up in several straight sections that could be more easily drawn as rectangles rather than polygons. The slight angles between the straight sections were covered with polygons to complete the bicycle path. However, this led to significantly less realistic behaviour, especially at the corners. This also counts for the created UDA's of TTC, that do not seem to work for two cyclists that are on different segments.

In another early version of the network, the bicycle path consisted of two overlapping polygons, as is depicted in figure 18. The path is 4 metres wide and each polygon has a width of 2.5 metres, meaning that there is 1 metre overlap. The two polygons are meant to represent the two directions of the bicycle path. The intention of this was to have the cyclists use the right side of the bicycle path in free flow condition, without making it impossible to use the other side of the path to overtake other cyclists. This was expected to work, as one needs to manually select exactly which areas should be used from origin to destination, during configuration of the routes in this bicycle path. However, it appears that this does not influence the positioning of the cyclists, as they cycle in the middle of the full path rather than in the middle of the polygon in free flow condition.

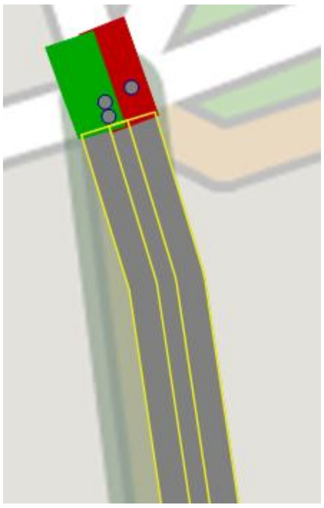

Figure 18, Early iteration of the bicycle network with two large areas representing the two directions of the bicycle path

The network being drawn using areas from the PTV VisWalk package rather than the regular links and connectors revealed another lesson. Namely, that it is impossible to have the agents behave according to a combination of the rule-based approach and the force-based approach. Section 4.2 describes how other academics use SFM as foundation, but find it insufficient on its own to simulate cyclist behaviour. Therefore, some of them propose a combination of a rule-based approach and a force-based approach generally aiming to improve their operational mental behaviour (i.e., positioning and path choice within route) (Huang et al., 2017; Yang et al., 2018; Li et al., 2021). However, a modeler using PTV Vissim is forced to choose either the rule-based approach or the force-based approach for each street or bicycle path.

Cyclist's types and classes
Another lesson drawn from this process regards the software's use of 'Pedestrian Types' and 'Pedestrian Classes'. It's important to take note of the fact that 'Pedestrian Classes' can only differentiate agents in the network on visual appearance. Once you want to have agents with, for instance, different types of behaviour or different speed distributions, then you should create a separate 'Pedestrian Type'.

Conflicts
Lastly, the measurement of conflict using TTC was challenging in PTV Vissim. The final result using User Defined Attributes (UDA's) provides sufficient results, but it is not perfect. Moreover, it relies on the fact that my network consists of only one bicycle path. As it allowed me to assume that the Y-coordinates are in the longitudinal direction of the bicycle path and the X-coordinates are in the lateral direction of the bicycle path.

5.4.2 Calibration
Grid size
In terms of calibrating the behaviour of cyclists, the most important lesson I have learned regards the grid size. Thijsen (2021), whose thesis has a similar subject to this study, stated that two-way bicycle streets could not be accurately simulated (using SFM in PTV VisWalk) at high densities due to too many collisions. However, their thesis also state that the grid size is kept at the default setting of 5 metres. It can be expected that the source of the issues Thijsen ran into has to do with this setting of

the grid size. As the cyclist can only see about 7.5 to 10 metres around, it is more likely that collisions occur as they can only anticipate a few seconds in advance.

Balancing parameter values

Also a few remarks should be made in terms of the use of the SFM within PTV Viswalk. First of all, finding the right balance of parameter values is inevitably a trade-off as different situations (e.g., different locations, different densities) lead to inconsistent outcomes in behaviour. For instance, when the repulsive forces are low, the cyclists behave well on high densities. But when there are few cyclists on the road, the sum of the repulsive forces remain low and the cyclists tend to graze each other when passing. But higher repulsive forces lead to a too high force which has the cyclists bouncing off each other in the lateral direction. Secondly, SFM is not suitable for making sharp turns. The way the SFM works in PTV Vissim, the cyclists do not anticipate their route. Instead, the driving force suddenly changes direction when the cyclist is at the crossroads. It leads to unrealistic behaviour as the cyclist does not slow down before making a turn. Moreover, it either leads to the cyclists spin out of the turn or it leads to a parameter calibration with a very dominant driving force (low Tau), which constraints the balance of forces in the SFM system. It constraints the balance of forces as the social forces then need to compete with the driving force by requiring higher values of A. However, this leads to a more volatile system of forces resulting in unnatural, jittery behaviour of the cyclists. Based on the described considerations, the parameter values have been calibrated to cyclist behaviour that looks the most natural in all situations.

Operational behaviour

The major limitations of the calibrated model all fall under the operational mental behaviour of the framework from Gavriilidou et al. (2019). The path of the cyclists go through the centre of the bicycle path when no repulsive forces are active, which is unnatural behaviour that possibly leads to many unnecessary conflicts. Moreover, the inability of the cyclists in this model to take sharp turns reveals a lack of anticipation from the cyclists in the simulation model. These cyclists are ‘unaware’ of their future trajectory and are solely led through the forces that act upon them. As a result, the cyclists do not slow down before taking a turn.

Such a turn also reveals an operational physical behaviour fallacy of the SFM, if the model is calibrated with a strong driving force. Because the cyclist then takes the turn in a short amount of time without compromising speed, which is not possible given the physical limitations of a bicycle. If the model is calibrated to have high repulsive forces, such as the model of Thijsen (2021), a similar fallacy of operational physical behaviour is displayed when two cyclists approach each other. The repulsive forces suddenly become big just prior to collision, which leads to both cyclists ‘bouncing’ in the lateral direction in an unnatural manner. However, I would argue that an improvement of the operational mental behaviour could also positively impact the operational physical behaviour. For instance, the determination of trajectories in the model of Rinke et al. (2017) should improve sharp turns as well as the handling of conflicts.

Such handling of conflicts is illustrated in figure 19 and 20. These figures show identical situations in the simulation model (i.e., the same simulation seconds, where the cyclists have the same desired speed). The only difference is the calibrated parameter values. Although moving images show the described observations more clearly, these figures should provide some insight on how my configuration is calibrated differently than that of Thijsen (2021). Especially the description of ‘bouncy behaviour’ which is used several times in this thesis, is clearly depicted in these figures.

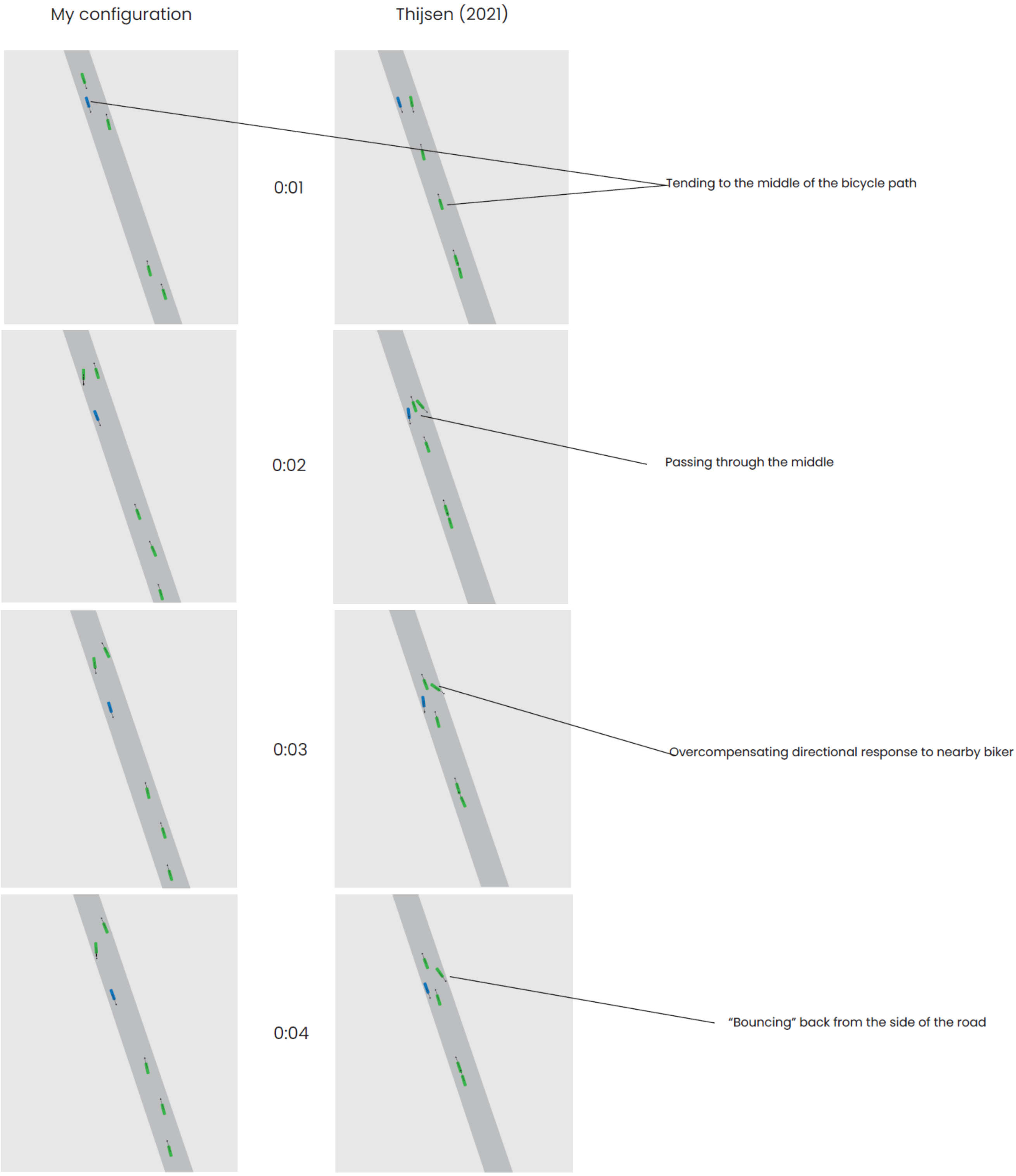

Figure 19, Simulation timeline depicting several observations for my configuration and the configuration of Thijsen (2021). (Veraart, 2024). Part 1/2

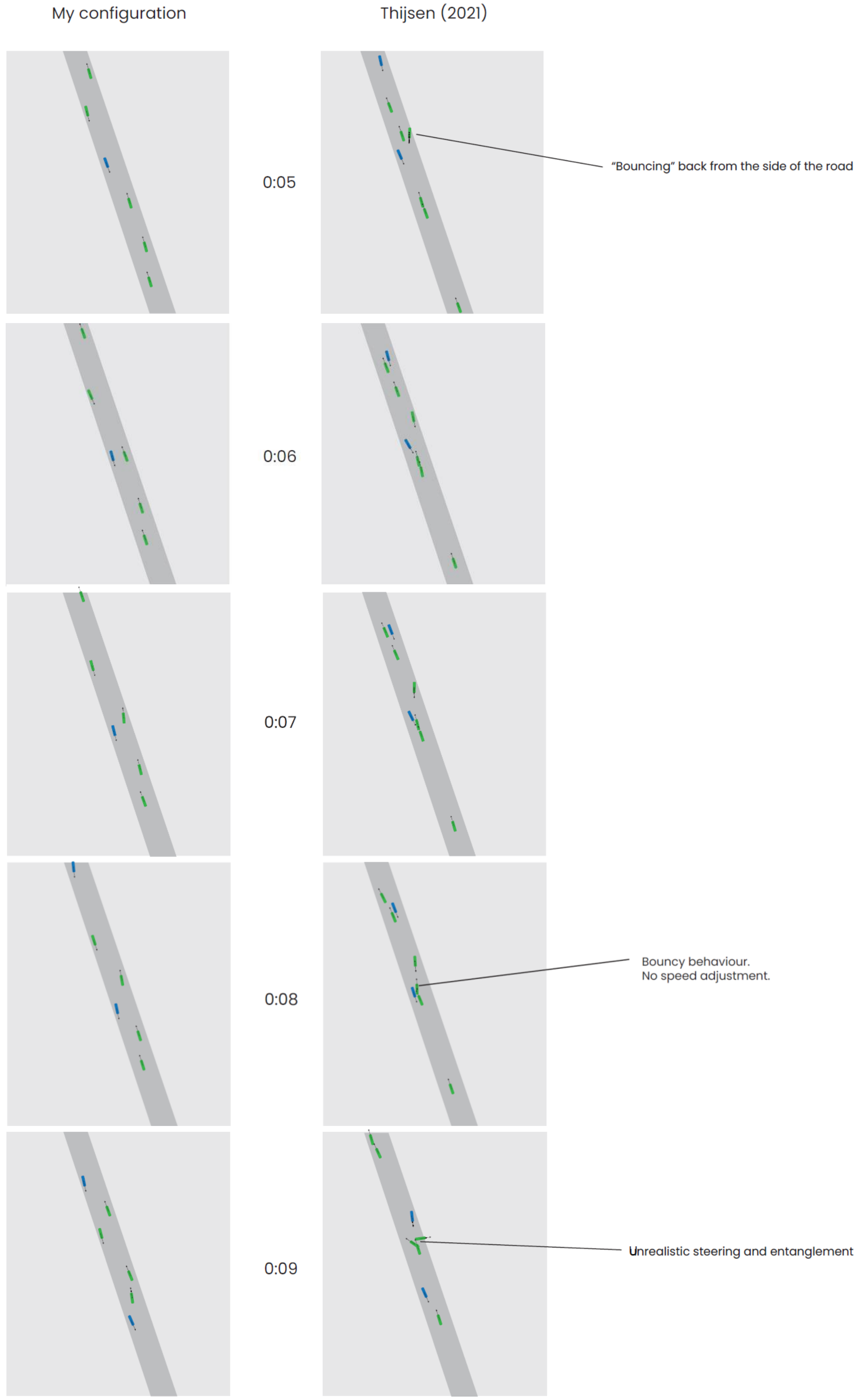

Figure 20, Simulation timeline depicting several observations for my configuration and the configuration of Thijsen (2021). (Veraart, 2024). Part 2/2

6. Simulation results

This section analyses the results of the simulations. These results are extracted as perl source files (.pp) from Vissim and analysed using Python. The code that processes this output data can be found in appendix III. The aim of this section is twofold. Firstly, it is to validate the calibrated model of the previous section. The completion of this case-study within my research might reveal additional insights on how cyclists should be simulated. Secondly, the aim is to study the effect of speed differences on the bicycle path, caused by different vehicle types. Specifically, the speed difference between conventional bicycles (CBs) and electric bicycles (EBs) will be researched.

6.1 Scenarios

Three different scenarios are defined in order to gain a better understanding of the effect of speed difference on the bicycle path. This subsection will shortly describe what aspects of the different scenarios will be the same, what will be different and what will be measured during the simulation of the three scenarios.

First there is a baseline scenario, which is aimed to replicate reality. This entails that real data is used to determine the cyclist volumes and the share of CBs and EBs. Then two other scenarios will be simulated which will be compared to the baseline scenario. The cyclist volumes will remain the same in all three scenarios, based on data provided by the municipality of Rotterdam. In the second scenario, there will be an even split of EBs and CBs. In this scenario, the speed differences will be the highest because there are as many EBs as there are CBs. In the third scenario, the share of CBs and EBs is inversed in respect to the baseline scenario. Thus, EBs will dominate the bicycle path in this scenario and CBs will be a minority. The absolute speed of bicycles will be highest in this scenario. Through these three scenarios, the effect of speed differences and absolute speed on conflicts can be tested by comparing scenario 2 and 3 to the baseline scenario respectively. Each scenario shall be validated through an examination of the average cycling speed at different densities on the bicycle path.

6.1.1 Cyclist volumes

There is one input that the three scenarios all have in common, which is the cyclist volume. This is based on data received from the municipality of Rotterdam of October 2022. This is hourly data for the entire month of October, 2022. Every simulation will be of 24 hours, which enables an analysis of the model at naturally occurring densities of the bicycle path. The volumes are displayed in the boxplot of figure 21. This plot reveals the wide range of number of cyclists that pass this bicycle path in an hour. It also shows that most cyclists go from the Rotterdam north district to the city centre during morning rush hour at 8 o'clock and take the path from south to north during the afternoon rush hour at 17 o'clock.

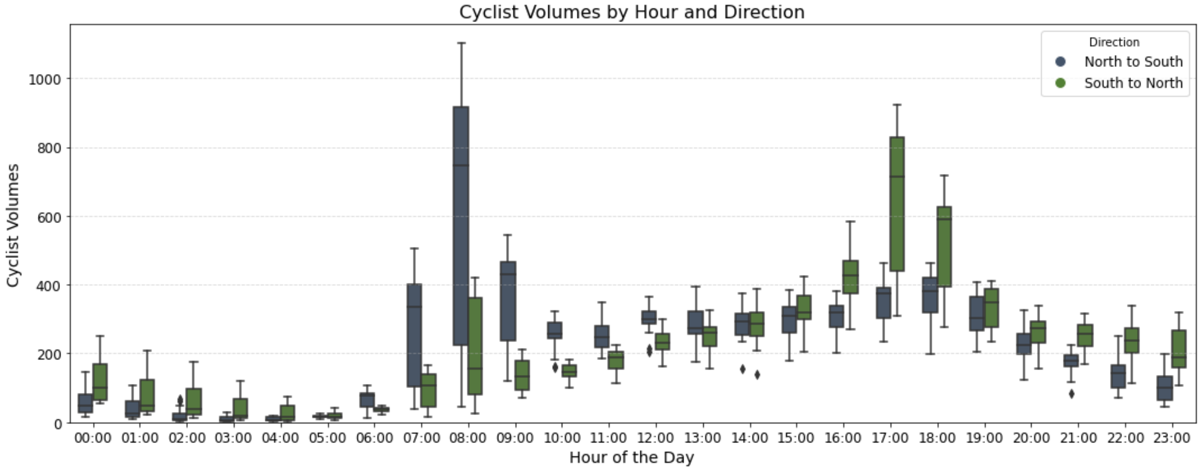

Figure 21, Number of cyclists that pass the Provenierstunnel at each hour of the day in October 2022, from the data provided by the municipality of Rotterdam (Veraart, 2024)

6.1.2 Modal share

A study on cycling experience commissioned by Tour de Force studied the Provenierstunnel along with seven other bicycle paths across four cities (Sweco & Datacount, 2022). They found in their study that only 1.9% of the users of the Provenierstunnel is an EB. Moreover, they found that 17% are mopeds and 76% are CBs. Attentive readers will have noted that this does not add up to 100%, the remainder of percentages go to racing bicycles (2.9%) and cargo bicycles (1.9%).

However, a survey from the municipality of Rotterdam reports that 19% of the respondents own an electric bicycle (de Graaf, 2022). This is a significant difference from the findings in the report of Sweco & Datacount. It is likely that the truth lies somewhere in the middle of these results from Sweco & Datacount and de Graaf. Therefore, this issue required my own measurements. I have counted users of the Provenierstunnel for an hour two times in September 2023. During rush hour, only CBs and EBs were tallied, due to the high density during that hour. On the other case, there was more space to also count other types of road users. The other road users are not implemented in the simulation model, but it provides some context on the users of this bicycle path. The results are depicted in figure 22.

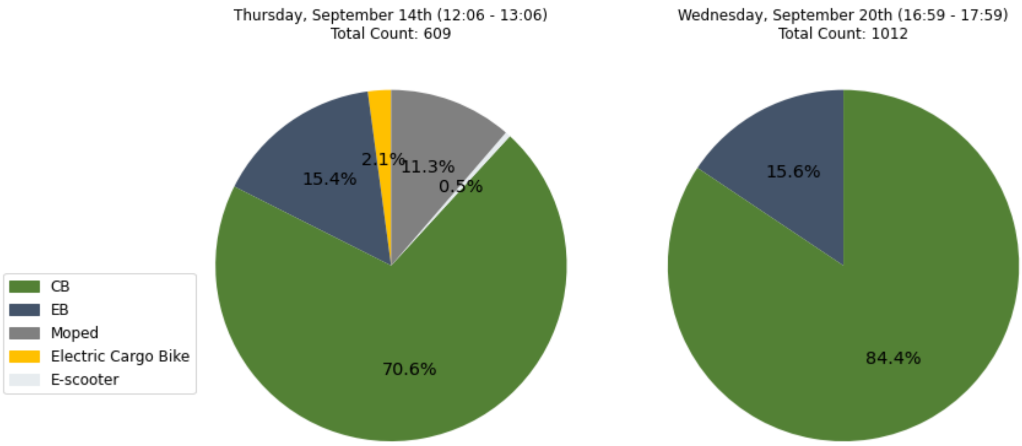

Figure 22, Road user count at the Provenierstunnel (Veraart, 2024)

Comparing only CBs to EBs (and adding electric cargo bikes to EBs), the share of bicycles (excluding mopeds and e-scooters) during the first measurement is 80.1% to 19.9% for CBs and EBs respectively. During rush hour, the tally of CBs was a bit higher, going up to 84.4% versus 15.6%. The average of these will be taken for the baseline scenario, giving EBs a share of 17.75% and CBs a share of 82.25% respectively. As is stated before, scenario 2 will have an even split of CBs and EBs and scenario 3 will have the inverse distribution compared to scenario 1, see table 9.

Table 9, Overview of the share of CBs and EBs in each scenario

	Scenario 1	*Scenario 2*	*Scenario 3*
Share of CBs	82.25	50	17.75
Share of EBs	17.75	50	82.25

6.1.3 Conflicts

The simulation model measures two types of conflicts. One is the number of 'collisions' between two cyclists, which is counted when a cyclist essentially comes in contact with another cyclist as is defined and described in section 3.2. The other is the Time-To-Collision (TTC) metric from the DOCTOR method. Theory on TTC can be found in section 3.2, and how it is applied in this simulation model is described in section 5.2.4.

The measured conflicts that are described in this graph are only between two cyclists that come from opposite directions. This decision is made while testing the conflict measurements in the simulation, because same direction collisions and TTC occurrences were observed at situations that were not threatening or (close to) collision. This is likely related to the high resolution of the simulation model in combination with how the measurements are designed as User Defined Attributes (UDA's). The model simulates 20 timesteps per second and each cyclist can (slightly) change its direction on each timestep. This increases the likelihood that two cyclists can get in each other's way at one instance (i.e., time-step), while the general direction of both cyclists gives no indication of conflict. Moreover, cyclists going in the same direction can get closer to each other while overtaking before the situation becomes dangerous. In other words, it is concluded that the use of same direction collisions and TTC would create less accurate output data.

It is expected that speed and speed difference are positively correlated to conflicts. These expectations stem from logic. Higher speeds limit the required reaction time to avoid conflict, it is therefore likely that higher speeds lead to more conflict. Higher speed differences create a more turbulent flow on the bicycle path, leading to more encounters among cyclists and more encounters likely increase the probability of a conflict occurring. The results of the three scenarios aim to test this hypothesis. The speed differences are highest in scenario 2 because as there are just as many CBs as EBs on the bicycle path, each with its own desired speed. Whereas the absolute speed is highest in scenario 3 because the electric bicycle is the dominant vehicle in this scenario.

6.2 Cycling speed

A method that can be applied to validate the model is to measure the speed with respect to the desired speed. Research shows that the average speed on the bicycle path decreases, as the volume on the same bicycle path increases. Twisk et al. (2021), observed in their study that the mean speed of cyclists is lower in urban areas than in rural areas for both CBs and EBs. They hypothesized that this phenomenon is likely related to the number of other road users one encounters while traveling, which is higher in the city. Figure 23 seem to follow the logic of this hypothesis, as the actual speed drops when the number of cyclists on the path (the cyclist volume) increases.

Twisk et al. (2022), which is a corrigendum to Twisk et al. (2021), denote a mean speed difference of 1 km/h and 2.1 km/h between rural and urban areas for CBs and EBs respectively. Therefore, the mean speed drops measured in the simulation model, depicted in figure 23, seem to be in the right magnitude, seen as the mean speed drops between 1 and 2 km/h at volumes between 600 and 1200 cyclists per hour.

However, figure 23 also shows that the higher speed drop for EBs, as observed by Twisk et al., is not represented in the simulation model. The speed drop of EBs measured in the simulation model is not as high as is observed by Twisk et al. (2022). This observation of Twisk et al. might indicate that EBs have slightly different behaviour patterns than CBs and should be calibrated accordingly. Unlike this research, in which CBs and EBs are calibrated to the same behaviour (see section 5). More research is required to find out what causes these differences in speed drops at different densities for CBs and EBs.

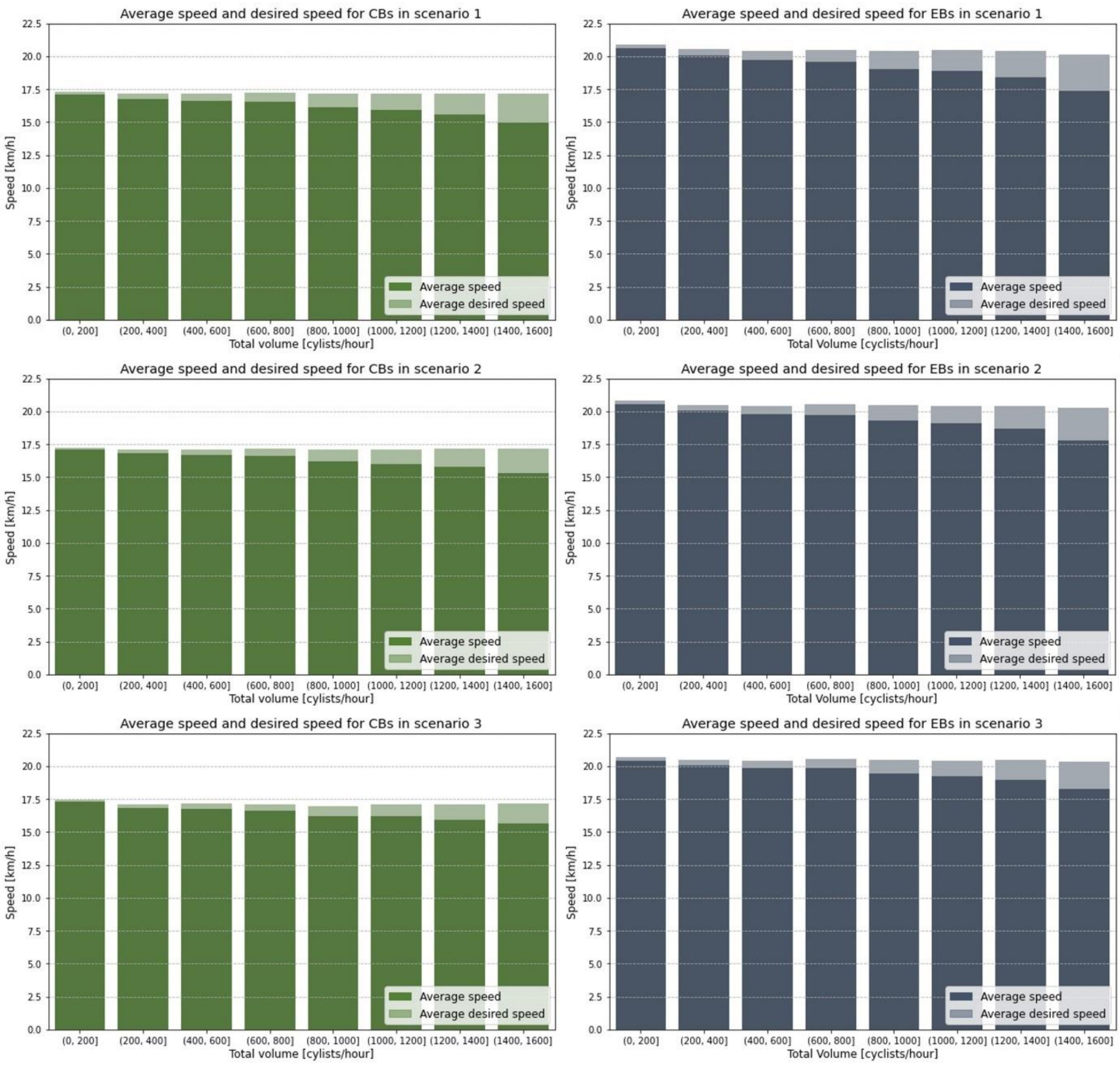

Figure 23, Plots of average speed and desired speed for each bicycle type in the three scenarios. CBs on left column, EBs on right column; scenario 1 (82.25% CBs; 17.75% EBs) top row; scenario 2 (50% CBs; 50%) EBs middle row; scenario 3 (17.75% CBs; 82.25% EBs) (Veraart, 2024)

Figure 23 reveals another finding in the plots of scenario 3. It seems that the average speed is higher in this scenario compared with the other two scenarios, especially at high cyclist volumes. The cause for this is uncertain, and requires more research. But it seems that the higher average speed on the bicycle path as a whole related to the predominance of EBs in scenario 3, seems to affect the mean speed of EBs as well as CBs.

6.3 Collisions

To start off, it is important to take note that collisions do not actually occur in the simulation as the cyclists are not physical objects. In other words, the cyclists go through each other when a 'collision' occurs instead of falling on the ground. The number of collisions is depicted in figure 24. The graph on the top shows the absolute number of collisions over the hourly cyclist volumes, while the graph on the bottom shows the number of collisions per 1000 cyclists. The graphs reveal a correlation between collisions and the number of cyclists on the bicycle path. A noteworthy difference between the two graphs is that the absolute number of collisions has a steeper curve than the relative collisions, but the relative collisions curve has an upwards trend still. This implies that the correlation between collisions and cyclist volumes is partly due to the fact that there is a higher probability of collision simply because there are more cyclists. The bottom graph proves that the density of the bicycle path also influences the number of collisions.

However, the graphs also reveal the imperfect nature of this simulation model as it is unlikely that hundreds of collisions occur every week on this bicycle path. Note that the graphs describes the number of cyclists involved in a collision. Since it takes two cyclists to create a collision, the number of collisions is half of what the graph shows. While counting the vehicle types in September (figure 24), I have not observed a single collision. There are several arguments that could be made to explain this unnatural number of collisions. For instance, a lot of collisions would probably be avoided if cyclists would travel on the side of the bicycle path instead of in the middle. Also, the cyclist behaviour in this model is calibrated in such a way that the maximal repulsive force is not very large. The reason for this was that stronger repulsive forces results in unnatural behaviour in a different way (i.e., 'bouncy' and 'wavy' behaviour), as is described in section 5.4.

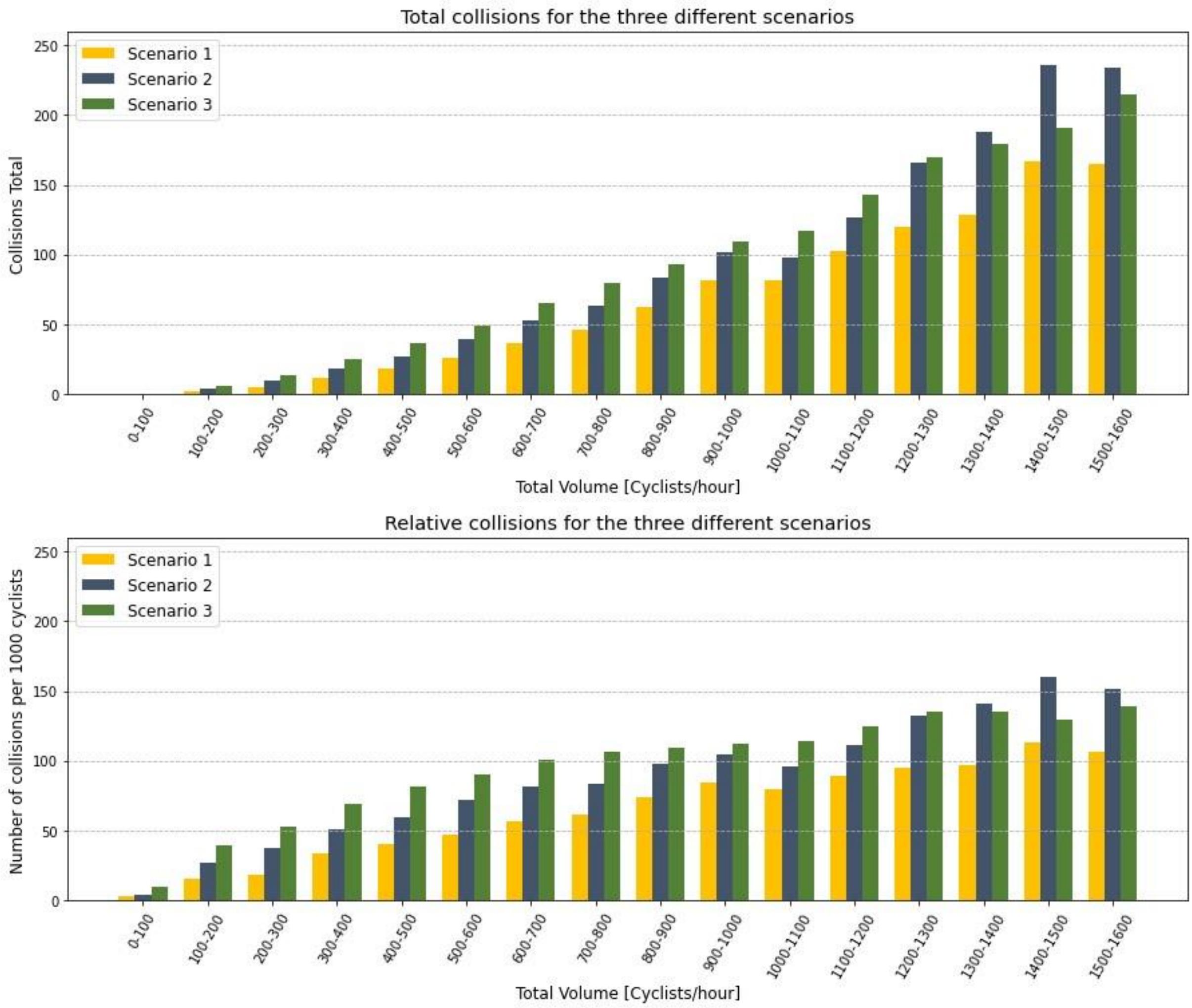

Figure 24, Number of collisions measured for each of the three scenarios (Veraart, 2024)

From these collision graphs in figure 22 can be concluded that the posed hypothesis in section 6.1.3 seems to be correct. These results suggest that there is a positive correlation between collisions and speed, as well as between collisions and speed difference, since there are more collisions in both scenario 2 and scenario 3 in comparison to scenario 1. These graphs also reveal an interesting relation to the density on the bicycle path (i.e., total volume). As most collisions at high volumes seem to have been observed in the simulations of scenario 2, but more collisions occur in scenario 3 for lower volumes. The tipping point can be seen at a volume of 1300 cyclists per hour in figure 22. This suggests that the density on the bicycle path is in some way also related to speed, speed difference and conflicts. However, more research in these interdependencies is required to make a conclusive statement on this matter.

Figure 25 depicts the share of CBs and EBs on the total number of collisions. An interesting detail is the ‘stairs-like’ shape of the plot in scenario 2 and 3. This implies an overinvolvement of EBs in collisions specifically at low cyclist volumes. An explanation for this could be that the simulation model created more EBs than average at low volumes. The percentage of CBs and EBs are set beforehand, but how the vehicle types are spread across the hours is randomly decided by the software. Such outliers are more likely to occur at low volumes because less cyclists evidently mean a smaller dataset (i.e., more likely to have irregularities). However, it is possible that there is more to it.

This detail could also be related to the interdependencies of speed, speed difference and conflict, as is previously described.

The graphs reveal that the volume of cyclists on the bicycle path does not seem to influence the involvement of either CBs or EBs on the number of conflicts. However, the graphs do reveal that EBs are consistently involved in more conflicts with respect to their share of the volume. EBs were involved in 30.7% of the total number of collisions in scenario 1, in 58.4% of the total collisions in scenario 2 and in 84.6% of the total number of collisions in scenario 3. For comparison, the respective percentage of EBs were 17.75%, 50% and 82.25% for scenario 1, 2 and 3.

These numbers also suggest that there is a dampening effect of EBs overinvolvement in collisions. The larger the share of EBs on the bicycle path, the smaller the overinvolvement of EBs on collisions.

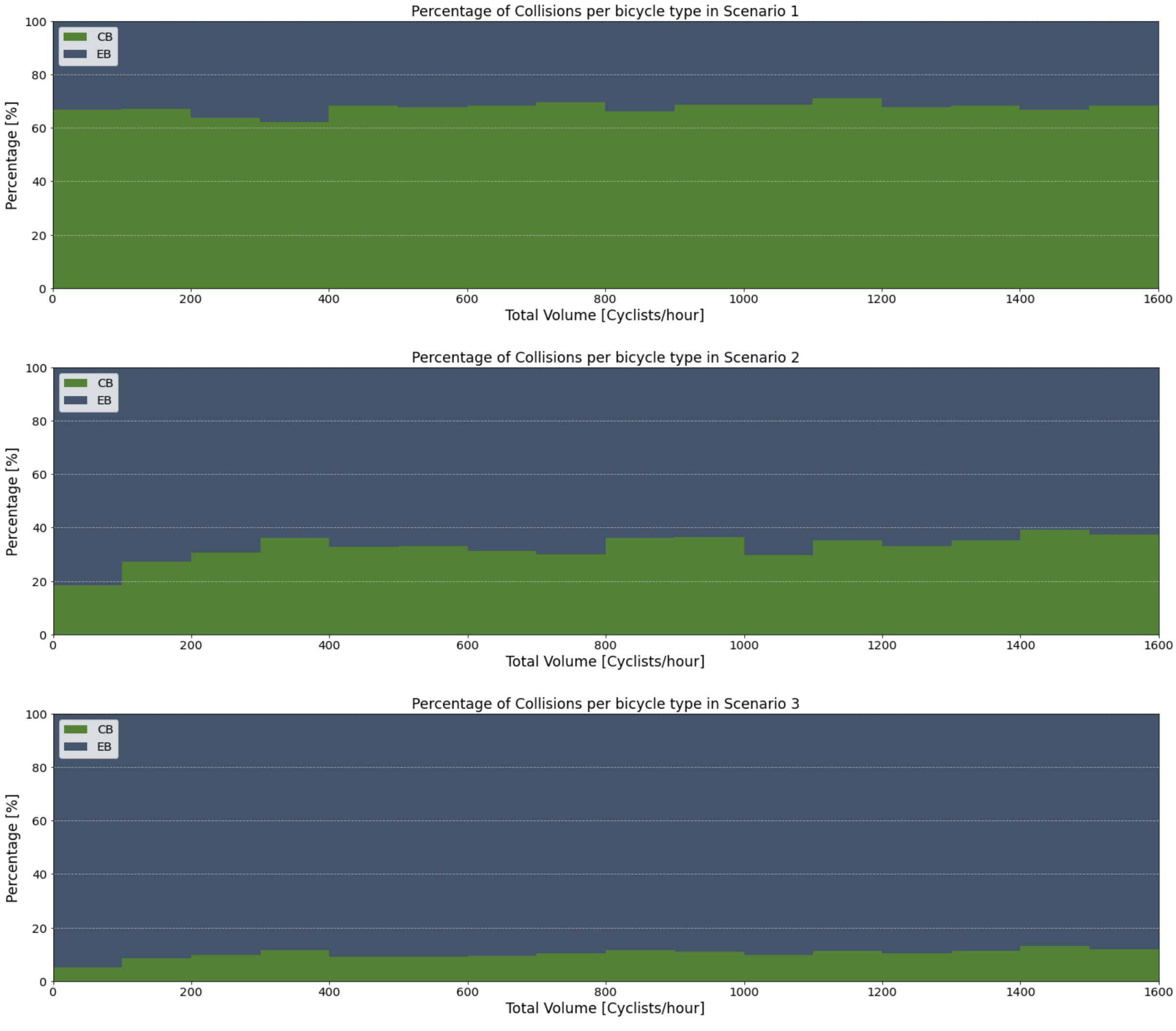

Figure 25, Percentage of collisions caused by different vehicle types (Veraart, 2024)

To summarize, the results show that higher speeds as well as higher speed differences lead to more collisions on the bicycle path. It is also observed that EBs are consistently involved in more collisions than their respective presence on the bicycle path. However, the number of collisions observed in these simulations also reveal that there is still potential improvement to be made in terms of simulating the behaviour of cyclists. Namely, the number of collisions is unrealistically high and in contrast to my own observation of the bicycle path in real life. Possible causes are stated at the start of this subsection and improvements to this fallacy is discussed in section 7.

6.4 Time-To-Collision

Time to collision is a variable that indicates in how many seconds two cyclists will collide if neither cyclist changes their speed or direction. However, the results show unexpected patterns.

First of all, the graphs of figure 27 show that the cyclists in the simulation model do not follow the characteristic graph of TTC (figure 26), as described by de Goede et al. (2013) and Hayward (1972). This characteristic graph of de Goede et al. suggests that the TTC is a continuous curve, that approaches 0 until one of the cyclists undertakes action. This implies that in order to reach a TTC of 0.5 seconds, one must also have had a TTC of 1, 1.5 and 2 seconds.

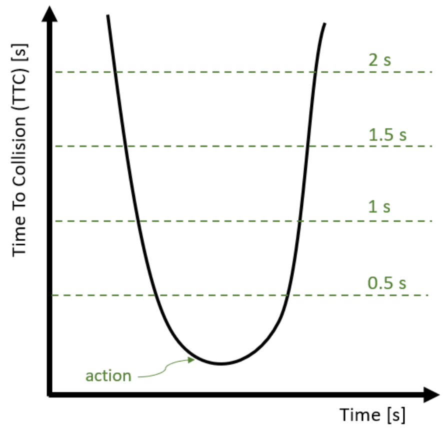

Figure 26, Characteristic graph of TTC with added measurement points for the simulation model. Adapted from de Goede et al. (2013)

However, the results of the simulation show that a TTC of 1.5 seconds occurs more often than 2 seconds and a TTC of 0.5 seconds occurs more often than 1 second. There are also more collisions measured than occurrences of TTS 0.5 seconds and TTC 1 seconds, which is unexpected for the same reason. Since a collision is essentially a TTC of 0 seconds. Closer examination of the simulation model shows that occurrences for TTC happen rather instantaneously. A cyclist slightly changes its direction every simulation step (=0.25s). Consequently, a cyclist can have a TTC of 1.5 seconds on one simulation step and not anymore the next step because its new direction does not go through another cyclist.

Secondly, the shape of the graphs are unexpected. The graphs were expected to show increasing occurrences of TTC when the cyclist volume increases, similar to collisions. However, the graphs for TTC 1.5 seconds and TTC 2 seconds depict a clear decline at high cyclist volumes. One explanation could be the fact that the UDA's that measure TTC only look at the nearest neighbour**.** This implies that TTC occurrences are not counted when another cyclist is closer to the cyclist in question. For instance, when two cyclists travel next to each other at the same speed, they will remain each other's nearest neighbour. Even when they are not creating conflicts for each other. This way, possible conflicts from other cyclists may remain unmeasured. This is especially relevant for high TTC values, as the two cyclists are then relatively far apart. For instance, when two cyclists that approach each other both travel at 5 m/s and they are currently at a TTC of 2 seconds, then they must be 20 metres apart from each other. At high volumes on the bicycle path, it is rather likely that there is another cyclist within 20 metres. When two high speed EBs approach each other, the required distance for a TTC 2 seconds to occur can go up to 30 metres. The graph of TTC 2 seconds strengthens this possible explanation, as scenario 1 suddenly measured the most occurrences while it consistently measured the least occurrences in the three other graphs. It is likely that scenario 1 measured the most TTC 2 seconds as the mean speed is lowest in this scenario. Therefore, the distance between two cyclist for a TTC 2 seconds to occur is generally lower in this scenario than in scenario 2 or 3. In other words, scenario 1 requires a lower distance between two cyclists for TTC 2 seconds to occur. Therefore, it is measured more frequently between a cyclist and its nearest neighbour coming from the opposite direction.

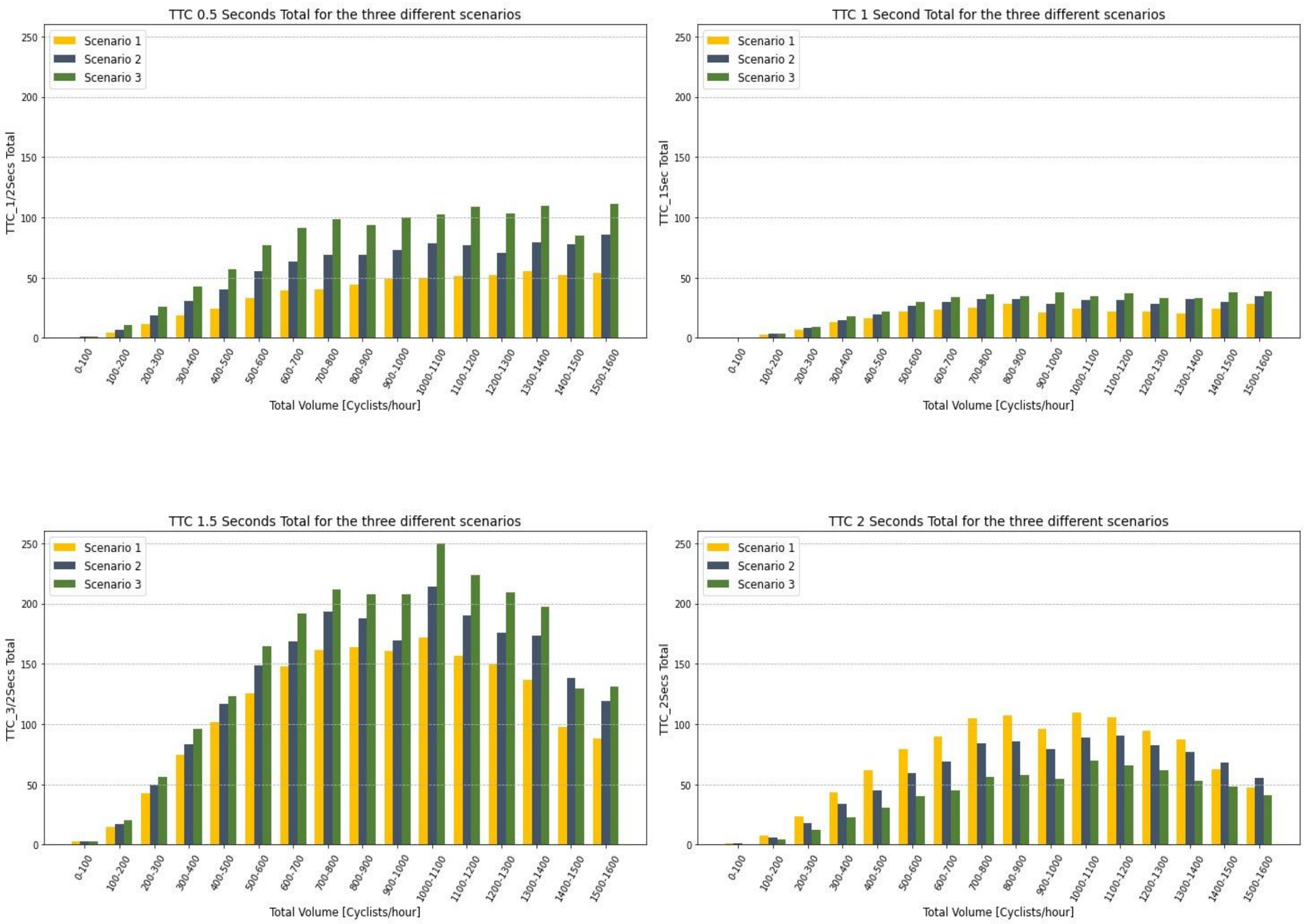

Figure 27, Measurements of TTC at 0.5 seconds, 1 second, 1.5 seconds and 2 seconds for each scenario. (Veraart, 2024)

However, there is one conclusion that can be drawn from this result. This conclusion stems from the contrast between the top two graphs in respect to the bottom graphs. It is clear that TTC 1.5 seconds and TTC 2 seconds occur significantly more often than TTC 0.5 seconds and TTC 1 second. Therefore, it is likely that cyclists often do take action between 1 and 1.5 seconds in order to avoid conflict.

All in all it can be concluded from these results that the TTC variable did not perform according to the description on which it was based (de Goede et al., 2013; Adjenughwure et al., 2023). It seems that the translation from theory to application in this simulation model created some unexpected caveats. Some explanations were given to describe how these unexpected results came to be. But it should be emphasized that these are only possible explanations for these results. It could be that these are only partly causing the unexpected behaviour or that it is caused by something which is not taken into account.

It is also important to note that TTC can be used in various ways. There is longitudinal and lateral TTC, which only looks at distance between two road users in the longitudinal or lateral direction respectively. But the way TTC is measured in this thesis more resembles 2 Dimensional TTC, where the total distance between road users is measured without regarding the longitudinal or lateral axis (i.e., it regards the 2 dimensional plane that is the bicycle path) (Guo et al., 2023). However, the calculation of future trajectories of cyclists are programmed within the constraints of PTV VisWalk's User Defined Attributes. These UDA's from my simulation model 'predict' the movement of the cyclist by drawing a straight line, using the cyclist's speed and orientation angle. While 2D TTC, as proposed by Guo et al. (2023), should predict more sophisticated trajectories of the road users. This lack of complexity in the UDA's might be a cause for these unexpected results.

6.5 Subconclusion

To summarize, the findings of this section highlighted imperfections of the simulation model. The measured speed drops at higher cyclist volumes was not bigger for EBs than for CBs, as was expected based on the study of Twisk et al. (2021). But the most important indicator of the suboptimal cyclist behaviour is the number of collisions observed in the simulations. Up to hundreds of collisions in a matter of hours is unrealistic and underpins the findings from previous sections. This will be further discussed in the next section.

In spite of the unrealistic number of collisions, the hypothesized correlation between conflict, speed and speed differences was found in the results for collisions. However, the TTC variable failed to confirm this result, as this measurement of conflict did not seem to work in the same way as it was intended.

Moreover, there were three interesting findings that require more research. Firstly, in scenario 3 where there is a large share of EBs show a smaller speed drop of cyclists at high cyclist volumes. Secondly, it seems that high speeds (scenario 3) have more influence on conflicts at low cyclist volumes, while high speed differences (scenario 2) have more influence on conflicts at high cyclist volumes. Lastly, EBs were consistently overinvolved in collisions on the bicycle path. However, this overinvolvement seemed to dampen as the share of EBs on the bicycle path increases.

7. Discussion

This section discusses the findings of the previous section, with the aim to contribute to better simulation of cyclist behaviour in the future. Table 10 below, reveals that the majority of the findings from the previous sections are criticisms on, or fallacies of the way cyclist behaviour is currently simulated. The following subsections will discuss how some of these findings could be improved on.

Table 10, Findings of section 4, 5 and 6 (Veraart, 2024)

No	Section	Finding
1	4	Although the SFM is most used as basis for a behavioural model of cyclists, the 'naked' SFM, as it is used for pedestrians, is insufficient.
2	4	Academics mostly formulate a critique of the operational mental behaviour of the simulated cyclists. Rinke et al. (2017) and Osowski & Waterson (2016) also criticize the operational physical behaviour.
3	5+6	The fallacy of the operational mental behaviour is also found in the case study, in the calibration phase as well as through the number of observed collisions.
4	4	Most academics solve the flawed operational mental behaviour by tinkering the SFM and adding rules to the model. However, each study does this differently.
5	4	All customized SFM's from studies have in common that forces are used to describe the movements of cyclists.
6	4+5	Most studies and their custom models are not replicable from their methodology sections and therefore not verifiable. The work of Thijsen (2021) was the exception to this rule.
7	5	Some improvements were found in the calibration of the simulation model in the case study. Namely, the two social forces can be used to mimic the perceptive space and reactive space of the PPFM. Also the grid size is found to be a crucial parameter for cyclist behaviour.
8	5+6	Using the TTC metric did not work as expected. Possible explanations are given, but no definitive conclusions can be drawn from the simulation result of this case study.
9	6	Speed drops are observed in the case study. But less higher speed drops for EBs, as was found by Twisk et al. (2021).
10	6	Scenarios with more EBs led to more collisions, as was hypothesized. However, the total number of collisions underpins the imperfect behaviour of cyclists using the SFM.
11	6	Simulation results describe the most collisions when speed differences are high and the density on the bicycle path is high. However the scenario with a high absolute speed registered more collisions at lower densities. This dynamic between speed, speed difference, conflict and density requires more research.

7.1 Towards a standardised model

There are several ways to simulate cyclist behaviour in traffic, as is described in section 3.3. The model of choice for this thesis has been the Social Force Model. Two reasons led to this choice. First of all, the SFM could be applied in the PTV software package VisWalk. Using an applied traffic simulation software was preferable given the timeframe of this project. Second, the majority of the found literature on the simulation of cyclists used the SFM as a basis. However, this does not automatically mean that the SFM is definitively the best way to simulate cyclist behaviour. Especially given the challenges that researchers, myself included, encounter when applying the SFM to cyclists (findings 1, 2, 3).

Finding number 4 describes how most academics solved their respective issues with the SFM, by creating additional rules or regimes on top of the SFM. Whether or not the proposed additional rules solved the issues of the SFM for cyclists, could not be tested (finding 6). Each journal article describes a different alteration to the SFM to accurately simulate cyclist behaviour. This indicates two things. Firstly, it implies that the academics are not building on each other's work, nor are they debating the best way to simulate cyclist behaviour. Secondly, it means that there is not one obvious solution for the challenges that the SFM provides for cyclists. Otherwise, the academics would have independently come to the same solution. Therefore, I argue that this tinkering has not been productive in improving the simulation of cyclist behaviour in general.

Instead, academics could work towards a standardised model for simulating cyclist behaviour. This standardised model should thoroughly examine all the aspects of the SFM, and decide whether it is also suitable for cyclist behaviour or only for pedestrians. There are two studies that already did this to a certain extent (Rinke et al., 2017; Osowski & Waterson, 2016). Interestingly enough, these are also the only studies from the described literature that formulate critique on the operational physical behaviour. This suggests that a thorough examination of the SFM for cyclists will highlight other points of discussion that are previously not considered by academics. In spite of their thorough examination, Rinke et al and Osowski & Waterson seem to agree that the use of forces are suitable to describe the movement of cyclists (finding 5). Although this is a fairly general observation, it is noteworthy that there is a common ground among all described academics for simulating cyclist behaviour.

7.2 Semantic discussion

The studies of Rinke et al. and Osowski & Waterson stand out as they criticize fundamental aspects of the SFM. Where other studies use the whole SFM as foundation and add rules to make it more suitable for their case study, Rinke et al. and Osowski & Waterson remove parts of the SFM that are not suitable for cyclists, before creating additional rules or layers. However, both studies describe the SFM as basis for their model.

Their approach reminds me of the ship of Theseus paradox. In this Greek myth, writer Plutarch poses a thought experiment. This thought experiment regards the identity of an object. If every component of an object is replaced, is it still the same object? If not, when does it get a new identity? The same question could be asked of the SFM adaptation of the described studies. To what extent are the models of Rinke et al. and Osowski & Waterson still the SFM at its core, as is stated by themselves, and to what extent are they creating a new type of model specifically for cyclists? This semantic discussion is relevant for improving cyclist behaviour simulation as it plays a role in the academic debate, or the lack of it, in this field.

In the study of Rinke et al. for instance, the behaviour of cyclists is mostly described by predetermined routes selected from several alternative route calculations. Their model only uses forces to describe the more fine-grained manoeuvres within their predetermined route. In the original SFM, the driving force will always try to bring the cyclist to its one desired speed and the force will always point in the direction of the shortest possible path towards its destination. In the model of Rinke et al., the predetermined route controls the direction of the driving force and the anticipation of sharp turns on the route allows to possibly change the desired speed for a smooth turn. Moreover, the route calculation in the model of Rinke and their colleagues relegates the importance of the repulsive forces as well. Since the model of Rinke et al. initially avoids conflict through route selection, the repulsive forces only come into play when an unforeseen conflict occurs on the predetermined route. In other words, the SFM ultimately plays a small role in the proposed model of Rinke et al. (2017). Therefore, I would argue that both Rinke et al. and Osowski and Waterson understate their critiques and proposed solutions by stating it is still based on the SFM. It might be that by doing this, these researchers obstruct a more fundamental discussion on simulating cyclist behaviour.

The review on simulation models for cyclists by Twaddle et al. also describe a model, with the same principles as Rinke et al., as a logic model instead of a Social Force Model. This implies that Twaddle and their colleagues seem to agree that such a model based on calculating trajectories should not be called SFM. However, it seems that their name of 'logic model' did not strike a chord in the academic world, as I have not encountered this term in any other scientific work.

7.3 The role of simulation software companies

It is previously discussed how academics can contribute to a standardized model of cyclist behaviour. However, academia has no monopoly on knowledge. PTV for instance has many research programs and publishes whitepapers (PTV Group, n.d.-b) Other traffic simulation software do not specialize in this mode of transportation either. This is a missed opportunity, as policy that promotes cycling is a recent trend among metropoles across the world (Osowski & Waterson, 2016). The health benefits, more efficient use of space and reduced infrastructure costs of cycling make an interesting business case for any city. Moreover, cyclist simulation would not only be a useful tool for cities that aim to promote cycling, it would also be a useful tool for established cyclist cities that are faced with new challenges in the mobility landscape. For instance, the interrelations described in finding 11 of table 10 could have an impact on future designs of bicycle infrastructure. Therefore, it is likely that municipalities are interested in researching cycling infrastructure for their city using simulation.

In addition, academics and commercial simulation software companies such as PTV could form a productive tandem to drive the creation of a standardised model forward. The review of different simulation software applications in section 2.1 found one software company that seems to be a proponent of such a tandem between academia and software developers. SUMO is an open source software that was founded in order to make simulation models by academics more accessible in order to improve their verifiability and replicability. At the time of writing, the SUMO website states that a behavioural model for cyclists is currently in construction (SUMO, 2023). Therefore, SUMO might be able to propel the development of cyclist behaviour simulation forward.

7.4 Methodological discussion

This subsection will discuss the used methods and the results of this thesis. This subsection aims to acknowledge potential flaws and hiatuses of this research.

Desk research

The desk research performed in section 4 was not a systematic literature review. It is therefore possible that the section does not describe the full academic landscape of the subject in question. The desk research was initially aimed at finding the most suitable model to use in my own research.

This resulted in a strong focus on the SFM for cyclists as it seems to be the most common model for simulating cyclist behaviour.

Another noteworthy point of discussion in the desk research, is the dominance of Chinese studies in the found literature. Naturally, this is not necessarily right or wrong. However, as a student in the Netherlands, I am inclined to prefer studies closer to home as they provide more certainty that cultural differences do not play a role in the findings of the studies. With literature from China, I was uncertain to trust their proposed solutions to simulating cyclist behaviour because I do not know to what extend the cycling behaviour in China and in the Netherlands are alike. Moreover, images of the cycling infrastructure in these studies seemed different than in the Netherlands. In the study of te Brömmelstroet (2014) on cycling behaviour, the influence of culture on cycling is also mentioned. He introduces his study by presenting the Netherlands as a unique cycling country, implying that the behaviour patterns he observed might be different on other places in the world.

Model configuration and calibration

The chosen software for the simulation model is PTV Viswalk, a package of PTV Vissim. However, other software, such as AimSun or SUMO, could also have been used as is discussed in section 2.1. Given the timeframe of this project, the software choice has been made in an early stage. After this decision, several other modelling choices have been made based on the provided possibilities by PTV Viswalk. Therefore, the use of different software might lead to different results or a different simulation model.

Finding 7 of table 10 describes two advancements that have been found in the calibration of the cyclist behaviour, using the SFM of PTV Viswalk. However, findings 3, 9 and 10 reveal that the cyclist behaviour of the calibrated model is still not as accurate as desired. Even though the SFM is the most popular model for simulating cyclists in academia, PTV Viswalk is explicitly designed for pedestrians and no alternative is offered for cyclists. As is stated in section 5, the cyclist's behaviour is unnatural as the cyclists choose the centre of the bicycle path by default, rather than the right side. Consequently, this occasionally leads to cyclists overtaking from the right in the simulation model, which is a rare sight on Dutch bicycle paths. However, the calibration of this model has led to improvements in modelling cyclist behaviour and new insights.

Thijsen (2021) also used PTV Vissim and Viswalk in their case study in Utrecht. They found that the SFM was unsuitable for cyclists at high densities and for two-way bicycle paths. In contrast to other studies, the work of Thijsen was replicable and their calibration has been tested by me. The calibration of Thijsen indeed led to unnatural behaviour as the cyclists were not able to look further than several meters ahead and kept recklessly bumping into each other. Not to discredit the work of Thijsen, as this was only one aspect of his study. His case study covered a much larger area than the one bicycle path of this thesis. The main improvement from Thijsen's calibration was to increase the grid size. This essentially increases the sight of the cyclists in the simulation model. Moreover, the parameters have been calibrated differently (finding 5). The social forces are much smaller, but they begin to act at greater distances to create more subtle direction changes from the cyclists.

These parameter values were the result of an extensive trial and error process with different values. This has produced rough values, but they are radically different from other studies. In particular, the addition of the mean force acting on the cyclist from long range (i.e., a B mean value of 25) has not been found in any other study.

Lastly, there is an aspect of the SFM that has not been used or discussed. These are the attractive forces that can act on a pedestrian or cyclist. These can be used to simulate social groups of people who belong together, or attraction because of interesting sightings in the window of a store for instance. To my knowledge, these attractive forces are not part of PTV VisWalk.

Simulation results

The results of the simulations for the case study raised three points of discussion. Firstly, the speed of CBs and EBs in the simulation assumes a normal distribution. However, it is not likely that the speed of EBs is normally distributed as the electric support stops at 25 km/h. This means that it is unlikely that cyclists have a desired speed higher than 25, which is now the case for about 11% of the EBs.

Secondly, Twisk et al. (2021; 2022), on which the speed distributions were based, observed a higher speed drop for Ebs than for CBs in urban areas (finding 9). Twisk and their colleagues hypothesized that this is due to the higher cyclist densities in urban areas. However, the simulation model did not display the same pattern at higher densities. The simulation model assumes the same behaviour for CBs as EBs. However, it might be that EBs should be calibrated slightly differently than CBs.

Lastly, the use of TTC in PTV Vissim led to unsatisfactory results (finding 8). The plotted patterns in section 6.4 reveal that the TTC measurements in the simulation model do not operate in the same way as the theory described by de Goede et al. (2013). The theoretical graph for TTC is presented as a continuous curve. This means that to reach a TTC value of 1 second, there must also have been a TTC value of all higher numbers (e.g., 1.5 seconds, 2 seconds, 1.73 seconds, etc.). However, the results measured more occurrences of a TTC of 1.5 seconds than of 2 seconds which should not be possible. Therefore, either the design for measuring TTC in the simulation model is wrong, or the theory of TTC works differently in reality. Section 6.4 describes a few possible explanations for these unexpected results, such as the lack of complexity in the created UDA's or the obligation to only measure the nearest neighbour of a cyclist. However, it should be emphasized that more research is required to definitively explain these results. Moreover, it is advised to research how TTC can be better applied in simulation software such as PTV VisWalk.

8. Conclusions

The following text will describe the conclusions of the subquestions that were posed in the introduction of this thesis. Afterwards, the main research question will be answered.

Subquestion 1: What is the state of the academic research on simulating cyclist behaviour using SFM?

The described studies on cyclist simulation reveal that the academic landscape on this subject is foggy and unclear. Since the conception of the Social Force Model for pedestrians in 1995, researchers of cyclist simulation faced a crossroads. Do cyclists behave like cars on the street (i.e., rule based model), or rather like pedestrians navigating a sidewalk or airport hall (i.e., force based model)? Somewhere in between, is the conclusion of many scientists. Thus, they propose a hybrid model. Herein, the SFM is constrained by additional rules, regimes or decision making processes. However, these propositions are tailored to cycling in a specific context (e.g., crossing an intersection or interacting with cars). Also, these proposed models are created in unmentioned software, using unmentioned programming languages. This hampers the possibility to replicate and verify their study, which in turn hampers the possibility to create a standardised method for simulating cyclist behaviour. Though, it was clear from these propositions that the SFM mainly led to unsatisfactory behaviour in terms of the operational mental behaviour. Critiques on the operational physical behaviour are also formulated, but are less dominant across the literature that was found.

The diversity of proposed additions to the SFM, in order to make it suitable for cyclist behaviour, suggests that this method does not solve every issue with cyclist behaviour simulation. Therefore, a more fundamental examination of the SFM is required in order to see what aspect of it is suitable for cyclists and what aspect is only suitable for pedestrians. This is already done in a few studies, but neither had the aim to create a standardised model for simulating cyclist behaviour. However, they could form a basis to create a new type of model, suitable for cyclist behaviour.

Subquestion 2: What can be learned about cyclist behaviour simulation by applying current simulation insights/tools and knowledge in a specific case?

The parameter calibration illustrates how cyclist behaviour could be simulated within the constraints of PTV Vissim. Most notable constraints by PTV, that have not been overcome in this study, are the tendency of cyclists to ride in the middle of the bicycle path and the indifference of cyclists to overtake on the left or the right of another cyclist. Another constraint was the inability for cyclists to take sharp turns in the model. This is caused by the cyclists being led by the forces that act upon them, rather than that they anticipate the direction they will be going in a few seconds time.

This issue could be tackled by changing the parameter calibration, specifically the relaxation time. However, it was found that changing the value of the relaxation time, along with two other parameters (i.e., A isotropic and A mean), was inherently a trade-off for the cyclist behaviour. A low value of Tau creates a dominant driving force leading to unnaturally sharp movements and aggressive behaviour. While a high value of Tau creates a small driving force which leads to slow and undecisive cyclists. Similarly, high values of the A parameters create high social forces that lead to 'jittery' and 'bouncy' behaviour of cyclists. While low values of A create low social forces that lead to indifferent behaviour and cyclists driving through each other. The simulation model of this thesis was calibrated to behaviour that looks the most natural. This resulted in relatively low values for A, as well as for Tau.

To conclude on a positive note, two advancements have been found that could prove to be useful in future research on cyclist behaviour using PTV Viswalk. First of all, the importance of increasing the grid size, so that cyclists can see further around. Secondly, the use of the two repulsive forces in a way that mimics the reactive space and perceptive space of the Psychological Physiological Force Model. The version of SFM as used by PTV uses two types of repulsive forces. This can be used to one's advantage by having one force act at long range (i.e., mimicking the perceptive space) and the other at short range (i.e., mimicking the reactive space). This way of using the repulsive forces has not been found in any other calibration.

Subquestion 3: To what extent can the calibrated model for the case study be validated through the measurement of conflicts between different vehicle types on the bicycle path?

The results of the simulation model highlighted imperfections of the cyclist behaviour. The found literature describes a higher speed drop for EBs at higher cyclist volumes. However, the measured speed drops at higher cyclist volumes were not bigger for EBs than for CBs. But the most important indicator of the suboptimal cyclist behaviour is the number of collisions observed in the simulations. Up to hundreds of collisions in a matter of hours is unrealistic and underpins the conclusions from the other subquestions.

The TTC variable failed to validate the created simulation model, as it created unexpected results which did not follow the underlying theory of TTC. These results could partly be explained through how the variable is designed within the simulation software. However, more research is required to better understand how the results came to be. It is also advised to study how TTC can be applied in various simulation software.

Main research question: How to improve cyclist behaviour simulation?

The overarching conclusion to the main research question is that academics and simulation software developers should work towards a standardised behavioural model for cyclists, similar to the SFM for pedestrians and the car-following model for motorised traffic. Such a standardized model does not mean that that should be the only way of simulating cyclist behaviour. For instance, the car-following model knows multiple subgenres that might be suitable for different applications. However, these subgenres all share a common leading principle. Namely that cars adjust their behaviour according to the position of the car in front of it (the leading vehicle). An example of such a leading principle for cycling behaviour could be a model where cyclists move along predetermined trajectories rather than being led by a driving force. This seems to solve the challenges researchers face regarding the operational mental behaviour of the cyclists.

It is also advised in future research to discuss the semantics of cyclist behaviour simulation. Literature that used this principle of predetermined trajectories still referred to it as a model based on the SFM. This understates the fundamental criticism on the SFM that is implied by fundamentally changing the model.

Lastly, commercial software companies are advised to actively partake in this process of creating a standardised model for cyclist simulation. With pro-cycling policy becoming more popular in cities all over the world, it is expected that municipalities and research institutes will show interest in a standardised model for cyclist behaviour when offered by a simulation software company. Moreover, such a standardised model incorporated in an applied simulation software should improve the verifiability and replicability of academic research. As a properly calibrated model for cyclist behaviour, would mean that less academics are inclined to create their own custom model for their research.

If these proposed developments come to fruition, other research subjects and applications become possible or more accessible. It should allow peer reviewers to test a researcher's simulation model more easily. It should enable urban planners and traffic engineers of local governments to quantitatively test their infrastructure designs. It also enables academics to study the rapidly changing urban mobility landscape. For instance, the found correlation between speed, speed difference and density in relation to conflicts could be more thoroughly studied. It also provides a possibility to experiment with these designs, aiming to tackle the contemporary challenges of established cycling cities.

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Appendix I Hand calculation social force

The repulsive force, or social force, consist of two parts. The social isotropic force is calculated by the parameters $A_{soc,iso}$ and $B_{soc,iso}$, and the distance $\overrightarrow{d_{ij}}$ between two cyclists (i and j).

$$\vec{F}_{soc,iso} = A_{soc,iso} * e^{\frac{-\overrightarrow{d_{ij}}}{B_{soc,iso}}}$$

The social mean force is similar, but it also takes the relative speed between cyclist i and j into account. The distance between cyclist i and j is denoted as a vector because the parameter Lambda also affects this force.

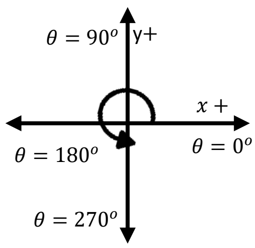
$$\vec{F}_{soc,mean} = A_{soc,mean} * e^{\frac{-\frac{1}{2}\sqrt{\left(d_{ij}+\left|\overrightarrow{d_{ij}}+\overrightarrow{v_{rel,ij}}*VD\right|\right)^2-\left|\overrightarrow{v_{rel,ij}}*VD\right|^2}}{B_{soc,mean}}}$$

In this formula, $A_{soc,mean}$, $B_{soc,mean}$ and VD are parameters in the simulation model. The parameters A and B act as the power and range of the force respectively for both of the social forces. VD is a parameter that multiplies the relative speed vector. Note that the social mean force is exactly the same as the social isotropic force if VD equals 0.

Another important part of these formulae are the vectors. The importance and inner workings of these vectors will be explained through a hand calculations of these forces using four example situations.

The situations are worked out with a few preconditions. First, the vectors go from the influencing agent to the influenced agent. For the situation, we calculate the force for cyclist i, thus this is the influenced agent and the influencing agent is cyclist j. Secondly, it is assumed that a vector is positive in the x direction when it points eastwards and positive in the y direction when it points northwards. The angle of the cyclist is 0° when it is facing eastwards, in the positive x direction. This is depicted in the figure on the right.

Parameter	Value
$\boldsymbol{\tau\ (tau)}$	1
$\boldsymbol{A_{soc,iso}}$	0.6
$\boldsymbol{B_{soc,iso}}$	2
$\boldsymbol{A_{soc,mean}}$	0.6
$\boldsymbol{B_{soc,mean}}$	25



The social isotropic force is the same for both situations, as the distance between the two cyclists is in both cases 2.5 meters:

$$\boldsymbol{F_{soc,iso} = 0.6 * e^{-\frac{2.5}{2}} = 0.1719}$$

The aim of working out the social forces for these two hypothetical situations, is to gain a better understanding of the social force model within PTV Vissim. Parameters A and B are in clear manner explained in the documentation of PTV, and can be seen as the power and range of the social force respectively. However, the effect of VD and relative speed are less thoroughly explained in documentation. The results of the two situations are as follows:

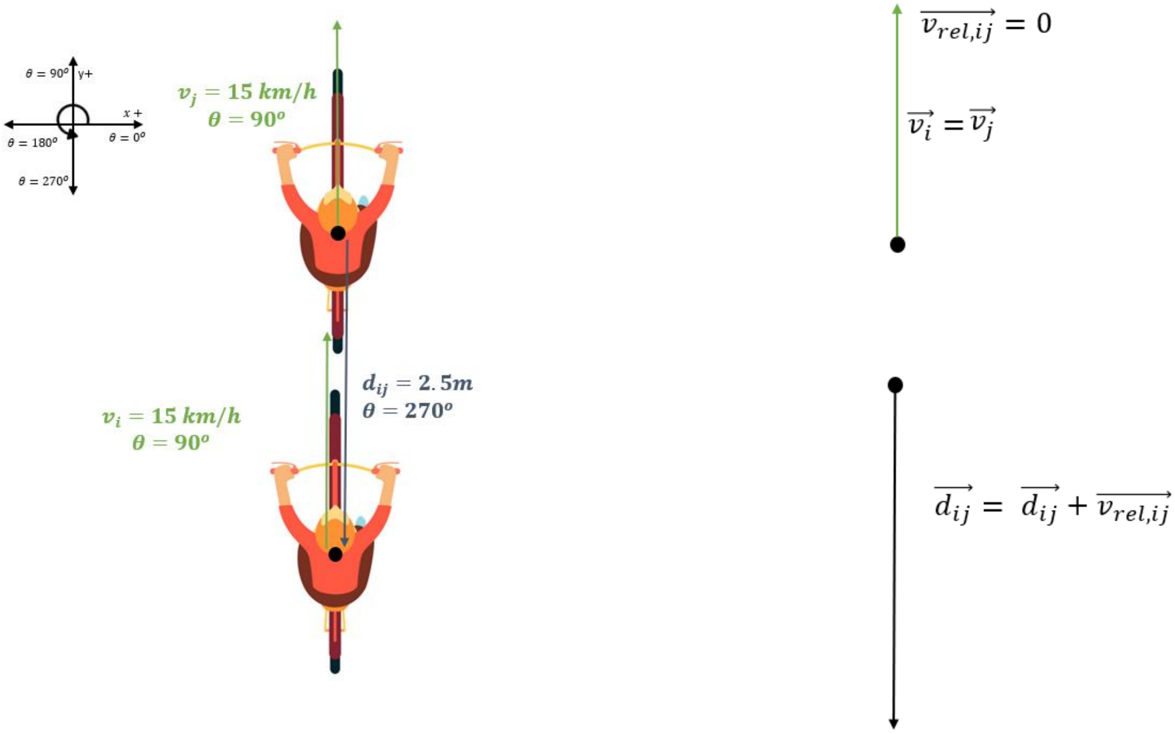
	VD = 1	VD = 5
Situation 1: Same direction same speed	0.600	0.600
Situation 2: Opposite direction collision	0.600	0.600
Situation 3: Same direction overtaking	0.530	0.487
Situation 2: Opposite direction evading	0.548	0.502

Conclusion

The results of the hand calculations in displayed in the table above shows that the social mean that a higher relative speed generally leads to a higher repulsive force. However, a higher VD results in a lower repulsive force.

Situation 1

In this hypothetical situation, the two cyclists are cycling in the same direction with the same velocity, meaning that the relative speed equals to zero. And because the parameter VD is always multiplied by the relative speed, the value of VD does not matter in this scenario.



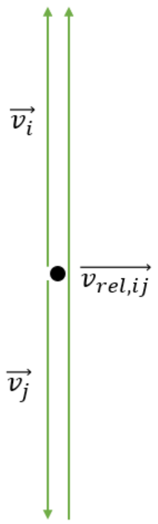
$d_{ij} = 2.5\ m$	
$\theta_{ij} = 270^o$	
$d_x = \cos(270) * 2.5 = 0\ m$	
$d_y = \sin(270) * 2.5 = -2.5\ m$	
$v_i = 15\ km/h = 4.167\ m/s$	$v_j = 15\ km/h = 4.167\ m/s$
$\theta_i = 90^o$	$\theta_j = 90^o$
$v_{ix} = \cos(90) * 5.556 = 0$	$v_{jx} = \cos(90) * 4.167 = 0$
$v_{iy} = \sin(90) * 5.556 = 4.167$	$v_{jy} = \sin(90) * 4.167 = 4.167$
$v_{rel,x} = v_{ix} - v_{jx} = 0 - 0 = 0$	
$v_{rel,y} = v_{iy} - v_{jy} = 4.167 - 4.167 = 0$	

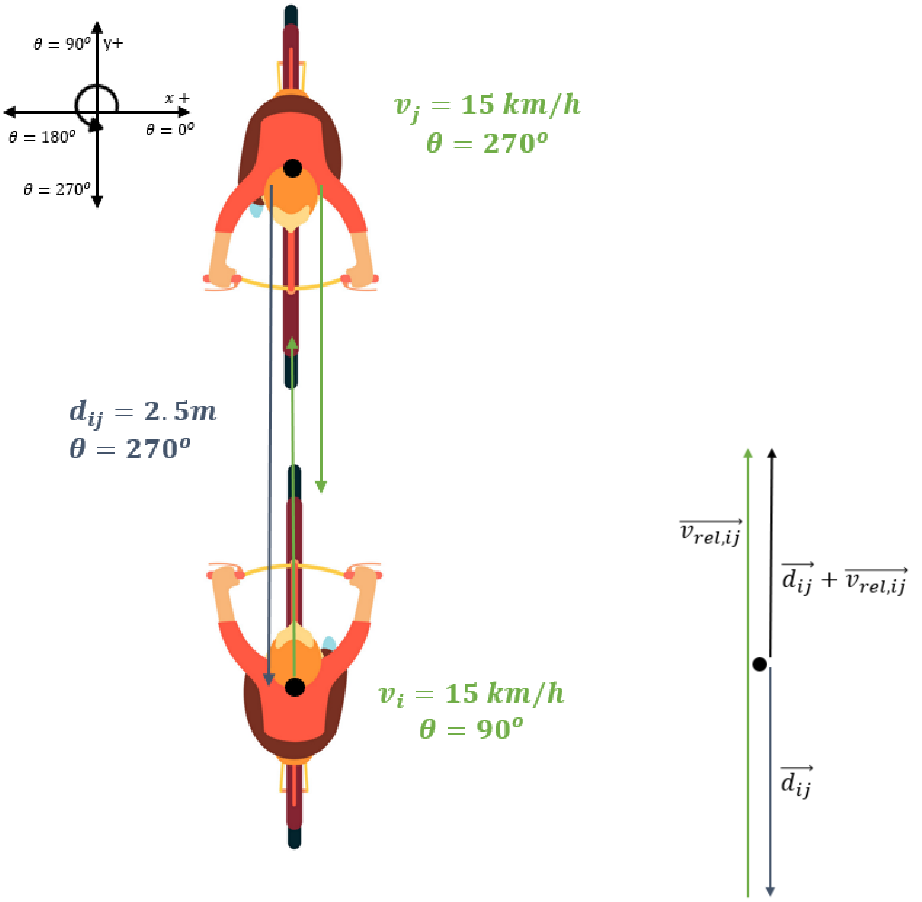
$$\left|\overrightarrow{d_{ij}} + \overrightarrow{v_{rel,ij}} * VD\right| = \left|\overrightarrow{d_{ij}} + 0 * VD\right| = \left|\overrightarrow{d_{ij}}\right| = |-2.5| = 2.5$$

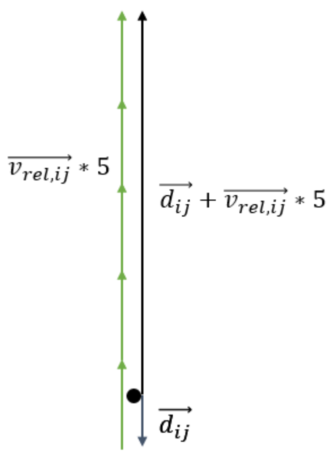
$$\vec{F}_{soc,mean} = 0.6 * e^{\frac{-\frac{1}{2}*\sqrt{(2.5+2.5)^2-0^2}}{25}} = 0.6 * e^{\frac{-2.5}{25}} = 0.543$$

Situation 2

In this hypothetical situation, cyclist i and cyclist j are on course for collision. They each go the same velocity, but in opposite direction, so the relative speed is the sum of their velocities.







$d_{ij} = 2.5\ m$	
$\theta_{ij} = 270^o$	
$d_x = \cos(270) * 2.5 = 0\ m$	
$d_y = \sin(270) * 2.5 = -2.5m$	
$v_i = 15\ km/h = 4.167\ m/s$	$v_j = 15\ km/h = 4.167\ m/s$
$\theta_i = 90^o$	$\theta_j = 270^o$
$v_{ix} = \cos(90) * 4.167 = 0$	$v_{jx} = \cos(270) * 4.167 = 0$
$v_{iy} = \sin(90) * 4.167 = 4.167$	$v_{jy} = \sin(270) * 4.167 = -4.167$
$v_{rel,x} = v_{ix} - v_{jx} = 0 - 0 = 0$	
$v_{rel,y} = v_{iy} - v_{jy} = 4.167 - (-4.167) = 8.333$	

If VD = 1:

$$d_x + v_{rel,x} * VD = 0 + 0 * 1 = 0$$

$$d_y + v_{rel,y} * VD = -2.5 + 8.333 * 1 = 5.833$$

$$\left|\overrightarrow{d_{ij}} + \overrightarrow{v_{rel,ij}} * VD\right| = \left|\sqrt{\left(d_x + v_{rel,x} * VD\right)^2 + \left(d_y + v_{rel,y} * VD\right)^2}\right| = \left|\sqrt{0^2 + 5.833^2}\right| = 5.833$$

$$\left|\overrightarrow{v_{rel,ij}} * VD\right| = \sqrt{v_{rel,x}^2 + v_{rel,y}^2} * VD = \sqrt{0 + 8.333^2} * 1 = 8.333$$

$$\vec{\boldsymbol{F}}_{\boldsymbol{soc,mean}} = \mathbf{0.6} * \boldsymbol{e}^{\frac{-\frac{1}{2}*\sqrt{(2.5+5.833)^2-8.333^2}}{25}} = \mathbf{0.600}$$

If VD=5:

$$d_x + v_{rel,x} * VD = 0 + 0 * 5 = 0$$

$$d_y + v_{rel,y} * VD = -2.5 + 8.333 * 5 = 39.167$$

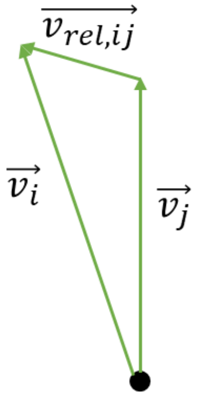
$$\left|\overrightarrow{d_{ij}} + \overrightarrow{v_{rel,ij}} * VD\right| = \left|\sqrt{\left(d_x + v_{rel,x} * VD\right)^2 + \left(d_y + v_{rel,y} * VD\right)^2}\right| = \left|\sqrt{0^2 + 39.167^2}\right| = 39.167$$

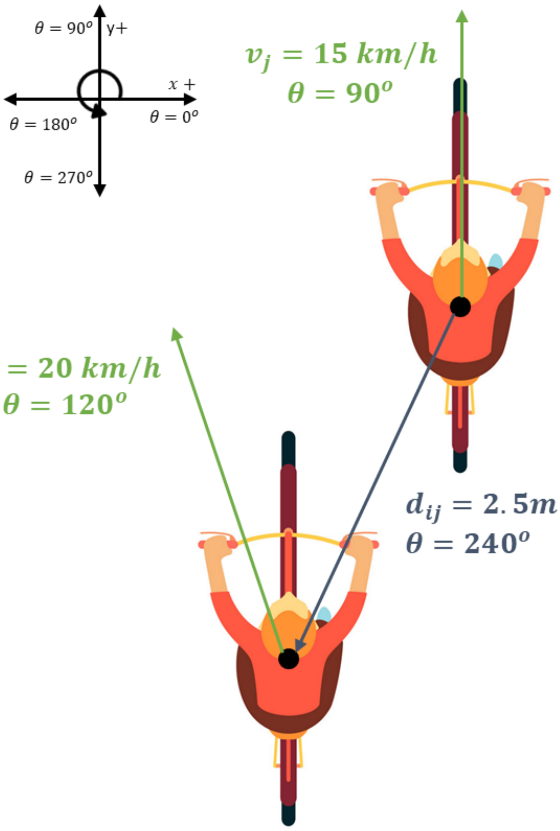
$$\left|\overrightarrow{v_{rel,ij}} * VD\right| = \sqrt{v_{rel,x}^2 + v_{rel,y}^2} * VD = \sqrt{0 + 5.833^2} * 5 = 41.667$$

$$\vec{\boldsymbol{F}}_{\boldsymbol{soc,mean}} = \mathbf{0.6} * \boldsymbol{e}^{\frac{-\frac{1}{2}*\sqrt{(2.5+39.167)^2-41.667^2}}{25}} = \mathbf{0.6} * \boldsymbol{e}^{\mathbf{0}} = \mathbf{0.600}$$

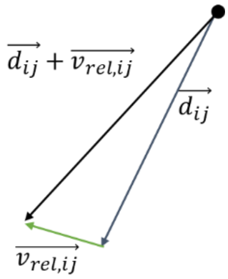
Situation 3

In this hypothetical situation, cyclist i is in the action of overtaking cyclist j, as it goes 5 km/h faster. There are two important vectors in calculating the repulsive forces: the distance between the cyclists ($\overrightarrow{d_{ij}}$) and the relative speed ($\overrightarrow{v_{rel,ij}}$). In the social mean force, the relative speed is multiplied by VD. As is depicted in the bottom sum of vectors, this impacts the direction of the resulting vector that is used to calculate the social mean force.

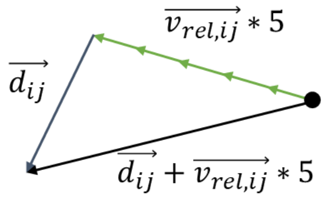




If $VD = 1$



If $VD = 5$



$d_{ij} = 2.5\ m$	
$\theta_{ij} = 240^o$	
$d_x = \cos(240) * 2.5 = -1.25\ m$	
$d_y = \sin(240) * 2.5 = -2.165\ m$	
$v_i = 20\ km/h = 5.556\ m/s$	$v_j = 15\ km/h = 4.167\ m/s$
$\theta_i = 120^o$	$\theta_j = 90^o$
$v_{ix} = \cos(120) * 5.556 = -2.778$	$v_{jx} = \cos(90) * 4.167 = 0$
$v_{iy} = \sin(120) * 5.556 = 4.811$	$v_{jy} = \sin(90) * 4.167 = 4.167$
$v_{rel,x} = v_{ix} - v_{jx} = -2.778 - 0 = -2.778$	
$v_{rel,y} = v_{iy} - v_{jy} = 4.811 - 4.167 = 0.645$	

If VD = 1:

$$d_x + v_{rel,x} * VD = -1.25 + (-2.778) * 1 = -4.028$$

$$d_y + v_{rel,y} * VD = -2.165 + 0.645 * 1 = -1.520$$

$$\left|\overrightarrow{d_{ij}} + \overrightarrow{v_{rel,ij}} * VD\right| = \left|\sqrt{\left(d_x + v_{rel,x} * VD\right)^2 + \left(d_y + v_{rel,y} * VD\right)^2}\right| = \left|\sqrt{(-4.028)^2 + (-1.520)^2}\right|$$
$$= 4.305$$

$$\left|\overrightarrow{v_{rel,ij}} * VD\right| = \sqrt{v_{rel,x}^2 + v_{rel,y}^2} * VD = \sqrt{(-2.778)^2 + 0.645^2} * 1 = 2.852$$

$$\boldsymbol{\vec{F}_{soc,mean} = 0.6 * e^{\frac{-\frac{1}{2} * \sqrt{(2.5+4.305)^2 - 2.852^2}}{25}} = 0.530}$$

If VD = 5:

$$d_x + v_{rel,x} * VD = -1.25 + (-2.778) * 5 = -15.139$$

$$d_y + v_{rel,y} * VD = -2.165 + 0.645 * 5 = 1.058$$

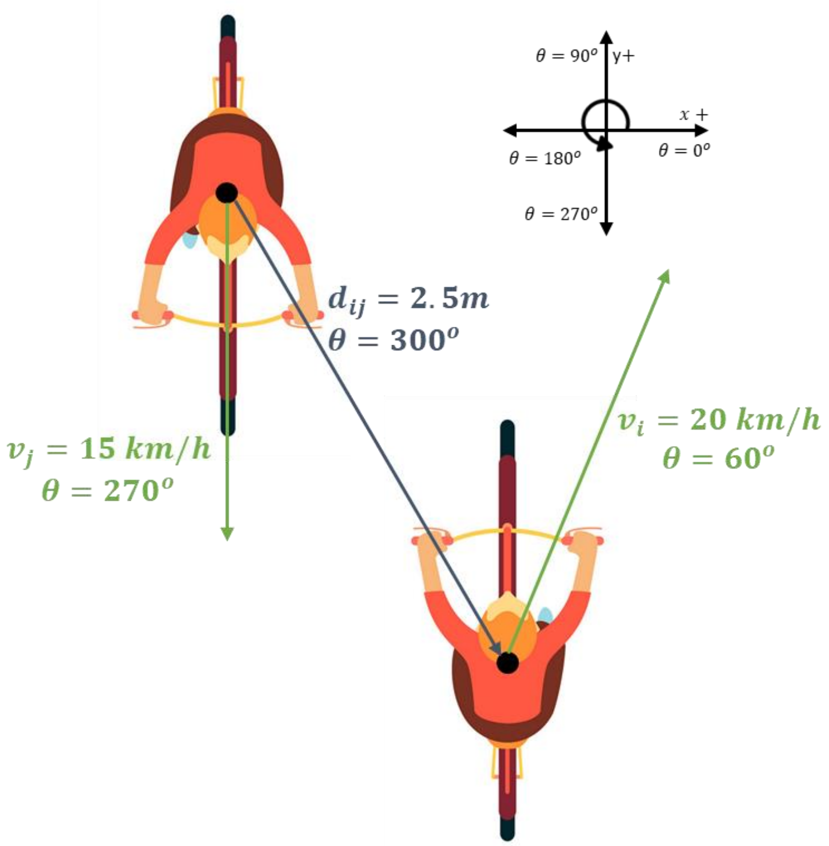
$$\left|\overrightarrow{d_{ij}} + \overrightarrow{v_{rel,ij}} * VD\right| = \left|\sqrt{\left(d_x + v_{rel,x} * VD\right)^2 + \left(d_y + v_{rel,y} * VD\right)^2}\right| = \left|\sqrt{(-15.139)^2 + (1.058)^2}\right|$$
$$= 15.176$$

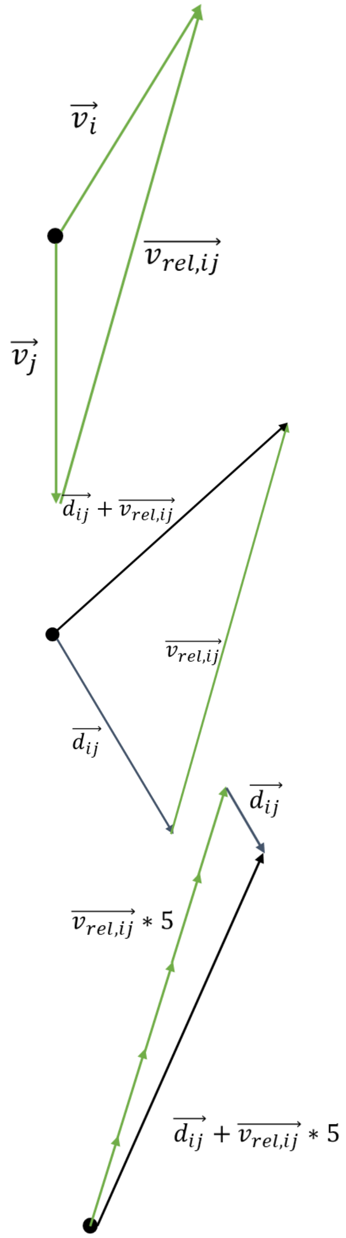
$$\left|\overrightarrow{v_{rel,ij}} * VD\right| = \sqrt{v_{rel,x}^2 + v_{rel,y}^2} * VD = \sqrt{(-2.778)^2 + 0.645^2} * 5 = 14.258$$

$$\boldsymbol{\vec{F}_{soc,mean} = 0.6 * e^{\frac{-\frac{1}{2} * \sqrt{(2.5+15.176)^2 - 14.258^2}}{25}} = 0.487}$$

Situation 4

In this hypothetical situation, the two cyclists are facing opposite directions. This leads to a higher relative speed in respect to the previous situation. In this situation, the social mean force is also calculated for two values of VD (1 and 5) in order to gain a better understanding of the effect of relative speed and the parameter VD on the social mean force. The social isotropic force is the same as in situation 1.





$d_{ij} = 2.5\ m$	
$\theta_{ij} = 300^o$	
$d_x = \cos(300) * 2.5 = 1.25\ m$	
$d_y = \sin(300) * 2.5 = -2.165\ m$	
$v_i = 20\ km/h = 5.556\ m/s$	$v_j = 15\ km/h = 4.167\ m/s$
$\theta_i = 60^o$	$\theta_j = 270^o$
$v_{ix} = \cos(60) * 5.556 = 2.778$	$v_{jx} = \cos(270) * 4.167 = 0$
$v_{iy} = \sin(60) * 5.556 = 4.811$	$v_{jy} = \sin(270) * 4.167 = -4.167$
$v_{rel,x} = v_{ix} - v_{jx} = 2.778 - 0 = 2.778$	
$v_{rel,y} = v_{iy} - v_{jy} = 4.811 - (-4.167) = 8.978$	

If VD = 1

$$d_x + v_{rel,x} * VD = 1.25 + 2.778 * 1 = 4.028$$

$$d_y + v_{rel,y} * VD = -2.165 + 8.978 * 1 = 6.813$$

$$\left|\overrightarrow{d_{ij}} + \overrightarrow{v_{rel,ij}} * VD\right| = \left|\sqrt{\left(d_x + v_{rel,x} * VD\right)^2 + \left(d_y + v_{rel,y} * VD\right)^2}\right| = \left|\sqrt{4.028^2 + 6.813^2}\right|$$
$$= 7.915$$

$$\left|\overrightarrow{v_{rel,ij}} * VD\right| = \sqrt{v_{rel,x}^2 + v_{rel,y}^2} * VD = \sqrt{2.778^2 + 8.978^2} * 1 = 9.398$$

$$\boldsymbol{\vec{F}_{soc,mean} = 0.6 * e^{\frac{-\frac{1}{2}*\sqrt{(2.5+7.915)^2-9.398^2}}{25}} = 0.548}$$

If VD = 5:

$$d_x + v_{rel,x} * VD = 1.25 + 2.778 * 5 = 15.139$$

$$d_y + v_{rel,y} * VD = -2.165 + 8.978 * 5 = 42.724$$

$$\left|\overrightarrow{d_{ij}} + \overrightarrow{v_{rel,ij}} * VD\right| = \left|\sqrt{\left(d_x + v_{rel,x} * VD\right)^2 + \left(d_y + v_{rel,y} * VD\right)^2}\right| = \left|\sqrt{15.139^2 + 42.724^2}\right|$$
$$= 45.327$$

$$\left|\overrightarrow{v_{rel,ij}} * VD\right| = \sqrt{v_{rel,x}^2 + v_{rel,y}^2} * VD = \sqrt{2.778^2 + 8.978^2} * 5 = 46.989$$

$$\boldsymbol{\vec{F}_{soc,mean} = 0.6 * e^{\frac{-\frac{1}{2}*\sqrt{(2.5+45.327)^2-46.989^2}}{25}} = 0.502}$$

Appendix II Simulation configurations using COM

```
# -*- coding: utf-8 -*-
#%% Import libraries
import win32com.client as com
import pandas as pd
import datetime
#import numpy as np
#import pywintypes

print("alles goed sectie 1")

#%% Link to Vissim
# Step 1: Create an instance of the Vissim COM object
Vissim = com.Dispatch("Vissim.Vissim")

# Step 2: Define the path to your .inpx file
network_file = r"C:\Users\Public\Documents\PTV Vision\PTV Vissim
2023\Thesis_Simplified.inpx"

# Step 3: Load the .inpx file in Vissim
Vissim.LoadNet(network_file)

print("alles goed sectie 2")
#%% Import files and create merged usable dataframe

# Import dataset with number of cyclists
dataset_file = r"C:\Users\marij\.spyder-py3\Datasets\okt-2022 fietsdata.csv"
df_dataset = pd.read_csv(dataset_file)


#Format dataset
df_dataset['Timestamp'] = pd.to_datetime(df_dataset['begintijd'],
format='%d/%m/%Y %H:%M')



#Remove unnecessary columns and rows
names_to_keep = [
    'CS Provenierstunnel tussen Proveniersplein en Conradstraat, Rotterdam']
df_NoCyclist = df_dataset[df_dataset['naam'].isin(names_to_keep)]

df_NoCyclist =
df_NoCyclist.drop(['locatiecode','type','intensiteit_beide_richtingen','meetpe
riode','gebruikte_minuten','data_error_intensiteit','peiling','betrouwbaarheid
','partnercode', 'partner', 'aannemer', 'meetapparatuur', 'licentiecategorie',
'beschrijving', 'breedtegraad', 'lengtegraad', 'technische_uitsluiting'], 1)
```

```python
# Split data so that 1 row is about the number of cyclists on 1 street in 1 direction
df_NoCyclist_op = df_NoCyclist.drop(['intensiteit_aflopend'], axis=1)
df_NoCyclist_af = df_NoCyclist.drop(['intensiteit_oplopend'], axis=1)

name_mapping = {
    'CS Provenierstunnel tussen Proveniersplein en Conradstraat, Rotterdam' :
'Proveniersingel Or' }
df_NoCyclist_op['Street'] = df_NoCyclist_op['naam'].map(name_mapping)
df_NoCyclist_op = df_NoCyclist_op.rename(columns = {'intensiteit_oplopend' :
'Cyclists'})

name_mapping_af = {
    'CS Provenierstunnel tussen Proveniersplein en Conradstraat, Rotterdam' :
'Weena Or'}
df_NoCyclist_af['Street'] = df_NoCyclist_af['naam'].map(name_mapping_af)
df_NoCyclist_af = df_NoCyclist_af.rename(columns = {"intensiteit_aflopend" :
"Cyclists"})

df_Cyclist_merged = pd.concat([df_NoCyclist_op, df_NoCyclist_af])




# Removing the days with contaminated data
days_to_remove = ["2022-10-03","2022-10-08","2022-10-09","2022-10-10","2022-10-11","2022-10-12","2022-10-13","2022-10-14","2022-10-15","2022-10-16","2022-10-17","2022-10-18","2022-10-30"]

# Convert 'Timestamp' column to datetime format
df_Cyclist_merged['Timestamp'] =
pd.to_datetime(df_Cyclist_merged['Timestamp'])

# Convert 'days_to_remove' to datetime format
days_to_remove = [datetime.datetime.strptime(day, "%Y-%m-%d") for day in
days_to_remove]

# Filter the DataFrame to keep only the rows with date not in 'days_to_remove'
df_filtered =
df_Cyclist_merged[~df_Cyclist_merged['Timestamp'].dt.date.isin([day.date() for
day in days_to_remove])]

unique_days = df_filtered['Timestamp'].dt.date.unique()
unique_days = [day for day in unique_days if day not in days_to_remove]


df_Volumes = df_filtered.drop(columns =['begintijd', 'naam'])
```

```
df_Volumes = df_Volumes.pivot(index=['Timestamp'], columns='Street',
values='Cyclists')
df_Volumes = df_Volumes.reset_index()

df_Volumes['Hour'] = df_Volumes['Timestamp'].dt.hour
df_Volumes['Hour'] = df_Volumes['Hour']+1

key_mapping = {'Provenierssingel Or' : 3,
               'Weena Or' : 4}

key_mapping2 = {3: 'Provenierssingel Or',
                4: 'Weena Or'}



print("Alles goed sectie import en data formatting")

#%% Simulation configurations

sim_run_period = 3600*24                           # Simulation run period for
24 hours
Vissim.Simulation.SetAttValue("SimRes", 20)

Vissim.Simulation.SetAttValue("SimPeriod", sim_run_period)


print("alles goed in sectie Simulation configurations")


#%% Scenario settings
# Days to simulate:
# 2022-10-01   2022-10-02
# 2022-10-04   2022-10-05   2022-10-06   2022-10-07
# 2022-10-19   2022-10-20   2022-10-21   2022-10-22   2022-10-23    2022-10-
24      2022-10-25    2022-10-26    2022-10-27   2022-10-28    2022-10-29
# 2022-10-31


# Define the date you want to simulate in the format "YYYY-MM-DD"
day_to_simulate = datetime.datetime.strptime("2022-10-31", "%Y-%m-%d").date()
day             = day_to_simulate

Share_CB = 17.75
Share_EB = 82.25


# Get the pedestrian composition object
ped_comp = Vissim.Net.PedestrianCompositions.ItemByKey(22)
```

```python
# Set the relative flow directly in the table
ped_comp.SetAttValue("RelFlow(400,1051)", Share_CB)
ped_comp.SetAttValue("RelFlow(500,1052)", Share_EB)

print("alles goed in sectie Scenario settings")

#% Program number of cyclists on the streets


Vissim.Simulation.RunSingleStep

street_key_list = [3,4]

processed_streets = set()  # To keep track of streets already processed


for day_to_simulate in unique_days:
    df_day = df_Volumes[df_Volumes['Timestamp'].dt.date == day]
    df_day = df_day.melt(id_vars=['Timestamp', 'Hour'], var_name='Street',
value_name='Volume')
    df_day = df_day.pivot(index='Street', columns='Hour', values='Volume')
    df_day['street_key'] = df_day.index.map(key_mapping)

    for street_key in street_key_list:
           if street_key not in processed_streets:
              street_name = key_mapping2[street_key]

              # Create a new vehicle_input object for the current street_key
              pedestrian_input =
Vissim.Net.PedestrianInputs.ItemByKey(street_key)
              for hour in range(1, 25):
                   if Vissim.Net.PedestrianInputs.ItemByKey(street_key):
                       # Get the cyclists_count from the corresponding cell in
df_Volume
                       cyclists_count = df_day.at[street_name, hour]

                       # Set the volume for the specific hour
                       pedestrian_input.SetAttValue("Volume({})".format(hour),
cyclists_count)

              processed_streets.add(street_name)  # Add the street to the set
of processed streets
              print("Day: {}".format(day), "Street: {}".format(street_name))

print("alles goed in sectie setting cyclist volumes")

#% Run simulation + actions during simulation

# Start the simulation
```

```
Vissim.Simulation.RunContinuous()
Vissim.Graphics.CurrentNetworkWindow.SetAttValue("QuickMode", 1)


#End the simulation and close Vissim when you're done
Vissim.Simulation.Stop()
#Vissim.Exit()


print("simulatie klaar")

#%%
```

Appendix III Output analysis

```
# -*- coding: utf-8 -*-
"""
Created on Sun Dec 24 16:10:45 2023

@author: marij
"""

import pandas as pd
#import matplotlib.pyplot as plt
import numpy as np

#%%

# Read the data into a DataFrame
# Assuming your data is in a file named 'simulation_data.csv'
df_Oct1 = pd.read_csv(r"C:\Users\marij\Documents\MADE\Jaar_2\Thesis\Simulation
output\Scenario1 80.25-17.75\01-10 Thesis_Simplified_001.pp", delimiter=';')


#%%
# Convert 'PED:SIMSEC' column to datetime
df_Oct1['$PEDESTRIAN:SIMSEC'] = pd.to_numeric(df_Oct1['$PEDESTRIAN:SIMSEC'],
errors='coerce')

df_Oct1['Hour'] = (df_Oct1['$PEDESTRIAN:SIMSEC'] // 3600).astype(int) * 3600


# Filter rows based on conditions
df_filtered_Oct1 = df_Oct1[(df_Oct1['CONSTRELNO'] == 22)]

# Create new columns with conditions
df_filtered_Oct1['Collision'] = np.where((df_filtered_Oct1['COLLISION'] ==
1)    & ~df_filtered_Oct1.duplicated(subset=['NO', 'NEARNEIGHB\\NO',
'COLLISION']) & (df_filtered_Oct1['NEARNEIGHB\\CONSTRELNO']==22) , 1, 0)
df_filtered_Oct1['Collision_OD'] = np.where((df_filtered_Oct1['OPPDIR'] ==
1)    & (df_filtered_Oct1['COLLISION'] == 1)    &
~df_filtered_Oct1.duplicated(subset=['NO', 'NEARNEIGHB\\NO', 'COLLISION']) &
(df_filtered_Oct1['NEARNEIGHB\\CONSTRELNO']==22) , 1, 0)

df_filtered_Oct1['TTC_1_2Secs'] = np.where((df_filtered_Oct1['TTC_1/2SEC'] ==
1) & ~df_filtered_Oct1.duplicated(subset=['NO', 'NEARNEIGHB\\NO',
'TTC_1/2SEC'])& (df_filtered_Oct1['NEARNEIGHB\\CONSTRELNO']==22) &
(df_filtered_Oct1['OPPDIR'] == 1), 1, 0)

df_filtered_Oct1['TTC_1Sec'] = np.where((df_filtered_Oct1['TTC_1SEC'] ==
1)      & ~df_filtered_Oct1.duplicated(subset=['NO', 'NEARNEIGHB\\NO',
```

```
'TTC_1SEC'])& (df_filtered_Oct1['NEARNEIGHB\\CONSTRELNO']==22)  &
(df_filtered_Oct1['OPPDIR'] == 1), 1, 0)

df_filtered_Oct1['TTC_3_2Secs'] = np.where((df_filtered_Oct1['TTC_3/2SEC'] ==
1) & ~df_filtered_Oct1.duplicated(subset=['NO', 'NEARNEIGHB\\NO',
'TTC_3/2SEC'])& (df_filtered_Oct1['NEARNEIGHB\\CONSTRELNO']==22)  &
(df_filtered_Oct1['OPPDIR'] == 1), 1, 0)

df_filtered_Oct1['TTC_2Secs'] = np.where((df_filtered_Oct1['TTC_2SEC'] ==
1)     & ~df_filtered_Oct1.duplicated(subset=['NO', 'NEARNEIGHB\\NO',
'TTC_2SEC'])& (df_filtered_Oct1['NEARNEIGHB\\CONSTRELNO']==22)  &
(df_filtered_Oct1['OPPDIR'] == 1), 1, 0)


# Group by hourly intervals and calculate required metrics
summary_Oct1 = df_filtered_Oct1.groupby(['Hour', 'PEDTYPE']).agg(
    Volume=('NO', 'nunique'),
    AvgSpeed=('SPEED', 'mean'),
    AvgDesSpeed=('DESSPEED', 'mean'),
    Collision=('Collision', 'sum'),
    Collision_OD=('Collision_OD', 'sum'),
    TTC_1_2Secs=('TTC_1_2Secs', 'sum'),
    TTC_1Sec=('TTC_1Sec', 'sum'),
    TTC_3_2Secs=('TTC_3_2Secs', 'sum'),
    TTC_2Secs=('TTC_2Secs', 'sum'),
).unstack()

# Flatten the MultiIndex columns
summary_Oct1.columns = [f'{col[0]}_{col[1]}' for col in summary_Oct1.columns]

# Reset index to make 'Hour' a regular column
summary_Oct1 = summary_Oct1.reset_index()



# Print or use the summary DataFrame as needed
print(summary_Oct1)
summary_Oct1.to_excel(r'C:\Users\marij\Documents\MADE\Jaar_2\Thesis\Simulation
output\Summary excels\Summary 1 Oct.xlsx', index=False)


#%%  Read the data into a DataFrame
# Assuming your data is in a file named 'simulation_data.csv'
df_Oct2 = pd.read_csv(r"C:\Users\marij\Documents\MADE\Jaar_2\Thesis\Simulation
output\Scenario1 80.25-17.75\02-10 Thesis_Simplified_001.pp", delimiter=';')

#%%

# Convert 'PED:SIMSEC' column to datetime
```

```
df_Oct2['$PEDESTRIAN:SIMSEC'] = pd.to_numeric(df_Oct2['$PEDESTRIAN:SIMSEC'],
errors='coerce')

df_Oct2['Hour'] = (df_Oct2['$PEDESTRIAN:SIMSEC'] // 3600).astype(int) * 3600


# Filter rows based on conditions
df_filtered_Oct2 = df_Oct2[(df_Oct2['CONSTRELNO'] == 22)]

# Create new columns with conditions
df_filtered_Oct2['Collision'] = np.where((df_filtered_Oct2['COLLISION'] ==
1)    & ~df_filtered_Oct2.duplicated(subset=['NO', 'NEARNEIGHB\\NO',
'COLLISION']) & (df_filtered_Oct2['NEARNEIGHB\\CONSTRELNO']==22) , 1, 0)
df_filtered_Oct2['Collision_OD'] = np.where((df_filtered_Oct2['OPPDIR'] ==
1)    & (df_filtered_Oct2['COLLISION'] == 1)    &
~df_filtered_Oct2.duplicated(subset=['NO', 'NEARNEIGHB\\NO', 'COLLISION']) &
(df_filtered_Oct2['NEARNEIGHB\\CONSTRELNO']==22) , 1, 0)

df_filtered_Oct2['TTC_1_2Secs'] = np.where((df_filtered_Oct2['TTC_1/2SEC'] ==
1) & ~df_filtered_Oct2.duplicated(subset=['NO', 'NEARNEIGHB\\NO',
'TTC_1/2SEC'])& (df_filtered_Oct2['NEARNEIGHB\\CONSTRELNO']==22) &
(df_filtered_Oct2['OPPDIR'] == 1), 1, 0)

df_filtered_Oct2['TTC_1Sec'] = np.where((df_filtered_Oct2['TTC_1SEC'] ==
1)      & ~df_filtered_Oct2.duplicated(subset=['NO', 'NEARNEIGHB\\NO',
'TTC_1SEC'])& (df_filtered_Oct2['NEARNEIGHB\\CONSTRELNO']==22)  &
(df_filtered_Oct2['OPPDIR'] == 1), 1, 0)

df_filtered_Oct2['TTC_3_2Secs'] = np.where((df_filtered_Oct2['TTC_3/2SEC'] ==
1) & ~df_filtered_Oct2.duplicated(subset=['NO', 'NEARNEIGHB\\NO',
'TTC_3/2SEC'])& (df_filtered_Oct2['NEARNEIGHB\\CONSTRELNO']==22)  &
(df_filtered_Oct2['OPPDIR'] == 1), 1, 0)

df_filtered_Oct2['TTC_2Secs'] = np.where((df_filtered_Oct2['TTC_2SEC'] ==
1)     & ~df_filtered_Oct2.duplicated(subset=['NO', 'NEARNEIGHB\\NO',
'TTC_2SEC'])& (df_filtered_Oct2['NEARNEIGHB\\CONSTRELNO']==22)  &
(df_filtered_Oct2['OPPDIR'] == 1), 1, 0)


# Group by hourly intervals and calculate required metrics
summary_Oct2 = df_filtered_Oct2.groupby(['Hour', 'PEDTYPE']).agg(
    Volume=('NO', 'nunique'),
    AvgSpeed=('SPEED', 'mean'),
    AvgDesSpeed=('DESSPEED', 'mean'),
    Collision=('Collision', 'sum'),
    Collision_OD=('Collision_OD', 'sum'),
    TTC_1_2Secs=('TTC_1_2Secs', 'sum'),
    TTC_1Sec=('TTC_1Sec', 'sum'),
    TTC_3_2Secs=('TTC_3_2Secs', 'sum'),
```

```
    TTC_2Secs=('TTC_2Secs', 'sum'),
).unstack()

# Flatten the MultiIndex columns
summary_Oct2.columns = [f'{col[0]}_{col[1]}' for col in summary_Oct2.columns]

# Reset index to make 'Hour' a regular column
summary_Oct2 = summary_Oct2.reset_index()



# Print or use the summary DataFrame as needed
print(summary_Oct2)
summary_Oct2.to_excel(r'C:\Users\marij\Documents\MADE\Jaar_2\Thesis\Simulation
output\Summary excels\Summary 2 Oct.xlsx', index=False)

############# Repeat for every simulation day ################
```