Design of a structure free intersection controller for connected bicycles and cars using model based control and a genetic algorithm

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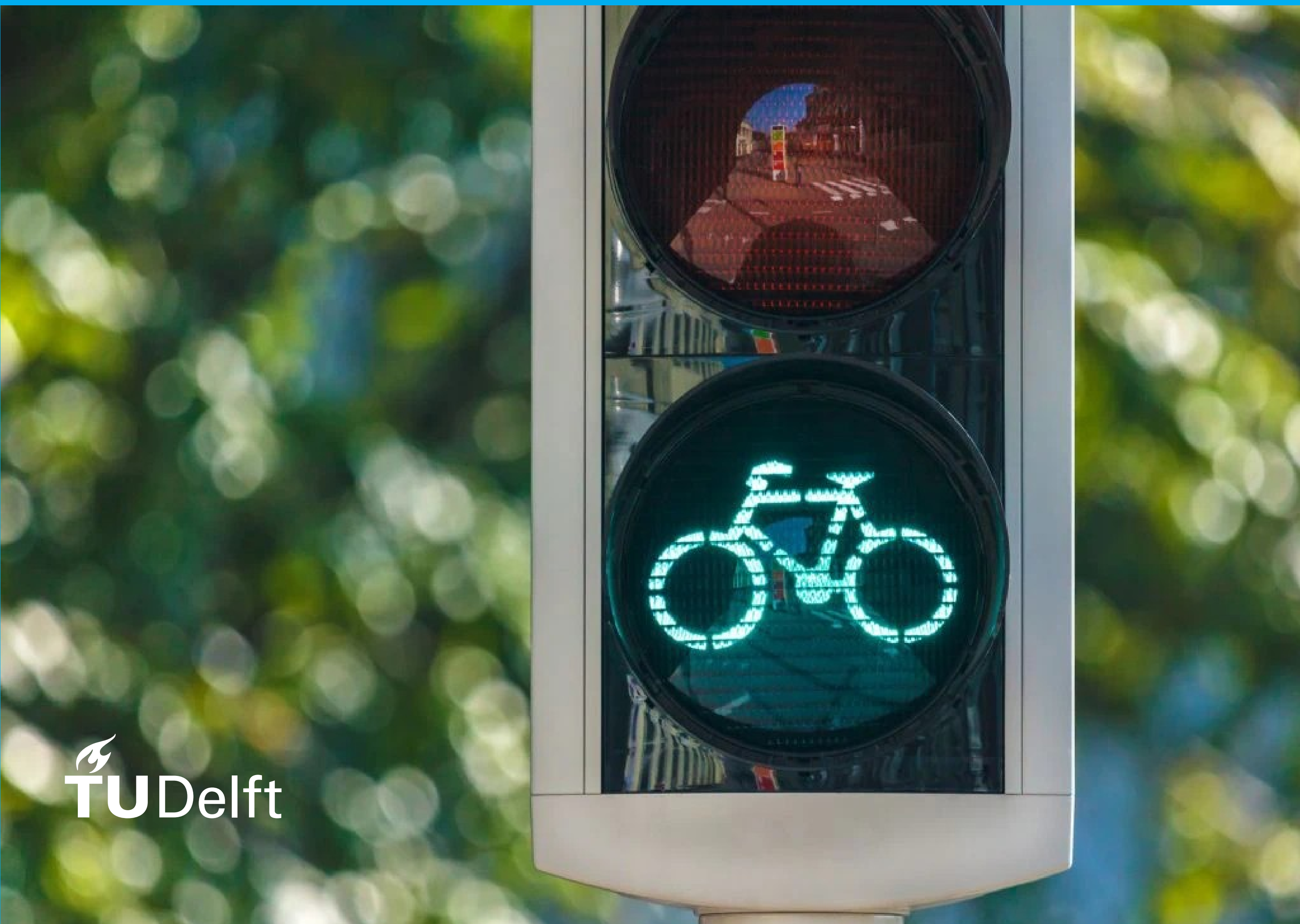

Summary

Bicycles have an important role to play in the transition towards a more sustainable mobility. In order to achieve the modal shift towards bicycles, more must be done to accommodate cyclists. Although controlled intersections do increase the (perceived) safety of crossings with motorized vehicles, they are seen as major obstacles, and cyclists tend to avoid them when possible. The negative effects of controlled intersections for cyclists may be reduced by new methods of intersection control.

This thesis combines the concepts of the connected environment and structure free control, to design an intersection controller that uses a genetic algorithm to determine the optimal signal plan, hereafter referred to as the SFGA controller. The controller is designed for an isolated intersection and considers car drivers and cyclists. Desires of cyclist with regard to controlled intersections, are identified by means of a literature review on the determinants of bicycle use, which are then projected on the controlled intersection. A traffic system model, based on validated models found in literature, is set up and a design for the structure free controller is proposed. A set of control objectives is proposed, including different metrics related to the desires of cyclists and car drivers. Objective function weights can be varied to achieve different levels of cyclist prioritization. A maximum waiting time of 100 seconds is enforced in order to prevent prioritization of cyclists to result in unreasonable delays for car drivers, because red light running probabilities increase at larger waiting times.

The performance of the structure free controller is evaluated for 15, 35 and 45% traffic saturation (percentage of intersection capacity), by means of a simulation based case study. The designed controller is benchmarked to vehicle actuated control (VA). VA has a cyclic, fixed control structure in which green times of movements are flexible and depend on the queue size. SFGA is benchmarked with an equal weight for the delay of car drivers and cyclists, and no weight included for the number of stops. The effect of incorporating weights that prioritize the desires of cyclists over those of car drivers is investigated. The SFGA controller results in average delays 1.8, 2.7 and 3.0 times lower than VAC for each of the evaluated traffic saturation levels. The number of stops is 1.9, 2.3 and 3.1 times lower. Including weights in the objective function to explicitly prioritize cyclists, results in even lower average delays and number of stops for cyclists. As is to be expected, this comes at the cost of additional delays for car drivers, especially for higher traffic saturation.

The better performance of SFGA is attributed to two main differences between the controllers. First of all, the structure free aspect allows for a larger degree of freedom to choose more effective combinations of traffic lights to show green at the same time, instead of following the fixed sequence of VA. Additionally, the controller allows traffic that otherwise would experience the largest total delay to cross first, even if this means delaying some travellers in close proximity of the traffic light. This contrary to VA, that extends green time based on detected traffic in the active block. Without inclusion of weights that prioritize the desires of cyclist over cars, the controller already tends towards prioritization of the cyclists. This is caused by the controller considering the number of travellers that are influenced by its' control decisions, combined with the higher traffic densities, that can be expected on bicycle paths in urban areas. Weights to prioritize cyclists can be included to include more priority, for example when bicycle traffic volumes are low.

This work implicates that, in order to better serve the cyclists, it is not explicitly required to prioritize cyclists over cars. In areas with large volumes of cyclists, considering the number of travellers and their proximity to the traffic light can already result in cyclists being served better. This work could be used as a starting point or inspiration to design and eventually implement more cyclist oriented intersection controllers.

Improvements for the controller and extensions for the research scope are proposed that are required for the controller to be suitable for practical implementation in the real world. If a future version of the controller is to be implemented, it will reduce the negative effects of controlled intersections on cyclists, thereby making the bicycle a more suitable replacement for the car.

Contents

List of abbreviations

Abbreviation	**Explaination**
CE	Connected Environment
CV	Connected Vehicles
DNN	Deep Neural Network
FTC	Fixed Time Controller
MILP	Mixed Integer Linear Programming
MIQP	Mixed Integer Quadratic Programming
NN	Neural Network
PT	Public Transport
RL	Reinforcement learning
RLR	Red Light Running
SFGA	Structure Free Genetic Algorithm (controller)
SQ	Sub question
v2i	Vehicle to intersection communication
v2v	Vehicle to vehicle communication
VA	Vehicle Actuated
VoT	Value of Time

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1 Introduction

Sustainable mobility is one of the major challenges for cities in the 21st century. Between 2005 and 2025, the number of trips made in urban areas is expected to increase by 50%. Cities around the world have to decide how to adapt to this increased demand. If the car remains the main mode of transport, this will lead to either gridlocked road networks or to larger networks and less space for urban life [81]. An alternative is to aim for a modal shift towards public transport (PT) or bicycles. This can help reduce negative effects of cars, like noise- and air pollution [74][17].

Bicycles have a number of advantages over cars. First of all, bicycles are responsible for fewer emissions then cars, since they are powered by human effort, while cars mainly run on fossil fuels. Bicycles also occupy significantly less physical space, both while in use and parked. This effect decreases when more people share the same car, however the average number of persons in a car is only 1.3 [5]. Increased bicycle use can contribute to public health by enhancing physical activity [112][114]. Another advantage of making the bicycle a more attractive mode of transport, is that a mode shift away from the car contributes to reduction of congestion on the road network [75]. A limitation of cycling is that it is mainly an alternative for short to medium distance trips. Therefore, people still need to have access to another mode of transport for longer trips. E-bikes help solve this issue to some extent because of a larger range [85]. In addition, bicycles have synergy with PT by presenting a good alternative for first- and last mile legs of multimodal trips, what can act as a replacement or long distance car trips [56]. Main disadvantages of bicycles are that it can be considered as a less comfortable mode of transport and that cyclists are at greater risk of injury from collisions with motor vehicle users [14]. In the Netherlands in 2019, 1.6 fatalities occurred per billion driven kilometers by car compared to 11 fatalities per billion kilometres cycled [9]. However, these numbers still can be considered relatively low and studies suggest the additional risk of an accident do not outweigh the health benefits of cycling [27].

The advantages of the bicycle as a means of transport, are being recognized more and more. Last decades have seen a large number of policies and construction projects, aimed at increasing bicycle usage all around the world. Projects include large scale construction and upgrades of bicycle infrastructure and implementation of bicycle sharing schemes [33]. Bicycle network expansion and upgrades in Bogota have for example led to an increase in bicycle mode split from 4.2% (635,000 trips) in 2015 to 6% (800,000 trips) in 2018 [20]. Transport for London (TfL) also claims a more than 50% increase in the number of cyclist only five months after the launch of four new bicycle path routes [65]. The outbreak of the COVID-19 pandemic has led to an increasing feeling of urge to implement bicycle policies, both for air quality, health and PT avoidance reasons. Cities like Rome, London, Milan, Berlin, Brussels and Paris all have sped up projects that lower speed limits for cars, close roads for cars and designate them as pedestrian/bicycle infrastructure, build new cycling infrastructure or make cars prioritize to cyclists [4].

A country that has become quite famous for its' high bicycle use is the Netherlands. The attractiveness of the bicycle in the Netherlands is reflected in the modal split. In 2019, 28% of all trips and 34% to 47% of short (0.5-5km) trips were made by bicycle. In absolute distance, the contribution of the bicycle is lower with a mode split of 8% [58]. Some of the key policies contributing to the high levels of cycling include separated cycling infrastructure parallel to heavily travelled roads, traffic calming in most residential neighbourhoods, ample bike parking, bicycle streets, short cuts for cyclists cars cannot use, extra green signal phases for cyclists at intersections with high traffic volume, integration between bicycle and PT, traffic education from a young age onward and mixed-use city development [84].

In order to achieve a mode shift towards bicycles, one must either make cycling more attractive or other modes of transport less attractive [90]. Making cycling more attractive can be done by better adhering to the desires of cyclists. The literature review in Section 2.2.1 identified the presence of slopes, rain, darkness, low temperatures, distance, effort, travel time, infrastructure, safety, bicycle parking, showers, changing rooms and transportation cost as factors that influence bicycle usage. The needs related to safety, travel time and required effort come converge at the signalised intersection. Although these crossings provide more safety, this comes at the cost of additional travel time and effort. The negative influences of a signalized intersection are acknowledged in Dutch cycling policies. A growing part of the Dutch bicycle infrastructure is designed as a so called *untangled* network, meaning the aim is to separate the main car and bicycle traffic flows as much as possible. Bicycle networks do not run parallel to the main road network, but follow other routes along less car heavy roads or standalone bicycle paths. Separate level crossings are a part of this untangled network, which can take on the form of tunnels or cycling bridges or even an intersection on two different levels for the two different modes. It is not always possible to separate the two flows, meaning a (controlled) intersection is required.

Negative effects of controlled intersections on cyclists may be reduced by incorporating objectives related to the desires of cyclists in the objective function of intersection controllers. Recent technological innovations in the field of the connected environment allow for controllers that do this to be designed. In a connected environment (CE), travellers can communicate information related to their speed, position and occupancy to intersection controllers (v2i). The controllers can this data to more accurately determine the traffic states near an intersection and control for a wider variety of control objectives [53][35].

The literature review on intersection control in the connected environment, which is provided in Section 2.1, illustrates the potential of the CE. Data driven intersection controllers have been developed that use large sets of historical data to optimize control plans of isolated intersections and connected networks, resulting in significant delay decreases compared traditional control methods [34]. Other controllers make use of the real time data influx, making more accurate arrival predictions on either individual traveller or platoon level, and adapting signal timings of cyclic control structures in real-time [121].

Most, but not all research in the CE focuses on adapting signal timings in cyclic, fixed control structures. Reductions in delay can be achieved by allowing some degrees of freedom in the controller, allowing the controller to make decisions on what traffic is allowed to cross the intersection first in the current cycle [13]. This is taken even further by the concept of structure free control (SFC). SFC does not impose a traditional, cyclic control structure. Instead, no structure whatsoever is imposed, allowing the controller to decide on any signal plan that it deems most effective within given constraints. Under perfect data quality the structure free controller outperforms cyclic control structures [80]. Combining the larger degrees of freedom of structure free control, with the large data volumes from the connected environment, can result in significant improvements in controller performance. The main disadvantages of CE based controllers and SFC is that both can require long computation times and result in loss of understanding of the functioning of the controller. The loss of understanding originates from the black box principle of data driven control. Increases in computation time originate from the large volumes of data that need to be processed and the wide decision tree that results from the lack of imposed structure. The effect of the latter is very extensive, as SFC does not require long prediction horizons for a good performance. The flexibility of SFC allows it to respond very fast to changes in the system, allowing it to recover from potential mistakes that are made in the next decision moment[80].

The largest share of research in the connected environment only considers cars as the user of intersections. If a secondary mode of transport is included, busses or pedestrians are considered. In other words, no intersection controllers in the CE have been found that actively control for cyclists as users of the intersection. In this case it can be said that the scientific field has fallen behind the practical implementation, as at least four commercial systems (Schwung, SMART, CrossCycle, SiBike) allowing cyclists to be request green on approach are already being developed and tested [110].

1.1. Problem statement and research questions

Bicycles are essential in the transition to more sustainable mobility. In order to achieve a modal shift towards the bicycle, more attention must be paid to the desires of cyclists. Controlled intersections provide safety in the form of protected crossings, but also have negative effects for cyclists in the form of extra travel time and the required effort needed for accelerating back to cruising speed. Controllers that result in reductions of these negative effects could help make cycling a more attractive mode of transport.

The connected environment and structure free control provide opportunities for a controller to be designed that is able to reduce these negatives. To the knowledge of the author, no such controllers have been published in literature. This thesis will aim to contribute to filling this knowledge gap in the scientific literature. This will be done by means of the following research objective goal:

To design and evaluate the performance of an intelligent intersection controller, that prioritizes the interests of cyclists, and that controls an isolated intersection in an environment with connected cars and bicycles, without causing unreasonable delays for car drivers

The following sub questions (SQs) have been formulated in order to help achieve this research objective:

1. What are the desires of car drivers and cyclists with regard to intersections and what is a reasonable trade off between these desires for an intersection controller that prioritizes the needs of cyclists?
2. What traffic system models can be used to describe the traffic system and the outcomes of SQ 1?
   (a) What traffic models, suitable for describing the behavior of car drivers, cyclists and traffic lights with respect to isolated intersections, suitable for formulating the outcomes of SQ 1, can be found in the literature?
   (b) What are the (dis)advantages of the above mentioned control methodologies
   (c) What model is best suited for the research objective and what is the mathematical formulation of his traffic model
3. What control methodology can be used for an intersection controller with the objective of prioritizing the desires of cyclists for an isolated intersection, without causing unreasonably high delays in conflicting, in an environment with connected vehicles and bicycles?
   (a) What different control methodologies are used in intersection control research in the connected environment using a rolling horizon?
   (b) What are the (dis)advantages of the above mentioned control methodologies
4. What does the design of an intelligent intersection controller, that controls the traffic system of SQ 2, and prioritizes the desires of cyclists as identified in SQ 1 consist of?
   (a) Which of the control methodologies described by SQ 3 is used?
   (b) What constraints are used?
   (c) What mathematical formulation is used?
   (d) What is the trade-off between the needs of cyclists and cars/what control objective is used?
5. What evaluation framework should be used to assess the performance of the designed intersection controller and what is the performance of the controller given this framework?
   (a) What performance indicators can be used to compare performance between controllers?
   (b) What controller is the designed controller compared to?
   (c) What are the differences in the performance indicators chosen in SQ 5a between the designed and the controller chosen in SQ 5b?

Answering sub questions 1,2 and 3 allows for gaining knowledge on options for the different aspects of controller design. Sub question four then relates to choosing the best options for each aspect and combining these options into a single controller design. Sub question four then considers the evaluation of the designed controller. If all the questions are answered, the research objective is realized.

By achieving this goal this thesis will provide a first design for a bicycle oriented intersection controller. By means of future research, this controller may be developed further up to the point of real life implementation. Two use cases are suggested for real life implementation. Most importantly, the controller can be used for busy urban centers where bicycle use is high. Equipping a number of successive intersections with a intersection controller like this can help create really bicycle oriented arterial cycle roads. Secondly, the controller can be used on isolated intersections to reduce dis-utility of scarce intersections alongside bicycle routes that cannot be avoided in the 'disentangled' network. When implemented, the controller may reduce the negative aspects of controlled intersections, that experienced by cyclists. By doing so, the bicycle becomes a more attractive alternative to the car, helping achieve a modal shift towards more sustainable mobility.

1.2. Scientific contributions

By fulfilling the research objective and answering all the sub questions stated in Section 1.1, two scientific contributions will be made.

A literature review was performed on the desires of cyclists with regard to intersections. This review is provided in Section 2.2 and showed that -to the best knowledge of the author- no extensive overview of all desires related to intersections has been published. In order to identify the desires, instead an overview of determinants of bicycle use was made. Such reviews have been published before. A scientific contribution of this thesis is that these determinants of bicycle use have been projected on controlled intersections to provide the first extensive overview of all the desires of cyclists with regard to controlled intersections. This overview may provide a strong foundation or starting point for future research with respect to cyclists and intersections.

The literature review on intersection controllers in the connected environment (see Section 2.1) has identified a major research gap. No published controllers consider bicycles as a main mode of transport. The structure free controller that will be proposed in this thesis will be the first controller in the connected environment that considers bicycles as a main mode of transport. This research may be an inspiration or starting point for other researchers interested in the intersection control and bicycles. Future research may improve this controller or adapt it to be able to function in a wider scope.

In terms of societal relevance, the controller likely will not yet be fit for real world implementation. The controller may not yet be fully equipped to deal with real life scenarios, behavior and regulations. Additionally, even though significant advances in connected vehicle technology are made, the technology may not be widespread enough to justify use of a controller that fully relies on the technology. A future version of the controller may however be implemented in practice. If this is the case, the controller can reduce the negative effects of intersections on cyclists, making the bicycle a more attractive mode of transport for more people. This has the benefit of transport causing fewer emission, requiring less space and resulting in larger health benefits.

1.3. Report Structure

The remainder of this thesis is structured as follows. Chapter 2 presents literature reviews on intersection controllers in the Connected Environment, the desires of cyclists with regards to controlled intersections, Traffic system models and control methods for intersection controllers. In this chapter, sub questions 1, 2 and 3 are answered.

Chapter 3 contains the methodology of this thesis, composing of the design methodology, traffic system model and controller design. In this chapter, sub question 4 is answered. Chapter 4 provides the evaluation framework that is used to assess the performance of the controller, answering sub questions 5a and 5b. Chapter 5 then presents the results of the case study, thereby answering sub question 5b. Chapter 6 then presents the conclusion and discussion, followed by Chapter 7 in which future work is discussed.

2
Literature review

The literature review for this thesis is performed in four parts. First, Section 2.1 provides an overview of the current state of the art, of intersection controllers that function in the connected environment. Then Section 2.2 identifies the desires of cyclists and car drivers, with regard to intersections and proposes a trade off for these desires. Section 2.3 investigates suitable traffic system models for this thesis. Finally, Section 2.4 presents different optimization methods, used in intersection control research. Note that all these reviews aim to present an overview of concepts that can be used in this study. The chosen traffic system models and the reasoning for this choice is presented in Section 3.2. The chosen control methodology is presented in Section 3.3.

2.1. Intersection control in the connected environment

This Section provides an overview of research, covering intersection control in the connected environment, with the goal of identifying a research gap. The majority of the literature in this Section has been found by forward snowballing, starting form the literature reviews [53] and [35], on the current state of the art of research in the field of connected intelligent intersection control. Additional sources have been found by a combination of recommendations and search queries.

A distinction can be made in intersection control research in the connected environment. On the one hand, data driven intersection controllers have been developed that use large sets of historical data, from induction loops or other more modern detectors like video cameras, to optimize control plans. Researchers use different techniques to optimize the performance of isolated intersections or connected networks. Control methods are often based on machine learning, more specifically reinforcement learning, because of these methods capability to make good predictions for nonlinear systems [24]. Deep neural network technology is often used to improve prediction capabilities and scalability in terms of computation time [34][62]. To the best knowledge of the author, all published data driven controllers only consider car drivers as the users of the intersection.

The second category of research focuses on using data from connected vehicles to improve intersection control. Real time data flow from individual vehicles allows for better arrival predictions, that can be used to adapt green timings in real time. Some controllers not only use v2i communication, but implement infrastructure to vehicle communication to give speed advice to road users. The CV based controllers mainly focus on cyclic control for isolated intersections, under-saturated traffic flows and cars as the main mode of transport. The general conclusion that can be drawn from the literature, is that the CE allows for major improvements in intersection control [53][35]. Under perfect system knowledge, even more performance increases can be achieved by abandoning the cyclic control structure and instead using structure free control [80]. A structure free controller has more degrees of freedom in the control choices, which allows it to respond very effectively to the detailed information that is available in the connected environment.

Most CV based literature is focused on the car as the only transport modality. However, if a wider definition of connected environment is used, namely every controller that assumes full system knowledge, controllers that consider additional modes of transport can be found. Busses are often considered as a secondary traffic mode. These controllers are vehicle actuated, have fixed control structures and aim to minimize delays by means of linear programming. Infrequently arriving busses make use of the same traffic lights as car drivers. Whenever a bus arrive at the intersection, a heavier weight is used for that specific traffic light [45][46][125].

Multi-modal controllers, that consider pedestrians as intersection users, can also be found in literature. These controllers assume full system knowledge, to determine platoon sizes of waiting pedestrians. Model based control is then used to control for minimized total delay. Different optimization methods are used, for example mixed integer linear programming (MILP) [127], mixed integer quadratic programming [126][122] or fuzzy logic [79].

No intersection controllers designs were found that include bicyclists as intersection users. Some research was found that investigates the effect of cyclists on controlled intersections, for example the interaction between cyclists and cars near intersections [22] and the effect of mixed bicycle and car traffic on intersection capacity [88].

2.2. Trade off for desires of car drivers and cyclists with regard to intersections

The introduction illustrated that bicycles can help cities achieve their sustainable mobility goals by achieving a mode shift towards the bicycle by either making cycling more, or other modes of transport less attractive[90]. Characteristics of bicycle and motorized vehicle use are very different, resulting in different desires with regard to controlled intersections. This literature review aims to identify these desires and propose a way to balance the needs of both cyclists and cars. To the best knowledge of the author, no derailed overview of the desires of cyclists with respect to controlled intersections is available. In order to determine these desires, a literature review is conducted on the determinants for commuting by bicycle. These determinants are then translated to desires and projected onto controlled intersections.

This review is structure the following way. Section 2.2.1 aims to describe all factors influencing bicycle use. Section 2.2.2 then explains how some of these factors converge in signalized intersections and how intersection design could be approached in order to better adhere to these needs. Section 2.2.3 then describes the needs of car drivers and proposes a trade off between the needs of both modes. Section 2.2.4 then provides a summary of the conclusions drawn from this literature review.

This section is written from the point of view of a commuter cyclist, since these are deemed to be the most important type of cyclist to influence in order to help reduce the negative effects of transport. How some factors influence cycling can differ for different types of cyclists, for example, where a slope is seen as a negative factor for commuters, the presence of a slope can be a challenge instead of a negative factor for a sports cyclist. Some determinants of bicycle use are very prevalent, but do not help with identifying the needs of cyclists. These factors will first be described in the following paragraph for completeness sake but will not be used for design purposes.

2.2.1. General desires of the commuter cyclist

This section aims to identify the desires of commuter bicyclists. This is done by evaluating the factors that are identified in literature to influence bicycle use and then translating these factors to the needs and desires of a cyclists. Leading in the identification of the needs has been the literature review [47] on bicycle frequency and duration determinants. Additional sources and references have been collected.

A lot of research has been done that describes the relation between cycling and a wide range of socio-economic factors. While a lot is known about the correlation between the two, the direction and the causality of these relations is less pronounced and large differences exist between countries[47]. Socio-economic factors can be useful tools for predicting mode choice, but are of little use when trying to identify the needs of cyclist. Therefore these factors will not be described in depth. Psychological factors also play a major role in the choice on travelling by bike and add greatly to the explanatory power of models. These factors are for example attitude, perceived social norms and habits[47]. Changing habits, social norms and attitude towards cycling can be of great help to achieve a mode shift, but are left outside of the scope of this thesis as they are not related to accommodating to the needs of cyclist. One can reason however that making cycling more attractive by accommodating to the needs of cyclist, attitude to cycling can change leading to more ridership and changing habits and social norms. The other factors will now be discussed.

2.2.1.1. Natural environment

Factors that relate to the environment can strongly influence a persons decision to cycle. While policies can only influence the landscape, weather conditions and climate on a very long time scale and not on a day to day basis, policies and designs can be aimed at reducing the negative impacts of these factors.

The presence of slopes has a negative impact on bicycle use. This can be explained by the additional effort required for passing over them[90][91]. Cycling frequency and duration is influenced by weather conditions as well. (The chance of) rain [73][18], darkness [98][36] and low temperatures [78][73] result in lower bicycle usage. These negative influences are more likely to come together during the winter season, which is illustrated by [16]. This research found that in Sweden the maximum cycled distance halved from 20km in summer to 10km in winter. It also identified a mode shift for short distances: In summer 25% of journeys below 3km were made by car, where this percentage rose to almost 40% in the winter. The drop between summer and winter differs across regions and is lower in countries with milder winters[98].

In order to adhere to the needs of cyclists, the slope of bicycle paths should minimized in the network design. Additionally, measures should be take to reduce the travel time of trips during bad weather conditions or to protect cyclists from said conditions.

2.2.1.2. Distance, Effort and Travel time

Trip distance is a factor that is used most of the time in mode choice models that consider bicycles[47]. The longer the trip distance, the lower share of bicycles. The resistance to travel for cyclists increases disproportionately with distance due to the physical effort required[116]. In order to adhere to the needs of cyclists, trip length should be as low as possible. This can be accommodated by more direct routes and a denser bicycle network layout. Short trip distances can also be achieved by urban planning measures, aiming for higher population densities and mixture of functions in urban cores.

Conclusions for trip distance also translate to travel time: people tend to cycle more when the travel time for bicycles is low. In route choice cyclists tend to choose routes with low travel time while minimizing interaction with motorized traffic. The trade off between travel time and interaction differs with the level of experience of a cyclist [99]. While travel time is an important variable for all travel modes, the variable is of much greater influence for cyclists. [115] identified that the cost associated with travel time is three times higher for cyclists then for other modes. This can be explained the same way as with distance: a cyclists needs to provide the power for propulsion by physical effort.

It is sensible that both longer distance and travel time are associated with lower bicycle mode splits, as both variables are related by velocity. Longer trip distances and longer duration means a cyclist has to provide physical effort for a longer duration. The effort that has to be provided is not a one on one relation. Some situations require a bicycle to slow down only to return to the desired speed a while later. This can be for example a sharp turn, stop sign or a red traffic light. The speeding up requires a lot of additional power. This is illustrated by [31], in which it is estimated that the average speed of a 70kg person producing 100W will be reduced by 40% for a road with a stopping sign every 90m. In order to keep the speed on an average of 20 km/h, a power output of 500W would be necessary, which is a power level that is only expected from a serious racing cyclist. It was also shown that avoiding stops by slowing down can go a long way to reducing the discomfort. Slowing down to 8 km/h requires 25% less energy to get back to the target speed.

In order to better adhere to the needs of cyclists, a bicycle network should be designed with direct routes, minimizing trip distance and travel time, preferably also avoiding interaction with motorized traffic. The network should allow for cyclists to travel at their preferred speed, minimizing situations that require a cyclist to slow down and accelerate later on, for example by avoiding sharp turns and intersections.

2.2.1.3. Infrastructure and safety

The presence of dedicated bicycle infrastructure is a big determinant in both bicycle mode choice and route choice. As mentioned earlier, travel time can be a source of resistance to travel, but [52] found that higher level of infrastructure leads to lower resistance, meaning a typical cyclist is willing to cycle for a longer duration when the trip is over higher level of infrastructure. The continuity of the infrastructure is also an important factor, because a segment without facilities can deter some people from cycling that route altogether[97]. Cyclists prefer routes with traffic calming measures over those without any facilities[118] and separate bicycle lanes are preferred to curb lanes[69]. Bicycle paths in turn are preferred over bicycle lanes[52].

[83] identified that countries with cycling facilities have high bicycle modal splits. This may be explained by the increased safety. Lower risk of injury is linked to higher bicycle use[90] and safety is often mentioned as a main reason for choosing not to cycle[47]. Two types of safety are to be considered: objective safety -related to the number of accidents- and perceived safety -related to how individuals perceive safety. [51] identified perceived safety and comfort of the cycling network to be barriers for encouraging more cycling in a city. Presence of dedicated bicycle infrastructure does increase perceived safety [61]. A literature review on exposure measurement in bicycle safety analysis concluded that well-maintained bicycle specific infrastructure improves objective bicycle safety as well[108].

In order to better adhere to the needs of cyclists bicycle networks should be as safe as reasonably possible, both in objective and perceived measures. A way to achieve this is by construction of designated bicycle infrastructure, preferably in the form of bicycle paths. Dedicated bicycle on itself also can help adhere to the needs of cyclist as it makes cyclists more willing to cycle longer distance.

2.2.1.4. Parking and Changing facilities

The literature overview [47] identified seven journal articles that found that the presence of bicycle parking infrastructure foremost, and showers and changing facilities to a lesser extend, are very highly valued by cyclists. No significant effect on bicycle ridership was observed, but this may be explained by the limited amount of research done in this area. A later review on bicycle parking infrastructure [48] claims the review supports investment in bicycle parking, but acknowledges that a proper evaluation needs to be conducted.

In order to adhere to the needs of cyclist proper parking and changing infrastructure should be present at destinations.

2.2.1.5. Transportation cost

As a final need for cyclist, transportation cost will be discussed. This cost that is associated with the money it costs to make a trip, is a relevant factor for all modes of transport and can even deter people from choosing to travel all together if the cost is too high. Within mode choice models the costs value relative to that of other modes is important [90][91]. Cycling is relatively cheap and this is one of the reasons why commuters choose to cycle [16]. Something that can be done to make bicycle an even more attractive mode is either increase the cost of travel by other modes (eg. higher parking costs) or lowering the costs of bicycle use. Another often mentioned policy measure that could help with this is paying commuters to travel to work using a bicycle, causing a negative transport cost[115].

Translating this to needs and desires of bicycle users, low transportation costs are desired. This can be low purchasing and maintenance costs for bicycles or even subsidising transport by means of a bicycle.

2.2.1.6. Summary of the general desires of cyclists

This section has identified a number of needs of cyclist by determining factors that influence bicycle use and translating these factors to practical needs. Summarizing in listed form, these identified needs are:

- Minimal slopes present in the bicycle network.
- Measures to protect cyclists from or reduce travel time during bad weather conditions.
- A network with direct routes, preferably while avoiding interaction with motorized traffic.
- A network that allows cyclists to minimize speed differences.
- Low risk on accidents.
- High perceived safety of the bicycle network.
- Construction of dedicated, separate bicycle infrastructure.
- Presents of proper parking and changing infrastructure at the cycling destination.
- Low transportation costs for travelling by bicycle.

The literature study provided knowledge on what the needs of cyclists are. However, it did not provide relative importance of these needs. This is mainly because the (relative) value of the determinants is not something the literature agrees upon. This is in part because the importance researchers found varies based based on variables like gender, age, type of cyclist. One could also argue that historic and cultural influences of the location of the conducted research play a big part in explaining the differences researchers found. Even though the relative importance is not agreed upon, The direction of the influence is generally agreed upon.

This heterogeneity in preferences is something that characterizes cyclists and something that makes research on the topic interesting, but also difficult. Better understanding how the needs of cyclists relate to each other is the key to better focusing efforts on how to serve the needs and how to most effectively make cycling a more attractive mode of transport.

2.2.2. The (in)convenience of intersections

The previous section provided an overview of the needs of cyclists. The needs related to having a low travel time, providing as little additional effort as possible and (perceived) safety come together in the controlled intersection. Controlled intersections can ensure protected crossings, but the additional safety that is provided comes at the cost of additional travel time and required effort in the form of reduced speed and stops. Protected intersections also introduce safety issues for cyclists due to cyclists low speeds. The negative aspects of controlled intersections make them a major obstacle for cyclists. This section will elaborate on the reasons why intersections cause inconvenience, explain the needs of cyclists related to a controlled intersection and how these needs can be translated into design requirements for an intersection controller that minimizes inconvenience for cyclists.

The inconvenience of controlled intersections is illustrated by the concept that cyclists generally will choose routes that avoid traffic signals[19][93] and are willing to make significant detours (average of 1.3km) to avoid routes with many of them[109]. Measures can be taken to separate the infrastructure networks of cyclists and motorized vehicles, but this is not always possible. A controlled intersection can be a necessity for crossings with high-traffic streets, to ensure a high enough level of both perceived and actual safety[19]. A need of cyclists is that they do not want other traffic to be allowed to cross their path -assuming no permitted conflicts- when they are crossing the road.

Encountering a red light protects the cyclists from crossing the street while conflicting directions do so - given no red light violations occur-, but it also necessitates a speed reduction or even standstill, followed by the inevitable acceleration back to their desired speed. This results in a loss of time and energy when compared to crossing the intersection at cruising speed. While this is the case for both cars and bicycles, the loss of energy is a significant larger problem for the cyclist. An illustration of the impact of speed reductions is provided in Section 2.2.1.2. A main difference between the effect speed reductions have on the two modes is that the spike in power necessary for acceleration can be easily provided by the engine for car drivers, whereas a cyclist needs to provide the power him/herself. Low speeds not only causes inconvenience for cyclists due to a high required physical effort for accelerating back to their desired speed, they also introduce safety concerns. At low speeds it is more difficult to balance a bicycle, even more so for e-bikes due to its' higher weight. A survey that was sent out to Dutch Cyclist that were involved in a bicycle crash and had to be treated at an Emergency care by [92] identified losing control at low speeds as the most frequent occurring cyclist-related single-bicycle crash. These crashes represented 16% of the total and 37% of the non-infrastructure related crashes. Losing control due to low speed mostly occurred while mounting or dismounting the bike and the likelihood of it happening is strongly increased among older cyclists. No threshold for what is considered a low speed was given or found in other literature. Concluding, a need of cyclists for controlled intersections is that they want to have to slow down as little as possible and avoid very low speeds and stops altogether.

The speed reductions and stops cause additional travel time, something that also goes against the needs of cyclists. In addition, one can argue that long waiting times are a reason for red light running behavior, which in turn causes safety concerns. Analysing registered traffic crash data showed that 11% of all bicycle crashes of which the cause is know was related to red light running[107]. It is safe to assume that far from all bicycle crashes get registered but these numbers illustrates the danger associated with red light running. Red light running may be an indication of cyclist feeling like they do not get served well and that for them the risk of running red light is outweighed by the benefits of not having to stop and lose time. [107] argued in a comparable matter that cyclists can be more likely to ignore traffic lights and cross when they deem the situation safe, because of the design of traffic control systems that result in higher waiting times for cyclists compared to car drivers, which makes cyclists more likely to cross red lights. His argument requires some nuance, but is quite fitting. The (much) smaller size of a bicycle, the lack of strict traffic lanes and the two dimensional movement of cyclists allow for a much higher saturation flow of green light when compared to cars. In the situation that all directions must be green in a cycle, this means that more cyclists are able to cross in a shorter duration of time and on average cyclists need to wait more for a car diver then a car driver needs to wait for a cyclist. The nuance that should be made is that this situation changes when measures like multiple green times in one cycle are implemented. One can conclude however that an low waiting time is a need of cyclists for controlled intersections.

Closer investigation of red light running behavior identifies another need of cyclists. [54] identified three types of red light runners, one of which is the 'impatients', who stop at a red light and waits, but start riding again before a green light. Further inspection showed all of these cyclist accelerated only after all crossing traffic has cleared the intersection. This may indicate that the clearance time that is enforced by the intersection controller is unpractical and too long for cyclists. They feel like they can already start moving -the intersection has been cleared- but the intersection controller waits for the programmed clearance time to pass by. The identified need of cyclists is that they can start moving as soon as the last vehicle from crossing directions has passed. It should be noted that no research was found that formulated this need as a conclusion, but it was formulated based on interpretation of [54]s conclusions.

In some situations the control structure of the intersection controller prevents a direction from turning green, even though no conflicting traffic is crossing the path. This is because cyclic control structures compose of a sequence of conflict groups, also called phases or blocks, all defined as a group of traffic lights or lanes that are allowed to be green at the same time. Only traffic lights in the active phase are allowed to be green. If there is only traffic in a subset of the lanes of the current block, it may occur that traffic that is waiting for a red traffic light does not see any conflicting traffic cross the intersection.

Inclusion of flexibility in the control diagram can reduce this effect. Flexibility entails inclusion of alternative paths in the control structure. For example, the controller may choose block 2a or 2b after ending block one, depending on in what lanes there is traffic detected. These phases can be chosen in a manner to allow traffic lights that are part of block three to be green in block two already if there is no conflicting traffic. Note that a lot of alternative paths need to be included to account for all the situations in which traffic must wait without any conflicting traffic. This number of alternatives increases exponentially with more complex intersection layouts.

Stopping is not confined to only once per intersection crossing. When the number of cyclist is high, it can occur that queues are not dissolved after a single green cycle. Stopping twice at a single intersection also can happen when making a left turn. When two crossings are required and traffic lights are not coordinated, this can cause a large total waiting time and annoyance. A need of cyclists is to prevent double stops.

As a final note, in some circumstances the relative importance of the needs of cyclists may be larger. Referring back to Section 2.2.1, the utility of cycling is lower during bad weather conditions or when encountering slopes. In these circumstances a cyclist would benefit more from reducing waiting time and speed reductions.

Summary of the wishes of cyclists related to a controlled intersection
A number of expectations from cyclists have just been discussed. These wishes are now summarized in listed form. Note that during bad weather conditions or when encountering slopes cyclists assign more value to the needs that can be related to total travel time and required effort.

- A cyclist does not want motorized traffic to be allowed to cross their path when they are allowed to do so.
- A cyclist wants to be forced to slow down as little as possible.

- A cyclist wants to avoid lows speeds, stops and double stop as little as possible.
- After stopping, a cyclist wishes to wait as short as possible.
- A cyclists wants to start moving as soon as possible after the last vehicle from crossing directions has passed and not have to wait for the light to turn green with for a couple of seconds without conflicting traffic passing.
- A cyclist wishes to be allowed to cross the road if no conflicting traffic is passing for a duration in which the cyclist could have crossed the road.

Modelling constraints that follow from the needs
The desires of the cyclist with regard to a controlled intersection can be translated to modelling constraints. Note that some requirements have some overlap: for example aiming to keep pace and prevent travelling at low speeds. However, keeping pace is mainly important to conserve energy and minimize delays, whereas there is an additional reason for avoiding low speeds: the safety aspect. Because of this the two are mentioned as two different requirements. The constraints for the intersection controller that follow from the needs are listed below. See Section 3.2.5 for a discussion of what constraints are included in the objective function of the designed controller.

- Prevent conflicting directions to have green at the same time
- Have a sufficiently large clearance time that ensures the next flow only can go after all traffic has passed, but a lower clearance time when no traffic is present.
- Aim to allow cyclists to keep their pace as much as possible.
- Aim to prevent travelling at low speeds .
- Aim to prevent stops, even more so for double stops.
- Provide cyclist with green often to ensure low waiting times.
- Assign higher values to the the needs of cyclists during bad weather conditions or when encountering slopes.

2.2.3. How to deal with cars when prioritizing cyclists?

The goal of this thesis is to design an intersection controller that prioritizes cyclists. But in order to do so, one sill has to make a trade off between the needs of the cyclists and the needs of car drivers. Subsection 2.2.3.1 describes the needs of car drivers and subsection 2.2.3 proposes how all the needs can be balanced.

2.2.3.1. Desires of car drivers

Drivers of motorized vehicles too have a their wishes and expectations of their optimal journey. Route choice models aim to identify these factors and assign values to them to investigate the extend by which they impact route utility. Factors identified in route choice models can be assumed to represent the wishes of car drivers and include the distance, free-flow travel time, time spent in congestion, travel time reliability, travel cost and number of turns[82][15]. In essence, car drivers want consistency, avoid congestion, and have the shortest route possible to their destination that costs them the least time and money. Most of these factors are relevant in an encounter with controlled intersections: travel time increases because of a lower speed and waiting time, monetary travel cost increases due to increased energy consumption and congestion is often occurring at or around intersections and can for a significant part be directly linked to them[63]. Increasing intersection efficiency is often seen as a way to reduce nativities for car drivers at intersections[35]. Spill back is one of the causes of additional delays, as a car driver can be blocked from reaching a his -empty- desired approach lane by a queue for another directions. Limiting the maximum queue length can be a way to prevent this from occurring. The threshold for this limit depends on the infrastructure layout and could be set equal to the length of the adjacent approach lane minus the length of a car.

Like for cyclists, the safe crossings that controlled intersections provide are important for car drivers. They do not want other motorized traffic or cyclists to be allowed to cross their path when they face a green light. Note that this may be different for permitted crossings but this is outside of the scope of this thesis. Because of the importance of ensuring protected crossing the intersection design should discourage red light running behavior. The most important predictors for RLR violations for cars are the position in the traffic flow, speed and yellow-onset distance to be traffic light [30]. Inadequate signal timing can also increase the probability of red light running (RLR)[49]. RLR probabilities are also higher for short green times that do not lead to a fully dissolved queue [95]. Specifically, if the green time is below 10 seconds, the probability of RLR is far larger then average: 40% for a green time of 6-7s and 25% for a green time of 8-10 seconds. RLR behavior also occurs more often with longer waiting times. Waiting times below 100 seconds result in very low RLR, but increase to up to 10% for waiting times between 100 and 300 seconds [95]. This suggests the waiting time should be limited to a maximum of 100 seconds. This research was performed in France. Different cultures can result in different values for this threshold. However, numerous countries have guidelines or laws for the maximum waiting time of the same order of magnitude as those that [95] found. For example, German and Dutch guidelines advise waiting times should not exceed 120 seconds[10][6]. The threshold of 100 seconds is used, because the research relates this threshold value to red light running probabilities, which in turn relates to the safety constraint described in desires overview in Section 2.2.2. When delays do not exceed this threshold, a trade off for delays can be made. This trade off is described in Section 2.2.3.2.

Summarizing, car drivers want to have a protected crossing, minimize their delay and have a limit to the time they have to be at a standstill. They do not want their path to be blocked by a queue for another direction and they do not desire short green times that do not fully dissolve the queue. Translating these needs to design constraints for an intersection controller, the controller should minimize the experienced delays, limit the queue length and limit the maximum waiting time. These requirements cars correspond with the parameters used to measure intersection performance in intersection control research: evaluation is almost always evaluated based on a combination of average delay and queue length. Sporadically the factors of intersection throughput or an energy consumption related variable are used as well[53]. For simplicity sake this thesis will only consider the delay and queue length are used to represent the needs of drivers as objectives.

2.2.3.2. The relative value of time

The objective of this thesis is to design an intersection controller makes a trade off between the needs of both transport modes, but prioritizes the needs of cyclists. Therefore it is not it us not unthinkable that the delays and queue lengths of cars will increase compared to a traditional intersection controller. The limit for queue length has been discussed in Section 2.2.3.1: the queue length should not block approach lanes that are not yet full. A maximum value for the waiting time was also provided: 100s. Below these limits the matter of how much priority is given to the wishes of cyclists is part of the weights that are to be assigned to objectives of the controller. This section will discuss how time -relevant for both total delay and waiting time- will be weighed between the two modes. This will be based on estimations of relative values of time (VoT) of the two different types of travellers.

If an intersection controller as designed in this thesis is ever to be implemented in real life, the choice on whether and to what extend to prioritize cyclists or cars is a choice of local politicians. The objective function of this controller therefore should allow for some variation of this trade-off in the form of variable weights. Some limits may be set on the value of waiting time relative These variable weights may be limited to a certain range however due to literature. This section will aim to provide an indication for reasonable limits. Should note research is subject to the culture in its country. Therefore this range should be considered to be an indication of possible values.

[115] identified that the cost associated with waiting time is three times higher for cyclists then for motorized vehicles. [32] investigated perceived vs actual waiting time for Dutch cyclists and found that travellers overestimate the waiting time by a factor of approximately 5. [119] investigated actual vs perceived waiting time for car drivers in the USA and found that on average the waiting time is slightly underestimated when the actual time is below 120 seconds, but for practical purposes the perception is approximated as equal to the actual time. [77] found that car drivers in India overestimate the waiting time by a factor 1.8. Based on on these estimations of value of waiting time the upper and lower limit for relative weight are constructed. The low limit is chosen as the ratio of the low estimate for bicyclist and the high estimate for car drivers: $3/1.8 = 1.7$. The higher limit is set based on the high estimation for bicycles and low estimation for drivers $5/1 = 5$.

2.2.4. Conclusion of the desire related literature review

This chapter has identified the needs of cyclists and cars with regard to intersections and translated these needs to requirements and constraints for an intersection controller. Some needs are identical for both modes, but some differ or are considered to be of greater importance to cyclists. Therefore the needs of cyclists are worked out a lot while for car drivers most of their desires are captured in the objective of minimizing delays. The desires identified in this chapter are:

- A cyclist does not want motorized traffic to be allowed to cross their path when they are allowed to do so.
- A car driver does not want motorized traffic or cyclists to be allowed to cross their path when they are allowed to do so.
- A cyclist wants to be forced to slow down as little as possible.
- A cyclist wants to avoid lows speeds, stops and double stop as much as possible.
- After stopping, a cyclist wishes to wait as short as possible.
- A cyclists wants to start moving as soon as possible after the last vehicle from crossing directions has passed and not have to wait for the light to turn green with for a couple of seconds without conflicting traffic passing.
- A cyclist wishes to be allowed to cross the road if no conflicting traffic is passing for a duration in which the cyclist could have crossed the road.
- A car driver wishes to minimize delays.
- A car driver wants to limit queue length to prevent blocking.
- A car driver wants to limit their waiting time.
- A car driver does not want short green times that do not fully dissolve the queue.

These desires have been translated into constraints and objectives for the intersection controller. Because the controller will prioritize cyclist the needs have been translated mainly to objectives. To limit the negatives experienced by car drivers, two constraints have been set (See Section 2.2.3.1). See Section 3.2.5 for an explanation on what objectives are included in the objective function of the designed controller.

- Objectives
  - Prevent conflicting directions to have green at the same time.
  - Have a sufficiently large clearance time that ensures the next flow only can go after all traffic has passed, but a lower clearance time when no traffic is present.
  - Aim to allow cyclists to keep their pace as much as possible.
  - Aim to prevent cyclists from travelling at low speeds.
  - Aim to prevent stops, even more so for double stops for cyclists.
  - Provide cyclist with green often to ensure low waiting times.
  - Assign higher values to the the needs of cyclists during bad weather conditions or when encountering slopes.
  - Aim to minimize delays for car drivers.
- Constraints
  - The queue length for cars may not exceed the length of adjacent sorting lane minus the length of a car.
  - The waiting time for a car driver may not exceed 100s.

A number of the objectives can be related to travel time. Because the objective of this thesis is to prioritize cyclists, a relative weight will be assigned to the value time for both modes. As no unambiguous value for this weight can be identified from the literature and it is debatable if a single value should be chosen at all, a range $[1.7, 5]$ is proposed in which these weights can be varied. See Section 2.2.3.2 for how this range is determined.

2.3. Traffic models

The intersection control problem must be formulated in traffic engineering terms. In other words, a mathematical formulation is required for the traffic lights and the behavior of cyclists and car drivers. This Section provides an overview of available traffic models and elaborates on the advantages and disadvantages of each model. The traffic system model of this research will be based on a model from the literature. For the traffic model that is used in this research and the reasoning behind this choice, see Section 3.2.

The remainder of this literature review is structured as follows. First, Section 2.3.1 discusses the level of aggregation in the traffic model that is required to formulate the desires of travellers. Section 2.3.2 discusses published behavioral models for cyclists and Section 2.3.3 presents car following models that include interaction with traffic lights. Section 2.3.4 then presents different mathematical formulations for traffic lights.

2.3.1. Level of aggregation

Section 2.2 identified desires for of cyclists and cars with regard to controlled intersections, which are summarized in Section 2.2.4. The mathematical formulations of cyclists, cars and traffic lights must accommodate incorporation of these desires as objectives. The identified desires concern phenomena and variables that are observed at individual level: they relate to the individual speed, number of stops and average delay for cyclists and the individual delay and queue length for cars.

In order to represent these variables, an individual, microscopic, representation for each traveler/vehicle is required.It is for example no longer possible to determine if a bicycle has stopped, when the average speed is used. For motorized vehicles it is not possible to enforce a maximum delay without individual representations. The common way maximum delay is enforced now is by a maximal cycle time. However, a structure free controller does not have a cycle time. A maximum red time could be used instead, but this creates new problems. If a car driver arrives at the stopping line, 15 seconds after the light has turned red, this car will be allowed to proceed when the maximum red time has passed. However, the car has been waiting for 15 seconds less than the maximum allowed waiting time.

Another reason why why individual representations are beneficial, is because it better allows for later incorporation of heterogeneity for both cyclists and motorized traffic. One of the major characteristics of cyclists is the large heterogeneity in characteristics and preferences of individuals. This thesis will include limited heterogeneity in its' scope, but anticipating on future research, it is beneficial to allow for easy implementation of heterogeneity by using microscopic representations. Individual representations of cars also allow for easier modelling of heterogeneous behavior of car drivers and incorporation of for example lorries, busses and other types of motorized vehicles.

Finally, this thesis focuses on unsaturated traffic flows. Unsaturated traffic flows are characterized by low volumes of traffic and in low numbers, individual agents have relatively high impact on averages. Aggregate variables may therefore be very sensitive to individual travellers, resulting in unrealistic system behavior.

The major disadvantage of microscopic representation is that it requires more computational power. However, as this Section has illustrated, a individual representation is required to accurately represent the objectives of the controller.

2.3.2. Behavioral model of cyclists

As discussed in Section 2.3.1, a microscopic representation will be used for cyclists. Microscopic models are multi-agent systems, in which agents can interact with each other and the environment. Microscopic models can be designed from different modelling paradigms: rule based, force based, velocity based and utility based. As this thesis is not focused on the design of a new microscopic method, an existing method will be used. This section will describe models that are available in published literature. See Section 3.2 for the choice of the traffic model and the mathematical formulation of the used model.

What model should be used mainly comes down to a trade off between two factors: the level of detail/realism in the cyclist behavior and the simplicity/computational effort of the model. A high computational efficiency is beneficial, as it means lower running times, but higher computation times can be accepted if the higher level of detail is beneficial. A high level of detail can better represents the actual behavior of cyclist, closer mimicking reality. However the question arises: what level is detail is required to achieve the objective of this thesis? This question is answered in Section 2.3.2.1. Then, microscopic models for cyclist are discussed. This collection is based on the literature reviews of Chou and Twaddle et al., but expanded with additional sources. Only models that are either validated or based on widely accepted dynamic formulations are considered, as validation of a model is not possible within time constraints of this research.

2.3.2.1. Cyclist model requirements

One of the most differentiating aspects of cyclists is the two dimensional nature of movement. Cyclist do not adhere to lanes in the same way that cars do, but have longitudinal and lateral movement at the same time. Although 2D movement allows for a more realistic representation of behavior, it is not required for the design of the intersection controller, as long as a model allows for overtaking. For a controller, the distance to the traffic light and the speed of cyclists are the most important for changing the signals, while the lateral position is of lesser importance. As long as the model allows for faster cyclists to overtake the slower cyclists, it can still fulfil the needs for this thesis. It would be beneficial if the model also limits the number of cyclists that can fit next to each other, thereby modelling faster cyclist that cannot overtake others due to spatial constraints.

A very important requirement, is that the model must represent stopping behavior, or at least incorporates realistic acceleration and deceleration, in addition to free flow cycling behavior. A red light demands deceleration, which results in entirely different behavior from that free flow conditions. Additionally stops need to be modelled, as the controller may have the objective of reducing the number of stops, one of the desires of cyclists. Phenomena like infrastructure friction (the nature of cyclists to keep some distance from the edge of the cycle path) and group behavior ('cycling together'), are beneficial to incorporate to closer mimics reality, but this is no requirement, because lateral movement is of lesser importance and group behavior can be assumed not to occur. A large heterogeneity is present in cycling behavior, much more then for vehicular traffic, both in in the form of different cyclists characteristics (inter-cyclist) and in how a single cyclists behavior changes when encountering a similar situation [103]. It is beneficial if the model allows for incorporation of heterogeneity in the cyclist behavior.

2.3.2.2. Rule based CA models

Cellular automata (CA) models use a rasterized representation of space and discretisized time. Each cyclist is represented by an agent that occuppies a position in the raster. Every time step, the agent can move one step through the raster in accordance with a set of predefined rules. Speed differences can be represented by a probability of an agent moving to the next position. The rule set can be simple and the same for all agents, but can also vary for different agent groups. More complex, environment dependent rules can be incorporated to represent thought processes. CA models are computationally efficient and follow simple, easy to develop algorithms. Downsides are they produce unrealistic movement behaviour and cannot model 'wall friction' [29]. CA models are the most commonly used models for representing bicycle traffic flow. They are however very limited in the lack of a continuous state space representation -2D movement- and cyclists heterogeneity -because of limited group of agents-[70].

[42] approaches the bicycle movement as a car following model that includes a lane changing model. The bicycle path is represented by two lanes, where agents generally travel in the right lane. A rule set is used for travel within a lane, that allows cyclists to accelerate to their desired speed if space is available and reduce speed is another cyclist is in front of them. Before opting to decelerate, rules for overtaking are followed. If there is a possibility to do so, the bicycle will move to the left lane, overtake and move back to the right lane after passing. The rule set in the model was validated by comparing average flow rates and density for the simulation with real life data. [101] used a similar strategy, however he used three lanes and incorporated group behavior, in which people cycle next to each other or follow each other while keeping the same speed. Both models did not include any rules related to stopping for intersections. If this model is to be used, addition of rules will be required to represent this phenomenon.

A note should be made that several researchers worked on Burgers cellular automaton models, an example of this is [120]. This type of model is not strictly a CA mode as it allows multiple cyclists to occupy a single cell. This allows for modelling overtaking and in an intuitive way, but it no longer has the advantages of a pure CA model [42]. Additionally, -as is claimed by the author as well- this type of model is a macroscopic, which means that it is not applicable for this thesis.

2.3.2.3. Position based rules using a kinematics model

Where CA models represent time and space as discrete variables, rules can also be implemented in continuous space. Cyclists are represented by their speed and position with respect to the intersection. The position and speed for the next time step are determined using mathematical formulas and rule sets for acceleration behavior [26][25]. These papers refer to the state of the cyclist as the combination of the position and speed. This terminology will also be used in this subsection.

In [25], bicycle acceleration is a control variable -by means on an on board speed advice-. This control variable and the state of the cyclist are used to calculate the state of the cyclist in the next time step. [26] uses a roadside speed advise instead of an on board advise and uses two different kinematic models, that represent acting in accordance with the speed advice or ignoring it. A rule system is used to determine what model the cyclist adheres to. This is fully dependent on the position of the cyclist. Different formulas for the acceleration are also used depending on the state of the traffic light. Note that these models have not been validated or calibrated using real life observations or a simulation. However, since they follow standard, established dynamic formulas, this is not considered to be a problem.

These models, that are based on simple kinematic models have the advantage of being really simple and fast to solve. They do not include any interaction between agents. This can be seen as an advantage and a disadvantage at the same time: no interaction is not realistic, but it also means overtaking is easily implemented: cyclists do not block each others way and are free to overtake each other at any point. Disadvantages of these models is that operational behavior and cyclist heterogeneity are not included.

More advanced kinematic models could also be used. Kinematic models that are for example described in [43], which modelled acceleration and deceleration as a nonlinear decreasing model based on fitting of experimental data in China under mixed traffic conditions. In this model, stopping behavior started 30 meters from the stopping line. [104] performed a study evaluating the the model of [43] and three others. Data was gathered from four intersections in Germany with separate bicycle infrastructure. It was concluded that the polynomial model proposed in based on the work of [66] provided the most flexibility and the most consistently low root mean square error (RMSE) values, although it did not perform best best under all circumstances. This model parameters were estimated using a large, real life data set including interference from signal control, but excluding interference from other cyclists. Different user characteristics for three different categories of cyclists are provided.

If a position based rule models is chosen, the kinematic models estimated in [104] could be combined with the rule set proposed by [26]. The first kinematic model is better suitable, because the latter has not been validated on real life data and is based on a car following model, whereas the model in [104] was created specifically for bicyclists.

2.3.2.4. Social force based models

Social force (SF) based models determine movement in continuous space, by representing the intended direction and interactions with an agents' environment as force vectors. A resulting vector is determined for each time step, that then is used to calculate the acceleration based on newtons second law. Force vectors can be both repulsing and attracting and the magnitude of the force can depend on proximity to other agents, infrastructure like curbs, or events like changing traffic lights.

SF models generally result in fairly realistic movement and interaction and can model infrastructure friction. However, the models are quite complex and require high computational effort [29]. Development of a model takes a lot of effort and time to calibrate and validate. No social force model, related to a controlled intersection with separate traffic lights for bicycles and cars, was found in literature. Because development of new SF model is outside the scope of this research, only an adapted version of social force models [50] and [64] are considered.

[50] used a social force simulation model to study behavior of cyclist, that cross an unsignalised mixed traffic intersection. The model was calibrated and validated with a large data set containing collected video

footage. It determines a desired path for all agents based on their origin and destination. If conflicts are detected, alternative paths are generated that avoid this conflict. These paths form the basis for the driving force, alongside the current and desired speed. The agents follow the paths and interact with other agents (and infrastructure) in their proximity. The social forces are based on elliptically shaped social force fields, that surrounds all agents. Forces are estimated whenever two ellipses overlap.

This mixed traffic aspect of this model would make it unsuitable for a separated infrastructure situation, as present in this thesis. However, because coefficients for interaction between modes were estimated separately, this model could still be used if only the interactions with other cyclists. However, the paper does not explicitly include stopping and queuing behavior. The collision avoidance with pedestrians may be used, as cyclists have to give right of way to pedestrians and therefore have to make a full stop. However, decelerating for a traffic light likely differs from decelerating to avoid moving pedestrians. Therefore this model is not suitable for this research.

[64] used a social force model to derive a fundamental diagram for cyclists. This model considers movement over an isolated cycle path. Cyclists are influenced by a driving force, a collision avoidance force, a friction force and a physical force. The driving force represents the desired speed, the collision avoidance forces represent interactions with cyclists over a distance in order to avoid conflicts and the friction force represents interaction with the edges of the infrastructure. Physical forces that represent interactions between cyclists are estimated when the circumellipses of two cyclists touch/overlap. Parameter values in the model were calibrated and validated by means of a simulation. However, this model does not include stopping behavior in any way.

Social force models can result in realistic movement behavior, but this comes at the cost of a high computational effort. The social force models that are found in published literature, do not include traffic lights or guarantee realistic stopping or queuing behavior. This behavior therefore would need to be added, which requires calibration and validation.

2.3.2.5. Velocity based models

The next modelling paradigm is the velocity based model. In velocity based models, space is continuous and 2D, while time is discretized. Agents aim to keep their desired speed and direction, but will avoid collisions. Cyclists can choose from a set of predefined combinations of speed and angles between the current velocity and candidate velocity. Considering other agents in a cyclists surrounding, optimal speed and deviation angles are chosen. This is done by penalising deviation from the current path, deviation of the current velocity and risk of collision. Velocity based models generally result in fairly realistic movement and interaction, but require high computational effort and have difficulty modelling infrastructure friction and less tangible features like lane preferences [29].

No movement models for cyclists based on this paradigm were found. If these models do actually exist, the applicability for this thesis may be good, as velocity based models are expected to deal fairly well with overtaking behavior in 2D space, because cyclists will evade the preceding cyclist. However, the models should include lane preferences, as cycling to the right side of the road is fairly common in cycling behavior.

2.3.2.6. Utility based models

Utility based models are somewhat comparable to velocity based models. They provide agents with a finite number of options -combinations of speed and directions- to choose from. Options are assumed to have a utility and the option with the highest utility will be chosen. Developed models aim to find the most realistic utility function and attributes and weights to mimic realistic cycling behavior. Factors are for example the occupation of the solution, proximity to destination, deviation from current path and velocity.

Bicycle models following this paradigm are limited. [102] created an cyclist utility based model, however he investigated gap acceptance in mixed traffic and not really a movement model. [37] used an utility based model to investigate behavior of cyclists when approaching a red light in order to model queue formations. He defined a two level framework, the first level representing path choice and the second level representing pedalling and steering behavior. Discrete choice models were created for each level and estimated using trajectory data gathered in the Netherlands and then validated using simulation. Path choice models entail choices on whether to take over, accept a gap, yielding, stopping for traffic lights and finding positions in a queue. The second level represents the steering and pedalling to determine direction and speed to comply with these choices made. The simulation resulted in patterns that could be recognised in the empirical data. However, -as the authors themselves note- there much improvement to be made by including other attributes. It is also mentioned that application of this model to situations other than modelling queuing behavior would need new model estimation. Even though queuing behavior is a very nice feature to have in this thesis, it is not the only thing required.

2.3.3. Behavior models of car drivers

As mentioned in Section 2.3.1, the movement model for the car should be able to represent the queue length and the waiting time of the first car in the queue. Additionally, the mathematical formulation must describe the interaction with the traffic light and other cars. The assumption of there being no interaction between travellers cannot be made for cars, as cars cannot overtake each other if there is only one traffic lane. Car following models are the standard within traffic research. Within these constraints, the most simple model should be chosen.

Two papers were found, that apply car following models with interaction with traffic lights. [123] proposed a car following model that included deceleration when approaching a red light that turns green, but not a green light that turns red. The model was proposed in a comparative study, in which it was verified and calibrated and then compared to another verified and calibrated model. No mention of validation was made, but the author claims *"The simulated outputs of the extended and the comparative models are basically in accordance with the measured data"*.

[117] describes an optimal velocity car following model, that includes braking for a traffic light and accelerating at a green light again after a full stop. The study also provides minimum and maximum distances to the stopping line, between which the model accurately describes the braking process. No mention was made regarding the validity of the model, but the model was compared to a original model and provided better accuracy, but the author only mentions the comparative model as the 'original'. However, as this article is published in a well renowned journal, the author deems this model usable, given that these concerns are discussed.

2.3.4. Traffic light model

Two main categories of traffic light representation can be identified in intersection control literature. The first group uses the active conflict group to represent the state of all the traffic lights of the intersection. The other group represents each traffic light individually and indicates the colour that is shows by means of a variable. These categories will be briefly discussed and then a choice is made on which one is most appropriate for application in this thesis.

2.3.4.1. Conflict group based representation

Phases, blocks or conflict groups are different names for the same thing: subsets of non-conflicting traffic lights that are allowed to be green at the same time. This representation is very common in intersection control research and are used in most intersection control research [127][80][121]. Sometimes the representation also includes additional variables indicating the green duration of the traffic light in the active phases [25][26].

In a phase based representation, the state of all the traffic lights of the intersection is given by the currently active group, i.e. the subset of traffic lights that currently is allowed to show a green light. In cyclic controllers, the controller activates blocks in accordance with an imposed cyclic sequence, which may include alternative paths. For this thesis, which aims to design a structure free controller, the control structure would look similar to the one provided in Figure 2.1. Note that this representation can contain even more blocks as the block consisting of directions 4, 6 and 1 can can be subdivided even further into the combinations 4-6, 4-1, 1-6, 4,6 and 1.

The main advantage of the phase based representation, is that is an intuitive and compact way of visualizing and understanding the state of the intersection. The current state of all the traffic lights can easily be captured by a single variable and conflict constraints are very easy to implement. Solutions also can be generated by means of sequential decisions of the controller.

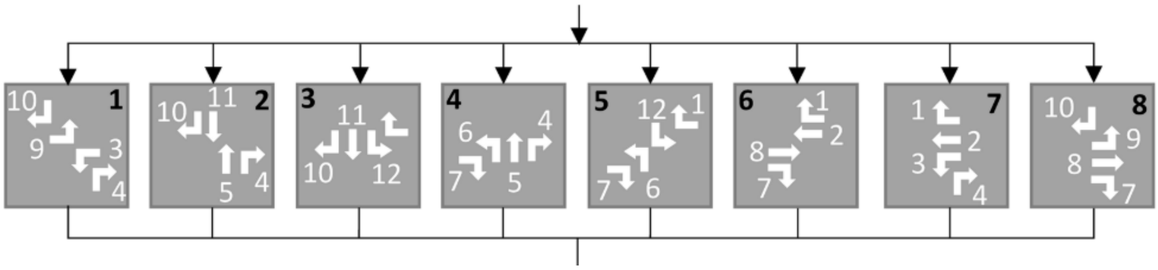


Figure 2.1: Simplified phase based control diagram for structure free control by [80]

The main disadvantage of phase based representations, is that decision trees that need to be generated to determine what phases can be allowed in the next time step. For cyclic controllers, this is fairly straightforward, but for structure free controllers not so. The decision tree must be generated in real time, and grows rapidly with increased prediction horizon [80]. Constraints with regard to minimum green time, yellow time and clearance time mean that not every phase can be allowed to follow after the current active phase. The size of the decision tree increases even faster, when the controller is allowed to make decisions on changing the state of individual traffic lights very frequently, for example every half second. The decision tree also becomes more complex if green time the active phase are allowed to end or start at different points in time. When all these degrees of freedom are implemented in a structure free controller, the conflict group based representation is no longer compact and intuitive, no longer hold, as it in essence results in representation of individual traffic lights.

2.3.4.2. Individual traffic lights

Researchers that represented traffic lights individually, all did so using a binary representation for the state of each traffic light at every time instant [40][113][100]. They represented red and green lights only. Yellow lights were not mentioned at all and may -as interpreted by this thesis author- be included within the red light, as the official rule regarding yellow light is 'stop'. The state of the entire intersection is captured in a matrix containing all states of all traffic lights at all time instances.

This representation allows for efficient matrix based calculations. It does not require decision trees that account for the numerous constraints to be generated, instead constraints on the matrix entries relative to each other can be formulated. The main disadvantage of this representation, it is very space inefficient, both in terms of visualization and computational memory. State matrices can become very large, but will grow linearly instead of exponentially with longer prediction horizons or shorter decision intervals. Another disadvantage is that solution generating algorithms should take into account constraints related to conflicts, clearance time, minimum green time, and yellow time, to prevent the majority of generated solutions being infeasible signal plans.

2.4. Optimization methods used in intersection control research

The third literature review is on optimization methods that can be used as the foundation of the structure free controller design. Section 2.4.1 discusses the requirements for the controller. Section 2.4.2 then discusses possible concepts from literature. For the choice of the control methodology that is used in this research and the reasoning behind this choice, see Section 3.3

2.4.1. Control method requirements

The controller must be suitable to control the traffic system model used in this thesis. The conceptual choice for the model is provided in Section 2.3 and a detailed description can be found in Chapter 3.2. Two characteristics of this traffic model are limiting factors for the selection of a control method. First of all, the mathematical formulation of the traffic system model has no closed form formulation. The consequences of this constraint are discussed in Section 2.4.2. Secondly, the traffic system model is a system that has memory, in other words, the state of the system is dependent on more than the state description in the previous time step.

In practical applications of intersection controllers, computation time can be a limiting factor, as the controller must function in real-time. No constraint is used with regard to the computation time however, as increases in computation power, parallelization and optimization of the underlying code can result in significant improvements in the actual controller compared to the design in this controller. Additionally, some aspects of the computation algorithm may be done preemptively in an offline environment[106]. Finally, the controller is not required to result in optimal system performance. Sub optimal performance may also be acceptable, if this results in delays lower than state of the art controllers [53]. Achieving the optimum can require a long computation time, whereas performance that approaches the optimum requires much shorter computation times.

The control problem will be formulated as a rolling horizon (RH) optimization problem. This is because both structure free design and individual traffic participant representation result in large solution spaces and long computation times, which increase rapidly as the prediction horizon increases. Therefore predictions into the far future become very impractical and may have little benefit. The rolling horizon formulation is visualised in Figure 2.2 and will be explained in more detail now. Within other disciplines this concept is known as receding horizon, moving window and dynamic optimization.

The RH concept means that for each current time step predictions will be made up to the prediction horizon and that everything that happens behind that point is not considered. New predictions are made for every control interval or every $t_{control}$ seconds, the value of which is to be later determined during the implementation phase. It is constraint to be equal or smaller than the prediction horizon. During the first control interval the controller has $t_{control}$ seconds to determine a signal plan, after which the second control interval will start. The first $t_{control}$ seconds of the plan plan determined in the previous interval are set to be fixed, providing again time for the controller to determine a new signal plan, of which the first $t_{control}$ seconds will again be fixed for the third control interval and so on.

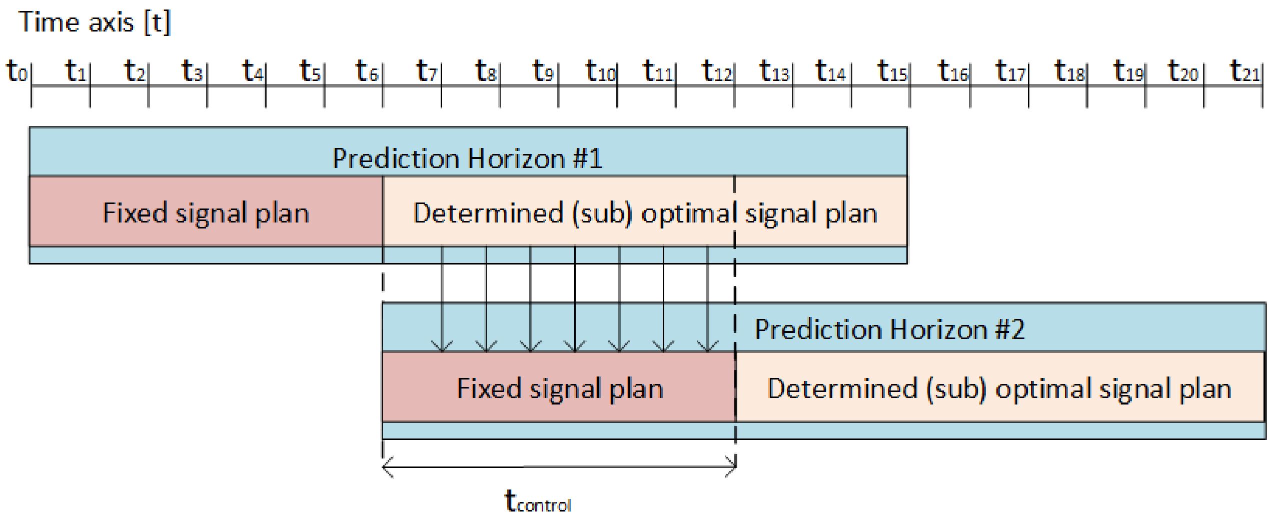


Figure 2.2: Rolling Horizon concept

As the controller is limited in the time it has to come to a conclusion, it is to be expected that an optimal plan is not often achieved. Therefore the controller aims for the most optimal solution it can provide within $t_{control}$ seconds. This may lead to the controller making mistakes, but a controller with a large degree of freedom -as is the case for structure free controllers- is able to compensate its' mistakes because of that freedom. A large degrees degrees of freedom also lead to the controller requiring a shorter prediction horizon compared to a more constraint controller[80]. Structure free controllers are able to perform well with a relatively short prediction horizon. This is beneficial, because of the high computation time associated with predictions further into the future. As with $t_{control}$, the exact value will be determined during implementation based on what works best. However, [80] provided indications for the performance of a structure free controller that can be used to get a rough estimate of what the horizon could be. He found a slight but almost non-existing increase of performance for RH of 15 and 30 sec.

2.4.2. Concepts overview

Roughly speaking, three different categories of controllers could be used within the scope of the thesis. These categories are model based control (MBC), Data driven control (DDC) and rule based control (RBC). These categories will now briefly be discussed.

Rule Based Control

RBC systems are provided with a set of rules that the controller follow. A decision process is imposed, where the choices the controller can make are influenced by measurements of the traffic system. Vehicle Actuated Controllers (VAC), the state of the art system used in the Netherlands, may be the best known rule based controller. This controller allows multiple predefined sets (Phases or blocks) of traffic lights to show green sub sequentially. A green light is provided if there is any traffic is detected in any of the lanes in the current block. After a fixed duration or if there no traffic detected in any of the lanes of the current phase, the next phase will be activated. Some flexibility may be included in the control structure to allow for multiple paths to be chosen based on what traffic is measured. Other rule based controllers found in literature are based on oldest arrival first algorithms[87], highest density first[13]. Control decision may also be made in a non absolute manner by inclusion of fuzzy logic[76][68][79].

Rule based systems can be very intuitive to create, but predicting of the effects of a rule set can be very difficult. Rule based systems are a very inflexible method of controlling. The performance of the controller is directly dependent on how the specific rules. And as these rules are chosen to work in mostly generic situations it is possible that these rules sometimes lead to poor results in less often occurring situations. Rule setting can also be quite time consuming as possible rules should be evaluated for a wide variety of scenarios to evaluate if they result in acceptable performance.

Model Based Control

Model based controllers use make predictions of possible control actions based on a model and measurements of the current traffic state. Online optimization is used to select the solution that performs best in terms of the (multi variable) objective function. The underlying models can be on individual traveller level[71] but are more common on on an aggregate level[67][127].

The open formulation and memory contained in the system do cause limitations on what types of controllers could be used. Because of the open form, mathematical optimization methods as mixed integer linear programming (MILP)[127][125] or mixed integer quadratic programming (MIQP) [126] [122] cannot be used. Because of this, simulation based control is the only model based control method that can be applied in this thesis. In simulation based control the effects of solutions are evaluated by means of a simulation and the best performing solution is chosen. This is often combined with heuristic search methods to speed up the search process through the solution space.

The main benefit of model based control is that the underlying model can make it relatively easy and intuitive to interpret and understand the trade offs the controller makes and what the effect of control decisions are. This contrary to DDC, in which the behavior of the controller is hidden in a so-called black box. Additionally, in this thesis there is the benefit that a traffic system model is already available (See Chapter 3.2) as the model is also required for evaluating the controller in the simulation based case study. Using identical models in the controller and the simulation environment allows for easy implementation of perfect prediction and data quality and for controlled implementation of errors, allowing to study the effects of errors on the controller performance in future work. See Section B for a more detailed explanation.

Disadvantages of model based control is that models often fail to capture the complex behavior of humans and assumptions made in models greatly simplify reality and heterogeneity in traveller behavior[94]. Because of the open form formulation of the traffic model, simulation based control is required. This type of control can result in a very large computation time. As was discussed in the requirements for the controller, large computation times are acceptable for the controller, but it can make the research process quite time consuming and troublesome. Heuristic methods are often used in simulation based control to speed up the search through the solution space and reduce the long computation time[21].

Researchers make use of both 'traditional' heuristic methods, most often the branch and bound method[40][80][41], or Genetic Algorithms (GA)[89][121][35]. Heuristic methods provide guidelines on how to vary input parameters with the result of a more efficient search process through the solution space compared to random searches. If variation of a parameter results in a better performance, the method will investigate neighboring solutions of this solution. Genetic algorithms are often used for problems with less straightforward formulations of solutions, in which there are more constraints on what can and is allowed to be varied.

Data Driven Control

Contrary to MBC, Data driven control does not involve a model that describes a relationship between the system inputs, the traffic state and solution, and outputs, the effect of any solution on the traffic state. Instead of using a model, often a neural network or reward function is trained offline with large quantities of data to learn relationships between it's control actions and expected outputs. A large variety of these machine learning based controllers exist. Data driven control has recently received a lot of attention in intersection control research[53][35]. Controllers can be based on reinforcement learning[62], simultaneous perturbation stochastic approximation[96], Markov decision processes[26] and many more. A large number of variants of said controllers exist, implementing more complex underlying methods with the purpose of increasing the performance.

Data driven controllers have the benefit that they have very strong non-linear approximation, which allows them to describe the complex behavior of humans better than model based controllers[94]. This is a very important advantage and the main reason why there is so much research being conducted on DDCs. The main disadvantages however are that the controllers can be very difficult to implement for complex systems, such as the traffic system in this thesis. Additionally, a lot of training time is required and there is no guarantee that the controller converges to stable behavior until after the training has commenced. Additionally, the reasoning behind why a data driven controller decides to make decision is more difficult to find out due to the black box principle. A final disadvantage is that these controllers are subject to the so called *Long tail* phenomenon, meaning that they can struggle with very infrequently occurring scenarios, because there is little training data for these scenarios.

2.5. Summary of the literature review

The literature review on intersection controllers in the CE (Section 2.1) found that the research field of intersection control in the CE is booming and has attracted a lot of attention in recent years. In the words of Jing et al., *"The field is still in its' infancy"*. The main research gap that was found it that no intersection controllers, that consider cyclists as main users of the intersection, are published. This research will aim to fill this gap.

The review on the desires of cyclists with regard to controlled intersections (Section 2.2) concluded that no work is published that explicitly covers this topic. A lot of research investigates determinants for bicycle use and route choice, but little attention is paid to the desires of cyclists at controlled intersections. This research therefore has summarized determinants of bicycle use and projected these determinants on controlled intersections. This has resulted in an overview of desires of cyclists with regard to controlled intersections, which is provided in Section 2.2.2.

A number of traffic models were found in the literature. The part of the review that covers these models, presented in Section 2.3, concluded that much more work is to be done to fully understand and describe cyclist behavior and movement. Models are either limited in included behavior, or limited in the applicability of the model. A promising trend is that recently, more work has been put into validation of models with real life data. The overview of control methods used in the connected environment (Section 2.4), concluded that the available control and optimization methods are quite extensive.

All together, the conclusion of the literature review is, that in traffic research and more specifically intersection control research, the cyclists can be somewhat seen as the forgotten child. However, recently cyclists have gotten a lot more attention. Given the interesting aspects of cycling, the abundance of research to do and the benefits of cycling for society, it is only to hope that this trend will continue. This research will contribute to filling one of the many research gaps, in the form of proposing a design for an intersection controller in the CE, that considers cyclists as a main intersection user.

3
Methodology

In this chapter, the methodology of this thesis will be discussed. First, Section 3.1 will discuss the design framework. Section 3.2 then provides the formulation of the traffic system model. Section 3.3 then provides the detailed design of the structure free controller.

3.1. Framework

The framework of this thesis composes of two parts. First, Section 3.1.1 provides the design methodology that is followed. Then Section 3.1.2 presents limitations on the scope of the design space.

3.1.1. Design methodology

The design methodology used in this thesis is the design methodology as described in [59]. The first step of this methodology -regarding problem definition- is described in the introduction. The steps included in this methodology are: Problem recognition and description, problem analysis in traffic engineering terms, problem analysis in control engineering terms, control approach selection and finally operationalization. The framework is visualized in Figure 3.1 below.

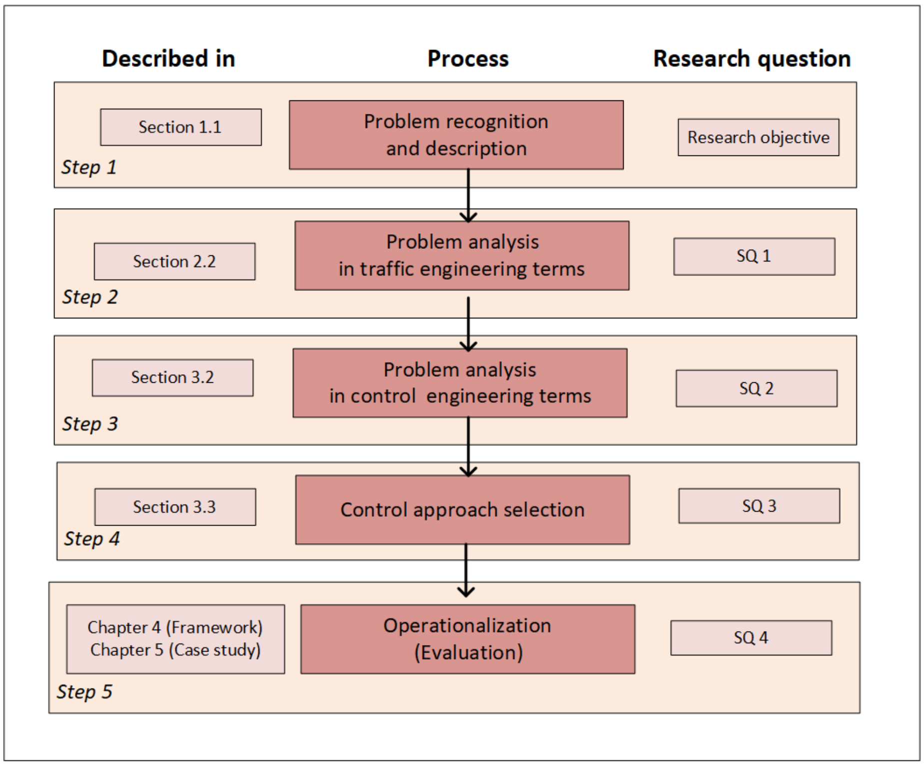


Figure 3.1: Design methodology

Problem recognition and description entails the description of what is undesired in the current situation and what the desired situation should look like. The problem definition has already been provided in the introduction (Section 1.1).

The second step identifies the causes of the undesired situation and what should be done different to achieve the desired situation. Translated to this thesis, this means identifying the needs of cars and cyclists and determining how to limit the delays for each mode. This corresponds with answering sub question 1, which will be done by means of a literature study. This literature study is provided in Section 2.2.

The third step in the methodology entails formulating the control goal, constraints and the system as a whole in mathematical formulation, This design step is covered in sub question 2. The literature study presented in Section 2.3 describes the different options and corresponding (dis)advantages of different formulations for the traffic system. The choice and (mathematical) formulation of the control goal, constraints and traffic system is provided in Section 3.2.

Step 4 of the methodology is the choice of control method. This choice, represented in sub question 3, is made using the gathered knowledge of the literature study presented in Section 2.4. The choice is presented in Section 3.3 on the controller design.

Step 5 from [59] entails the actual creation of the controller and the tuning of parameters that are required. This is represented by sub question 4 and entails combining all the answers of the previous sub questions to create the controller. The design is described in Chapter 3.3.

The fifth step from the methodology in [59] entails implementation and evaluation of the design. It is the aim of this study to perform this evaluation by means of a simulated case study. The experimental setup for the evaluation is discussed in Section 4.1 and the outcome of the evaluation will be provided in Chapter 5

Summarising, the methodologies used in this thesis are a literature study and a simulation based case study. The literature study is performed to investigate options and help make design choices for the controller. The simulation based case study is performed to evaluate the design.

3.1.2. Scope of the design space

This section will elaborate on the high level assumptions on the environment in which the designed controller must function. As this thesis is -to the knowledge of the author- the first attempt at designing a structure free intersection controller, prioritizing bicyclists in the connected environment, the scope will be quite limited. After a solid foundation has been designed, future work can improve the design and add additional features to make the controller better suited for operation in the actual world. The framework that is provided, composes of the environment in which the controller is able to function and a number of assumptions that allow for a simplified representation of reality. Future work (see Section 6.1) will provide a road map with additions for the framework for improved versions of the controller and the experimental setup (Section 4.1) will discuss the set up for the case study in which the controller will be evaluated.

The thesis will focus on an isolated intersection instead of a road network. This is mainly for simplicity and to keep the simulation environment limited. Cars and bicycles are the only traffic modes that are considered. A higher number of modes increases complexity significantly, which is to be avoided due to the limited time for this thesis. An argument can be made to include pedestrians, because pedestrians are a significant factor in urban environments, especially in those that have low numbers of motorized vehicles. For simplicity, all conflicts are protected and no negative clearance times are allowed.

Regarding flow saturation, only unsaturated flows will be considered for the design and evaluation of the controller. The objective of this thesis is to reduce the waiting time and number of stops for bicycles. One can reason that in unsaturated flows, more unnecessary stops occur and more improvement can be achieved by a larger variety in signal block combinations. Therefore it is reasoned that the largest impact can be made in these situations.

As was explained in the first paragraphs of the Introduction, the connected environment allows vehicles to share information with the intersection controller. The controller can also communicate advise speed to travellers. A choice has to be made on what information flows are included in the scope of this thesis. It is chosen that both cars and cyclists communicate their position, speed and destination to the intersection controller. Additionally personal characteristics related to driving and cycling behaviour are assumed to be known by the controller, allowing the controller to make detailed arrival predictions. Speed advice is excluded from the scope. The reasons for this are threefold: it requires a large number of (unsubstantiated) assumptions to be made, current technical capabilities limit the practical implementation for speed advise to bicycles and including speed advise for cars adds little value to the objective of this thesis. These arguments will now be elaborated upon.

First of all, it is complex to determine whether or not an active mode user is willing and capable of adhering to the advise speed. Assumptions would have to be made on when cyclists receive advise, if they follow the advise and how this advise influences their behavior. These questions get more complex when more differentiation between types of cyclists are made. An elderly person, for example, will not be able to speed up the same way as an younger person is able to and a cyclist on a city bike is not able to reach the same speeds as a commuter on an e-bike. Including speed advice will make the scope of this thesis much more about the speed advise part, and prevent conclusions to be drawn based on the effect of the structure free control and cyclist oriented control.

Secondly, the question of how speed advise would be given arises. The current state of the art communication technology for on-board speed advise is the mobile phone. Given that this technology is used, it is not desirable from a safety point of view that travellers pay close attention to their phones while cycling. Of course it is possible to develop other forms of speed feedback, like a dashboard on a future bike or light indicators alongside the bicycle paths, but these technologies are not yet developed/implemented.

Implementation of a speed advise for cars would be more simple and profound. The mechanical abilities within urban road rule regulations are more homogeneous then cars and is possible to show the advise speed using the display on the dashboard. However, the question arises what benefits it would bring to the objective of the thesis to provide speed advise to cars. Assuming this speed advise does not get above the roads speed limit, in most cases it will result in advise to lower speed, preventing full stops. Although this is can reduce energy consumption for cars, this would not contribute to the objective of the thesis of better serving the needs of cyclists.

The initial thesis scope will assume the connectivity penetration rate for both traffic modalities to be 100%, resulting in a data flow from all travellers in the environment to the intersection controller. It should be noted that this is a significant assumption, since this is unlikely to be the case whenever this technology gets implemented in the real world and connectivity penetration rate is a big factor influencing the performance of intersection controllers in the connected environment[53]. The simulation environment and controller must be designed in a way that allows for later inclusion of lowered penetration rates. In addition to the assumption on connectivity rate, it is also assumed that the data provided to the intersection is 100% accurate.

The list of all the assumptions in the framework is provided as follows:

- A single isolated intersection is considered.
- Included transport modes: cyclists and cars (motorized vehicles).
- The controller will not be imposed a cyclic control structure
- All conflicts are protected and no negative clearance times are allowed.
- The controller is designed to function best in unsaturated traffic flow conditions.
- The controller will have computation times that allow for real life implementation.
- Cyclists and cars provide their location, speed, destination and personal characteristics to the intersection controller.
- No speed advice is given to either bicyclists or cars.
- The connectivity penetration rate of both modalities is assumed to be 100%.
- The controller is assumed to receive data with perfect quality.

3.2. Traffic system model

This section provides the mathematical formulation and underlying assumptions of the behavioral models of cyclists and car drivers, as well as the description of the traffic light and the associated constraints. Because a full model validation is not possible within the time span of this thesis, the traffic system model will be based on validated models that are published in literature. For an overview of options for these models, see the literature review of Section 2.3.

First, Section 3.2.1 introduces notation conventions and system wide mathematical sets. This is followed by the Mathematical formulation for traffic lights in Section 3.2.2. Sections 3.2.3 and 3.2.4 discuss the chosen underlying model for representing cyclists and car drivers respectively. These sections also include the detailed mathematical formulation that has been set up. The control objectives are then proposed in Section 3.2.5. Section 3.2.6 then summarizes the model limitations and assumptions for the presented traffic system model. No values are provided for the parameters in the traffic system model. The values that are used in the case study are provided in Appendix C. Model verification and validation, of which the latter is outside of the scope of this thesis, is discussed in the case study chapter in Section 4.1.5.

3.2.1. System wide sets and notation conventions

The traffic lanes $i, j \in I$ are modelled as separate subsystems, with no interaction between agents in different lanes. The only interaction between the different lanes is by means of coordinated traffic lights plans. Individual agents on each movement are represented as $c_i^{cyc} \in C_i^{cyc} \forall I$ when the i represents the traffic light of a cycle path, or $c_i^{car} \in C_i \forall I$ when the traffic lane is used by motorized vehicles. All sets C_i^{cyc} and C_i^{car} are part of the larger set C containing all agents in the system.

The system will be simulated over a time horizon. This horizon is represented as set of time indices $k \in K$ in the range $[k_0, k_{max}]$ where $k_{max} = T_{max}/\Delta T$, with T_{max} representing the length of the prediction horizon and ΔT the constant time step.

The following notation shall be used. Lower case letters (eg. s) represent individual values or variables. Capital letters (eg. S) represent vectors or sets. Notation of a matrix and matrix entry is entries are $S[i, k]$ and $s_{i,k}$ respectively. Referring to column or row vectors within is done the following way: $S_i[k]$ refers to the vector in S with fixed value i containing all all values of k.

3.2.2. Mathematical representation of the traffic lights

The literature review in Section 2.3.4 described the advantages and disadvantages of two possible representations of traffic lights: binary individual traffic signals and signal groups. The individual traffic light representation is best suited for the traffic system model of this research. When no cyclic control structure is imposed and the controller is allowed a large degrees of freedom, there is little benefit in using signal groups. Decision trees would need to be generated in real time, that grow rapidly with increasing prediction horizons. Additionally, yellow time and clearance time constraints in the model must be enforced on individual traffic light level. Given the sets of directions $i, j \in I$ and the set of time indices $k \in K$, the set of individual traffic signal states for each time step is defined as $s_{i,k} \in S$. The binary values of a traffic signal state is defined as follows:

$$s_{i,k} \begin{cases} 0, & \text{if red or yellow} \\ 1, & \text{if green} \end{cases} \qquad \forall i \in I, k \in K \tag{3.1}$$

A binary representation is beneficial as it allows for fast calculations. However, three colors should be represented: red, yellow/amber and green. Therefore the amber light must be incorporated in one of the two or divided between the two. How this is done will effect the way conflicts can be constraint, as well as how the clearance time could be incorporated. This is because, provided no negative clearance times are allowed, traffic lights of two conflicting directions are not allowed to be green if the other is either green, yellow or in its' clearance time.

It is chosen to incorporate yellow as the first *yellow time seconds* of the red time duration. First of all, this is done because the official message an amber light carries is *Stop if you are able to*, making it sensible to group it with the red light. See sections 3.2.4 and 3.2.3 for how car drivers and cyclists respectively are assumed to react to a yellow light. Incorporating yellow as part of the green phase can also be defended, because the amber light is sometimes seen as part of the 'effective' green, allowing the amber to be used for crossing. A second argument of combining amber with red is that the system should be able to distinguish the amber from the color it is grouped with. This is more easily done when it is part of the red state by means of a variable that keeps track of the red duration. If this variables' value is below the yellow threshold, the light is yellow, otherwise it is red. This can again be stored in a binary variable, which is 1 when the light is amber. This is described in the section describing conflict constraints.

The individual states in set S are used as the control variables of this controller. To allow for the use of linear algebra operations, the individual states are organised in a matrix, which can be seen in in Equation 3.2. Signal states are defined for each signal and for each time step.

$$S = \begin{bmatrix} s_{1,0} & s_{2,0} & \cdots & s_{i_{max},0} \\ s_{1,1} & s_{2,1} & & \vdots \\ \vdots & & & \vdots \\ & & & \\ s_{1,k_{max}} & \cdots & \cdots & s_{i_{max},k_{max}} \end{bmatrix} \tag{3.2}$$

Minimum and maximum green time

Constraints for minimum and maximum green time require keeping track of how many time steps the traffic lights has been green. Minimum and maximum green times are defined as $g_{min,i} \in G_{min}$ and $g_{max,i} \in G_{max}$. Equation 3.3 describes the green duration variable $G_d[k]$, which calculated each time step and compared to minimum and maximum green times to see if these constraints are violated. The green duration is determined by adding the outcome of element wise multiplication of G_d of the previous time step with signal plan of the current time step $S_{k-1}[i]$, to the current signal plan $S_k[i]$ times the time step (Equation 3.3). This is done fairly similar for the the red duration as well in Equation 3.4. The red duration can be used to distinguish red and yellow lights (Equation3.5).

$$G_d[k] = G_d[k-1] \odot S_{k-1}[i] + S_k[i] * \Delta T \tag{3.3}$$

$$R_d[k] = R_d[k-1] \odot |S_{k-1}[i] - 1| + |S_k[i] - 1| * \Delta T \tag{3.4}$$

$$Y_{state}[i,k] = \begin{cases} 0, & if R_D[i,k] < Y_{time}[i] \\ 1, & \text{if else} \end{cases} \qquad \forall i \in I, \tag{3.5}$$

Minimum green time constraints can be enforced the following way. If the green duration is zero or larger then the minimum green time the future states are kept at zero, meaning these future states are still allowed to be controlled. If the green duration is below zero and the minimum green time however, the values in the traffic light state vectors will be fixed to zero up to the minimum green time. Enforcing the maximum green time happens in a similar way.

$$S[i,k+1] = 1, \qquad \text{if} \quad G_D[i,k] < G_{min}[i] \tag{3.6}$$

Protected conflicts, yellow time and clearance time

One of the most important constraints of an intersection controller is that conflicting directions must be protected from simultaneously showing a green or yellow light. Additionally, in some occasions a delay is required between two subsequent green times of conflicting traffic lights, called the clearance time. In order to enforce these constraints, a delay $T_{delay}[i,j]$ matrix is defined. This matrix contains the required delays between the end of green of traffic light i and the allowed start of green for light j. This delay equals zero if two directions do not conflict. If the two traffic lanes are defined as protected crossings, i.e. conflict in the framework of this thesis, the value of t_{delay} equals the sum of the yellow time and clearance time (see Equations 3.7 and 3.8). The yellow time and clearance time conflicts are enforced by means of the constraint shown in Equation 3.9

$$T_{delay} = \begin{bmatrix} t_{delay(1,1)} & t_{delay(1,1)} & \cdots & t_{delay(1,j_{max})} \\ t_{delay(2,1)} & & & \vdots \\ \vdots & & & \vdots \\ t_{delay(i_{max},1)} & \cdots & \cdots & t_{delay(i_{max},j_{max})} \end{bmatrix} \tag{3.7}$$

$$t_{delay(i,j)} = \begin{cases} 0, & \text{if i and j do not conflict} \\ t_{yellow}[i,j] + t_{clearance}[i,j] & \text{else} \end{cases} \tag{3.8}$$

Where,

$t_{yellow}[i,j]$ = required yellow time between end of green time of i and start of green time of j
$t_{clearance}[i,j]$ = required clearance time between end of green time of i and start of green time of j

$$S[j,k_2] = 0, \qquad \text{if} \begin{cases} S[j,k_1] = 0 \\ k_2 - k_1 < T_{delay}[i,j] \end{cases} \qquad \forall i,j \in I, \forall k_1 \in K, \forall k_2 > k_1 \tag{3.9}$$

3.2.3. Mathematical model for cyclists behavior

Multiple microscopic bicycle behavior models were described in the literature review in Section 2.3. The choice for a movement model for cyclists is furthermost limited by the few options that are available. Velocity based models were not found and social force based models do not guarantee decelerating and stopping behavior. The utility based model includes model stopping behavior but does not include acceleration or cycling operation at constant speeds.

Rule based models occur in two different manners: CA models and models with simple kinematics based on the position of the cyclist and the color of the traffic light. The CA models have the disadvantage that they do not include rules related to stopping for red lights. Because no other traffic models are suitable for representing individual cyclists and their interaction with traffic lights, a the rule based model with simple kinematics will be used. The rule based system used in [26], that describes when and how cyclists interact with traffic lights are combined with the validated kinematic model of [104].

System description

This section describes the longitudinal movement model a cyclists moving towards the intersection controller and crossing the road. Some cyclists have the destination straight on, some have to make a left turn thereby being part of both cycle lane systems (Figure 3.2). For clarity, three different categories of cyclists are distinguished: the straight on travelling cyclists, from now on referred to as a type 1 cyclist, the turning cyclist (type2.1) and the turned cyclist(type 2.2). The turning cyclists and the turned cyclist refer to cyclists making a double crossing. The turning cyclist is located in the first system, before making the left turn whereas the turned cyclist has made a left turn and now is located in the second lane, upstream of the traffic light. Type 1 and type 2.2 agents behave in accordance with the same behavioral rules, but type 2.1 cyclists follow a different set of decision making rules.

Straight on travelling cyclists enter the system at the entry point, travelling at their preferred speed v^{cyc}_{pref}, and leave the system at the exit point. A turning cyclist enters the system enters the system at the entry point travelling at v^{cyc}_{pref} and leaves the system at the crossing point with turning speed v_{turn}. It then enters the second system with v_{turn} at the after turn entry point and leaves the system at the exit point.

Figure 3.3 visualises the movement of the cyclist in a single lane. A cyclists position $x(t)$ is represented with

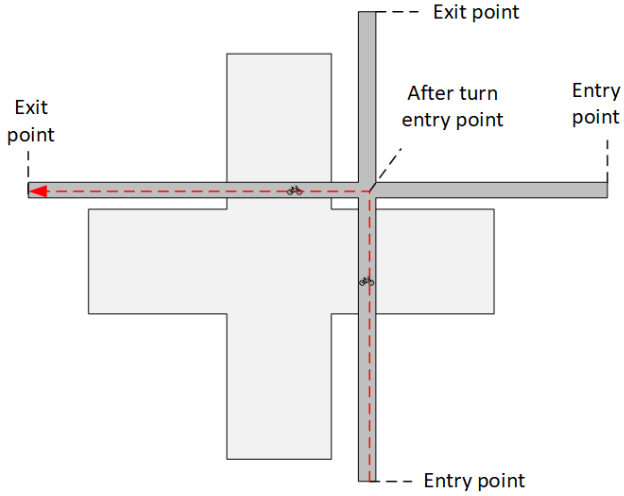


Figure 3.2: Exit and entry points of straight travelling and double crossing cyclists. Trajectory of a cyclist making a double crossing is indicated.

respect to the entry point. Depending on their location, cyclists are located in one of six different areas. These areas are the entry area, approach area, light approach area, turn approach area, crossing area and exit area. These areas are defined by the entry point, the light approach point, turn approach point, traffic light point, crossing point and exit point. Note that the light approach and turn approach area for turning cyclists (type 2.1) overlap. The (light) approach areas represent areas in which the behavior of a cyclist is influenced by the state of the traffic light. Note that the location of this areas is influenced by personal characteristics, but not by the state of the traffic light. In the turn approach area a cyclists decisions are influenced by the fact that they have to make a turn at the crossing point. By definition, type 2.1 cyclists are located in either the light approach area or the turn approach area, whereas type 1 and type 2.2 cyclists always occupy the approach area.

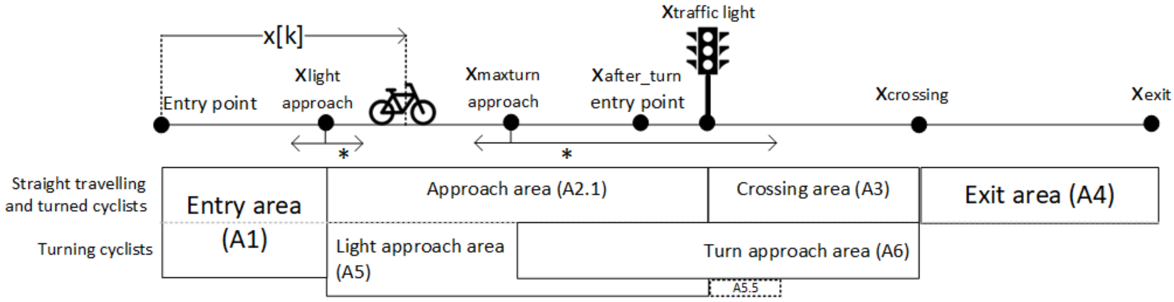


Figure 3.3: System description of bicycle lane. Note that cyclists that make a left turn pass through two systems (See Figure 3.2).

Cyclists choose their behavior based on what area he/she is in. The location of the after turn point, the traffic light point, crossing point and exit point are fixed and based on the infrastructure layout. The location of the light approach point and the turn approach point are dependent on personal characteristics. The following personal variables are associated with a cyclist:

- $L^{cyc}_{turn} = 0, 1$. A binary variable that represents if a cyclists wants to travel straight or make a left turn.
- v^{cyc}_{pref}. The personal preferred speed of an individual cyclist.
- v^{cyc}_{target}. The target speed to which a cyclist wants to accelerate.
- a^{c}_{max}. A cyclists' the maximum comfortable acceleration rate.
- d^{c}_{max}. A cyclists' the maximum comfortable deceleration rate.

Kinematic Model

The basic movement of cyclist is modeled according to the simple kinematic model shown in Equations 3.10,3.11 and 3.12. Every time step the position, speed and acceleration are determined. The position is found by taking the previous position and adding the previous speed times the time step. The speed is found the same way: take the previous speed and add the previous acceleration multiplied with the time step. The value of the acceleration depends value is more complex and depends on the current speed, position and state of the traffic light. The remainder of this mathematical model description will explain how the values for the acceleration is calculated. First, the situation for cyclists travelling straight through will be explained followed by the rules for left turning cyclists.

$$x[k] = x[k-1] + v[k-1] * \Delta T \tag{3.10}$$

$$v[k] = v[k-1] + a[k-1] * \Delta T \tag{3.11}$$

$$a[k] = f(x[k-1], v[k-1], s_i[k-1]) \tag{3.12}$$

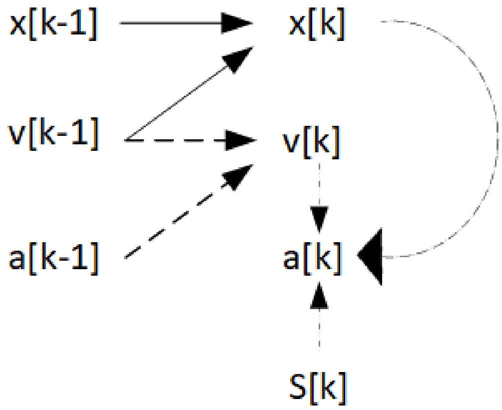


Figure 3.4: Variable dependencies

Straight travelling and turned cyclists

The behavior of straight travelling and turned cyclist is relatively straightforward. Unless a red light is faced, these cyclists will always aim to be travelling at their preferred speed. First the process of accelerating to the preferred speed is discussed, then the influence of the red light will be explained.

The acceleration of a cyclist is calculated with Equation 3.13. This model and the model parameters are adopted from the work of [104], which is validated on real life data. The Equation features model parameters C, a_{max}, B, a and c. These model parameters are different for each individual cyclist and represent personal characteristics. The formulation also includes the speed ratio: a variable that relates the current speed, the initial speed when the cyclist started accelerating, and the final target speed. This results in more realistic behavior, because in practice a cyclist makes decisions on how much to accelerate or decelerate based their given and desired speed. The speed ratio, which is based on the work of [11], is described in Equation 3.14. For type 1 and 2.1 cyclists, the target speed v_{target} always equals the preferred speed v^{cyc}_{pref}. For turning cyclists it can also take on the value of v_{turn}. This is explained further down.

$$a[k] = a(\theta_s) = C^{cyc} * a^{cyc}_{max} * (\sin(\pi\theta_s[k]) + B^{cyc} * \sin(2\pi\theta_s[k])) + (\frac{1}{\theta_s^2 + c^{cyc}} + a^{cyc}) \tag{3.13}$$

Where,

$a[k] = a(\theta_s)$ = Acceleration/deceleration at speed ratio θ_s,
θ_s = speed ratio,
a^{cyc}_{max} = Maximum (Comfortable) acceleration/deceleration,
$C^{cyc}, B^{cyc}, c^{cyc}, a^{cyc}$ = Model parameters based on personal characteristics,

$$\theta_s[k] = \frac{v^c[k] - v_i}{v_{target} - v_i} \tag{3.14}$$

Where,
$\theta_s[k]$ = speed ratio,
$v^c[k]$ = current speed,
v_i = Initial speed when acceleration started,
v_{target} = Target speed after acceleration $\in \{v^c_{pref}, v_{turn}\}$

In case the cyclist is located in the (light) approach area and faces a red light, he/she makes a stop or go decision. First the underlying deceleration model is explained, then the stop or go decision is elaborated upon. Deceleration is assumed to commence as a constant deceleration model with value d^{cyc}_{model}. This model is also adopted from the cyclist kinematic model, validated on real life data as described by [104]. The rate at which a cyclist decelerates is based on personal characteristics.

As previously stated, cyclists are assumed to only react to a traffic light when located in the approach area. The location of the approach point is defined as the *Point at which a cyclist will need to start braking with d^{cyc}_{model} to ensure coming to a complete standstill at the stopping line* and is described in Equation 3.15. The formulation also includes a variable v_{stop}. This variable describes the threshold from which cyclists are assumed to be fully stopped. Speeds $v[k]$ below this threshold will be rounded down to zero.

$$x_{lightapproach} = x_{cyclelight} - \frac{v^2_{stop} - v^2_{pref}}{2 * d_{constant}} \tag{3.15}$$

When a cyclist is within the approach area and the traffic light shows red, the deceleration rate that will allow the cyclist to come at a complete standstill at the traffic light, $d_{reqlight}$, is calculated . This is shown in Equation 3.16. Note that if a cyclist enters the approach area while a red light is showing this rate will equal d^{cyc}_{model}, but if the light turns red while a cyclist is further downstream the light approach point this rate will be larger then d^{cyc}_{model}.

The calculated required deceleration rate is then compared to the personal maximum deceleration rate. If it is larger (i.e. less negative), this the cyclist will decelerate with the $d_{reqlight}$. In case it is smaller -more negative-, this would indicate the cyclist needs to decelerate faster than he or she is comfortable with. Cyclists in this scenario are assumed to threat the red light as if it was green and thereby choosing to accelerate to v^{cyc}_{pref} in accordance with the regular acceleration Equation 3.13. This is shown in Equation 3.21. The assumption to base the stop and go decision on the required deceleration and maximum deceleration, is common in intersection control research for cars and therefore deemed acceptable for this intersection control thesis.

$$d^{cyc}_{reqlight} = -\frac{v^2_{stop} - v^2[k]}{2(x_{light} - x[k])} \tag{3.16}$$

$$a[k] = \begin{cases} a(\theta_s), v^{cyc}_{target} = v^{cyc}_{pref} & \text{if } S[k] = 0, d^{cyc}_{reqlight} > d^{cyc}_{max} \\ d^{cyc}_{reqlight}, & \text{if } S[k] = 0 \ \& \ d^{cyc}_{reqlight} < d^{cyc}_{max} \end{cases} \tag{3.17}$$

Summarizing the decision process on the acceleration for straight travelling cyclists is as follows:

$$a[k] = \begin{cases} d^{cyc}_{reqlight}, & \text{if } S[k] = 0 \ \& \ x[k] \in A2.1 \ \& \ x_{lightapproach} \le x[k] \le x_{trafficlight} \\ a(\theta_s), v^{cyc}_{target} = v^{cyc}_{pref} & \text{else} \end{cases} \tag{3.18}$$

Cyclists that make a left turn

The kinematic model for cyclists that make a left turn is more complex. These cyclists enter the first cycling path at the entry point and leave it at the crossing point travelling with turning speed v_{turn}. They enter the second traffic lane at the after turn point with the turning speed and traverse the lane to the exit point. This is visualized in Figure 3.2. For practical purposes, in this section a clear distinction is made on how turning cyclists are referred to, depending on what system they are located. In the first system they are defined as *Turning Cyclists*. In the second system cyclists are defined as *Turned Cyclists*.

Similar to straight travelling and turned cyclists, the turning cyclist will in the basis aim to be travelling at its' preferred speed, following the basic acceleration Equation 3.13. Divergence from this behavior is caused by two different factors: they have to accelerate or decelerate due to the traffic light and because they want to arrive at the crossing point with the turning speed, which is lower than the preferred speed. First the influence of arriving at the crossing point at the turning speed is explained, followed by the effect of a red traffic light.

Cyclists only start considering the turn they have when they are located in the turn approach area (A6), defined as the area between the maximum turn approach point and the crossing point (see Figure 3.3). The maximum turn approach point is defined as the location from where a cyclist, travelling at his preferred speed, must start braking - using the comfortable deceleration rate d_{model}- to reach the crossing point with the turning speed (See Equation 3.19). This point can be located upstream or downstream of the traffic light, depending on personal characteristics.

$$x_{maxturnapproach} = x_{crossing} - \frac{v_{turn}^2 - v_{pref}^2}{2 * d_{constant}} \tag{3.19}$$

Note that being located in the turn approach area does not by definition mean a cyclist will be braking. A cyclist that is travelling below its' preferred speed may have to start braking later or even be accelerating, for example because he/she was waiting for a red light. A distinction is made between cyclist that are travelling below and above the turn speed. Cyclists in A6, travelling below the turn speed will accelerate towards target speed v_{turn} following the basic acceleration Equation 3.13.

Cyclists in A6 travelling above the turn speed are assumed to keep travelling at this speed up to the point that they need to start braking with d_{model}- to reach the crossing point with the turning speed. This is assumed because it does not make sense for cyclists to first accelerate back to their preferred speed, keeping in mind they would have to start braking harder than is comfortable for them. Cyclists of whom the maximum turn approach point is located downstream of the traffic light will fist keep accelerating towards their preferred speed until they enter A6. This situation is visualized in Figure 3.3 as area A5.5. These cyclists have low preferred speeds so they have to start braking relatively short before the crossing area and accelerating does make more sense for them.

$$x_{braketurnmax} = x_{crossing} - \frac{v_{turn}^2 - v_{pref}^2}{2 * d_{constant}} \tag{3.20}$$

Turning cyclists react to the traffic light the same way that the other types of cyclists do. When located in the light approach area, when facing a red light, they evaluate the deceleration rate that is required to come to a complete standstill at the stopping line (Equation 3.16). If this deceleration rate is smaller than their maximum they will start braking with the required deceleration rate. Is it larger than their maximum they will cross the yellow or red light and behave as they would facing a green light. After reaching the crossing point and leaving the current system, cyclists enter the other bicycle path and behave as is described in earlier paragraphs.

$$a[k] = \begin{cases} a(\theta_s) \text{ with } v_{target} = v_{pref}, & \text{if } v[k] \le v_{pref} \ \& \ x < x_{braketurnmax} \\ a(\theta_s) \text{ with } v_{target} = v_{turn}, & \text{if } v[k] \le v_{turn} \ \& \ x_{braketurn-current} < x[k] \le x_{crossing} \\ d_{req}, & \text{if } v[k] > v_{turn} \ \& \ x_{braketurn-current} < x[k] \le x_{crossing} \end{cases} \tag{3.21}$$

Queuing of cyclists
The model does not consider interaction between cyclists. Therefore, when a signal shows a red light, the system description will lead to multiple cyclists stopping at exactly the same location just before the traffic light. This behavior can be seen as realistic as long as the number of cyclists at standstill does not exceed three or four. Three cyclists can easily stand next to each other and start accelerating at the same time, but the controller predictions get increasingly more unrealistic when more people are waiting for a red traffic light. This is for two reasons: stops at other locations and queue discharge rates.

Firstly, the controller aims at predicting stops. The movement model requires cyclist to stop directly in front of the traffic light, but in reality cyclists would have to stop a bit more upstream as another bike is obstructing their way. The controller providing green to prevent a stop just ahead of the signal now is redundant, as the cyclist in reality would have had to stop earlier.

Secondly, it does result in unreasonably fast queue discharge rates. In case of three waiting cyclists, the cyclists now all depart at the same time whereas in reality the third cyclist would have to wait until the proceeding cyclists move. [124] even found different queue discharge rates depending on the location of the waiting position relative to the stopping line, something that also is not included in the model as described in this section.

However, as this controller is designed to function in unsaturated flow conditions, one may ask the question if queues of more than two cyclists will be common and therefore if the queuing behavior should be incorporated in some other way. The definition [80] used for unsaturated traffic flows is *"Almost no queues present"*. Additionally, a back of the envelope calculation shows a traffic demand of $300/h$ for a single bicycle path leads to an average headway of $12s$. This traffic demand is already quite high for a single lane and means that on average a queue exceeding three bicycles will only occur with a red time larger than 36 seconds. Of course these are averages, so fluctuations in demand generation could lead to this situation more often.

For now it is decided that queuing behavior will not incorporated, as on average a situation causing unrealistic queuing behavior is not expected to occur frequently. Even with a number of cyclists higher than four waiting at the same time, average delays for waiting cyclists are expected to be influenced only slightly for the first additional waiting cyclists. Delays for cyclists that arrive at high speeds at the end of the queue and overtake all the waiting cyclists are less realistic, as in real life these cyclists would have to decelerate or even reach a full stop.

Putting a hard limit on the number of cyclists allowed to be in a queue at the same moment is a trade off between accuracy and usability. Allowing only two cyclists in the queue can limit the demand levels used for performance evaluation. The suggested limit is six to eight. Based on the assumption of a saturation headway of approximately 1.5s [124] this will add an error in delay of approximately 0.75s to the cyclists waiting in the queue, which is deemed acceptable. Future work could fully dissolve this problem by modelling the queue a vertical queue with a location moving upstream. The discharge rates for this queue could be based on the work from [124].

3.2.4. Mathematical model for car driver behavior
The movement model of the cars are based on the movement model of [117], who developed a car following model incorporating interaction with the red and green state of traffic lights for a single lane without overtaking. This model is chosen as it was the only car following model that was found in the literature overview presented in Section 2.3 that includes behavioral assumptions with regard to interaction with traffic lights.

The position of cars is determined the same way as for bicycles: by adding product of the current speed and the time step to the previous position (see Equation 3.10). For simplicity and to stay within the applicability range of the validated model, sorting lanes of the intersection are assumed to start at the system boundary and car drivers are assumed to enter the system on the correct lane designated for their destination. All vehicles $c^{car} \in C^{car}$ have their own speed $V^{v}[k]$ and enter the system at the speed limit v_{max}. Cars determine their new speed based on the current speed and acceleration. Acceleration is calculated based on a cars' current and optimal speed V_{opt}, which differs depending on a red or green traffic light. This occurs in accordance with the following Equations.

$$
\begin{aligned}
v^m[k] &= v^m[k-1] + a^v[k-1] * \Delta T \\
a^v[k] &= 0.85(V(\Delta x_m(k)) - v^m[k])
\end{aligned}
\tag{3.22}
$$

Where,
$V(\Delta x_m(k))$ = A vehicles' optimal velocity

The optimal velocity for a vehicle following another vehicle is defined in Equation 3.23. Vehicle length is part of this Equation, but this is assumed to be a fixed value of $2.5m$ in accordance with the assumption made in [117]. When a traffic light is red, optimal velocity is defined as a function of the distance between the car and the stop line l_n (Equation 3.24). These functions assume an uniform vehicle length of $2.5m$. [117]s model is made for straight traveling traffic. In order to apply the model to turning vehicles as well, a modification is made. The maximum allowed speed for cars making a turn is set to 30km/h. This value is the average of the pace boundaries of scenarios used by [128], who modelled two dimensional vehicular movement at intersections.

$$
V(\Delta x_{car}[k-1]) = \frac{v_{max}}{2} * (\tanh(0.13(\Delta x_m[k-1] - 12.5) - 1.57) + \tanh(2.22))
\tag{3.23}
$$

Where,
$x_{car}[k-1]$ = Previous position of the vehicle
$\Delta x_m[k-1]$ = Headway between current vehicle and its' predecessor
v_{max} = Speed limit $\in \{30, 50\}[km/h]$

$$
V(\Delta x_{car}[k-1]) = \frac{v_{max}}{2} * (\tanh(0.13(x_{light} - x[k-1] - 7.5) - 1.57) + \tanh(2.22)
\tag{3.24}
$$

Where,
$\Delta x_m[k-1]$ = Headway between current vehicle and its' predecessor
x_{light} = Location of traffic light

[117] also defined upper (L^m_{up}) and lower bounds (L^m_{low}) for the distance to the stop line from where the deceleration profiles are reliable in simulating the vehicles braking process. His model assumes all cars follow Equation 3.23. If the traffic light shows a red light, the first car between L^m_{up} and L^m_{low} starts braking in accordance with Equation 3.24. Cars that are downstream of L^m_{low} will keep on driving. These assumptions will be taken over in the movement model for this thesis. L^m_{up} and L^m_{low} are calculated in accordance with Equation 3.25. The formula for L^m_{up} is taken directly from [117], the lower bound is a quadratic interpolation of numerical results originating from Table 2 of the same paper. This interpolation has an R^2 value of 0.9994.

$$
\begin{aligned}
L^{car}_{up} &= \frac{\arctan h(\frac{2v_o}{v_{max}} - \tanh 2.22) + 1.57}{0.13} + 7.5 \\
L^{car}_{low} &= -0.014 * v_o^2 + 1.022 * v_o - 0.017
\end{aligned}
\tag{3.25}
$$

Where,
v_o = Initial speed when braking starts

3.2.5. Definition of control objectives

For simplicity, only a subset of the desires of cyclists identified in the literature review in Section 2.2.2 are included in the objective function. These two variables are the delay of cyclists and the number of stops cyclists have to make. These variables are chosen, as they represent the two main negative effects of intersections on cyclists very well, namely the additional travel time and the additional required effort.

Delay for cyclists and cars

In an ideal scenario, a cyclist will approach a traffic signal showing a green light. He/she will not be forced to diverge from the desired speed. This is the ideal situation to which the total time spent (TTS) in the system will be compared in order to find the delay. This formula holds for both bicycles and vehicles.

$$\begin{aligned} D^{cyc} &= TTS^{cyc} - v_{pref} * x_{exit} \\ D^{car} &= TTS^{car} - v_{max} * x_{exit} \end{aligned} \tag{3.26}$$

Number of stops

For cyclists one of the objectives that is controlled for is the number of stops they have to make. A simple counter, combined with a fixed threshold v_{stop} will be used to keep track of this value.

$$N^c_{stops} = \begin{cases} N^c_{stops} + 1, & if\, v^c[k-1] < v_{stop} \leqslant v^c[k] \\ N^c_{stops}, & \text{if else} \end{cases} \qquad \forall c \in C, \tag{3.27}$$

3.2.6. Model limitations and assumptions

The objective of this thesis is not to create a detailed movement model, but to design an intersection controller, of which a movement model is part. As described in Section 3.2, full creation of an movement model would be a thesis on itself. For this reason the movement models that are used are based upon validated literature as much as possible and careful attention was paid to the selection of movement models and the models are expanded upon with assumptions the author of this thesis deems acceptable to be made. Full validity cannot be ensured however. This subsection will elaborate on what additional assumptions are made parts of the used, validated models. Some of these assumptions are already described in earlier paragraphs. First an overview of these points is provided in the form of bullet points, followed by textual explanations of these assumptions.

One of the main conclusions was that movement models for cyclists and interaction of cars with traffic lights are limited. Therefore, the controller will be designed in a way that movement models can be easily interchanged with other, better models when these become available.

- Related to traffic light representation:
  - Yellow time is used as a stopping command, instead of as effective green.
  - No negative clearance time allowed.
- Related to the cyclist kinematic model:
  - Simplified red light running behavior.
  - No interaction between cyclists.
  - Only three types of cyclists to represent heterogeneity.
- Related to the car following model:
  - Anticipation based on the headway with a single predecessor.
  - No personal characteristics and identical driving behavior.
  - Lower speed in turns is enforced with a lower maximum speed.

Traffic lights

The assumption that yellow light is part of the stopping command could be debated, as some researchers like to work with the effective green concept, using as much of the yellow phase to move agents through the intersection and increase efficiency. It is argued that both these assumptions can be defended and none of the approaches are wrong. Reasoning on why this method is chosen is found in Section 3.2.2. However, when comparing performance with other controllers, this difference should be taken into account.

Another assumption is that conflicting traffic flows are not allowed to have a green and yellow light at the same time. In some countries it is common to allow this, and recently this has also has been implemented in some cities in the Netherlands. This may be allowed when the entrance time is larger than the exit time, resulting in negative clearance times (See Appendix C.1 for a full explanation). Inclusion of negative clearance times can reduce loss time and help increase intersection throughput. This may be especially beneficial for a structure free controller, as this controller can be expected to switch more often between the states of traffic signals. However, for simplicity no negative clearance times are used. Inclusion of negative clearance times would introduce another reason for differences in performance, increasing the difficulty of extracting causes of performance differences.

Bicycle movement model

No movement models were found in the literature that fully covered the movement behavior this thesis needs to describe. Therefore a model was developed, based on the movement model presented in [104]. This research proposes a model, validated with real life data, on how cyclists accelerate and decelerate when confronted with traffic lights without interaction with other cyclists. It lacks description on when these cyclists start braking and whether they obey or speed trough yellow and red lights. This thesis therefore must make assumptions on these matters. It is assumed that all cyclists obey the traffic light and behave in accordance with the kinematic model that allows them to come to a complete stop at the stopping line. This is not realistic as real life red light running behavior is far more complex [54]. The conclusions from this thesis should therefore not be directly translated to expected results when a controller like this would be implemented in real life, but used instead as an indication of what advantages could be achieved using structure free control.

Another major assumption in the model is the fact that bicyclists do not interact with each other. Assuming cyclist do not interact with each other is a step away from reality, as many studies have been done that aim to get insights in exactly how this interaction takes place and what influences cycling behavior. However, as the controller is scoped to function during unsaturated traffic flows, the number of times cyclists would get close enough for this interaction to have effect are expected to be low. The realism in the prediction will decrease however with increasing traffic flows. The lack of interaction allows cyclists travelling at different speeds to overtake each other, which is an important phenomenon to include and the current model allows for fast computation times, which is beneficial as real time control would be preferable. When better, more complete movement models for cyclists, that include interaction with traffic lights, other cyclists and realistic accelerating and decelerating behavior, are available, these models should be implemented instead of the current model.

The assumption of no interaction has a bigger effect on the queuing behavior and saturation rates, because queues are eminently a situation in which cyclists influence each other [124]. This is something that can be accepted, as long as the number of cyclists waiting for the red traffic light does not get much higher than two, as no interaction in the queue is a valid assumption for two cyclists waiting next to each other. Accuracy of the predictions decreases with increasing number of waiting agents. A large queue can also lead to a cyclist having a stopping point further upstream of the traffic light, something which currently is not taken into account. Measures that can be taken to include queuing behavior are described in the *How to deal with Queuing* subsection in 3.2.3. Currently this is not yet included as these situations are not expected to occur frequently, given the unsaturated traffic flows.

Validating the movement model that results from combining the model of [104] with new assumption regarding queuing and interaction would be an extensive task and may be a thesis in itself. This is the main reason for not including assumptions on these matters. As was mentioned in the beginning of this section, the focus of this thesis is not to create a valid movement model, but to create a structure free controller. Other research has been done that assumes the (simplified) movement of cyclists to be known and continue to work based on that assumption[25][26]. The author therefore goes forward with the explicit assumption that the movement model described in Section 3.2.3, accurately describes the cyclists movement. Note that the controller design is able to function with any movement model that describes travellers on individual level.

A final major assumption made in this thesis is the generalization in types of cyclists. As mentioned often throughout this report, one of the most important aspects of cyclists is the wide variety of personal characteristics exists and desires. This variety is reduced to implementation of three types of cyclists with a distinct combination of characteristics: fast, average and slow cyclists. See Section C.1.1 for the specific values for characteristics.

A less impact full assumption is the implicit assumption that cyclists on two crossing cycle paths do not interact with each other. A queue for a red light or arriving cyclists can block cyclists that have just crossed the car road and now have to cross the cycle path. This phenomenon is not included in the current movement model.

Car movement model
The model used to represent the movement model of cars is taken from [117]. This model is chosen because it was the only model that was found, describing both car following behavior and interaction with traffic lights. It too provides bounds between which distances from the traffic light the stopping behavior is accurate. The model is also calibrated.

The model is based on a car following model. Car following models can include a wide range of driving behavior and characteristics, ranging from further forward anticipation on multiple vehicles instead of one predecessor to a large variety of personal driving characteristics. The car following model used in this thesis is relatively simple: anticipation is only done based on the headway with a single predecessor and no personal characteristics are included. Vehicle length is assumed to be $2.5m$ and equal for all vehicles. This is a simplified version of reality, but one that is acceptable to make, provided this model was the only model found to incorporate validated interaction with traffic lights.

The model assumes vehicles move on a single lane without overtaking. The traffic signals function for traffic lanes only. An additional assumption has been made to incorporate turning behavior by enforcing a lower speed limit downstream of the traffic light. A realistic lower speed limit is taken based on the validated model of turning cars by [128]. This assumption could lead to unvalidated decelerating behavior when a car approaches and passes a green light at $v_{max} = 50km/h$ and then has to decelerate to $30km/h$. This part of the model is not validated, but is not expected to lead to a situation where conclusions cannot be drawn due to this assumption.

Because the model only assumes a single lane without overtaking, the assumption is made that the sorting lanes are infinitely long up to the system boundary, and cars enter the system at the lane corresponding with their destination. Although this is not realistic, as sorting lanes for turning traffic often are shorter, this assumption is made to prevent inclusion of assumptions on lane changing models that would need to be re-validated.

3.3. Controller design

Section 2.4 provides an overview of possible control methodologies, and their advantages and disadvantages. The knowledge that is gathered with this literature review ,is used to choose the best suited control method for the traffic system model described in Section 3.2. Simulation based control is deemed the best suitable control method for the scope of this thesis, for the following reasons.

Rule based control is not used, because the inflexibility of this method is seen as too big of a disadvantage. The performance of the controller is very dependent on the environment in which the rules are used. The rules that are effective for a given intersection layout, may turn out to be very ineffective when other traffic lanes are added, or when traffic demand changes. Model based control (MBC) and data-driven control(DDC) are more flexible. Even though the performance of the controllers can be influenced by the environment, MBC and DDC include optimization components, which allows for the ability to better adapt to changing circumstances.

Model based control is preferred over DDC for two reasons. First of all, DDC introduces errors in predictions, that are difficult to control for. If the performance of the controller is evaluated for variables like data quality and connected vehicle penetration rate, it is important to have control over the extend of prediction errors. This is possible with MBC, but not with DDC. Note that for real world applications and testing, DDC is deemed the better choice. This is because of its' capability to predict complex human behavior significantly better than MBC [94]. However, the design and testing of initial prototypes of the structure free controller, benefit greatly from better explanatory value and the ability to control for errors. The second reason why MBC is preferred over BDD, is that the potentially long training time is seen as too big of a disadvantage, given the limited time scope of this thesis. Especially because a short training time may result in poor predictions and therefore poor performance of the controller.

Because long computation times are one of the main disadvantages of simulation based control, a heuristic method will be used. Heuristic methods provide guidelines on how to vary input parameters, with the result of a more efficient search process through the solution space compared to random searches. If variation of a parameter results in a better performance, the method will investigate neighboring solutions of this solution. Implementation of regular, simple heuristic methods for this intersection control problem is difficult, because of the nature of the control problem. The possible solutions, signal plans in the form of a matrix of ones and zeros, do not allow for step wise variation of the input parameters, because of the large interdependency of the individual matrix entries. This dependency is the result of the wide set of constraints on signal plans, like the minimum green time, protected conflicts, clearance time and others. Therefore, changing any of traffic light state input variables ($s[i,k]$) is likely to result in an infeasible solution. Instead, solutions should be generated by means of algorithms or decision trees that consider these constraints.

These algorithms must be able to generate feasible random solutions, but must also be able to adapt or combine solutions that perform well. Genetic algorithms (GA) generate sets solutions, evaluate the performance of the solutions, and combine or adapt the best performing solutions for the next iterative step and are therefore very suitable as a heuristic method for this research. Newly created algorithms are required, as no such algorithms have been found in literature. The GA may include a rule based solution in the first generation, to provide the algorithm with a guaranteed, reasonably well performing solution that speeds up the process even further. The designed, structure free genetic algorithm controller will from here on be referred to as SFGA.

The remainder of this section is structured as follows. Section 3.3.2 provides a high level description of the functioning of the controller. Then Sections 3.3.3 and 3.3.4 describe the solution generation and evaluation process respectively.

3.3.1. Interaction between the controller and the traffic system model

The controller must determine the best signal plan for a simulated scenario with duration T_{max}. In this main simulation, travellers react to the signal plan that is decided upon by the controller. At the start of the main simulation, this signal plan is still undefined, but every $t_{control}$ (t_c) seconds the controller decides upon the plan for the next t_c seconds. In other words, the control problem is formulated as a rolling horizon (RH) problem. This is visualized in figure 3.5 and will be explained in more detail now. The procedure is provided in pseudo code in Algorithm 1.

At the start of the main simulation, the first t_c seconds of the signal plan of the entire simulation are defined as the traffic lights being all red. Every t_c seconds, the controller chooses the signal plan for the next t_c seconds by means of simulation based optimization over the prediction horizon T_{RH}. The first t_c seconds of the prediction horizon are already fixed, as this part of the signal plan has already been decided upon in the previous control moment. This fixed part of the signal plan represents the time available for computation, were the controller to be implemented in real life.

Using the fixed part of the signal plan as starting point, new, feasible, signal plans are created. Simulations are used to evaluate the signal plans. The state of the main simulation, at the start of the RH window, is used as the starting point. The RH simulations are performed entirely independent of the main simulation, and evaluate the effect of generated signal plans over the duration of T_{RH}. Prediction errors can be included if this is deemed necessary (see Appendix B, however this is not done in this research. After deciding on a signal plan, which follows the process described in Section 3.3.2, the first t_c seconds of the next prediction horizon are fixed and included in the signal plan of the main simulation. This entire process is repeated until the main simulation has ended.

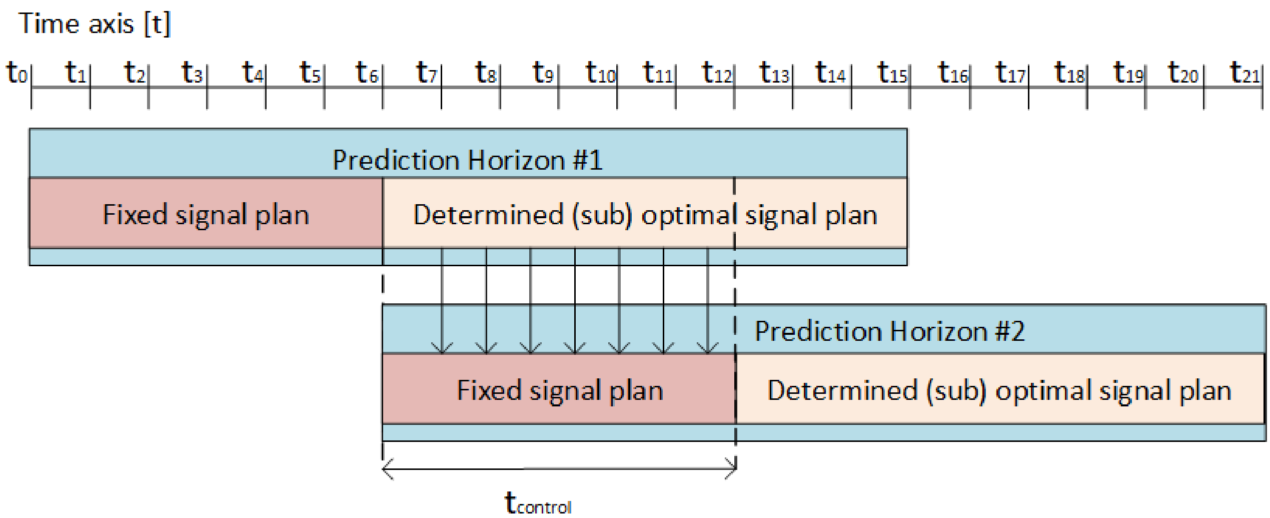


Figure 3.5: Rolling Horizon and control interval

Scenarios for the main simulator are generated by means of a scenario seed. This seed determines at what moment in time travellers enter the system, the personal characteristics of these travellers, and in which traffic lane they spawn. The RH simulations follow the same scenario as the main simulation.

Algorithm 1 Interaction traffic system model and GA controller

Initialize:
  Signal plan for main simulation. First $t_{control}$ seconds all red, remainder filled with NaNs
  Scenario for main simulation
for all $k \in \{k_0, k_1, k_2, ..., T_{max}/\Delta T\}$ **do**:
  new travellers enter the system
  update main simulator using traffic system model
  if k corresponds with multiple of $t_{control}$
    GA control procedure: ▷ Full GA procedure in Section 3.3.2 and Algorithm 2
      Generate solutions
      Initiate RH simulations, starting with the traffic situation of current time step
      update main signal plan with first $t_{control}$ seconds of the best performing RH signal plan

3.3.2. Model Based Control using a GA

The controller functions as follows. At the start of each control moment, a fixed number N_{pop} (Population size) of random solutions (Signal plans S, composing of traffic signal states $s[i,k] \in S$, see Equation 3.2) are generated. The effect of this generation of solutions is determined, by simulation using the traffic system model described in Section 3.2. After evaluation, a predefined number of the best performing solutions (N_{keep}) are stored and used to generate new solutions. Variations of the best performing solutions are made by means of altering (Mutating) one, or combining two solutions (Crossover). Every time a random selection is made to decide which of the kept solution(s) are used.

The newly formed set of solutions, is complemented with randomly generated solutions up to the population size. The second generation is evaluated, and this process is repeated N_{gen} times. Due to randomness, it may be possible that the controller does not generate a reasonable good solution within the given number of generations. In order to guarantee a minimal performance, one of the solutions in the first generation is generated using a rule based system. The whole process is visualized in Figure 3.6 and provided in pseudo code in Algorithm 2.

Algorithm 2 GA controller algorithm

```
Initialize:
    Fixed part of the signal plan
    Starting point for RH simulations from main simulation
for all N_generation ∈ {1,2,3,...,k_0,k_1,k_2,...,N_generations} do:
    if N_generation = 1 do
        Generate one rule based solution and N_pop − 1 random solutions
    else do
        Generate N_pop solutions by means of mutations, crossovers and random solutions in accordance
            with the M/C/R rate.                ▷ M/C/R rate for case study provided in Section 4.1.4

    Simulate all solutions for duration T_RH
    Determine Objective value for each of the solutions
    Select the best N_keep solutions as input for the next generation

update signal plan of main simulation with the first t_control seconds of the newly determined signal plan
```

3.3.3. Solution generation

The solution generation process uses a signal plan, with the length of the minimum green time, a starting point to create feasible solutions of T_{RH} seconds. Genetic algorithms generally entail a combination of random solution generation, mutations and crossovers. Algorithms for these solutions will be discussed in this section. Before that, Section 3.3.3.1 explains some ways of adapting solutions that should be included in the mutations and crossovers.

The random solution generation algorithm is the most generic algorithm of the four. Therefore this one is explained first in Section 3.3.3.2. Sections 4,3.3.3.4 and 3.3.3.5 then explain the workings of the two mutation and the crossover algorithm. Section 3.3.3.6 finally elaborates on the rule based solutions. For the mathematical formulation of the traffic light related mathematical formulation and constraints see Section 3.2.2. For the GA parameter values and solution generation probabilities, used in the case study, see Section 4.1.4.

3.3.3.1. Solution algorithm requirements

In practice, a number of decisions can be made to make variations of signal plans. Genetic algorithms make use mutation and crossover algorithms to make variations of existing solutions, without breaking any of the constraints. This section will discuss what decisions can be made to make variations in signal plans in traffic engineering terms, which is then followed by whether this can be best captured in a mutation or a crossover algorithm.

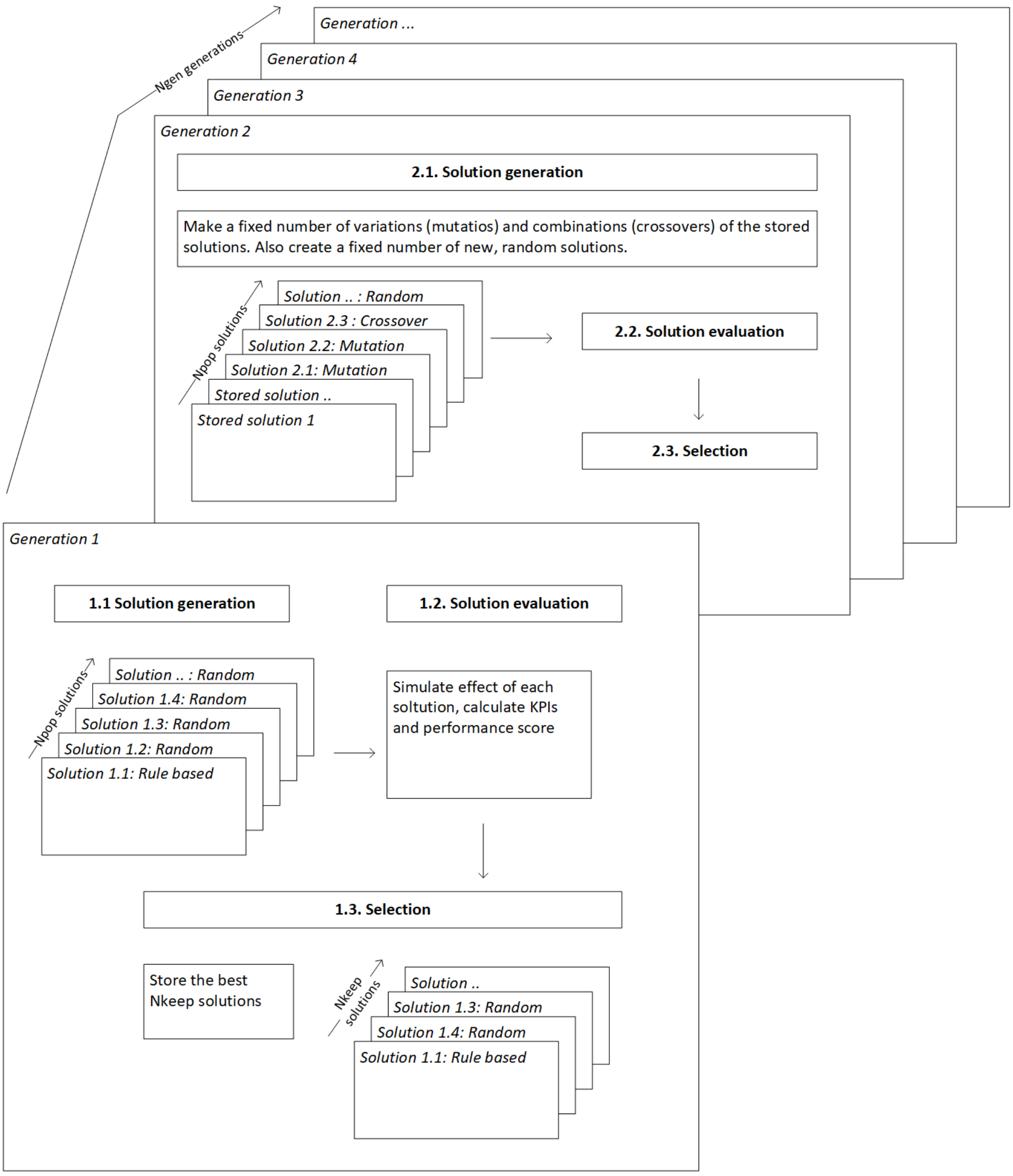


Figure 3.6: Genetic Algorithm

The sequence of traffic lights that show a green light, should be investigated to see what sequences result in a good performance. This sequence will be referred to as a rough signal plan for the remainder of this chapter. Finding a rough signal plan is important, as it allows for a priority sequence to be determined. The combination of traffic lights with the most travellers benefiting from a green light can be served first, followed by the traffic lights second most benefit and so on. Combinations of well performing rough signal plans could be mixed to achieve faster convergence to the optimal sequence.

In addition to the sequence of traffic lights, the exact timing of the change between subsequent green periods has to be determined. It may be beneficial to allow a traffic light to be green for a couple of seconds longer, if this allows a traveller to cross that otherwise would face a red light and would have to wait until a new green period starts. A green time may be ended earlier, if there are no travellers making use of this green time and the green time prevents other traffic lights to show green. Changing the timing of switches between subsequent green times of conflicting traffic signals can be achieved by earlier starts of green, green time extensions and green truncation. This must be done in a way that the changes in green time of one traffic light, do result in conflicts with other traffic lights or the minimum green time constraint. Ideally a green time would be shortened enough, that another movement can fit between two subsequent green periods.

All these phenomena can in theory be achieved by mutation algorithms, crossovers and random solutions. However, not all not all phenomena can be guaranteed with each type of algorithm. Prolonging and shortening green time only occurs by crossovers, when the two parent solutions have similar rough signal plans, but differ in green time duration. As this is not always the case with two parent solutions, changes in exact timing of changes between subsequent green periods will be enforced in a mutation algorithm.

Provided it does not conflict with any constraints, green times can be prolonged and shortened or reduced at the start and at the end of a green time. Both should be incorporated in the mutation algorithms. Shortening the green time at the end of one green period, may allow for an earlier start of the green time of another traffic light. In the same way, extending green may require a delayed start of the green for another movement. Therefore, only two mutation algorithms are required to capture earlier start of green, later start of green, earlier end of green and green time extension. Every time a mutation is performed, a random choice is made between the two.

Creating different rough signal plans will be done by means of crossovers. If a solution scores well because it allows a lot of agents to pass a green light in traffic direction A, and another scores well because it does the same with direction B, a crossover will combine directions A and B as long as they do not conflict or target have both green periods follow each other. Note that again, this can occur with random generation and mutation as well, but crossovers are expected to achieve this behavior by default instead of by chance.

3.3.3.2. Random solution generation algorithm

The random solution generation algorithm is the most generic of the four different solution generators. It's workings are explained in this section. A visual representation can be found in Figure 3.7. The text in this section will refer to steps in this figure. Algorithm 3 shows the pseudo-code and mathematical formulation.

As input, the algorithm uses the fixed signal plan, which are already filled with either zeros or ones. The remainder of the matrix entries are empty, or not yet defined (Step 0). The algorithm uses knowledge of the system and logic, to fix matrix entries of which it can be known that a zero or one is necessary in order for the solution to be feasible (1.1-1.4 in Figure 3.7). This concept, similar to the functioning of the so-called Japanese Puzzle or Nonogram, will be explained in more detail in the next paragraph. When this is done, one of the remaining empty spots is randomly chosen and gets assigned the value one(1.5). This process is then repeated until the matrix is fully filled.

The knowledge of the system, represents fixing matrix entries of which you can determine their value, given that the solution must be feasible and adhere to the constraints. First ones are placed based on the minimum green time constraint (1.1). If a traffic light shows red and then turns green, a feasible solution requires the next G_{min} seconds to be green as well, allowing these entries to be fixed. Note that this can always be done as long as a traffic light has shown red less then G_{min} seconds before the green. For example, if a light was red two seconds before it shows green, it must also be green for the next $G_{min} - 2$ seconds (2.1).

Next, zeros are placed on empty locations based on the conflict (1.2) and clearance time (1.3) constraints. If a traffic light is green, a feasible solution requires all conflicting directions to be red at the same time step. Similar for clearance time, if direction A shows green, direction B must remain red up to at least the clearance time.

After a couple of iterations, it can occur that the signal plan for a traffic light has an empty gap between two red times (3.1-3.3). If this gap is smaller than the minimum green time, it is not possible for the light to show green in this period and therefore must be red (3.4).

3.3.3.3. Green time extension mutation

This section will explain the algorithm that performs the Green time extension mutation. A visual representation can be found in Figure 3.8. The text in this section will refer to steps in this figure. Algorithm 4 shows the pseudo-code and mathematical formulation. Only finding the mutation location and changing a zero from a one is straightforward. However in many cases this will lead to infeasible solutions, as the extended green time 'eats away' from a clearance time or yellow time. Therefore a slightly more sophisticated algorithm is required.

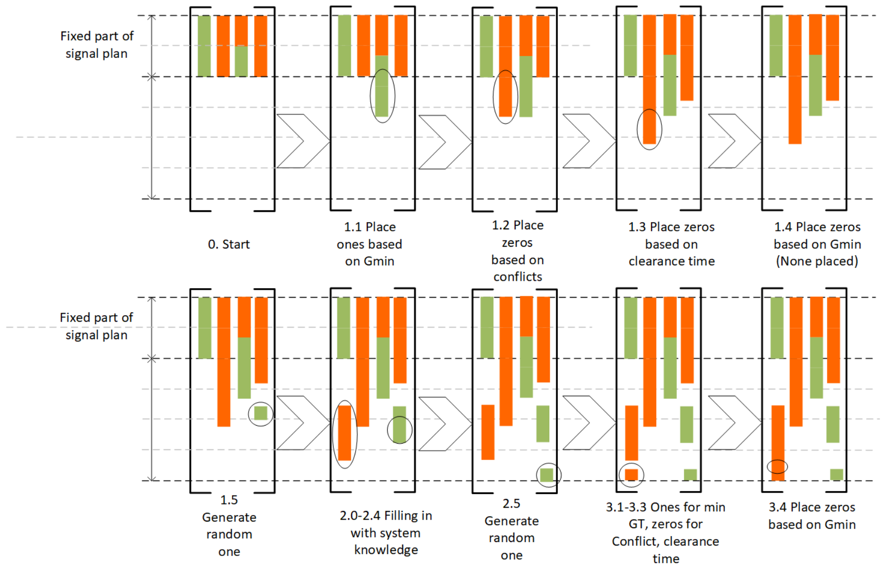


Figure 3.7: Genetic Algorithm

The extension algorithm searches for matrix entries that represent the start of a red time i.e. a zero below a one in the parent. A condition for this is that the red time start lies after the first fixed G_{min} seconds, as a mutation cannot occur here (0. in Figure 3.8). A random start of red time (k_n, f_n) is chosen. Then all the rows up to k_n are copied from the parent to the child, every row below that is kept empty. A one is placed in the mutation location. From this point on, the algorithm will row by row fill the remainder of the child solution. This is done by first using system knowledge to place ones and zeros in all locations of it is required for a feasible solution. See the section on random solution for a more detailed description of how these mechanics work. After this, the remaining empty entries earliest row of the child solution are copied from the parent solution. These two steps are repeated until the matrix is fully filled. Alternating between system knowledge and copying from the parent ensures no constraints are broken but at the same time keeping as much genetic information as possible.

As a final note, the reader should be aware that this algorithm does only extend green time with steps of 0.5 seconds. For extension of a longer duration, this mutation needs to performed multiple times in successive generations.

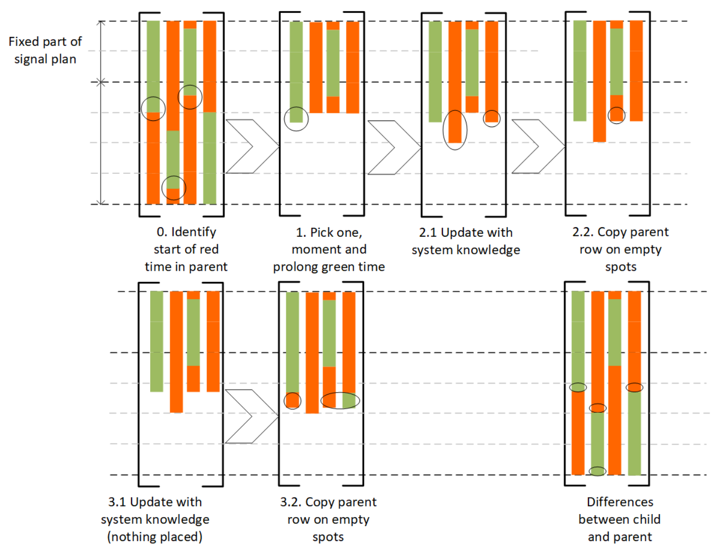


Figure 3.8: Green time extension mutation. Step 0 shows a parent solution. Other steps illustrate the generation of the child solution

Algorithm 3 Random solution generator

Initialize sets:
  Empty spots E: $e(k, f) \in E$
  Set of ones: $o(k, f) \in O$
  Set of zeros: $z(k, f) \in Z$
  Discrete time steps up to G_{min}: $D \in \{0, 1, 2..G_{min}\}$
while $E \neq \emptyset$ **do**:
  for all $o(k, f) \in O$ **do**: ▷ Place ones based on G_{min}
    for all $d \in D$ **do**:
      $S(x, f) = 1$ for $x \in \{k, k+1...k+G_{min}-d\})$
      $S(X, f) = 1$ for $x \in \{(k+G_{min}-d), (k+G_{min}-d-1), .., k$
  update E, O
  for all $o(k, f) \in O$ **do**:
    $s(k_2, f_2) = 0$ if $p(f, f_2) = 1$ ▷ Place zeros based on conflicts
    $s(k, f_2) = 0$ if $k_2 - k_1 < Cl(f, f_2)$ ▷ Place zeros based on clearance time
  update E, Z
  for all $f \in F$: ▷ Place zeros based on G_{min}
    for all $\Big(o(k_1, f_1), o(k_2, f_1)\Big) \in \begin{pmatrix} n \\ k \end{pmatrix}$:
      $s(k_1 : k_2, f) = 0$ if $S(k_1 : k_2, f) \in E$ and $k_2 - k_1 < G_{min}$
  update E
  N = random index from E ▷ Generate a random empty location and place a one
  $e_n(k, f) \leftarrow 1$
  update E, O, Z

Algorithm 4 Green time extension mutation

Initialize:
  $s_p(k, f) = \{0, 1\} \in S_{parent}$
  $s_c(k, f) = e(k, f) \in S_{child}$
  $R = \big\{(k, f)$ if $s(k-1, f) * s(k, f) = 0 \wedge s(k, f) = 0 \wedge k > 6s\big\}$: ▷ Set of start of red time
  $n(k_n, f_n)$ ▷ Randomly chosen start of red time to postpone
  $S_{child}(0 : (k_n - 1), f) \leftarrow S_{parent}(0 : (k_n - 1), f)$
  $S_{child}(k_n, f_n) \leftarrow 1$
for all $k_{copy} \in \{k_n + 1, k_n + 2, ...k_{max}\}$ **do**:
  update S_{child} with system knowledge, E
  $S_{child}(k_{copy}, f) \leftarrow S_{parent}(k_{copy}, f) \forall (k_{copy}, f) \in E$

3.3.3.4. Earlier end of green mutation

This section will explain the algorithm that performs the Green time extension mutation. A visual representation can be found in Figure 3.9. The text in this section will refer to steps in this figure. Algorithm 5 shows the pseudo-code and mathematical formulation. Only finding the mutation location and changing a one to a zero is straightforward, however this ignores the fact that the reduced green time may allow another traffic light to start its' green time earlier. The proposed algorithm allows for this.

The green time reduction algorithm identifies all the matrix entries that correspond with the end of a green time. Two constraints are that this entry must be be after the first fixed G_{min} seconds of parent solution, and the green period must be more than G_{min} seconds long, as green time reduction would otherwise lead to a conflict with the minimum green time constraint (0. in Figure 3.9). A random pick is made from this selection, and is changed from red to green (1.). Then, all the matrix entries that conflict or fall within the required clearance time window, are cleared (3.). System knowledge is used to fill in the matrix locations that are required to be red (3) and from that moment on, the algorithm iterates between generating a random one (4.1) and updating the matrix with system knowledge (4.2) until the entire matrix is filled.

This algorithm does only reduce green time with steps of 0.5 seconds. For more reduction, this mutation needs to performed multiple times in successive generations. Because the algorithm allows other traffic lights to start showing green earlier, this type of mutation will not allow an entirely new direction to be introduced between two green times.

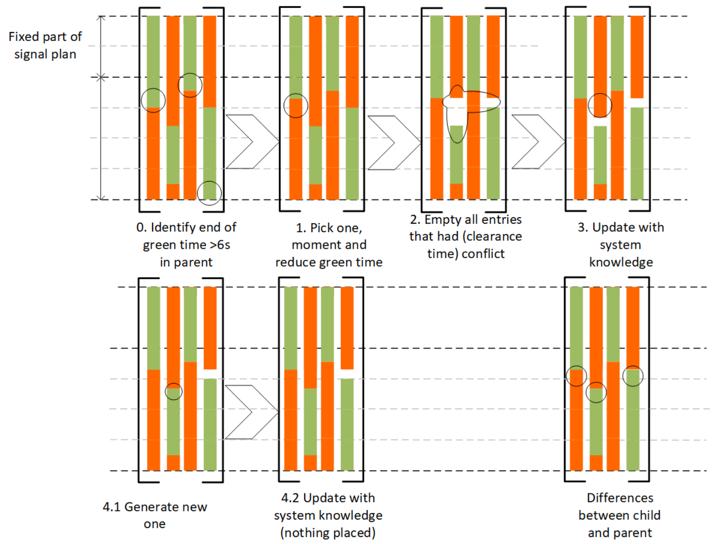


Figure 3.9: Green time reduction mutation. Step 0 shows a parent solution. Other steps illustrate the generation of the child solution

Algorithm 5 Early end of green mutation

Initialize:

$s_c(k,f) = \{0,1\} \leftarrow S_{parent}$

$G_{end} = \big\{(k,f)\big\}$ if

$\big(s(k,f) = 1 \wedge k = k_{max}\big) \vee \big(s(k,f) * s_n(k+1,f) = 0 \wedge s(k,f) = 0\big)$

$k > 6[s]$ and

$s(k-6[s],f) = 1$ ▷ Set of end of green time

$n(k_n, f_n)$ ▷ Randomly chosen start of red time to postpone

$S_{child}(k_n, f_n) \leftarrow 0$

$S_{child}(k,f) = e(k,f)$ if $p(f_n,f) = 1$ ▷ Clear entries based on conflicts

$S_{child}(k,f) = e(k,f)$ if $k_2 - k_n < Cl(f_n,f)$ ▷ Clear entries based on clearance time

while $E \neq \emptyset$ **do**:

$m(k_m, f_m)$ ▷ Place random one

$S_{child}(k_m, f_m) \leftarrow 1$

update S_{child} with system knowledge, E

3.3.3.5. Crossover algorithm

This section will explain the algorithm that performs the Green time extension mutation. A visual representation can be found in Figure 3.10. The text in the following paragraphs will refer to steps in this figure. Algorithm 6 shows the pseudo-code and mathematical formulation. The algorithm aims to formulate an child solution from two parents, while keeping as much genetic information from both the parents as possible.

The first G_{min} seconds of one of the parents is taken as the fixed part of the child solution. Note that it does not matter which of the two parents is chosen, as the first G_{min} seconds are identical by definition. The matrix is updated with system knowledge (Indicated with 0. in Figure 3.10). A random pick is made from the matrix entries that are empty in the child solutions and have a one in a parent solution. A one is placed on that location in the child (1.1.). Then, the child is again updated with system knowledge, ensuring no constraints will be broken later on. Alternating between the two parents, this process repeats until there is no longer any overlap between the locations of ones in either parent, and empty spots in the child. At this point, it is no longer possible to use genetic information of any of the parents to fill the matrix of the child solution. If at this point the child solution still has empty spots, random generation is used to fill the remainder of the matrix.

The main purpose of crossover algorithms is to determine the sequence of traffic lights that should show a green light, in other words a rough signal plan. This is done by combining two well performing parent solutions. By randomly taking a one from each of the parents, a combination of the plans is constructed. The intermediate updating of the child solution with system knowledge ensures none of the constraints get broken. It can occur that both parent solutions have quite similar different rough signal plans. This makes the algorithm ineffective at generating a new signal plan. In this case, the crossover algorithm will result in a solution that alters the exact timing of switches between the green time of two subsequent conflicting traffic lights. It may speed up this process compared to mutation algorithms, as mutation algorithms extend or reduce green time step wise, while the crossover algorithm results in a randomly picked moment, somewhere between the timings of the two parent solutions.

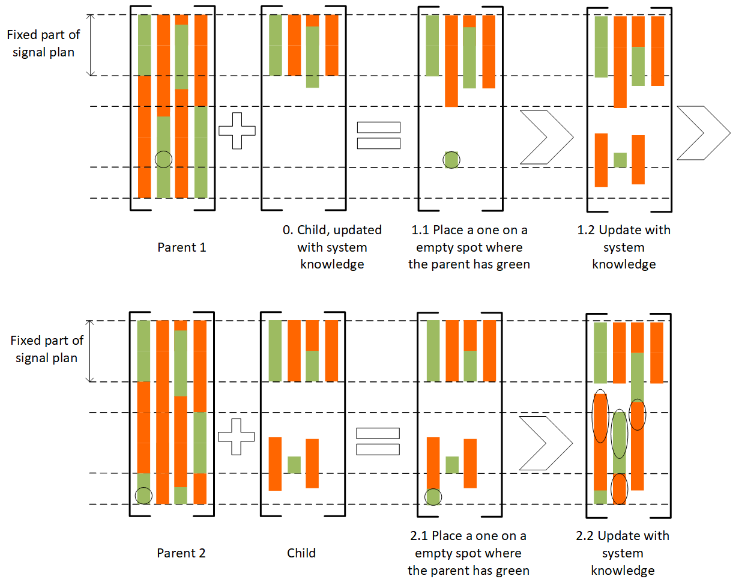


Figure 3.10: Crossover algorithm

Algorithm 6 Crossover algorithm

Initialize:

$S_{parent_1}, S_{parent_2}$

$s_c(k,f) = \{0,1\} \leftarrow S_{parent_1}(k,f)$ for k < 6s ▷ Fix first six seconds of the solution

update S_{child} with system knowledge, E ▷ Also update empty subset of S_{child}

$N_{iterations} = 0$

while $E \neq \emptyset$ **do**:

$S_{Options1} = \{(S_{parent1} \cap E\}, S_{Options2} = \{S_{parent2} \cap E\}$

if $S_{Options1} \neq \emptyset$ and $S_{Options2} \neq \emptyset$ **do**:

if $N_{iterations}$ is even $\vee$ $S_{Options2} = \emptyset$ **do**:

$n(k_n, f_n) \in S_{Options1}$

elif $N_{iterations}$ is uneven $\vee$ $S_{Options1} = \emptyset$ **do**:

$n(k_n, f_n) \in S_{Options2}$

else do:

$n(k_n, f_n) \in E$ ▷ Select a random empty location

$S_{child}(k_n, f_n) \leftarrow 1$

update S_{child} with system knowledge, E

3.3.3.6. Rule based solution generation

A rule based solution is used to generate one solution in the first generation. This is common practice with genetic algorithms, and aims to speed up the convergence process, as rule based solutions generally tend to provide a reasonable performing solutions as a starting point for mutations and crossovers [55]. No genetic algorithms in intersection control research have been found to apply this method however.

The rule based system used for solution generation is based on the objective of this thesis: prioritizing the desires of cyclists. Therefore the solution generation follows the principle of providing cyclists with a green light, unless one of two conditions are met. Rough predictions are made on the arrival of cyclists, with error margins up to one and a half seconds compared to a perfect prediction. When a gap in arrivals, larger than the minimum green time for cars is identified, the respective cyclist traffic light will turn to red and allow cars to cross. Green time is truncated after the minimum green time has passed, but may be extended by the green time extension or crossover algorithms in successive generations. Cars are also allowed to cross, when a car driver otherwise will be waiting for more than the maximum allowed waiting time.

The solutions generated by the rule based system did not tend to outperform the solutions that were randomly generated. Therefore it was decided to exclude this solution generation process later on during the research.

3.3.4. Evaluation and selection

After the generation phase, all solutions of the current generation are simulated over a time horizon of T_{RH} seconds, to determine the effect of signal plans on the traffic system. The evaluation and selection procedures used in the controller, are fairly trivial for a genetic algorithm [55].

For each simulation a run, the delay, waiting time and number of stops of all travelers are determined and a performance cost R_c is calculated, representing a weighed cost for the control objectives delay and number of stops (See Section 3.2.5). Note that a lower cost corresponds with a better performance. The equation for calculating R_c is provided below. The objective function also includes a penalty for travellers exceeding the maximum waiting time. The weight of this penalty is orders of magnitude larger than the other weights, causing signal plans that result in violation of this constraint to not be selected for the next generation. Delay and number of stops are calculated with history in mind: delay experienced before the start of the rolling horizon window is included.

$$R_c = \sum^{cyc} \left(W_{cycdelay} * D^{cyc} + W_{stop} * N_{stop}^{cyc} \right) + \sum^{car} W_{cardelay} * D^{car} + W_{maxwaitingtime} * N_{maxwaitingtime} \tag{3.28}$$

Where,

R_c = Run performance cost
D^{cyc} = Delay of a single cyclist ($[s]$)
$W_{cycdelay}$ = Weight for cyclist delay ($[s^{-1}]$)
N_{stop}^{cyc} = Number of stops made by a cyclist
W_{stop} = Weight for a stop of a cyclist
D^{car} = Delay of a single car driver ($[s]$)
$W_{cardelay}$ = Weight for car driver delay ($[s^{-1}]$)
D^{cyc} = Delay of a single cyclists
$W_{maxwaitingtime}$ = Weight for travellers exceeding the maximum waiting time ($>> W_{cycdelay}, W_{stop}, W_{cardelay}$)
$N_{maxwaitingtime}$ = Number of travelers that exceeded the maximum waiting time

The best N_{keep} performing solutions are be carried on to the next generation and used as input for the solution generation algorithms. Note that it may occur that duplicate solutions exist, and this selection procedure should not carry over multiple identical solutions. Run performance cannot be used as an indicator for uniqueness, because two different solutions can have the same score. For example, if if two solutions allow traffic in one movement cross, by the first solution does so with double the green time, the solutions can have an identical run performance.

To distinguish the overlap between two solutions, the overlap factor $O_f = \in [0,1]$ is introduced, where a 0 indicates no overlap at all and a 1 indicates a fully identical solution. The overlap factor between two solution matrices S_1 and S_2 is described in Equation 3.29. Element wise multiplication of the two matrices returns the value one only when both solutions have a one in that location. Doing the same after subtracting 1 from both matrices, returns a one when both solutions have a zero in the same location. Summation of both products and division by the size of the matrix returns a value between 0 and 1 that provides a score of similarity.

$$O_f(S_1, S_2) = \frac{\sum S_1 \odot S_2 + \sum (S_1 - 1) \odot (S_2 - 1)}{f_{max} * k_{max}} \tag{3.29}$$

The algorithm first determines how many unique scores result from evaluating the current generation. Then it goes though these scores one by one, storing solutions until the best N_{keep} solutions have been stored. This means that solutions that performed well in previous generations, are stored until there are more than N_{keep} better performing solutions. For each score, it is determined how many solutions have that score. If there is only one, this solution is stored and the next score is investigated. If there are multiple, the overlap score is used to identify how many unique solutions exist. All the unique solutions get stored and, unless now more than N_{keep} solutions are stored, the next score is evaluated. When multiple, different solutions have the same score it can result in more than N_{keep} solutions being stored. Therefore, a check is implemented that removes all but the first N_{keep} solutions.

4
Evaluation Framework

This chapter will discuss evaluation framework, used to evaluate the performance of the structure free controller. The evaluation is performed in two steps. In the first stage, the structure free controller is compared to a benchmark controller. In the second stage, the performance of the structure free controller is evaluated for different prioritization levels. These two stages of comparison allows for distinction of the differences in performance caused by controller design and by prioritization of cyclists.

Section 4.1 discusses the experimental setup. Then Section 4.1.6 discusses the evaluation metrics and the expected results for the first stage comparison. Section 4.2 then does the same for the second stage of comparison.

4.1. Experimental setup

Performance evaluation of the SFGA controller will commence in two stages. In the first stage, the performance of the controller is benchmarked against vehicle actuated control (VA). The structure free controller will weigh the desires of car drivers and cyclists equally. This configuration will from here on referred to, as the Basic Structure Free GA Controller or SFGA. The first stage of comparison establishes a baseline for the performance, that can be attributed to controller design. In each simulation run, the parameter setting for both controllers are fixed to value discussed in Sections 4.1.3 (VA) and 4.1.4 (SFGA).

In the second stage of comparison, different combinations of cyclist prioritizing weights are evaluated in order to draw conclusions on how prioritization of cyclists influences the performance of the structure free controller. Configurations of the structure free controller that prioritizes cyclists, will be referred to as the Prioritizing Structure Free GA Controller or SFGA. Parameter settings of the SFGA are provided in Section 4.1.4.

4.1.1. Simulation environment

As was discussed in Chapter 3, the controller is evaluated by means of a simulation based case study. In order to have as much freedom as possible in adaptation of the simulation environment and interaction between controller and simulation environment, no available software packages such as Vissim are used. Instead, a custom micro simulation environment is created in Python. Another benefit is that this also allows for multiple simulations to be run simultaneously on the DelftBlue Supercomputer [28], which does not allow for Vissim to be installed.

Scenarios are defined by means of a seed number. In each scenario, traffic is generated based on simulation duration, traffic demand and mode split. The number of to be generated travellers is determined, from the the simulation duration and the traffic demand. Every traveller is assigned a time stamp at which they enter the system, following an uniform distribution, and a traffic modality, following probabilities in accordance with the modal split. Finally, all cyclists are distributed uniform over all cycle paths of the infrastructure layout and all car drivers are distributed uniform over all the car lanes. After generation, all travellers follow the traffic system model presented in Section 3.2.

The intersection layout used in the simulation environment is provided in Figure 4.1). For simplicity sake, the intersection layout has been chosen to be as simple as possible, while meeting criteria that prevent the controller to be forced into cyclic control behavior. The included movements must require at least three different conflict groups. Additionally, the movements must allow for the three different conflict groups to be constructed in different compositions.

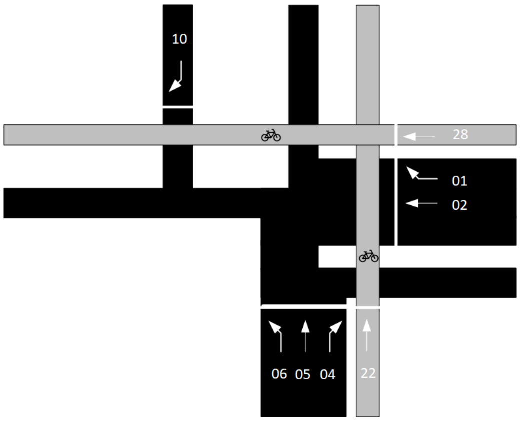


Figure 4.1: Intersection layout of the case study

4.1.2. Simulation run parameters

This section will discuss parameter setting for the experimental setup. These parameters are summarized in Table 4.1. For an overview of all the traffic system model parameters that are used in this case study, see Appendix C.

Table 4.1: Experimental setup overview

Variable	First stage	Second stage
Simulation time	180s	180s
Modal split (Cyclists)	0.5	0.5
Turn rate (Cyclists)	0.3	0.3
Saturation rates	{15%, 30%, 45%}	{15%, 30%, 45%}
Scenarios evaluated (per variable combination)	14	7
Weight car delay	1	1
Weights cyclist delay	1	{1, 1.7, 3.3, 5}
Weight cyclist stops	0	{0, 15}
Structure-free genetic control setup	Section 3.3. Tuning in Section 4.1.4.	
Benchmark controller	VA (Section 4.1.3)	-
Prediction quality	Perfect	Perfect

Simulations in both the first and seconds stage comparison cover a scenario with a duration of 180 seconds. This value is chosen mainly with regard to limiting computation time. Unless said otherwise, the modal split in simulations is Cyclist/Car = 0.5. In other words, half of the travellers travel by car and the other half by bicycle. This value is based on the average modal split for trips between one and seven kilometres in a Dutch urban cores [57]. This value is chosen as it fits the use cases of the controller, described in Section 1.1. Note that there is a large variety in the mode split at intersections, both in terms of different geographical locations, as well as in differences in time of day.

Cyclist heterogeneity is included by means of three different types of cyclists with different personal characteristics (See Appendix C). Thirty percent of the cyclists travelling on the cycle path that allows a left turn do make a turn. This value is arbitrarily chosen, as no theoretical support for this value was chosen in the literature and this intersection is not based on any real life infrastructure, preventing the use of historical data to determine the turn rate.

The performance of both controllers will be compared with regard to three traffic demand levels, represented as the saturation rate: the percentage of the intersection capacity. The intersection capacity is approximately 7000 travellers per hour, divided roughly equal between cars and cyclists. The resulting saturation rates, used for evaluation are 15%, 30% and 45%. Because both traffic demand, due to a mode split of 0.5, and intersection capacity are divided equally between the modes, the saturation rates for both separate modes are equal to the saturation rate of the entire intersection. The three saturation rate levels are chosen because of applicability limitations caused assumptions with regard to interaction between cyclists in the traffic system model (Chapter 3.2). At traffic saturation levels larger than 45%, the assumption on no interaction between cyclists starts introducing unrealistic results. The interested reader can find more in this in Appendix C.2.

In the first stage comparison, the only parameter that is varied is the traffic saturation level. As explained in the previous paragraphs the levels 15%, 30% and 45%, corresponding to traffic demands of 1050, 2100 and 3150/h, will be used. All other simulation parameters are be fixed, therefore all differences in results can be attributed to differences in controller, demand levels or stochasticity of the simulations. In order to account for this stochastic behavior, 14 scenarios (seeds) are run for each combination of controller and saturation rate. As many scenarios as possible were run, constraint by the available computation time on the DelftBlue supercomputer. The combination of these setting allow for comparison in performance metrics between the two different types of controllers for different traffic demands. The performance metrics used for performance evaluation are described in Sections 4.1.6 and 4.2.

To account for stochasticity, caused by randomness in solution generation algorithms, arrival patterns and personal characteristics of cyclists, 14 scenarios are run for each combination of experimental setup variables.

The second stage of comparison consists of a evaluation of the performance of the structure free controller with and without objective function weights for cyclists priority. This allows for evaluation of the impact special priority for cyclist has on total performance of the controller, but also on how these weights effect each mode individually. As was done in the first stage of comparison, the three demand levels of saturation rates 15%, 30% and 45% are used for evaluation. The baseline values of for mode split (0.50) and cyclist turn rate (0.30) are used for all scenarios. The weight for a full stop and the ratio of delays between cyclists and cars are varied.

The literature review in Section 2.2, on desires of cyclists and car drivers, proposed values for weights on cyclist delay and for full stops. The review presented a low, average and high (1.7, 3.3, 5) estimation for the relative VoT of cyclists compared to car drivers. These estimations are used as the relative weights of the cyclist delay compared to that of car drivers in the objective function of the SFGA. The different weights used for full stops are zero and the equivalent of 15 seconds of car driver delay. As no theoretical support for any value for this parameter was found in literature, this value is somewhat arbitrarily chosen. Experimenting with different parameter values showed 15 to be a value that influences controller performance, without forcing the controller into always prioritizing cyclists over cars. Future work should try to find a better foundation for this value and investigate controller sensitivity to this parameter. Because a car driver delay equivalent is used, the contribution of this weight to the performance cost of a possible signal plan is independent of the delay weights for cyclists.

In total this results in 24 combinations of variables: three demand levels, four weight ratios and two values for the weight of full stops. Each of this combination is run for identical traffic scenarios. To account for stochasticity, 14 different scenarios are simulated.

4.1.3. Performance comparison benchmark

Even though the majority of the papers reviewed in this thesis (See Chapter 2) compared the performance of controllers to fixed time control, this thesis will benchmark the performance of the designed controller against a vehicle actuated controller. This is done for three main reasons. First of all, the state of the art of intersection control in the Netherlands is vehicle actuated control. Because the intersection layout, consisting of separate traffic lanes and lights for bicycles, is also inspired on the Dutch standard, which is quite uncommon in other countries, the performance of the controller is benchmarked against the Dutch standard. Second of all, because of limitations on maximum computing time of computational clusters [28], a short simulation duration of 180 seconds has been used. This relatively small period would fit only one full cycle (common maximum cycle time in the Netherlands is 120 seconds [6]). This would make the results very sensitive to what phase is the first phase to be green, distorting the results. Note that VA is also sensitive to this, however this is to a lesser extend as VA often has cycle times lower than the maximum cycle time. Finally, as was discussed in the design methodology (Section **??**), the controller is designed to function best in unsaturated traffic flows. Fixed time controllers perform most optimal at full saturation and the lower traffic demands used in this thesis might result in an distorted image on the performance of the structure free controller.

This remainder of this section will elaborate on the chosen control structure and parameters of the vehicle actuated controller used for comparison. The term VA covers a wide range of implementations. Choices in how the controller functions, for example when travellers are detected, the control structure and the choice of the maximum green time, can significantly effect the performance.

The vehicle actuated controller follows a fixed sequence of combinations of traffic light, so called phases or blocks, that are active after each other. The control structure is visualized in Figure 4.2. This control structure has the lowest minimum cycle time for the infrastructure layout of Figure 4.1 and has been generated by VRIGen software.

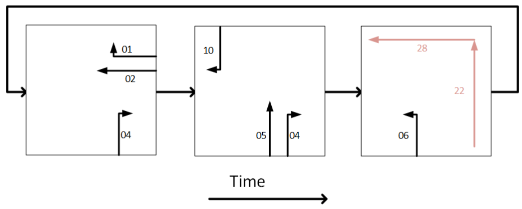


Figure 4.2: Control structure of VA, used for baseline comparison

Only traffic lights that are part of the current active phase are allowed to show green. If a traffic light has been green for less than the minimum green time, or if the controller detects traffic in this lane, green time is extended up to the maximum allowed green time. When the current phase has been active for the maximum allowed green time, or if no traffic is detected in any of the active traffic lanes, the next phase is activated. Conflicts related to yellow time and clearance time are enforced, similar to SFGA.

Because this research considers the CE, traffic is not detected by means of induction loops, but instead instead VA is assumed to detect any traffic located in the dilemma area. This area is the area in which travellers are assumed to make a stop and go decision. The dimensions of the dilemma area are calculated based on Gee. The start of the dilemma zone is located a distance equal to the yellow time multiplied by the maximum speed upstream of the stopping line and ends at the stopping line. Similar to the SFGA controller, VA is aware of the personal characteristics of travellers and hence the distance from where the travellers are detected differs per traveller type. This is shown in Table 4.2.

Table 4.2: Detection distance of VA

Traveller	Slow cyclist	Average cyclist	Fast cyclist	Car driver
Detection distance upstream of traffic light [m]	18.2	28.9	42.02	65.7

The full procedure followed by the VA is provided in Algorithm 7. The full code can be provided on request and has been stored on TU Servers. Values on the minimum green time, maximum green time, yellow time, clearance time and maximum speed of different types of travellers are provided in Appendix C.1

This vehicle actuated control represents a very basic version within the spectrum of what is considered VA. More sophisticated versions of VA allow include flexibility. This means that the Control structure has alternative paths the controller can choose, depending on the measured traffic. This can allow for some traffic lights in the next phase to start earlier, For example, there may be an alternative path from block 2 to block three. This block 2.5 could contain the traffic lights 04 and 05 from block two and 06 from block three. This alternative can allow the green time of block four to start earlier, given there is no traffic detected in the conflicting lane 10 from block two. It is chosen not to include flexibility like this because of two reasons. First of all, even though inclusion of flexibility will increase the performance of the benchmark, this performance is very dependent on what alternatives are included. This makes it very difficult for other researchers to compare controllers they designed to the controller that is proposed in this thesis. For this reason, comparing the structure free controller to a basic version of VA is deemed a good baseline. The

Algorithm 7 VA control algorithm

Initialize system state:
Active block B_a
Active block duration B_d

for all $k \in \{k_0, k_1, k_2, ..., T_{max}/\Delta T\}$ **do**:
new travellers enter the system
update main simulator using traffic system model
if k corresponds with multiple of 0.5: ▷ Any controller can change signal plans every 0.5 seconds
if $B_d = 0$ ▷ $B_d = 0$ corresponds with all red phase
Activate random block with travellers in dilemma zone. Update B_a and B_d
If there is no block with travellers in dilemma zone, $B_d = 0$
if $0 \leq B_d \leq G_{max} - Gmin$
Traffic lights with green duration < G_{min} prolong green
Traffic lights in active block without traffic in dilemma zone become red
Traffic lights in active block with traffic in dilemma zone become green
If there is no movements that are green, activate the next block
if $G_{max} - G_{min} \leq B_d \leq G_{max}$
Traffic lights with green duration < G_{min} prolong green
Traffic lights in active block without traffic in dilemma zone become red
If all traffic lights are red, activate next block

second reason, of lesser importance, is that including any flexibility in the system makes the controller significantly harder to program and include in the simulator.

For the same reason that flexibility is not included in the VA, it was also chosen not to include any performance enhancing options, aimed at reducing delays for cyclists, in the controller. Examples are provide green twice as often in case of rain or snow, leading to shorter waiting times when weather conditions are unfavorable[8]. Some intersections also include an 'all green' phase for cyclists, allowing a large number of cyclists to cross at the same time and allowing left turns to be made in a single instance[2][3]. Other systems focus on providing cyclists with more information, such as countdown to green timers or show the fastest way to make a double crossing or to reach a major destination like the train station[1].

4.1.4. Tuning parameters of the GA

A genetic algorithm needs tuning before it can be used in practice. Tuning in this context means determining the size of the population, how many generations to evaluate and the ratio between mutations, crossovers and randomly generated new solutions within a population. The most common procedure is to try different values and choose the combination that provides the best performance [44]. Literature can provide insights in initial values or ranges for values to start testing.

The literature review [44] on choosing mutation and crossover ratios (CM ratios) identified that GA usually perform best when combining a small population (25,50,100) with a large number of generations or the other way around. Crossovers tend to be more efficient in large populations and mutations in small populations. The most standard practice is to use a fixed ratio of 0.03M,0.9C. For more optimal performance an adaptive ratio can be implemented, but for complexity sake no such ratio will be implemented. The above mentioned review is not scoped on intersection control research but on the GA in general. An example of a GA used in intersection control research can be found in [121]. The algorithm is used to optimize block duration of a fixed phase sequence and the parameters for population, generation and CM rate are 40,500 and C0.8,M0.05.

The complexity of this optimization problem in [121] is orders of magnitude lower than this thesis, as it does only have four variables that must be chosen. These four variables represent the timing of the four phases in the block diagram of the controller and the four parameters are only dependent on each other via one constraint: a maximum cycle time. The traffic state of the solutions in this thesis is described by the signal plan matrix (S), consisting of state of all individual traffic lights at every time step of the variable. These states are very interdependent, due to the constraints on minimum green time, conflicts, clearance time and yellow time. For this reason the specific algorithm settings tuning from this work cannot be directly applied in this thesis and GA parameters are determined, following the most common approach of experimenting with different values and then selecting the one that results in the best performance [44].

GA tuning was done by staring with 40 generations and a population size of 10, trying different CM rates, evaluating the resulting performance and convergence over successive generations. Then the number of generations and population size were varied with the best performing CM rates. This process was repeated a number of times until there were no longer large changes in parameters. Note that no strict definition of good performance and converge was used and different researchers may conclude on different tuning parameters. This is in part, because in addition to performance and convergence, the run time of simulations played a significant role in the decision process. Limits on computation time of the computing clusters resulted in limited choice opportunities and combinations for the GA parameters.

Mutation and crossover algorithms seemed to be equally important for achieving increases in performance, but no strict optimal value for crossover and mutation probability was found. The best initial guesses were made by random solutions. The probabilities that were deemed the best for crossovers, mutations and random solutions are 0.4, 0.4 and 0.2 respectively. These probabilities are used with a population size of 25 and ten successive generations. Interestingly, with performance converged to the best found solution really fast, often in the first couple of generations. In simulation runs with significantly larger population sizes and a higher number of generations, marginal improvements were made over time. However, to limit computation time, these parameters are capped at 10 and 25.

A prediction horizon of 20 seconds is used. This value is the result of a trade off between computation time and performance. With longer horizons, computation time increases exponentially due to the large solution space. Generally speaking, structure free controllers do not benefit from very large prediction horizons, a window between 15 and 30 seconds was found to be very effective by [80].

Table 4.3: GA parameters

Variable	**Value**
Prediction horizon	20 [s]
Population size	25
Number of generations	10
Crossover probability	0.4
Mutation probability	0.4
Random solution probability	0.2
Stored best performing solutions	8

4.1.5. Model verification and validation

The traffic system model and the controller are verified after implementation in Python. Validation of the traffic model has not been performed because of time limitations. Instead, the traffic system model is based on validated models published in literature (See Section 3.2). Adaptations on these models are assumed to be valid.

The traffic model is verified by means of a level one verification. A level one verification ensures basic functionality of the simulation model by comparison between the conceptual model and the simulation model. Because the simulation environment is created to be used within this study area and not as a general assessment tool, a level one verification suffices [23]. A set of 52 detailed scenarios, consisting of different types of travellers, traveller locations and speeds and states of traffic lights (see appendix D) was made. These scenarios cover all different types of behavior that is expected from travellers. The simulated outcome of each scenario is compared to the expected behavior in terms of visual comparison of the trajectories, inspection of the key performance indicators (KPIs) and close inspection of the speed of agents at points of interest around changing behavior. Scenarios were run with some start up time and cool down time, allowing agents to enter and exit the system.

The verification process for cyclists mainly resulted in debugging of the implemented code, but it also resulted in a few model changes. Most model changes are minor changes, implemented to deal with overshoot problems caused by discretization. These adaptations will not be explicitly covered. The verification process also led to the identification of a number of shortcomings of the kinematic model of car drivers. These changes are included in Appendix D.

Verification of the controller and its' interaction with the traffic system model, have been performed by imposing manually created signal plans the controller and RH simulations (See Section 3.3.1 for an explanation on the concept of RH simulations). These signal plans were very simple, usually confined to allowing traffic on only three movements to cross. The choice of these movements varied to signal plans that were deemed very effective, with large traffic volumes in these traffic lanes, and very ineffective, with little to none traffic. This made it easy to manually identify how the controller performed and how signal plans should evaluate in order to perform better.

The effect on the RH simulations was evaluated by means of trajectory plots, similar to the traffic model verification. Successive generations of solutions and the corresponding RH simulations were inspected to determine whether delay decreases over successive generation and whether or not the successive solutions change, both in terms of what movements receive green and when this happens.

4.1.6. Performance evaluation metrics and expected results first stage

For the first stage of comparison, the comparison between VA and the structure free controller without special priority for cyclists, a trajectory plot of a single run will be provided as proof of concept for the structure free controller. The performance of the controllers will then be compared by means of the average delay, average delay per mode and the percentage of cyclists that needs to make a full stop when crossing the intersection. The mathematical formulation for delay can be found in Equation 3.26 and the formulation for the number of stops can be found in Equation 3.27. Results are expected to differ because of two main reasons. These will be explained in the *Average delay* section. Other metrics, related to different control decisions that are mad, will be presented afterwards to support the understanding on difference in performance. All metrics will now briefly be mentioned in listed form. Following paragraphs will explain the metrics and the expected results. Note that none of the expectations discussed in this report are tested with statistics.

- Performance metrics:
  - Average delay and delay spread.
  - Average cyclist delay and cyclist delay spread.
  - Average car driver delay and car driver delay spread.
  - Percentage of traffic light approaches resulting in a full stop for cyclists.
- Metrics related to explaining differences in performance:
  - Average number of travellers in the dilemma area over time.
  - Probability density of delays experienced by travellers.
  - Percentage of green time ends with different number of travellers in the dilemma zone.
  - Effective green use (Average crossing headway).
  - Average total green time.

Expectation for average delay

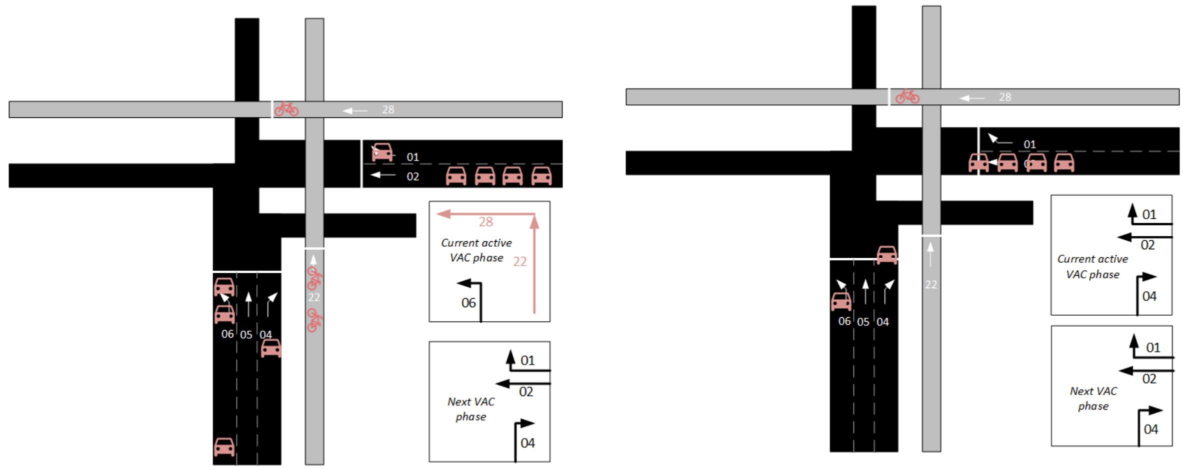
Average delay is one of the most used performance metrics for intersection controllers and allows for a baseline on what intersection performs best[121]. The expectation is that the basic structure free controller will outperform VA at all the traffic saturation rates. The difference between the average delay of both controllers is expected to be small at at very low traffic levels, enlarge with higher traffic demand and shrink back back to a small difference when approaching full traffic saturation. As was explained in the previous section, evaluation is performed at saturation rates of 15, 30 and 45%. It it likely that these values do not capture the full range of expectations, therefore future work may investigate the full extend of the traffic saturation rates with improved traffic models.

The SFGA is expected to result in a lower average delay than VA because of two main reasons, that together are expected to result in a lower number of travellers that are waiting for a traffic light and a larger share of travellers that is able to cross the intersection with a relatively short delay. The genetic algorithm of the SFGA predicts simulates the effect of control decisions and converges to the best moment to switch to another combination of green traffic lights. Because of this, the SFGA is expected to sometimes end green time, even when there are travellers relatively close to the traffic light. It may do so if this allows a larger number of travellers in another traffic lane to cross the intersection. This results in a more efficient use of green time as a larger number of travellers can make use of the green time. Similarly, it will result in lower total delays, as the delay is experienced by fewer travelers. VA does not make such a trade-off. Secondly, the structure free aspect of SFGA allows the controller to use more effective combinations of traffic lights compared to VA. The VA system only allows green in the currently active phase, while another combination may be better suited for the current traffic state, as another combination may allow more travellers to cross the intersection. Depending on the traffic conditions, this can lead to more total green time or similar amounts of green time where the green time of the SFGA is used more effective. The two main reasons will now be explained in further detail by means of two scenarios. These two reasons will now be explained more in depth.

The SFGA is expected to make better choices on when to end green time than VA, which is expected to lead to a lower average delay. This is best explained by means of a scenario. The traffic on the intersection is visualized in Figure 4.3a. In this scenario, regardless of the controller, traffic lights 06, 22 and 28 have been showing green for longer than the minimum green time already. Both controllers extend the green times in order to allow all cyclists and the car drivers in lane 06 to cross. This would be fairly effective, as five travellers that are close to the stopping line can cross. This comes at the cost of some delay for the six other travellers. After the five travellers have crossed the stopping line, it is more effective to end green time for lane 06. This allows the five car drivers in lane 02 and 04 to cross, at the cost of delaying the third car driver in lane 06. Assuming the third car is in the dilemma area, VA will not end green time, as the car driver in 06 still 'actuates' the controller. This will allow this car driver to cross, but as a result may cause more total delay as a large number of travellers have to wait some additional time. By the time this car almost crosses the stopping line, the second cyclist in lane 28 may have been detected by the VA as well, causing another green time extension, keeping the current phase active. A small trickle of individual travellers entering the dilemma zone and extending green time can continue until the maximum green time is reached and the phase is ended. The structure free controller on the contrary will predict it is more beneficial to end the green time and do so, resulting in a lower average delay.

Note that some VA systems adapt to a lower maximum green time at moments of low traffic demand, reducing the negative effect of travellers 'trickling' in. However, this lower maximum green time may have some negative effects as well. The controller may end green time because the maximum limit has been reached, even if a larger platoon of travellers arrives just after the maximum green time has passed. A maximum green time is not implemented in the structure free controller, instead a maximum waiting time for individual travellers is enforced. The differences in when both controllers decide to end green time can result in similar decisions, but in this instance the SFGA likely will choose to extend the green time and allow this larger platoon to cross. Instead of following a set of predefined rules, as VA does, the structure free controller evaluates the effect control decisions have on the total delay (See Section 3.3.4). This may result in green time extension or in ending green time. Even in situations where there are larger platoons arriving in other traffic lanes, a choice may be made not to end green time, as the additional loss time introduced by the red and yellow time can impact the overall. And in some occasions, an inefficient green time end may be forced because a traveller is waiting for almost the maximum allowed waiting time. The notion that it makes a trade off and chooses the predicted most optimal solution, instead of following a fixed set of rules as VA does, is expected to result in lower average delays.

The second reason for why SFGA is expected to outperform VA relates to more effective combinations of traffic lights that show green at the same time. This reason will be explained using the scenario shown in Figure 4.3b. The start of this scenario is the result of ending green after the first five travellers of scenario one have crossed the stopping line. VA would activate the next phase and allow travellers on lanes 01, 02 and 04 to cross the intersection. Because there is no traffic in lane 01, this traffic light will remain red. In this scenario, the cyclist in lane 28 would have to wait, even though there is no conflicting traffic. SFGA can choose any combination of non conflicting traffic lights to show green and will allow traffic in lane 02, 04 and 28 to cross. The traffic light of lane 28 will be green for the minimum green time, allowing the cyclist to



(a) Reason 1: Ending green time earlier

(b) Reason 2: More efficient combinations of traffic lights to show green

Figure 4.3: Scenarios used to explain expectations

cross the intersection. In this scenario, the structure free controller provides more total green time than VA. Most of this green time is unused however, but it is still more effective than what VA would do. As the cyclist is allowed to cross due to a better combination, the average delay will be lower.

Note that some VA systems include flexibility, allowing for an alternative control sequence in case there is no traffic measured in some of the traffic lanes. In this case the VA system could also provide green to traffic light 28, as there is no traffic in lane 01. This alternative could fairly easily be implemented as the intersection layout and therefore the control structure used in this thesis is fairly simple, but as intersection layout becomes more complex, exponentially more alternatives are required to account for all scenarios, making the controller more complex.

Even if all possible alternatives would be included in the control structure of VA, the larger degrees of freedom are still expected to result in better performance for the SFGA. This is because using more effective combinations of green is not limited to scenarios where there is no traffic in any of the lanes of the currently active VA phase. This is explained with the same scenario that was just described (figure 4.3b), but instead of no cars and one cyclist in lane 01 and 28, there are two cars and six cyclists in the respective dilemma zones. If flexibility was allowed for the VA, the controller would show green on traffic light 01. The structure free controller would prioritize the cycle path over lane 01, as there are more travellers there and allowing them to cross is more efficient. Contrary to the situation without traffic in lane 01, in this case the SFGA would not result in more but ineffectively used green time, but to a similar green time that is used more effective.

Summarizing, the differences between the VA and the SFGA can be condensed to 1) different choices on when to end green time and 2) differences in the used combination of traffic lights that show green in comparable traffic scenarios. These differences are expected to allow SFGA to have a lower number of travellers waiting for a red traffic light and allow it to prioritize traffic lanes with the largest platoons, resulting in a lower delay for a larger share of travellers, shifting the median delay closer to zero. Depending on the traffic scenario, these factors are expected to allow SFGA to increase the effective green use or provide additional, mostly unused, green time when compared to VAC.

Delay spread

The variation of delay is expected to be very large, as big differences between delay for cyclists and car drivers are expected. This big difference originates from choices made on modal split and infrastructure layout. The infrastructure layout consists of six car lanes an two cycle paths(figure 4.1. The fact that there are more traffic lanes for cars, combined with a modal split of 0.5, which means traffic demand is split equally between cyclists and car drivers, results in higher traffic densities on the cycle paths than on the car lanes. As the structure free control is expected to prioritize the larger platoons over smaller platoons, and traffic densities of cyclists are higher, the average delay of cyclists is expected to be lower.

For VA the bias towards prioritizing cyclists is likely less profound. On the one hand, if the traffic light of cyclists is green, higher traffic densities can result in a higher likelihood of starting green or causing green time extensions because of the trickling arrivals effect, providing more relative green time for cyclists and resulting in lower delays. Note that this effect is different for state of the art VA, where low gap-out times may prevent trickling. The VA system of this research functions in the CE however, and detects any cyclist in that is in his or her dilemma area (See Table 4.2). This makes the system more susceptible for the trickling effect. The trickling effect can also cause green time extensions for car drivers, resulting in longer waiting times for a large number of cyclists. These cyclists have to wait until the active phase contains the traffic light for which they are waiting. Since evaluation will commence at low traffic levels, the trade offs for VA likely still result in lower delays for cyclists, but this is to a lesser extend than for the SFGA. Delay spread for VA is still expected to be very large, but this is not expected due to a difference between car drivers and cyclists, but is more attributed to the underlying control methodology of VA, in which travellers have to wait for their turn.

Average delay per traffic mode and number of full stops cyclists
As the objective of this thesis is to design a controller that prioritizes the desires of cyclists, performance metrics that relate to this objective will be provided as performance evaluating criteria as well. These metrics are the average delay of cyclists the percentage of cyclists that has to make a full stop. In order to allow insights on how a higher or lower delay for cyclist effects car drivers, the average delay for car drivers will be provided as well. A higher average delay of car divers may be acceptable if this results in much lower delays or number of stops for cyclists.

For both controllers the average delay of cyclists is expected to be lower than that of the average delay of car drivers. This is because combination of infrastructure layout and modal split results in a bias towards prioritizing cyclists over cars. The bias originates from the fact that there are six lanes for car traffic and only two for cyclists (see Figure 4.1). Combined with the fifty fifty mode split, half of all traffic being dispersed over only two bicycle lanes and the other half over six car lanes. Traffic density on car lanes therefore will be three times lower than that of bicycle paths, which likely results in cyclists arriving at the intersection earlier and in larger numbers car drivers do, resulting in more green time for those bicycles because of the prioritization of the many (SFGA) or a larger likelihood of causing green time extensions (VA).

At very low traffic saturation, not much difference between the average cyclist delays is expected between the two controllers. This is because, as explained in last paragraph, both controllers bias towards prioritizing cyclists and in low traffic situations priority often results in a first come first serve situation, which both controllers are expected to control in the same way. For higher levels VA is expected to have a higher average delay for cyclists, mainly longer average green times for car lanes, due to VA not being allowed to truncate green time for cars when there is traffic in the dilemma area, even when that prevents a (relatively) large number of cyclists to cross. It may be the case that this scenario does not occur often in any of the saturation rates used for evaluation. With increased saturation rates, the difference between the two controllers is expected to increase. The average delays are expected to increase for both controllers, but the extend of this increase is likely larger for VA. This is expected because traffic densities in the cycle paths are relatively high, and this is result in the SFGA prioritizing cyclists more often, whereas the effects of this density on VA are lower.

At any of the saturation rates used for evaluation, average car driver delay is expected to be larger for VA than for the SFGA. This is for the same reasons the general performance of the VA is expected to be worse than that of structure free. For higher saturation rates this may change to VA resulting in lower delays for car drivers because of the different implementation for maximum waiting time. The maximum waiting time of 100s is implemented in VA as a maximum red time of 100s. This means that a car driver arriving after 30 seconds of red time will only have to wait 70 seconds before he/she can cross the intersection. The structure free controller adheres to a strict waiting time limit: someone arriving after 30 seconds of red time will still a maximum waiting time of 100s. Note that the VA could also be designed in a way that it considers waiting time instead of a maximum red time, but this is not the case for the VA system used in this research.

The average number of stops for cyclists is expected to be relatively low for both controllers because of the bias towards prioritizing cyclists. Very similar results are expected for the lowest saturation rate for the same reasons as similar results for bicycle delay are expected: in low traffic situations priority often results in a first come first serve situation, which both controllers are expected to control in the same way. For higher levels the number of stops is expected to increase more for VA, as cyclists will have to wait for the green time of cars to end until no more traffic is in the dilemma zone, whereas structure free control is expected to end green times earlier due to a lower predicted total delay.

Standard deviations for car driver delay and delay and full stops of cyclists are expected to be relatively large due to the relatively low number of scenarios that will be evaluated. The influence of randomness is quite large for in what traffic lane and what moment cars enter the system, and this is of large influence on the signal plans controllers decide upon and thus the resulting performance metrics. Note there also is randomness in the generation of cyclists, but cyclist demand is spread over only two lanes, therefore the effect randomness has on the entire system is lower.

Robustness to mode split and cyclist turn rate for mode specific delay and cyclist stops is expected to be low and high respectively. This is because mode split is, and turn rate is not expected to influence the bias towards cyclists significantly. Different modal splits change the number of cyclists in the system by a large amount, thereby changing the effect of the bias significantly. The turn rate has a much smaller effect on the total number of cyclists in the system and therefore the bias.

Metrics related to understanding the differences in performance
As was explained earlier, lower delays are expected when the intersection is controlled by the SFGA because this controller is expected to result in fewer people waiting for the traffic light and a larger share of travellers that is able to cross the intersection with a relatively short delay. To test if this is indeed the effect of the structure free controller, two metrics are introduced. The first metric is the average number of travellers in the dilemma area over time, and the second it the occurrences of ranges of individual delays.

The notion that the structure free controller tends to prioritize larger numbers of travellers to cross will likely result in more people crossing the intersection earlier in time compared to VA. VA will allow these travellers to cross as well, but at a later moment, resulting in a higher delay for these agents. Why and how the structure free controller prioritizes larger number of travellers is explained in the *Expectation for average delay* section, by means of scenario two (Figure 4.3b). The dilemma area is used to have an area upstream of the traffic light that is of similar effect on both cars and cyclists. Additionally, the largest share of the delay can be expected to originate from people in the dilemma area. The scenarios in the simulation are identical for both controllers, therefore the arrivals of travellers are identical. The only factors contributing to the number of travellers upstream of the intersection is the number of agents the controllers manage to have cross the intersection.

Because the structure free controller is expected to allow a larger share of people to cross the intersection earlier in time, the distribution of the delays of individual travellers will be different from that of VA. This difference is mainly expected to be a shift towards a lower median delay. This expectation will be tested by means of a histogram. In this histogram, the average occurrence of delays will be shown for both controllers. The expectation is that the bins of the histogram closer to zero will be higher than VA. The shape will approach zero relatively fast, but the tail may have a larger height than VA as well, as the prioritization of the many likely results in somewhat larger delays for the few. The head of the histogram of VA is expected to be more uniform and lower in height than VA, as more travellers will likely have to wait for a somewhat longer duration, resulting in delays likely somewhat more distributed over lower values.

The differences in delay spread and number of people in the dilemma area are caused by differences in choices, or control strategies made by VA and the SFGA. The SFGA is expected to end green time prematurely more often in order to achieve more effective green use, and use allow different combinations of traffic lights to show green at the same time. In some situations, this is expected to result in higher effective green use compared to VA and in some occasions it is expected to provide additional green time, but this green time will not be used very effective. The latter of which is expected to occur more often at lower traffic demands. In order to test these hypotheses, two metrics will be included in the results: one related to effective green, the other to total green time. Finally, two metrics will be shown that can help test whether or not the SFGA does make use of the larger variety of combinations and the ability to cut off green time when there is traffic in proximity of the traffic light.

Effective green use will be indicated by means of the average headway of two travellers when crossing the intersection. If the average headway is low, travellers will follow each other very closely and therefore little green time will be lost. If the average headway is longer, more green time will be lost. Because of the different nature of bicycles and cars, a distinction will be made between the headways of the two modes. For very low saturation rates, the average headways are expected to be quite similar for both controllers, as with low traffic volumes, individual travellers crossing a traffic light are likely to occur more. The headways may even be higher for structure free, at this controller may provide more total green time, resulting in even more individual crossings. VA will have travellers wait before the phase containing the traffic light is activated, providing more time for additional travellers to arrive, which results in more effective use of green, even though the delay is higher. At higher saturation rates platoons are more likely to form. In these situations the SFGA is expected to prioritize the larger platoons, resulting in higher effective green use. VA will provide green to whatever traffic light is allows to at the current moment, even if there is low traffic density. The average headways VA will therefore likely be smaller.

Total green time will provided for each of the separate modalities as well, as the controllers may have a bias towards any of the modes. This can be caused by higher densities in the bicycle paths than in traffic lanes. Note that it is not uncommon to see larger densities on bicycle paths, due to the smaller size of bicycles. However, the modal split of 0.50 and a larger number (six) of car lanes than bicycle paths (two) in the infrastructure layout (See Figure 4.1) will enlarge these differences. Separating the total green time of the two modes may provide insights in the extend of this bias. With regard to the expectations on total green time, in low saturation rates, when there is no traffic in one of the traffic lanes of the active VA block, this traffic light will be red. The structure free controller may allow traffic in another lane to cross instead, providing additional green time. The total green time provided by the SFGA is expected to be higher than that of VA for low saturation rates. At higher saturation rates, the situation where a red light is shown by VA will occur less, resulting in similar green times. However, the SFGA is expected to switch more between what lanes may cross, causing additional loss time caused by yellow time and clearance time. The average may therefore be even slightly lower for SFGA at higher saturation rates.

It may be debated whether or not the SFGA does make use of its' characteristics, allowing it to switch lights more often and between a wider variety of combinations. In order to verify this, two additional result plots will be provided. The first one has to do with the switching behavior and will show a histogram of the number of people in the dilemma area at the moment each of the controllers ends green time. Both controllers likely will end green time most often when there are no more travellers in the dilemma zone. VA will only end green time earlier when the maximum green time is reached and the SFGA will only end green time early if this is results in a lower total delay than letting the travellers in the dilemma zone pass. Because of the low, unsaturated, traffic flows VA is not expected to end green time prematurely very often. SFGA is expected to do this however, mainly to counteract the trickling in effect extending green times for VA. Therefore the heights of the histogram bins with more people in the dilemma zone are expected to be higher than those of VA. It is less likely to end green time the more people are in the dilemma area, as the cost of ending green time would increase. Therefore the height of the bins is expected to decrease with increased travellers in the dilemma zone. The second characteristic of structure free control is that it is allowed to use a wider variety of signal combinations. In order to verify this, a histogram will be provided with the average occurrence of combinations of traffic lights that are green at the same time. In addition to a wider range of combinations, the total height of all the bins together for the SFGA is likely larger, as it is expected to switch more often between combinations as well.

4.2. Performance evaluation metrics and expected results second stage

As was described earlier, the second stage performance comparison will compare the performance of the structure free controller when using different weights with respect to the delay of cyclists and the number of full stops cyclists have to make. Performance will be evaluated using the same metrics as stage one: average delay, average delay per mode and the number of full stops for cyclists. These metrics are now provided in listed form for convenience of the reader returning briefly at this section from reading the results section.

Performance metrics:

- Average delay and delay spread.
- Average cyclist delay and cyclist delay spread.
- Average car driver delay and car driver delay spread.
- Percentage of traffic light approaches resulting in a full stop for cyclists.

Increasing the weight of cyclist delay relative to car delay is expected to reduce the average delay for cyclists and, in order to do so, cause higher delays for cars drivers. The lower delays for cyclists will most likely be achieved by starting green time earlier and extending green time more often, allowing more cyclists to pass in the same green period. It is not likely that each additional second of average delay for car driver results in a one section reduction for cyclists, as the controller evaluates the effect of control choices like extending green time or what traffic light to switch to green, based on an assigned score. The score of the effect of choices is influenced by the weights, and higher weights will most likely increase the probability of this choice being made in favor of the cyclists.

With a low weight, the there will be less instances where the choice turns from car towards bike. The higher the weight, the more often the car will be disadvantaged. Therefore it is expected that for higher waits, the controller will result in exponentially higher delays for car drivers. The extend of what additional delays are acceptable will not be a conclusion of this thesis, but the results may provide indications on what weights can be used to shift delays in equal amounts, and from what delay on the controller will become way less effective as a whole -i.e. from what weight onward the average delay increases become very large. The higher weights for delay will likely also result in a reduction of the number of stops for cyclists, as the cyclists get prioritized over the cars more often.

In a similar manner, inclusion of the weight for stops of cyclists is also expected to result in a lower delay for bicycles and a higher delay for car drivers. The controller will more often make the decision on extending green or starting green earlier, allowing a cyclist to cross without having to stop, also resulting in lower delays. The extend of how much the weight for full stops will influence the difference between traffic modalities is likely smaller than that of weights for delay, because the delay punishment keeps increasing after a stop, whereas after a full stop is made, there is no longer a reason to allow cyclists to cross earlier: the stop has already been made.

The effects of the delay weights are expected to result in disproportionately more delay for cars, with increasing traffic saturation levels. This is due to the higher traffic densities in cycle paths. Note that part of this difference in densities originates from the smaller area occupied by bicycles, but can in some extend also be attributed to the choice of infrastructure layout in this case study. The higher densities in cycle paths and hence larger number of travellers in cycle paths, are already, excluding prioritizing weights, expected to provide longer and more frequent green times to cyclists. However, at low saturation rates stochastic effects in the time and the lane at which agents enter the sytem, can allow for some larger than average headways that can allow cars to cross. At higher saturation rates, the chances of such a gap occurring reduce, which can result in cars being delayed longer up to the point that such a gap does occur or the maximum waiting time is bound to be broken.

The effect of the weight for full stops is expected to decrease for higher saturation rates. As there are more cars in the system, the negative reward of a stop becomes less likely to be larger in size than that of the additional delays otherwise caused for all of the car drivers. Of course, the higher demand levels also result in more cyclists in the cycle path, for which stops can be avoided. However, delays accumulate over time and the stops occur spread out over time. There is still some effect expected at higher saturation rate, as in some occasions larger platoons of cyclists will arrive at the intersection and the controller may choose to prioritize platoon, as it will prevent a multitude of stops.

4.3. Summary of the evaluation framework

Section 4.1 provides the experimental setup in more detail. Sections 4.1.3 and 4.1.4 discuss the benchmark controller and the tuned variables of the structure free controller respectively. Then Sections 4.1.6 and 4.2, in which the performance metrics and expected results of the two stages of comparison are discussed. For reader convenience, the a short summary of the evaluation framework is provided here in listed form.

- The structure free controller is benchmarked against VA.
- Performance metrics are:
  - Average delay and delay spread.
  - Average cyclist delay and cyclist delay spread.
  - Average car driver delay and car driver delay spread.
  - Percentage of traffic light approaches resulting in a full stop for cyclists.
- Performance evaluation will compose of two stages.
  - First stage: comparison of the controller with equal weights for the desires of car drivers and cyclists against VA.
  - Second stage: comparison of the effect cyclists prioritization weights in the objective function of the structure free controller.

5
Case study: Results

5.1. Performance of the SFGA Control compared to VA Control

This section will provide the results of the benchmark comparison between SFGA and VA control. The objective function of SFGA consists of delay only, weighing the delay of cyclists and car drivers equally. The performance is discussed in terms of average delay first (Section 5.1.1), followed by delay of both modalities and full stops of cyclists in Section 5.1.2. A summary of the performance metrics is provided in Table 5.1. Section 5.1.3 discusses metrics that explain the differences in performance between the two controllers.

Unless said otherwise, the following simulation parameters are used: mode split $\frac{\text{cyclist}}{car} = 0.5$, cyclist turn rate = 0.3, minimum green time = 6[s], maximum waiting time 100[s], maximum green time (VA only) = 48[s]. Traffic saturation rates of 15%, 30% and 45% for both traffic modalities are used for evaluation. To account for the stochastic behavior of the system, 14 different simulation runs have been performed, using identical scenarios for each of the controllers. See Chapter 4.1 for a full description of the experimental setup.

5.1.1. General performance

To ensure the reader that the presented results are reasonable and make sense in the context of intersection control, trajectories of a single simulation run are provided in Figure 5.1. This figure shows scenario seed 40 with a traffic saturation level of 15%. The state of the traffic signal is shown as a colored, horizontal line at the location of the stop line. Cars going straight on have a constant speed when approaching a green traffic light, but turning cars briefly decelerate, because cars have to travel at a lower speed when making a turn (See Section 3.2.4). In some occasions, cars enter the system in close proximity of each other. For example in Direction 04. If this happens, the cars will influence each other and the following car may have to reduce speed. The trajectories of some of the cyclist in direction 22 end earlier than others. These cyclists make a turn and appear in direction 28, just upstream of the traffic light. Finally, in some occasions travellers make use of yellow and red lights. See for example bicycle path 28 around 160s. This happens when the required deceleration of a cyclist exceeds his or her maximum acceptable deceleration rate (See Section 3.2.3).

The average and the 75th percentile of a travellers delay are provided in Figure 5.2. For each evaluated saturation rate, the average delay and the delay spread of the SFGA controller is lower than that of VA. The difference between the two controllers is a factor 1.8 at 15% saturation, but increases to 2.7 and 3.0 for 30 and 45% respectively.

In relative terms, the average delay of VA increases more rapidly with higher traffic saturation than SFGA. The delay of VA increases from 8.7 seconds (15%) to 28.1 seconds (45%), whereas the delay of SFGA increases from 4.7s at 15% saturation 9.3s at 45%. For both controllers, a higher number travellers that want to cross the intersection results in larger average and total delays. However, the structure free controller is better able to accommodate these additional travellers within its' signal plans, resulting in lower additional delays per additional traveller, compared to VA.

Figure 5.2 shows the error band of SFGA is less wide than that of VA, indicting the controller does result in a more consistent delay for travellers, with fewer and lower high delays. This makes sense, as the SFGA controls for individual delays and therefore is inclined to allow travellers to cross, when their delay grows larger. This contrary to VA, where travellers have to wait until it is their turn to cross. Delay spread becomes larger at higher traffic saturation levels, as situations with no conflicting traffic occur less often with higher traffic demand, and therefore travellers have to wait longer duration.

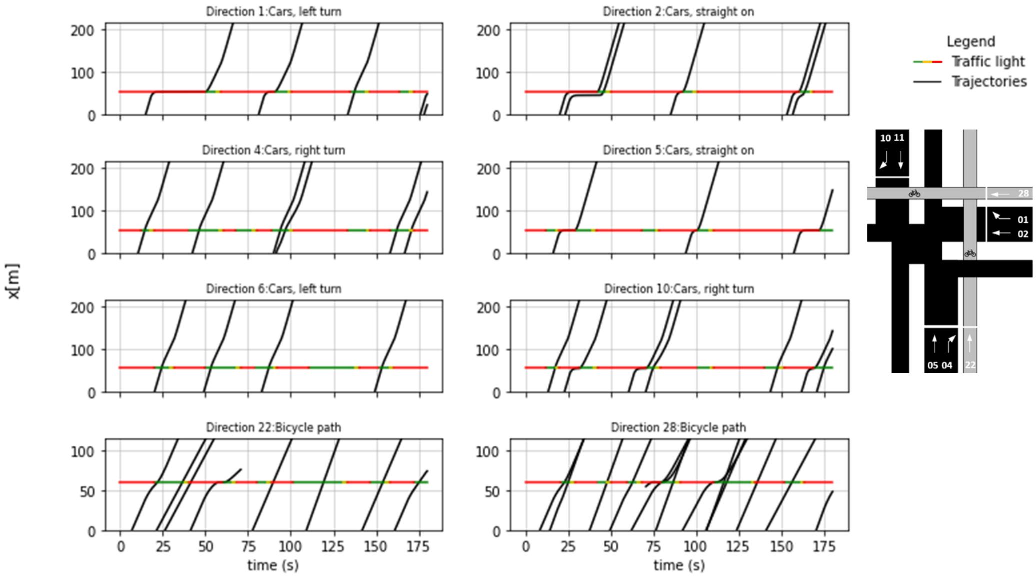


Figure 5.1: Trajectories as result of structure free controller with 15% traffic saturation (demand = 1050/h).

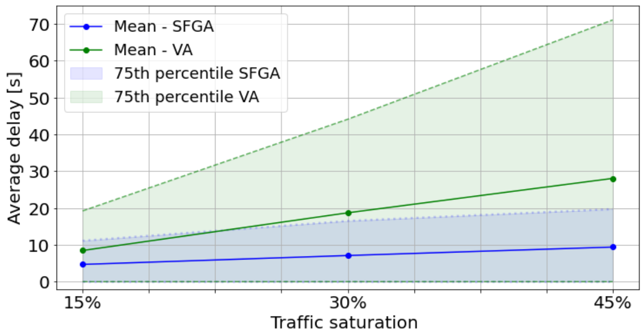


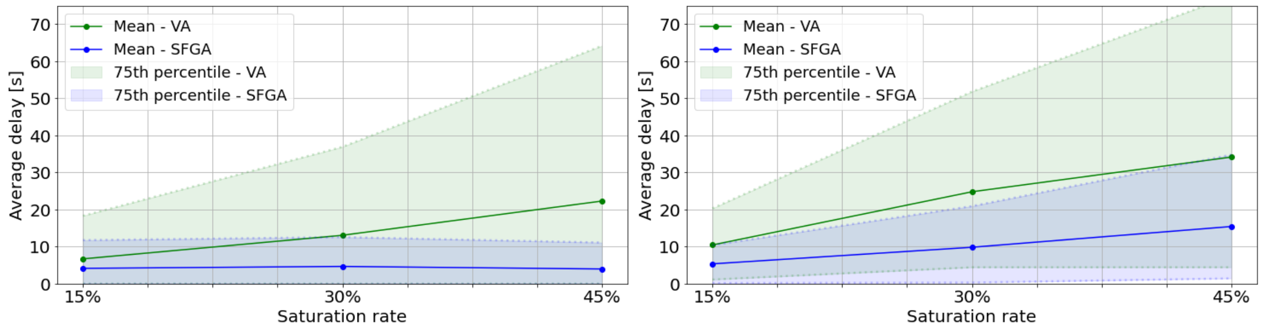
Figure 5.2: Delay of a traveller crossing the intersection

5.1.2. Performance with respect to separate transport modalities

The previous section shows that the SFGA outperforms VA in terms of average delay. This section presents the performance of the SFGA and VA with respect to the delay of the separate modalities (Figure 5.3) and the probability of a cyclist making a full stop on a traffic light approach (Figure 5.4).

When a distinction is made between the average delay for both traffic modes, the conclusion that SFGA control outperforms VA can still be drawn. For both modalities, the SFGA realizes a lower average delay than VA for all evaluated saturation rates. The difference with regard to cyclists is most profound. At 15% traffic saturation, the controllers perform relatively similar, with 4.1s and 6.7s average delay for the SFGA and VA respectively. At the two higher traffic levels, the average delay for cyclists for VA increases to 12.0s and 22.3s, but for SFGA increase to 4.6s at 30%, and decrease to 4.0s at 45% saturation. A similar effect can be seen in the error bands of cyclist delay in Figure 5.3a.

The consistent average cyclist delay, can be contributed to the functioning of the SFGA. The controller considers the effect of its' control decisions on the delay of all travellers, therefore it is to be expected that traffic lights with a large number of travellers impacted by a potential red light, get prioritized. Provided large traffic volumes of cyclists, the traffic densities on the bicycle lanes can expected to be higher in bicycle paths than in car lanes. This results in SFGA prioritizing cyclists over cars. Car drivers are allowed to cross, when the first car in the queue approaches the maximum waiting time, car queues have built up far enough to compete with a large number of cyclists, or when there are few cyclists in proximity of the traffic light. The latter two are less likely at higher traffic levels, therefore it is reasonable to see that the cyclist delay actually decreases with larger traffic demand. At even higher traffic levels, car drivers will approach the maximum waiting time more often, forcing green time ends for cyclists, which will result in higher delays for cyclists.



(a) Delay of cyclists

(b) Delay of car drivers

Figure 5.3: Impact of controllers on delay for separate modalities

Note that some part of the differences in traffic densities between car lanes and bicycle paths, can be attributed to the choice of modal split and intersection layout. The intersection layout (see Figure 4.1) composes of six lanes for car traffic and only two for cyclists. Combined with the fifty fifty mode split, half of all traffic is dispersed over two bicycle lanes, and the other half over six car lanes. This does not mean that the conclusions on the controller performance cannot be generalized. The traffic density differences are enlarged due to choices in experimental setup, but can be expected in other scenarios as well. With a similar number of car drivers and cyclists making use of an intersection, which can be expected in urban areas, physical size differences between car and bicycles result in higher traffic densities in bicycle lanes than in car lanes.

In this case study, VA control also result in lower delays for cyclists than for car drivers: average delays are 6.7s, 13.0s and 22.3s for cyclists and 10.4s, 24.8s and 34.2s for car drivers at each of the evaluated saturation levels. From these results, one could conclude that this means VA does also prioritize cyclists over car drivers. However, this conclusion should not be drawn. This is because, contrary to SFGA, VA does not control for individual delays but bases the control decisions on a binary *'Is there traffic in the active phases dilemma zones?'*. Where SFGA systematically prioritizes based on density, VA only does so in some occasions. For VA, high traffic density, can result in more green time extensions, and therefore more total green time and a lower average delay. This does does require uniform arrivals however, because when travellers instead arrive in platoons, the higher density results in fewer extensions than with with uniform arrivals. High traffic densities are only beneficial, if the traffic light is already green. Facing a red light, travellers have to wait for the active phase to cycle back to the block containing the cycle lights. A large number of travellers waiting for the traffic light in this case only means that a lot of travellers are waiting, resulting in a higher total delay. In these scenarios, cyclists do not benefit from the high traffic density, but instead benefit from the low traffic density in car lanes, which results in fewer green time extensions. In scenarios with low volumes of car traffic, early green time ends in car lanes can occur more often, allowing VA to cycle back to the conflict group with the bicycle paths. At higher traffic levels, this becomes increasingly unlikely to happen, thus it cannot be said that VA actively prioritizes cyclists. This contrary to the SFGA, that consistently prioritizes traffic lanes with higher densities. For VA, the lower delays of cyclists compared to cars, likely originates from very low traffic levels in car lanes. In Figure 5.3a, between 30 and 45% traffic saturation, the average delay of cyclists increases more rapidly than between 15 and 30%. This corresponds with the notion that with larger traffic volumes, the relative benefit of cyclists at VA decreases. At traffic saturation levels higher than 45%, the average delay of cyclists may even exceed that of car drivers.

The expected results (Section 4.1.6) indicated that some prioritization of cyclists was already expected for both controllers, at the cost of higher delays for car drivers. Figure 5.3b shows the delay of car drivers is indeed larger than the delay of cyclists for both controllers, but this comes at a higher cost for VA control than for SFGA. The larger delays of car drivers in VA may be caused by infrequent green time extensions in conflicting movements, resulting in delays for a larger number of waiting car drivers. This contrary to SFGA, which can decide to truncate green in conflicting movements with few travellers in proximity to the traffic light, in order to allow a larger number of cars to cross. SFGA may also force the first car driver in the queue to wait a little longer, contrary to VA where the traffic light would now start green time when the previous phase has ended. This can result in lower average delays, because it may allow a car driver following this car to now cross in the same green duration, instead of having to wait for the next cycle.

The structure free controller also outperforms VA, with respect to how often cyclists have to make a full stop on a traffic light approach. The SFGA performs 1.9 times as well at the lowest saturation rate, and 2.3 and 3.1 times better for 30 and 40% respectively. This difference may again be explained by the higher traffic densities in the cycle lanes and the prioritization of the many, but may also originate from the better performance of SFGA in general.

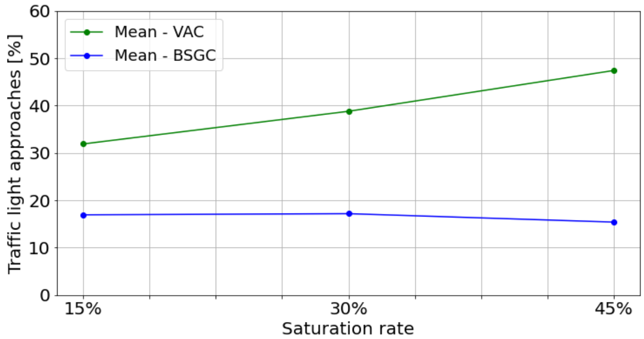


Figure 5.4: The percentage of traffic light approaches requiring cyclist to make a full stop

All together, the results have shown that the structure free controller outperforms VA in all of the performance metrics. The relative performance of the controllers (KPI_{SFGA}/KPI_{VA}) is summarized in Table 5.1. At the lowest saturation rate, performance is the most similar between all metrics, with SFGA performing at most twice as good as VA on all accounts. In absolute terms the difference is only a couple of seconds. With increased saturation levels the differences between the controllers increase in both relative and absolute terms. Only in terms of average car driver delay the relative performance is quite similar over all saturation levels.

Table 5.1: Performance ratios (SFGA/VA)

	Saturation rate		
	15%	**30%**	**45%**
Average delay	1.8	2.6	3.0
Avg. delay - Cyclist	1.6	2.8	5.6
Avg. delay - Car driver	2.0	2.5	2.2
Traffic light approach with stop - Cyclist	1.9	2.3	3.1

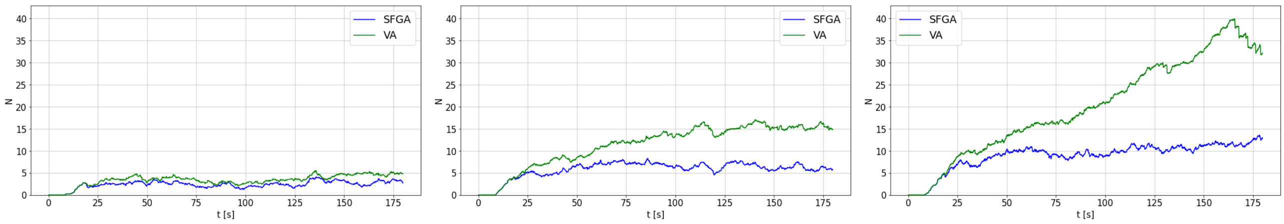
5.1.3. Understanding the differences in performance

The experimental setup (Section 4.1) described that the expected differences between VA and SFGA likely originate from fewer people waiting for the traffic light and a larger share of travellers that is able to cross the intersection with a relatively short delay.

SFGA does indeed result in fewer people waiting for the traffic light. This can be seen in Figure 5.5, that shows the average number of travellers in the dilemma zones for both controllers. For all saturation rates, there are always fewer people in the dilemma area for SFGA than for VA. Initially the results are very similar. Over time the number of travellers in the dilemma area grows, and after a while becomes relatively constant, indicating some warm up time until the controllers function at a equilibrium. Such an equilibrium is not as clearly identifiable for VA at 45% saturation. The absence of a clear equilibrium may be caused by higher cycle times, due to higher traffic numbers, resulting in fewer cycles fitting in the total simulation time of 180s.

Because the controllers are evaluated for identical traffic scenarios, the inflow of both controllers in the dilemma area is similar, and the output differs because of control decisions. Therefore, the fact that both controllers seem to converge to an equilibrium, indicates that both controllers achieve a similar throughput of the intersection. However, in order to achieve this throughput, VA requires, on average, a higher number of travellers in the dilemma areas, waiting for the traffic lights. SFGA manages a similar throughput with a lower number of waiting travellers, resulting in lower average delays.

The lower number of travellers in the dilemma area required for SFGA to achieve throughput similar to VA, may be caused by the larger variety of combinations of traffic lights the controller can use. Without any implemented flexibility, VA must wait for a traffic light to be a part of the active conflict group, in order for it to be allowed green. This contrary to SFGA, that can allow any traffic light show green, as long as no conflicting traffic lights are active at the same time. A second reason for fewer people in the dilemma areas, is that SFGA prioritizes lanes with more travellers over lanes with fewer travellers. This means that it may choose a movement with three travellers to cross, instead of a movement with one traveller that VA allows to cross because it is in the active conflict group.

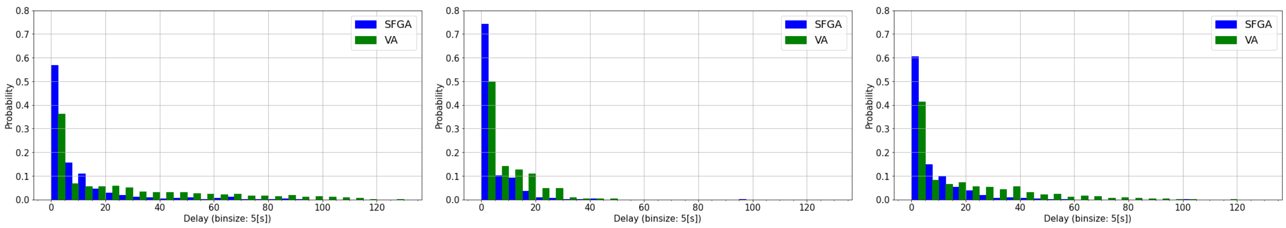


(a) 15% traffic saturation (b) 30% traffic saturation (c) 45% traffic saturation

Figure 5.5: Average number of travellers in the dilemma area over time for the three different saturation rates

The structure free controller prioritizes traffic lights with larger platoons of travellers, over traffic lights with less effect on the total delay. VA only considers whether or not there is any number of travellers in the dilemma zone of the active group when deciding on if a green light is shown (See Section 4.1.3). This difference results in the median delay of the structure free controller being lower than that of VA. Figure 5.6 shows a histogram with the individual delays of travellers of both controllers, for the three different saturation levels.

The figures show that, compared to VA, the shape of the histograms of the SFGA tend to be shifted more towards lower delays. This means, if the intersection is controller by SFGA, a higher number of travellers experience lower delays compared to VA. This supports the expectation that SFGA allows a larger number of travellers to cross the intersection at the cost of a lower number of people that are delayed. Interesting is, that the delay of this lower number of travellers does not tend to be very long, as for all saturation levels, the delay probabilities of SFGA converges to zero faster than VA. This indicates that the prioritization of the many does not necessarily lead to additional, much longer delays for the few. Instead, it indicates that there is a choice to be made on what group of travellers to delay briefly, and what group travellers to delay for a longer time.



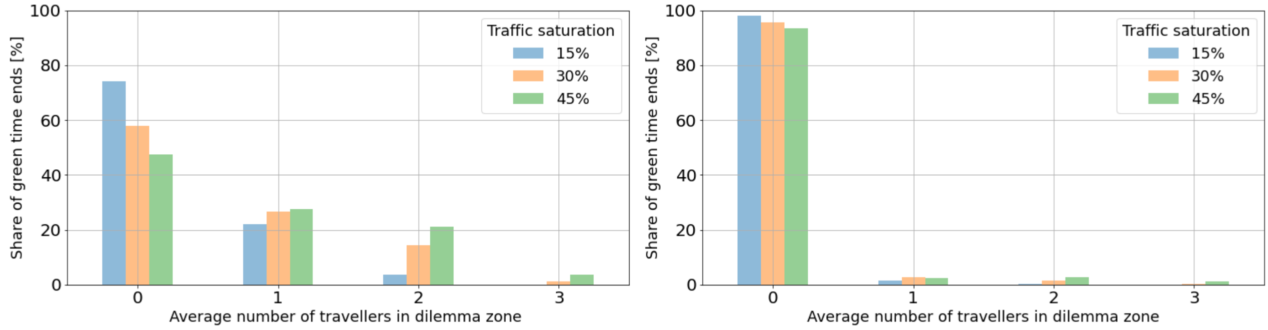
(a) 45% traffic saturation (b) 15% traffic saturation (c) 30% traffic saturation

Figure 5.6: Histogram, normalized by the number of runs, of delays experienced by travellers

VA and SFGA follow different procedures when deciding on the control actions for a given traffic situation. A number of metrics related to the control strategies will be discussed. These metrics relate to the total green time, effective green use, traffic light combinations that show green at the same time, and how often a specific number of agents is in the dilemma zone when a controller ends green time.

SFGA is expected to sometimes truncate green time, even if there are travellers in the dilemma zone. Figure 5.7, that shows how often green time is truncated as a function of the number of travellers in the dilemma zone, supports this hypothesis. In almost all occasions, VA ends green time when there are no longer any people in the dilemma area. In the few that this does not happen, the maximum green time has been reached. This contrary to SFGA, for which there are still travellers in the dilemma area, in a significant share of the green time end. This likely happens, when there is a larger number of travellers waiting in a conflicting movement, or a combination of conflicting movements. The controller may also decide to truncate green, when travellers in the active movement are relatively far upstream of the traffic light, allowing other travellers to cross, at a relatively small cost for the traffic now facing a red light. Finally, the controller can also be forced to end a green time because a traveller in a conflicting direction has been waiting for almost the maximum waiting time.

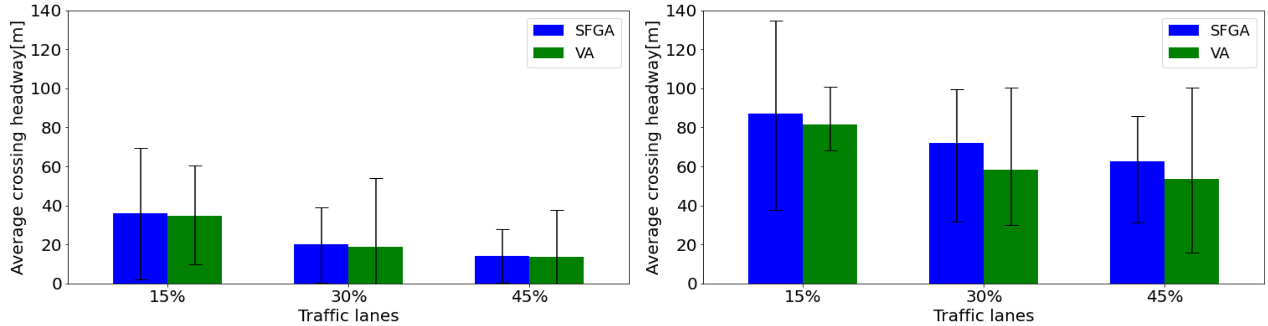
Figure 5.7 shows clearly, that the more travellers there are in the dilemma zone, the less often SFGA truncates green time. This is because the controller will only end green, if this is beneficial in means of total delay. The cost of ending green time is larger with more people in the dilemma area. The figure also shows, that with higher traffic saturation, SFGA more often chooses to end green time, and does so more often with more people in the dilemma area. This too is sensible, because even though the cost of ending green time increases with more people in the dilemma area, the cost of not doing so is also higher when there are more travellers waiting for other traffic lights.



(a) SFGA (b) VA

Figure 5.7: Spread of green time endings over how many agents are located in the dilemma area in the moment of switching

When and who controllers allow to cross, can result in differences in effective green use. The structure free controller chooses to end green time if it predicts that it is more effective to let another traffic light show green instead. It is expected that this is often the case when there is a larger number of people benefiting from the other traffic light being green. If there are more people benefiting from the green light, the effective use of green time is likely higher. As discussed in the experimental setup (Section 4.1), the average headway at the moment of crossing the stopping line is used as a metric for effective green use. Figure 5.8 shows this average headway of cyclists and cars for the two controllers at three saturation rates.



(a) Cyclists (b) Cars

Figure 5.8: Average headways at the moment of crossing the stopping line. A lower average headway indicates more effective use of green, as travellers follow each other more closely.

Results contradicts the expectations with regard to effective green use: on average, crossing headways are larger for the SFGA controller than for VA. This may be because the structure free controller is expected to show green more often and earlier in time than VA. This results in more time for queues to form for VA, which in turn results in more effective green use. However, this SFGA allows individual travellers to cross more often, resulting in fewer cars waiting, but also in less effective use of green time. This behavior of SFGA can be seen in the trajectories presented in Figure 5.1.

Differences in when and where a green light is provided, are expected to be visible in the total green time. As was explained in the experimental setup (Section 4.1), at low traffic levels, it may occur that there are no travellers in the dilemma zone upstream of a traffic light in the active phase of VA, causing the traffic light to show red. No movements outside the active phase are allowed to show green for VA, contrary to SFGA, which can allow another traffic light to be green, resulting in more total green time. At higher traffic levels, this is less likely to occur and the total green time of SFGA may even be lower, because of the more frequent switching behavior of the SFGA, resulting in more loss time and hence less total green time. Figure 5.9 shows average the total green time.

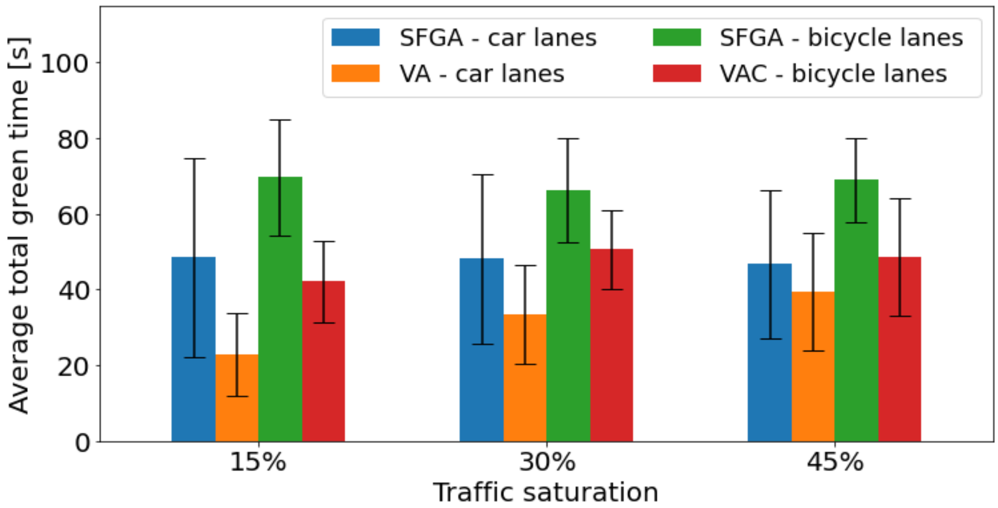


Figure 5.9: *Average total green time by travel mode in a simulation of 180s*.

The average total green time provided by SFGA is higher than that of VA, for all saturation rates. As was explained in the previous paragraph, this was only expected to be the case for low traffic saturation levels, due to the larger degrees of freedom of SFGA. This may indicate that the scenario, in which there is no traffic in proximity of the traffic light in any of active movements, is more profound than expected at the evaluated saturation rate. That the scenarios in which VA shows green for only a subset of the traffic lights in the conflict group, is supported by the VA showing more total green time for car lanes at higher saturation levels. Because there is more traffic, these scenarios should occur less often and total green time should increase.

Interesting is that SFGA results in very similar total green times, independent from the traffic saturation. This is likely due to a design choice of the structure free controller. The controller will only end green time when it is more effective to show green somewhere else. This means that, if there is no traffic benefiting from a green light, the controller will make a random decision on what traffic light shows green, even if this does not have any use. This unused green can been seen in Figure 5.1, around 125 seconds in lane 06. Inclusion of a cost for total green time, orders of magnitude smaller than the cost for delay, may help resolve this and allow for more profound conclusions based on the total green time.

The final metric that explains differences in performance for the controllers, is the variety of traffic light combinations that show green green at the same time. The histogram, showing this metric, provided in Figure 5.10, clearly shows SFGA makes use of a larger variety of combinations. The fact that SFGA makes use of so many alternative options, hints that there may be significant efficiency gains by using alternative paths in the control structure of VA. Note that of all but one of the combinations, that are only used by SFGA, could be implemented as alternatives in the control structure of VA, if flexibility had been allowed. Only the combination [01, 04, 10] could not be included, because these traffic lights are part of three different phases, where all other combinations can be made up of combinations of two subsequent phases of the control structure of VA (See Figure 4.2).

One should be careful to conclude that inclusion of flexibility would allow VA to perform similar to the SFGA. First of all, the structure free controller uses the genetic algorithm to determine what combination of traffic lights results in the lowest delays. Even if VA is allowed to use the same combinations, it will only use the alternatives if there is no detected traffic in a movement that otherwise would be used. If there is any traffic detected, a less effective combination in terms of resulting delay may be used. Secondly, in this case study, a large number of combinations can be included as alternatives, because the intersection layout of this case study is very simple and includes only three conflict groups (See Figure 4.1). With three conflict groups, the probability that a combination can be made up from the movements of two subsequent conflict groups is larger than when four or more conflict groups would be included. Therefore, at more complex intersections, it can be expected that fewer combinations that are used by SFGA, can be implemented as alternatives.

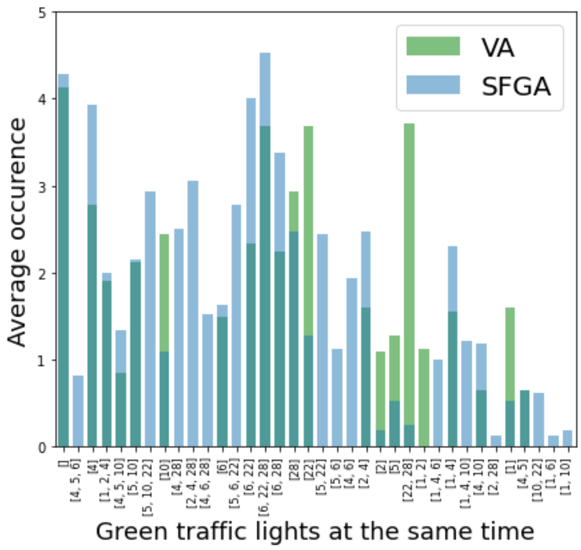


Figure 5.10: Average occurrence of green traffic light combinations in a single simulation run.

As a final note, a lot of the reasoning on why the structure free controller performs better been attributed to the fact that densities are higher on cycle lanes. This is an unintended bias, introduced by the combined choices of infrastructure layout and modal split. However, it must be noted that by default bikes occupy less space than cars do. A car travelling at 50 km/h occupies roughly $140m^2$, whereas a moving bicycle occupies only $5m^2$ [39]. Therefore, these higher densities on cycle paths may not even be that far-fetched compared to the real world. The results have shown that for VA, the average delay of cyclist increased, whereas the structure free controller kept this delay fairly constant. All the results together indicate that the SFGA controller as of itself, so without any cyclist prioritization, already will serve the needs of cyclists way better than VA control.

As was explained in the experimental setup (Section 4.1, there are things things that can be done to adapt VA to perform more like the structure free controller. Other changes to VA can be made as well, for example having green for bicycle traffic light twice each cycle. But even with these adaptations, the structure free controller does actively control for traffic density, something VA by definition does not do. Therefore, this thesis does contribute to the evidence that controllers, other than VA may be better suited for serving the needs of other modalities than the car.

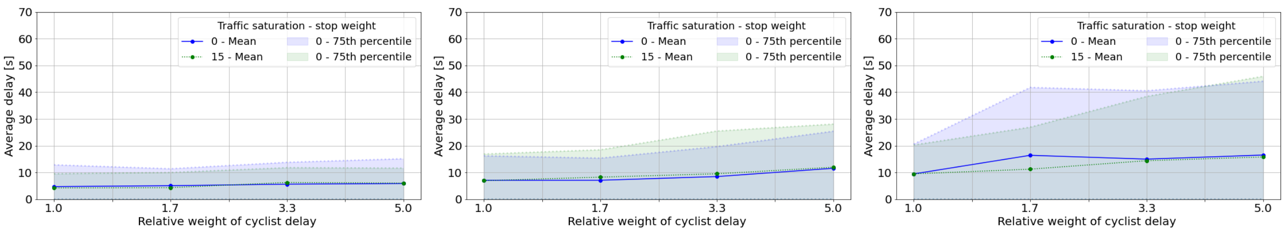
5.2. Performance of SFGA control with cyclists prioritization

The previous section compared the SFGA controller to traditional VA. This section will now discuss how performance of the structure free controller changes, when it objective function includes weights that prioritizes the desires of cyclists over those of car drivers. Two parameters are varied: the relative weight of delay for cyclists compared to car, and the weight for a full stop made by a cyclist. See Section 4.1 for the full experimental setup.

Figure 5.11 shows the effect of varying relative weight for cyclist delay and the stop weight on the average delay of all travellers. The effect of the weights on the average delay is very limited at 15% traffic saturation, but at higher traffic saturation the parameters do lead to bigger changes, both in mean delay and in delay spread. Note that less influence on the average delay does not necessarily mean that the parameters have no effect, as delay may shift from cyclists to car drivers.

The inclusion of weights that prioritize cyclists, result in choices of the controller on ending, extending or starting green time, are more often made to the benefit of the cycle paths. Because the weights result in negative effects for cyclist contribution more to the objective function, solutions that result in lower delays or number of stops for cyclists are stored and selected for adaptation in successive generations. As was expected, the average delay increases when larger weights for delays of cyclists are used, and these increases are larger at higher traffic saturation rates (Section 4.2). At higher saturation rates the chance of a trade off resulting in a green light for any of the cars decreases, because with more travellers in the system, total delays increase and the relative effects of the weights increase. The (small) improvements in cyclist delay can therefore result in (larger) increases of car driver delay. As delays for the traffic modalities scale disproportionately, the average delay can increase. Interesting is the observation that the average delay for 45% saturation is larger at a relative weight of 1.7 than at the weight of 3.3. This phenomenon will be discussed alongside the discussion of the effect of the stop weight on the delay of cyclists and car drivers, later on this section.

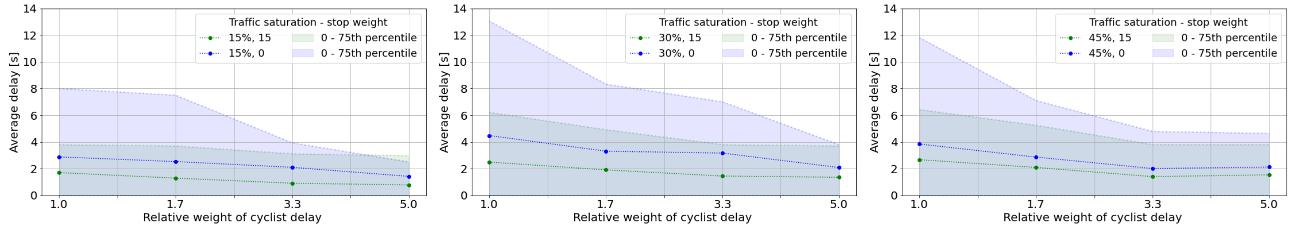
Regardless of the relative weight for delays, the effect of the weight for full stops on the average delay is fairly limited. This indicates that this weight either has little effect whatsoever, or does a better job at proportionally shifting delay from cyclists to car drivers. Generally, the increases in delay are limited for any of the saturation rates as well. This contradicts the expectation, as the effect of this weights was expected to be the largest at low saturation rates and decrease with increased traffic demand. This may be explained by the controller decisions at low traffic levels, resulting in a 'who to allow to cross first' choice, and inclusion of cyclist prioritizing weights allow cyclists to cross first. This in turn does result in car driver delays, proportional to the delay the cyclist would otherwise have endured.



(a) 15% traffic saturation (b) 30% traffic saturation (c) 45% traffic saturation

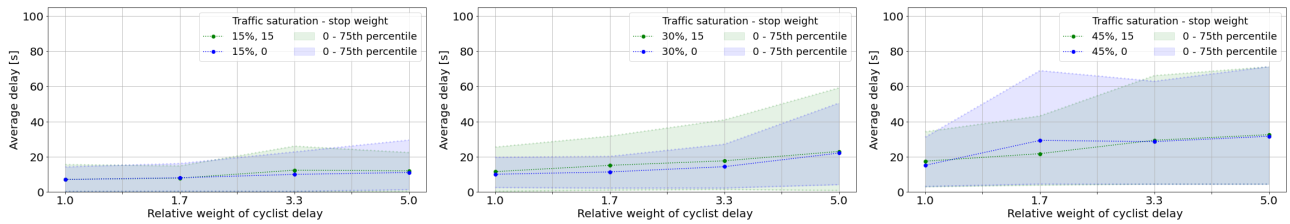
Figure 5.11: The average delay and the 75th percentile delay as a result of different relative weights (1.0, 1.7, 3.3, 5.0) for cyclist delay for each of the saturation levels

Figures 5.12 and 5.13 show the average delay of cyclists and car drivers respectively, as a result of different combinations of delay and stop weights for all evaluated saturation rates. As was expected, the weights result in decreases for average delay for cyclists, and increases in delay for car drivers. Generally, the largest decreases in average cyclist delay are achieved by the 1.7 and 3.3 weights, while improvements are less substantial with a weight of five. In a similar manner, increases in car diver delay are generally quite low for 1.7 and 3.3 and increase more rapid with a weight of five. This can be explained by the exponential impact of the weights that was discussed in the previous paragraph, and indicates that some small prioritizing effects may be the most suitable for prioritizing cyclists. The relative smaller weight results in prioritization in cases where little additional harm is done to car drivers, but does not choose to prioritize cyclists when this causes very large negative effects for car drivers.



(a) 15% traffic saturation (b) 30% traffic saturation (c) 45% traffic saturation

Figure 5.12: Average cyclist delay and the 75th percentile cyclist delay as a result of different relative weights (1.0, 1.7, 3.3, 5.0) for cyclist delay for each of the saturation levels



(a) 15% traffic saturation (b) 30% traffic saturation (c) 45% traffic saturation

Figure 5.13: Average car driver delay and the 75th percentile car driver delay as a result of different relative weights (1.0, 1.7, 3.3, 5.0) for cyclist delay for each of the saturation levels

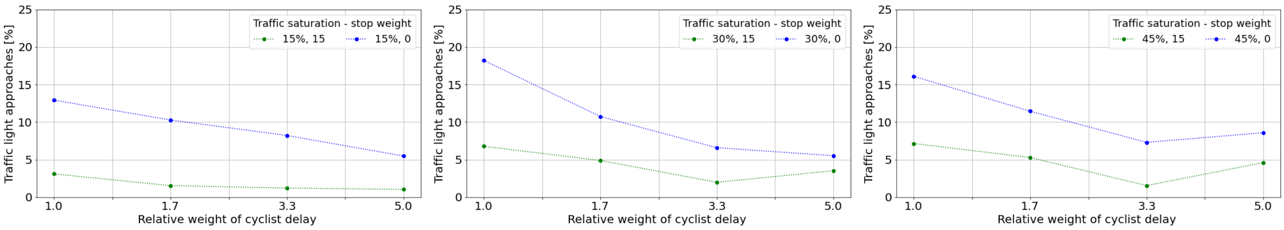
The average delay graph (Figure 5.11a) shows the weight for full stops results has a small effect on the average delay. This was attributed to either very little effect whatsoever, or to this weight being able to shift delays relatively proportional from cyclists to car drivers. Figures 5.12 and 5.13 help substantiate the latter. Delays of cyclists get reduced by roughly three seconds by inclusion of this weight, whereas car driver delays roughly increase with a similar, though slightly larger amount. This indicates that green time distribution may not be changed significantly but the timing of green green duration may be translated in order to avoid stops. This in turn is also more effective in terms of cyclists delay, but is slightly less effective in terms of absolute average delay. This also indicates that, even though the values for relative delay weight are based on literature, metrics that do result in disproportional delay differences, are not suited for transferring delay from one mode to another. Disproportional delay differences may of course not be a problem, depending on what goal is aimed for by implementing the controller.

Another interesting observation is that average delays for car drivers do not seem to increase to much more than 30 seconds. This is likely because of the imposed maximum waiting time of 100 seconds. When car drivers get delayed in order to allow cyclists to cross first, after a while the first car driver a the queue will approach the maximum waiting time. No matter how large the weights for cyclists are, this car driver will be allowed to cross. Other cars, queuing behind this traveller, can also make use of this green time, as the light is green for at least the minimum green time, allowing multiple travellers to cross the stopping line. This results in averages lower than 100 seconds. This also means there is a maximum to what can be achieved by including weights for cyclists prioritization. At some points car drivers will be allowed to cross anyway.

The maximum waiting time may also provide an explanation for why the average delay of the system is higher with a relative weight factor of 1.7, compared to 3.3 when evaluation at 45% traffic saturation. Figure 5.13c illustrates that the average car driver delay is relatively constant, around 30 seconds, for any of the relative weights. As explained, this is likely due to the maximum waiting time. The larger weight can however still result in lower delays for cyclists, what does happen according to Figure 5.11). A constant car driver delay but a lower average cyclist delay results in a lower average delay because of the fifty fifty modal split.

Another noteworthy observation is, that the delay of car drivers is lower at 45% saturation with inclusion of the stop weight, than without. This may be explained by the translations of green duration as a result of the stop weight being less harmful for car drivers. These decisions with less impact on cars are not chosen without the inclusion of cyclist weight, because the relative delay weight of 1.7 makes the impact on car drivers of lesser importance than those of cyclists.

Figure 5.14 shows the probability of a cyclist having to make a full stop on a traffic light approach. This figure confirms the expectation that the relative weights for delay also reduces the number of stops for cyclists. However, the constant weight turns out to be way more effective in doing so. A relative weight of five is required to approach the same effect as the stop weight. In relative terms, the stop weight contributes less to stop reduction the higher the relative weight of delay. This is sensible, as when delays of cyclists are already at a very low value, there is less room for improvement. Additionally, the relative cost of one stop compared to one additional second of delay becomes lower, thus the relative importance of stops is reduced.



(a) 15% traffic saturation (b) 30% traffic saturation (c) 45% traffic saturation

Figure 5.14: The percentage of traffic light approaches of cyclists resulting in a full stop as a result of different relative weights for cyclist delay for each of the saturation levels

6 Conclusion and Discussion

Section 6.1 presents the conclusion of this Thesis. Section 6.2 then provides the discussion, containing some high level nuances that should be kept in mind when applying the conclusions of this thesis to other work.

6.1. Conclusion

The research objective of this thesis is *To design and evaluate the performance of an intelligent intersection controller, that prioritizes the interests of cyclists, and that controls an isolated intersection in an environment with connected cars and bicycles, without causing unreasonable delays for car drivers.* A number of sub questions were formulated and all are answered in order to fulfill this objective.

A literature review has been performed to identify the desires of car drivers and cyclists with regard to controlled intersections. It is concluded that, cyclists want no motorized traffic to be allowed to cross their path when they are allowed to do so, slow down as little as possible, avoid low speeds and full stops, short waiting times and delays, and to be allowed to start moving as soon as the last conflicting traffic has crossed. The most important desires of car drivers are concluded to be to minimize their delay and waiting time, to prevent queues from blocking approach lanes of other traffic lights and sufficiently long green times. These desires have been translated to control objectives, and a trade off is proposed. For simplicity sake, a subset of these desires has been selected, based on the main negative effects of intersections on cyclists. Average cyclist delay and full stops have been chosen the most important metrics to represent cyclists' desires. Car drivers' desires are represented by the delay of car drivers. Based on literature, a value of time 1.7 to 5 times higher is concluded to be a reasonable range for the weight of cyclists delay compared to cars. Unreasonably long waiting times are concluded to be waiting times longer than 100 seconds, because RLR probabilities increase above this threshold.

A literature review conducted on traffic system model for cyclists, cars and traffic lights, has concluded that a microscopic, rule based kinematic model to be best suitable model to represent the identified desires of cyclists. A car following model from literature and individual representation of traffic lights were concluded to be the best suited for representing cars and traffic lights. Literature review on control methodologies has concluded that simulation based control with optimization by means of a genetic algorithm is the best control methodology for the controller. Vehicle actuated control is concluded to be the best benchmark for performance.

The results of the case study allow for the conclusion that the designed structure free controller is suited as a controller for an isolated intersection that prioritizes the interests of cyclists, without causing unreasonable delays for cars. This conclusion is drawn for traffic saturation rates of 15, 30 and 45 % of intersection capacity. In terms of average delay, regardless of the transport modality, the controller outperformed the benchmark by a factor 1.8, 2.7 and 3.0 for each of the evaluated saturation rates.

The controller does not require explicit prioritization of cyclists, in order to result in lower delays for cyclists than for cars. The percentage of cyclists that has to make a stop is also drastically reduced compared to VA. The controller allows for different weights for delay, as well as for inclusion of a weight for the number of full stops. Introducing any of these prioritizing weights, results in even better performance metrics for cyclists, but this comes at the cost of disproportionate increases of delays for car drivers. Whether or not this increase of delay of car drivers is acceptable is up for personal interpretation. It is concluded that that the higher the delay priority ratio, the more disproportionately delays of car drivers increase compared to cyclists. A low delay priority factor, or a cost for a full stop for cyclists is suggested to be the least intrusive method of providing additional priority for cyclists. Following the definition of reasonable delays as a waiting time exceeding 100 seconds, no unreasonable delays for car drivers are caused by the SFGA controller.

The better performance of the structure free controller compared to the benchmark is attributed to the the fact that the SFGA optimizes with a large degree of freedom, whereas VA follows a predefined set of rules based. It is unlikely that state of the art methods, that improve VA control performance, can achieve a same level of performance.

Without inclusion of weights that explicitly prioritize cyclists, the SFGA controller already tends to prioritize cyclists. This is attributed to higher traffic densities on cycle paths compared to car lanes, resulting in the controller prioritizing traffic on these lanes over car lanes. These higher densities can be expected in situations that follow the use case for this thesis: urban cores with lots of bicycle traffic.

In the case study, VAC also resulted in lower delays for cyclists than for car drivers. It is concluded that this lower average delay should be mainly attributed to the choices in infrastructure layout. The conclusion that the structure free controller better prioritizes cyclists' desires can be made, provided a large number of cyclists make use of the intersection compared to the number of cars. The SFGA considers individual travellers and prioritizes the movement that benefits the most from crossing first. Cycle paths, with higher density, are prone to be prioritized over car lanes, with lower densities. The reason that VAC has led to lower delays for cyclists, is that the infrastructure layout has led to more frequent green time extensions and scenarios in which the cyclists can pass, because no traffic in other signal groups has been detected. This will change with changing infrastructure layout, while the reason why the SFGA controller structurally prioritizes cyclists.

All in all, the main conclusion to be drawn from this thesis is that a controller does not necessarily need to weigh the desires of cyclists more heavily than those of car drivers, in order to have a tendency towards prioritization of the interests of cyclists. When actively controlling for the delay of travellers on the intersection, instead of following predefined sequences, the desires of cyclists are already represented better in the controller decisions, because of the higher traffic density that is often associated with bicycle paths. The controller can be applied for cycle paths with lower demand, however inclusion of weights that explicitly prioritize cyclists over car drivers may be required to achieve prioritization of cyclists.

6.2. Discussion

Some precautions should be taken when interpreting the conclusions drawn in Section 6.1. The absolute values, regarding relative performance of the structure free controller, are calculated based on a single case study, which is subject to the effects and assumptions in the traffic system model, thesis scope and intersection layout. This section will discuss the most important things to keep in mind when applying the conclusions outside the scope of this thesis.

First of all, this thesis assumes perfect data quality and penetration rate for CV technology. Both these assumptions are major simplifications of reality that can have a large effect on the performance of a controller in the connected environment [80][53].

Evaluation is performed in a simulated environment. Because of this, assumptions have had to be made with regard to behavior of cyclists and car drivers. These assumptions are to a large extent based on models provided in the literature, but there always is a discrepancy between models and the actual behavior of humans. For car drivers, the model assumes infinitely long approach lanes and no lane switching behavior. Additionally, the car following model is fairly simple and only includes distance to the predecessor and a drivers' own speed as predictors. The major simplification made in the model of cyclists behavior is, that nearby cyclists do not influence each other, and therefore there is no queuing behavior included in the traffic model. This can result in increasingly large underestimations of delay for higher traffic volumes. This assumption is the reason that performance evaluation has been done up to 45% saturation rate. A more sophisticated traffic model for cyclists, considering interaction between cyclists as well as the interaction with traffic lights would greatly improve the applicability of this research.

Additionally, behavior of travellers is, as is often done in intersection control research, generalized. All car drivers are assumed to behave identical, and cyclists are subdivided in three different categories. This is a major simplification for both modalities, but likely has more impact on cyclists, as cyclist behavior is very heterogeneous.

Finally, the design of the infrastructure layout and modal split influence the results. The combined choice of these values, has unintentionally led to amplification in the traffic density difference between car lanes and cycle paths. Conclusions on controller performance can still be drawn, as the use cases for this controller are likely to have higher densities in bicycle paths than car lanes, but the extend to which the amplification of density differences influences performance is yet unknown.

Finally, this controller is designed and evaluated only for an isolated intersection. Prioritizing the desires of cyclists may have relatively low negative impact on individual intersections, but it may cause problems elsewhere in the road network. Note that the SFGA controller is designed to function in unsaturated traffic flows, so the effects on network level may be low, but this should be researched before actual conclusions on this can be drawn.

7
Future work

As this thesis represents -to the best knowledge of the author- the first work with regard to a structure free controller in the connected environment that includes cyclists, the work on this thesis has identified in a lot of suggestions for future work. These suggestions are organized in five main categories: improvements for traffic system model, improvements of the controller itself, a wider range of case studies to evaluate performance, expansion of the scope in which the designer is ought to function and other detection methods that do not require CV technology.

7.1. Improved traffic system model

The underlying kinematic models for both transport modalities have been chosen mainly because these models are the only models found in literature that approach the requirements of this thesis. No existing micro-simulation models were found that combine the interaction between travellers, the interaction with a traffic light and more complex aspects of driving and cycling behavior.

If such a model is to be formulated and validated in future research, this is likely to be of great benefit for the functioning of the controller designed in this thesis, as well as for research on connected vehicle based intersection controllers that include cyclist in general. This is not limited to connected environment only. Traditional intersection control research will also benefit greatly from such a model.

7.2. Improvements for the controller design

The genetic algorithms converges to good solutions within few generations. The next generations achieve only marginal performance improvements. This may mean that the algorithm is very effective, but it can also indicate the algorithm only finds near optimal solutions. Improvements in current solution generation algorithms, alongside inclusion of additional algorithms may achieve better performance. Improvements in the algorithms are also desirable to reduce computation time, as the minimum green time constraint is not captured very effectively. Each generated solution is evaluated for conflicts with any of the constraints. These tests discarded 29% of solutions based on the minimum green time constraint. Reducing the number of discarded solutions, allows for the computation time to be used more effectively. Finally, efficiency improvements of the simulation and controller code, in terms of both run time and memory consumption, can allow for simulations of a longer duration with identical resources. This means either a longer simulation time, or more freedom to choose the controller tune parameters (See Section 4.1.4). The controller design improvements will now be discussed in depth.

The effectiveness of solution generation can be improved in three ways. First of all, the share of infeasible solutions can be reduced. The algorithm iterates between randomly assigning a green duration of half a second and updating the solution based on system knowledge, see Section 3.3.3.2. This is done to generate a solution as random as possible, but can in some occasions result in two randomly generated green duration preventing each other from being prolonged to the minimum green time. This may be improved by changing the duration of the first green time of a single light to the minimum green time. Second, mutation algorithms should include green time extensions and reductions of some random duration instead of incremental steps of 0.5 seconds each generation. This can result in fewer generations required to achieve the optimal green duration. Using another set of rules for the rule based solution generator, may also speed up the convergence process of the GA. The proposed rule based system did not contribute to faster convergence. Instead, a highest density first approach may perform better.

Finally, a new mutation algorithm should be included that has the goal of ending green time of some movements earlier and starting the green time of the succeeding traffic light later, in order to squeeze through traffic from another movement. This was ought to be achieved by the current green time extension and reduction algorithms, but this failed. Firstly, because solutions that would extend and reduce green time are not stored in successive generations, because of higher delays. However, a higher delay may be temporarily required, to make a large improvement later on. As these solutions are not stored long enough, no possibility for a third intermediate traffic light to be green is available. Secondly, green time reductions immediately result in longer green time for already active traffic lights, even if this has little additional benefit. Including a weight for the total green time in the selection procedure, may also help reduce this effect. This weight, that should be orders of magnitude smaller than the negative rewards for delay and other control objectives, will also result in less unused green time. This is because it allows the controller to, in a situation with two different solutions that result in identical delays, select the solution with less green time.

Another improvement for the controller is that it is expected to be very beneficial, is to include some penalty for travellers still waiting at the end of the prediction horizon. In its' current form, the controller may decide on a signal plan that does forces a cyclist to reduce speed, but does not result in a full stop yet. However, if the prediction horizon would be one second longer, this cyclist would be forced to make a full stop. Similarly, a traveller forced to slow down will experience more delay after the prediction horizon than a traveller at cruising speed, as this traveller does need to accelerate. These phenomena are not captured in the decision making process of the proposed controller. Note that the controller has the ability to 'correct' its' mistakes, as in the next window, the decision that forces the cyclist to stop is overruled. However, inclusion of a weight penalty for travellers still waiting or travelling at reduced speed at the end of the prediction horizon may improve predictions and thereby the effectiveness of the controller.

7.3. Extension of the evaluation framework

The performance of the structure free controller is evaluated in a single case study. The extend of this case study is fairly limited, as the traffic saturation is only varied between three discrete values, the largest of which was only 45%. Evaluation in a wider range as well as with smaller intervals can substantiate the conclusions drawn in this thesis and allow these conclusions to be generalized. Note that in order for the traffic saturation rate to exceed 45%, the traffic model must be improved to include queuing behavior for cyclists. The controller should also be evaluated for a wider range of weights for a full stop of cyclists to fully understand the influence this weight has on controller performance.

Similar to saturation rate, case studies with more variation in modal split and infrastructure layout can provide a stronger foundation for the benefits of the designed controller. This also will allow to quantify the relative differences in performance caused by the controller design and traffic density differences due to modal split and infrastructure layout.

Finally, this thesis has assumed perfect data quality and penetration rate. These are quite large assumptions, and evaluation for these variables is required to have a clear understanding of the implications of using the designed controller in the connected environment.

7.4. Expansion of the design framework

Finally, future work recommendations are now provided that relate to expanding the design scope of the thesis as described in Section 3.1.2. The scope of this thesis is fairly limited, due to time restrictions and because this is, to the best knowledge of the author, the first controller of its' kind.

First of all, a larger subset of the desires of car drivers and cyclists may be selected to function as control objectives. This can provide more insight in the extend of the what improvements for cyclists can be achieved an how these improvements (negatively) effect other traffic modalities. Research on a more profound quantification of the relative importance of these desires for cyclists may help in prioritizing these desires.

Some improvements may be achieved fairly simple. Relaxations on constraints of clearance time, yellow time and minimum green time could already provide significant improvements in controller performance, regardless of the type of controller. At low saturation levels, the loss time due to these factors is relatively large. Additionally, CV technology may allow for these relaxations without significant decreases in safety.

As was explained in Section 7.3, the controller should be evaluated for different data quality and connectivity penetration rates. In order to perform better under sub-ideal data circumstances, the missing data estimation may become essential, This can be model based, but data can also be enhanced using fixed place sensors or vehicles as mobile sensing nodes, as proposed in [111].

Finally, a wider range of transport modalities should be included in the controller to be better suited to function in the real world. Think of pedestrians, public transport or automated vehicles. More determination in the types of travellers should also be made in terms of behavior and personal characteristics. Examples are differentiating between cars and trucks, mechanical bicycles and e-bikes, experienced and inexperienced cyclists or elderly and younger cyclists. This also allows for more safe decisions to be made with regard to ending green, as some types of travellers can decelerate faster than others, resulting in different abilities to stop.

If all the before-mentioned improvements to the controller and extensions to the framework are made, controlled tests of the controller in real life may be feasible. This would be a very large undertaking for the researcher taking up this challenge, however it could provide very interesting results and represent a major step in the CE research field. Eventually, the controller might even be used for practical implementation.

7.5. Connected environment without connected vehicles

The connected environment can help significantly improve vehicle detection and provide information on personal characteristics that influence movement behavior. This is not a purely positive development, as it rises a lot of questions with regard to privacy. A survey from the American League of Bicyclists found 40% of respondents are not willing to be connected to vehicles and infrastructure around them[7]. Other, less privacy invasive detection methods do exist, for example traffic cameras that locally convert video image of travellers to points, with some characteristics. This less privacy sensitive data could then be used for controlling as well. The initial motivation for this thesis was to show that these less privacy invasive methods could provide comparable or even better performance.

This was not feasible within the time limit of this thesis. It is however still one of the major recommendations for future work. In addition to being less privacy invasive, these camera based may even result in better performance, once factors as a non perfect penetration rate are incorporated for CV technology. This is because a camera may still have (near) perfect knowledge, even though this would be in a more limited area.

7.6. Future work summary

This chapter has provided an extensive list of future work that may be inspired by this research. A wider availability of validated traffic system models will be very beneficial for the the designed controller, as well as for other bicycle related intersection control research. Improvements for traffic system model are proposed, mainly with regard to improvements in and additions of solution generation algorithms. Additionally, inclusion of a penalty for green time, orders of magnitude smaller than contributions of delays and stops has been proposed as a means to reduce unnecessary green time. A penalty for travelers waiting at the end of the controllers prediction horizon is proposed as a means to achieve lower delays.

Extension of the evaluation framework, to solidify the claims made in this research, and the design framework, to expand the applicability of the controller are proposed. Finally, this chapter proposes the use of other detectors, like traffic cameras, as a means to circumvent the use of connected vehicles in order to attend to privacy related concerns that are associated with them.

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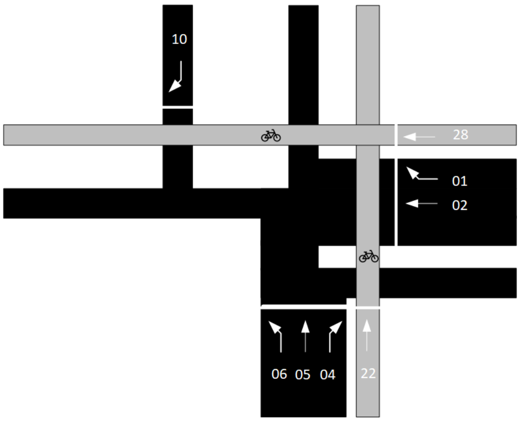
A

Intersection dimensions and capacity calculation

The intersection layout is provided in the figure below. A rough estimation to be made on the capacity of the intersection. The intersection contains six car lanes of which four are turning lanes and two are straight going lanes, which have a capacity of $1800 veh/h$ and $2000 veh/h$ respectively[12], and two cycle lanes, with saturation rate estimates between the 4.500 and 6.500 bicycles per hour[124].



	1	2	4	5	6	10	22	28
1	0	0	0	0	0	0	0	0,5
2	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0,5
6	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0
22	2	1	0	0	0	0	0	0
28	0	0	0	0	0	2,5	0	0

Figure A.1: Intersection layout, flow numbering and clearance time matrix

The capacity of one full cycle can be estimated by multiplying the capacities of each lane with the maximum green time of that lane in one full cycle. The hourly capacity of the intersection can then be found by multiplying this factor by one hour divided by the cycle time and equals approximately 7000/h. Both car lanes and cycle paths contribute roughly half to this capacity.

$$C_{est} = (4 * 48 * \frac{1800}{3600} + 2 * 48 * \frac{2000}{3600} + 2 * 48 * \frac{5500}{3600}) * \frac{3600}{152} \approx 7000/h \tag{A.1}$$

B
The connected environment and prediction errors

As was explained in Chapter 3.3.2, the same traffic system model is applied for the simulator used for evaluation and the structureless controller to make predictions. This results in perfect system knowledge, something that is not realistic. This appendix discusses how the traffic system model can be split into two different simulators: the evaluation simulator and the controller simulator. This is done in a manner that allows for controlled variation of the prediction error. Controlled variation of the prediction error may allow to assess the impact of prediction error on the functioning of the controllers in future work. In this thesis, perfect predictions will be assumed.

The traffic system as a whole can be interpreted as follows. At regular time intervals ΔT each cyclist communicate his or her position $x^{cyc}(t)$, speed $v^{cyc}(t)[m/s]$ and other relevant data to the intersection controller. This information is used to make predictions up to the prediction horizon on the future location $x^{cyc}[k]$ and speed $v^{cyc}[k]$ of the cyclists. When no prediction error is assumed, the actual position of the cyclist in the next time step of the evaluation simulator is equal to the position predicted by the controller, i.e. $x^{cyc}(t+\Delta T) = x^{cyc}[k+\Delta k]$. The cyclist would send the new updated position, $x^{cyc}(t+\Delta T) = x^{cyc}[k+\Delta k]$, to the intersection controller who uses tho start making new predictions. With perfect predictions, there is no benefit for the controller to start predicting again with the newly received data, as this will result in the same outcomes of the previous predictions. If the newly sent prediction does not equal the predicted location, the controller simulator would need to start predicting again, using the newly received inputs.

This more realistic behavior can be achieved by introducing an error between the actual position of agents and the predicted position. This concept is shown in in equation B.1 and Figure B.1. This error can be introduced in the form of a normal distribution around the predicted position. A normal distribution is proposed, as CV technology currently relies upon GPS technology[35] and the prediction error of GPS over the reference distance of 1 metre follows a normal distribution $(\mu, \sigma^2) = (0.2, 0.3)$ of which the systematic error can be neglected[86]. For more realistic behavior the error will should introduced around the speed of a traveller instead of the position. It would be unrealistic for a cyclist to all of a sudden make a jump of half a metre during a discrete time interval of $0.1[s]$. The shape of the prediction error for speed is the same, as speed is the function of position variables[86].

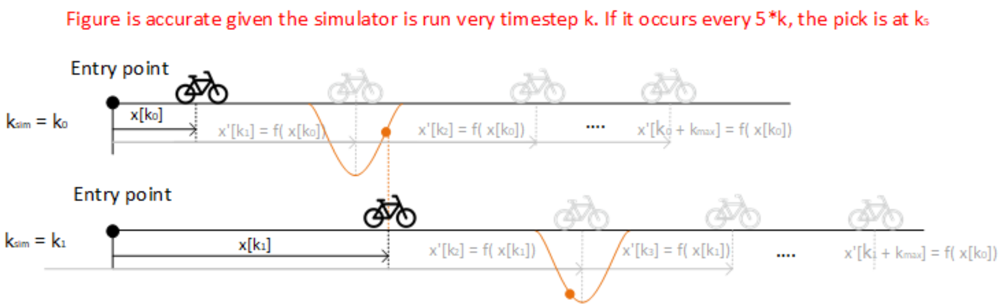


Figure B.1: Example of the difference between actual position and predicted position with $\sigma \neq 0$. Note that for initial evaluation sigma will be fixed to zero in order to exclude data imperfection as a factor that influences results

$$x_{new} = x_{old} + v * \Delta T + v_{random} * \Delta T \tag{B.1}$$

It should be noted that this randomness is not introduced when on the verge of the stopping line as this could lead to situations where a cyclists waiting for a red light could cross the stopping sign and run the light. Note that for the initial evaluation sigma and therefore the v_{random} will be fixed to zero as an assumption for perfect data quality.

C

Elaboration on Case study parameter values

C.1. Traffic system model parameters

This appendix provides values for the variables of the traffic system model described in Section 3.2 combined with the source or reasoning on which this value is based.

C.1.1. Behavioral model of cyclists

The traffic model introduces personal characteristics for cyclists: their preferred speed v_{pref}, constant deceleration rate d_{model} a maximum comfortable acceleration rate a_m and a maximum deceleration rate d_m. The traffic model is based on the work of [104] and in this work, cyclists are classified in three clusters: slow, average and fast cyclists. This classification for cyclists is used in this thesis as well and personal characteristic values are extracted from graphs in this paper. The rate of occurrence of each of the categories of cyclists is also based on the occurrence in the data set of of [104]. The used parameter values are presented in Table C.1.

Table C.1: Personal characteristics of cyclists

Type of cylcist	**Slow**	**Average**	**Fast**
vpref	4	5	6
Poccurance	0.25	0.42	0.33
dmodel	-0,37	-0,43	-0,49
dmax	-0,5	-0,63	-0,81
amax	0,625	0,675	0,79

A the last model parameter is the turning speed v_{turn}. As this variable was not included in [104], another source is required. No direct source has been found that provides information on the speed at which bicyclists make turns. The information closest resembling this information is figure 3 in the research of [38]. This figure provides cumulative probability graphs of the average speed 6 metres upstream and downstream of merging bicyclists on a T-junction. The average speed provided by all runs was closely read at the cumulative probabilities 0.5, representing a first estimation of the average turning speed. However, these speeds are the average speed 6 metres before and after the turn. Therefore these speeds are translated by a the deceleration that can be achieved in 3 metres using the standard deceleration rate of the movement model in this thesis. This results in a turning speed of $v_{turn} = 2[m/s]$.

C.1.2. Behavioral model of car drivers

All but the maximum speed parameters for the kinematic model of cars are taken from the model proposed in [117]. The maximum speed is chosen to be $50[km/h]$, based on the standard speed limit in Dutch cities. Note that a speed of $30[km/h]$ could also be defended, as many cities choose to enforce this lower speed limit. The speed limit for car drivers that make a turn has been artificially lowered to represent the lower speed used when making turns. This is done by enforcing a lower speed limit slightly upstream of the traffic light up to the point that the car has crossed the intersection. The location of enforcement and magnitude of the speed limit has been manually tuned up to the point that cars make a turn with speeds corresponding to turning speeds found in [128].

C.1.3. Traffic light related parameters

All traffic light timing related parameters are rounded to half seconds. This allows the intersection controllers to make a control decision every half second. For convenience, traffic signal related parameters are rounded to half seconds as well.

Minimum green time is fixed to six seconds for all traffic lights. This is a very common value in the Netherlands [60]. Note that in some occasions different values are used, also with lower minimum green time for cyclists. The maximum green time, which is only enforced for VAC, not for the structureless control, is set to 48 seconds. This is done so the waiting time of any traveller will never exceed the maximum waiting time of 100s, which was set based on the literature review on desires of travellers in Section 2.2.

The yellow time is based on the Dutch current practice relation between the required yellow time for both cars and bicycles for a range of speed limits and deceleration rates, described in [10]. Evaluation of the simulation model shows a resulting deceleration rate for cars of 6 ms^{-2}. Combined with a speed of 50 km/h this results in a yellow time of 2.2 seconds, or two seconds when rounded to halves. The required yellow time for cyclists is 2.1 seconds, which rounded down also is 2 seconds.

Clearance time, the time between the start of red for one direction and the start of green of a conflicting direction, is an important parameter within signalized traffic control. Figure C.1 illustrates the conflict and all relevant parameters to explain and calculate these values. The conflict zone is the area that overlaps between the lanes of two conflicting directions. If traveller two crosses the stopping line just before the traffic light turns green and traveller 1 were to given green directly, one can imagine the two colliding, as traveller two has not yet cleared the conflict zone when traveller one enters it. Therefore a non-negative clearance time is calculated that ensures traveler 2 has cleared the conflict zone before traveller one can reach it i.e. equation C.1. The clearance time is different for all combinations of conflicting flows. It also depends on the sequence: it takes longer to ensure 2 has crossed and traveller 1 enters then the other way around.

$$t_{clearance}(i,j) = t_{exit}(i) - t_{entrance}(j) => 0 \tag{C.1}$$

A lot of researchers make the simplifications of a zero second clearance time in their traffic system representation. This assumption could be challenged as a clearance time increases the cost of switching signals. Especially in case of a structureless controller, where one can expect more signal switches, this assumption should not be made as the cost of switching signals should be considered. Another simplification that is often made is a equal clearance time for all flow combinations. This simplification will also not be made this will lead to either over or underestimations for the cost of changing signals.

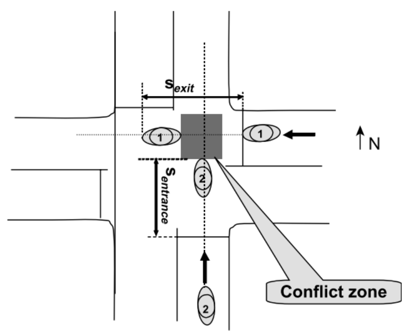


FIGURE 1 Traffic streams and conflict zones.

Figure C.1: Illustration for clearance time by [72]

Clearance times are calculated by determining the exit and entry times for all combinations of conflicting directions. The exit time can easily be calculated according to $t_{exit} = s_{exit}/v_{exit}$ with $v_{exit} = v_{max}$. The entrance time is more complex and requires a model for assumed movement behavior. For safety the lowest possible clearance time should be used. This thesis follows the method as described by [72] to estimate it. This model assumes travellers brake the last possible second with a braking rate that would bring them to a standstill at the stop line. The light then turns green and -after a reaction time- they accelerate back to v_{max}. However, as the traffic model of this thesis does not include a reaction time this value is assumed to be zero. Analytically this translates to the following three equations.

$$t_{entrance} = \sqrt{\frac{2 * s_{entrance}}{a_{acc} - adec}}\, if\, s_{entrance} \leq s_{critical} \tag{C.2}$$

$$t_{entrance} = \frac{s_{entrance}}{vmax} + \frac{vmax}{2 * (a_{acc} - a_{dec})}\, if\, s_{entrance} > s_{critical} \tag{C.3}$$

$$s_{critical} = \frac{v_{max}^2}{2 * (a_{acc} - adec)} \tag{C.4}$$

The traffic system model assumes a constant acceleration and deceleration rate. For cyclists, the values of the most aggressive type of cyclist from [104] are taken. For car drivers, [72] itself proposes $a_{acc} - adec = 2.4$ provides the best fit of the entrance times for dutch car drivers. This value will therefore be used.

Values for $s_{entrance}$ and s_{exit} are chosen based on points of investigation as described in [6]. Distances between the points are based on the dimensions of the intersection. No smooth curves were assumed. This means the clearance times are a rough approximation and the values presented in Figure C.2 may diverge slightly from a real intersection. This is acceptable, as it is important to show include a reasonable cost for changing signals, not the exact cost.

	1	2	4	5	6	10	22	28
1	0	0	0	0	0	0	0	0,5
2	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0,5
6	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0
22	2	1	0	0	0	0	0	0
28	0	0	0	0	0	2,5	0	0

Figure C.2: Clearance times of the intersection controller

C.2. Reasoning behind the evaluation saturation rates

The assumption that there is no interaction between cyclists, leads to unrealistic behavior when more than three cyclists are waiting in front of a red line. The underestimation of delay is estimated to be 1.5[s] per cyclist for the second group of three cyclists, 3[s] for the third group of three cyclists and so on. A hard limit of eight cyclists in a queue was proposed in cChapter 3.2. Translating this limit to a maximum demand level is difficult as the the stochastic nature of the system and type of controller can result in different number of cyclists in a queue for different runs with the same demand levels and controller. A visual inspection of multiple trajectory plots for a number of different demand levels is deemed the best way to set this limit. A more exact analysis could be performed but has not been done to save time.

These visual inspections were done for runs controlled by VAC for practical reasons, as computation time for runs using this controller are significantly shorter than the structureless controller (30s versus 20h). The inspection resulted in observations that up to demand demands up to 2500/h (saturation rate ≈ 36%) queues containing more than eight cyclists are rare. Between traffic demands demands of 2500 and 3500 (saturation rate = 50%) cyclists queue lengths grow to approximately eight and above 3500 queues of eight and more appear frequently. Three equally spaced values below 50% are chosen for evaluation, resulting in saturation rates of 15%, 30% and 45%.

D
Verification scenarios and model changes

As was explained in Section 4.1.5, the verification process has led to a few minor model changes to deal with overshoot problems caused by discretization, which are not described in this thesis. Larger changes have been made to the kinematic model of car drivers. These are described now. Starting on the next page, a list of all the scenarios used for verification are provided.

Firstly the upper bound application limit of [117] becomes infeasible in the scenario where a cars speed equals the speed limit v_{max}, meaning no upper limit can be calculated once a cars speed approaches the speed limit. This is because the argument of the term $arctanh(2v_0/v_{max} - 0,9762)$ (Part of Equation 3.25) exceeds one at the speed limit, which is mathematically impossible. Because the model assumes an lower boundary of $-tanh(2.22)$, a mirrored value of $+tanh(2.22)$ is assumed in these situations. Secondly, in some cases [117]s formulation results in negative optimal speeds when the leading car approaches the stop line, resulting in car drivers driving backwards very slowly. A non-negative constraint is added to the optimal speed to prevent this from happening. Finally the assumption related to the speed limit for turning cars was revised after verification. The initial speed limit was enforced after the stopping line, but this led to a speed when turning which is too high, as the cars did not spend sufficient time in the turning area that they could not achieve this lower speed. Therefore this boundary was shifted to 5 metres before the stopping line, which leads to cars entering the turn at the lower turning speed and accelerating to the actual speed limit again after the turn is made.

Verification performed for the three different types of cyclistsL

Scenario	Expectation
1 cyclist (straight)	
Enter with red light, light stays red	Approach at constant speed, at some point start constant deceleration and stops at stopping line
Enter with red, light turns green with x < x_approach	Keep constant speed throughout simulation
Enter with red, light turns green with x > x_approach	-
1) Before full stop	Approach at constant speed, at some point start constant deceleration, start accelerating to v_pref when the light turns green
2) After full stop	Approach at constant speed, at some point start constant deceleration and stops at stopping line. Then start accelerating to v_pref when the light turns green
Enter with green light, light stays green	Keep constant speed throughout simulation. Required deceleration should increase starting at x_approach from -0.42 up to maximum deceleration
Enter with green light, light turns red and required acceleration > a_max	Keep constant speed throughout simulation
Enter with green light, light turns red and required acceleration < a_max	Start decelerating from the moment the light turns red. Stop at the stopping line
Enter with green light, light turns red and required acceleration < a_max, light turns green before full stop	Start decelerating from the moment the light turns red. Start accelerating to v_pref when the light turns green
1 cyclist (turning)	
Before turning left	
Enter with red light, light stays red	Approach at constant speed, at some point start constant deceleration and stops at stopping line
Enter with red, light turns green with x < x_approach	Keep constant speed, start decelerating to v_turn, starting upstream of the crossing point
Enter with red, light turns green with x > x_approach	-
1) Before full stop	-
1.2.) & v < v_turn	Approach at constant speed, at some point start constant deceleration, start accelerating to v_turn when the light turns green

1.2.) & v > v_turn	Approach at constant speed, at some point start constant deceleration. Keep constant speed after the traffic light turns green, later on start decelerating to v_turn upstream of the crossing point.
2) After full stop	Approach at constant speed, at some point start constant deceleration and stops at stopping line. Then start accelerating to v_pref when the light turns green
Enter with green light, light stays green	Keep constant speed, start decelerating to v_turn, starting upstream of the crossing point
Enter with green light, light turns red and required acceleration > a_max	Keep constant speed, start decelerating to v_turn, starting upstream of the crossing point
Enter with green light, light turns red and required acceleration < a_max	Start decelerating from the moment the light turns red. Stop at the stopping line
Enter with green light, light turns red and required acceleration < a_max, light turns green before full stop	-
1.2.) & v < v_turn	Start decelerating from the moment the light turns red. Start accelerating to v_turn when the light turns green
1.2.) & v > v_turn	Start decelerating from the moment the light turns red. Keep constant speed starting when the light turns green. Start decelerating later on again to v_turn.

Turning left

Agent should enter the system of the other lane using the same personal characteristics, at location x_turn with speed v_turn.

After turning left

Enter with red light, light stays red	Approach at constant speed, at some point start constant deceleration and stops at stopping line
Enter with red, light turns green with x > x_approach (Always happends)	-
1) Before full stop	Approach at constant speed, at some point start constant deceleration, start accelerating to v_pref when the light turns green
2) After full stop	Approach at constant speed, at some point start constant deceleration and stops at stopping line. Then start accelerating to v_pref when the light turns green

Enter with green light, light stays green	Keep constant speed throughout simulation. Required deceleration should increase s tarting at x_approach from -0.42 up to maximum deceleration
Enter with green light, light turns red and required acceleration > a_max	Keep constant speed throughout simulation
Enter with green light, light turns red and required acceleration < a_max	Start decelerating from the moment the light turns red. Stop at the stopping line
Enter with green light, light turns red and required acceleration < a_max, light turns green before full stop	Start decelerating from the moment the light turns red. Start accelerating to v_pref when the light turns green
Multiple cyclists	
Multiple agents should be able to be in the system at the same time	Everyting is expected to occur as described in earlier mentioned scenarios, as cyclists do not hinder each other.
1 car (straight)	
Enter with green, light stays green	Keep constant speed
Enter with green, light turns red with x < x_up	Keep constant speed up to x_low, then decelerate and stop at stopping line
Enter with green, light turns red with x > x_low	Keep constant speed.
Enter with green, light turns red with x_up > x > x_low	Keep constant speed, decelerate when light turns red and stop at stopping line
Enter with red, light stays red	Keep constant speed up to x_low, then decelerate and stop at stopping line
Enter with red, light turns green before full stop	Keep constant speed, decelerate when light turns red and start accelerating to v_max again when the light turns green
1 car (turn)	
Enter with green, light stays green	Keep constant speed, decelerate to 30 km/h after passing traffic light. Accelerate again afterwards
Enter with green, light turns red with x < x_up	Keep constant speed up to x_low, then decelerate and stop at stopping line
Enter with green, light turns red with x > x_low	Keep constant speed, decelerate to 30 km/h after passing traffic light
Enter with green, light turns red with x_up > x > x_low	Keep constant speed, decelerate when light turns red and stop at stopping line
Enter with red, light stays red	Keep constant speed up to x_low, then decelerate and stop at stopping line
Enter with red, light turns green before full stop	Keep constant speed, decelerate when light turns red and start accelerating again to 30 km/h when the light turns green
Multiple (3) cars	
Any scenario	No overtaking
Green light all the time	Constant headway

Enter with green, red forcing first car to stop	Headway decreasing to approx. 20/3 60s after a red light. (Minic graph from paper)
Enter with green, first car crosses, then light turning red	Cars 2 and 3 stop

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Paper: Design of a structure free intersection controller for connected bicycles and cars using model based control and a genetic algorithm

Paper starts on next page

Design of a structure free intersection controller for connected bicycles and cars using model based control and a genetic algorithm

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Abstract

Bicycles have an important role to play in the transition towards a more sustainable mobility. This thesis proposes a design for a structureless intersection controller in the connected environment that is able to control for and prioritize the desires of cyclists. The desires of cyclists are identified and used as control objectives. The proposed controller design uses simulation based control, combined with a genetic algorithm to speed up the optimization process. A simulation based case study shows the controller, even without active prioritization, outperforms the benchmark controller significantly. Active prioritization improves the performance with regard to cyclist related metrics, but this comes at the cost of of disproportionate decreases in car related metrics.

1. Introduction

Sustainable mobility is one of the major challenges for cities going in the 21st century. Between 2005 and 2025 the number of trips made in urban areas are expected to increase by 50%. Cities around the world will have to make choice to decide how they want to adapt to the increased demand. If the car remains the main mode of transport this will lead to either gridlocked road networks or increasingly larger networks resulting is less space for urban life[1].

Bicycles have a number of advantages over cars. First of all, bicycles are responsible for noise and air pollution than cars[2][3]. Bicycles also occupy way less space than cars, both while parked and in motion. Additionally, replacing motor vehicle trips by bicycle can also help increase health via increasing health enhancing physical activity[4][5]. Bicycles are most competitive in low to medium distance trips, which are common in urban centers. In the urban cores of the Netherlands for example bicycles contribute to 28% of all trips and 34% to 47% of short (0.5-5km). In order to achieve a modal shift towards bicycles, more attention must be paid to the desires of cyclists[6].

Controlled intersections do allow for protected crossings for cyclists with motorized vehicles, but this comes at the cost of increased travel time and required effort for accelerating back to cruising speed. The inconvenience of controlled intersections is illustrated by the concept that cyclists generally will choose routes that avoid traffic signals[7][8] and are willing to make significant detours (average of 1.3km) to avoid routes with many of them[9].

Recent research on structureless intersection control [10] and technological connected vehicles [11][12] has shown the potential of both concepts. Combined, they may allow for the design of an intersection controller that is able to control for or even prioritize the desires of cyclists over cars. This may provide a boost to bicycle use and help achieve a modal shift towards more sustainable mobility. This paper proposes an intersection controller design for an intersection controller in an environment with connected cars and bicycles, which can be used to prioritise the interests of cyclists over car drivers. The performance of the controller is evaluated with a simulation based case study.

This paper is organized as follows. Section 2. establishes the desires of cyclists and car drivers with regard to controlled intersections and proposes a trade off between these desires. Section 3. presents the system description. The fourth section describes the proposed controller design. The experimental setup and the results of the case study is provided in Section 5.. The conclusion and future work recommendations are presented in Sections 6. and 7..

2. The desires of cyclists and car drivers with regard to controlled intersections

A literature review was performed, with the goal of identifying the desires of cyclists with regard to controlled intersections and proposing a trade off with the desires of car drivers. In order to do so, determinants of bicycle use were investigated and projected on controlled intersections. Leading in this review has been the literature review of [13] on bicycle frequency and duration determinants. Additional sources and references have been collected.

2.1 Determinants of bicycle use

The resistance to travel for cyclists increases disproportionately with travel time and trip distance. While these factors are important for all travel modes, the variables are of much greater influence for cyclists than for car drivers [14][15]. This difference be explained by different power sources: a cyclists needs to provide the power for propulsion by physical effort.Sharp turns, stop signs or red traffic lights, require a bicycle to slow down and provide a lot of effort to accelerate back to the cruising speed. This is illustrated by [16], in which it is estimated that the average speed of a 70kg person producing 100W will be reduced by 40% for a road with a stopping sign every 90m. In order to keep the speed on an average of 20 km/h, a power output of 500W would be necessary, which is a power level that is only expected from a serious racing cyclist.

The presence and continuity of dedicated bicycle infrastructure are big determinants in both bicycle mode and route choice [17][18]. This may be explained by the increased safety. Lower risk of injury can be linked to higher bicycle use[6][19] and the presence of dedicated bicycle infrastructure does improve perceived and objective safety for cyclists [20][21].

Finally, transportation cost, social-economic factors and psychological factors can help determine bicycle use, but cannot be directly influenced by intersection control. This is also the case for the presence of slopes, that negatively impact cyclist utility because of additional effort [6][22], and weather conditions [23][24], however, under these conditions one could argue that factors related to travel time and effort have larger impact on the total cycling utility.

2.2 Projecting determinants on controlled intersections

The factors travel time, required effort and (perceived) safety come together in the controlled intersection. Controlled intersections can ensure protected crossings, but the additional safety that is provided, comes at the cost of additional travel time and required effort, in the form of reduced speed, stops, and safety concerns for cyclists due to cyclists low speeds. The inconvenience of controlled intersections make them a major obstacle that cyclists tend to avoid [7][8]. Stops are not confined to only once per intersection crossing. When the number of cyclist is high, it can occur that queues are not dissolved after a single green cycle. Stopping twice at a single intersection also can happen when making a left turn.

It can even be argued that long waiting times are a reason for red light running behavior, which in turn reduces the positive safety effect of protected crossings. Red light running may be an indication of cyclist feeling like they do not get served well and that for them the risk of running red light is outweighed by the benefits of not having to stop and lose time. Red light running also occurs often when a cyclist stops at a red light and waits, but start riding again before a green light. Further inspection showed all of these cyclist accelerated only after all crossing traffic has cleared the intersection[25]. This may indicate that the clearance times enforced by the intersection controller is unpractical and too long for cyclists.

Altogether, the desires cyclists with regard to controlled intersection can be summarized by the following points. A cyclist wants

- no motorized traffic to be allowed to cross their path, when they are allowed to do so.
- to be forced to slow down as little as possible.
- to avoid lows speeds, stops and double stops.
- to short waiting times.
- to start moving as soon as possible after the last vehicle from crossing directions has passed and not have to wait for the light to turn green with for a couple of seconds without conflicting traffic passing.
- to be allowed to cross the road if no conflicting traffic is passing for a duration in which the cyclist could have crossed the road.

2.3 Trade off with desires of car drivers

Trip distance distance, free-flow travel time, time spent in congestion, travel time reliability, travel cost and number of turns are used in research on route and mode choice for car drivers [26][27]. Projected on controlled intersections, car drivers want to minimize their delay. The safety provided by protected crossings is of also important for car drivers and the intersection controller should discourage red light running (RLR) behavior. In French cities, waiting times below 100 seconds result in very low RLR probabilities, but these probabilities increase to up to 10% for waiting times between 100 and 300 seconds [28]. This suggests the waiting time should be limited to a maximum of 100 seconds.

When delays do not exceed this threshold, a trade off between the delays of cyclists and car drivers has to be made. Delays can be weighed equally, or can take the different values of time (VoT) into account. Based on estimations on perceived vs. actual waiting time for cyclists (3 [15], 5 [29]) and car drivers, (1 [30] and 1.8 [31]), a low ($3/1.8 = 1.7$) and high ($5/1 = 5$) estimation for relative VoT is proposed.

3. Traffic system model

This section proposes a traffic system model, that describes the movement of individual cyclists and car drivers over an intersection. Cyclists follow a set of rules based on their position and speed. The kinematic model used is the model proposed by Twaddle and Grigoropoulos, which is validated using real life data. The car following model is the model proposed by Wen-xing, Jing-yu, and Ze-Rui. Traffic lights are represented individually, instead of the common conflict group based representation.

The traffic lanes $i, j \in I$ are modelled as separate subsystems, with no interaction between agents in different lanes. Individual agents are represented as $c_i^{cyc} \in C_i^{cyc}$ and $c_i^{car} \in C^{car}$. The system is simulated over the time indices $k \in K = [k_0, k_{max}]$ where $k_{max} = T_{max}/\Delta T]$, with T_{max} representing the length of the prediction horizon and ΔT the constant time step.

3.1 Traffic lights

Given the sets of directions $i, j \in I$ and the set of time indices $k \in K$, the set of individual traffic signal states for each time step is defined as $s_{i,k} \in S$. The binary values of a traffic signal state is defined as follows:

$$s_{i,k} \begin{cases} 0, & \text{if red or yellow} \\ 1, & \text{if green} \end{cases} \qquad \forall i \in I, k \in K \tag{1}$$

Minimum and maximum green time constraints ($g_{min,i} \in G_{min}$, $g_{max,i} \in G_{max}$) are enforced by evaluating the green duration $G_d[k]$ (Equation 2) of all traffic lights every time step.

$$G_d[k] = G_d[k-1] \odot S_{k-1}[i] + S_k[i] * \Delta T \tag{2}$$

Protected conflicts, yellow time and clearance time constraints are enforced by Equation 3. A delay t_{delay} is imposed between two subsequent greens, consisting of the required yellow time $t_{yellow}[i, j] \leq 0$ and clearance time $t_{clearance}[i, j]0$.

$$S[j, k_2] = 0, \quad \text{if} \begin{cases} S[j, k_1] = 0 \\ k_2 - k_1 < T_{delay}[i, j] \end{cases} \qquad \forall i, j \in I, \forall k_1 \in K, \forall k_2 > k_1 \tag{3}$$

3.2 Mathematical model for cyclists behavior

The position of a cyclist is defined as the location with respect to the entry point of the system, as is shown in Figure 1. No interaction between cyclists is assumed. Position, velocity and acceleration are related by Equations 4 to 6. The acceleration of the cyclist is dependent on the state of the traffic light, a cyclists velocity and the area in which a cyclist is located.

$$x[k] = x[k-1] + v[k-1] * \Delta T \tag{4}$$

$$v[k] = v[k-1] + a[k-1] * \Delta T \tag{5}$$

$$a[k] = f(x[k-1], v[k-1], s_i[k-1]) \tag{6}$$

Straight travelling cyclist

Unless located in area A2.1 (See Figure 1) and facing a red light, a straight travelling cyclist is assumed to accelerate towards their preferred speed v_{pref} in accordance with Equation 7. In this equation, the acceleration is a function of the speed ratio $a(\theta_s) = (v^c[k] - v_i)(v_{target} - v_i)$, relating a cyclists current speed $v^c[k]$, initial speed when acceleration started v_i and target speed $v_{target} \in \{v^c_{pref}, v_{turn}\}$ (Equation **??**). The equation also includes a^{cyc}_{max}, representing a cyclists personal maximum (Comfortable) acceleration rate and $C^{cyc}, B^{cyc}, c^{cyc}, a^{cyc}$, which are model parameters based on personal characteristics. Three different types of cyclists are included to represent heterogeneity, identical to the categories used by [32].

When located in A2.1, bound by the traffic light approach point and the traffic light, and facing a red light, cyclists make a stop and go decision. They evaluate their required deceleration rate $d^{cyc}_{reqlight}$, which is described in Equation 8). In this equation, deceleration rate is related by the stop velocity v_{stop}, a cyclists current speed $v[k]$ and location $x[k]$) and the location of the traffic light x_{light}. If the required declaration rate exceeds a cyclists maximum acceptable deceleration rate d^{cyc}_{max}, they will continue ignoring the red light. Otherwise, they will decelerate and stop at the stopping line. The location of the traffic light approach point depends on personal characteristics and is described in Equation 9. This equation also includes a deceleration rate $d_{constant}$, which is taken from the work of Twaddle and Grigoropoulos

$$\begin{aligned} a[k] = a(\theta_s) = C^{cyc} * a^{cyc}_{max} * (\sin(\pi\theta_s[k]) \\ + B^{cyc} * \sin(2\pi\theta_s[k])) + (\frac{1}{\theta_s^2 + c^{cyc}} + a^{cyc}) \end{aligned} \tag{7}$$

$$d^{cyc}_{reqlight} = -\frac{v^2_{stop} - v^2[k]}{2(x_{light} - x[k])} \tag{8}$$

$$x_{lightapproach} = x_{cyclelight} - \frac{v^2_{stop} - v^2_{pref}}{2 * d_{constant}} \tag{9}$$

Cyclists that make a left turn

Turning cyclists leave the first cycling path the crossing point travelling with turning speed v_{turn}. They enter the second traffic lane at the after turn point with the turning speed and

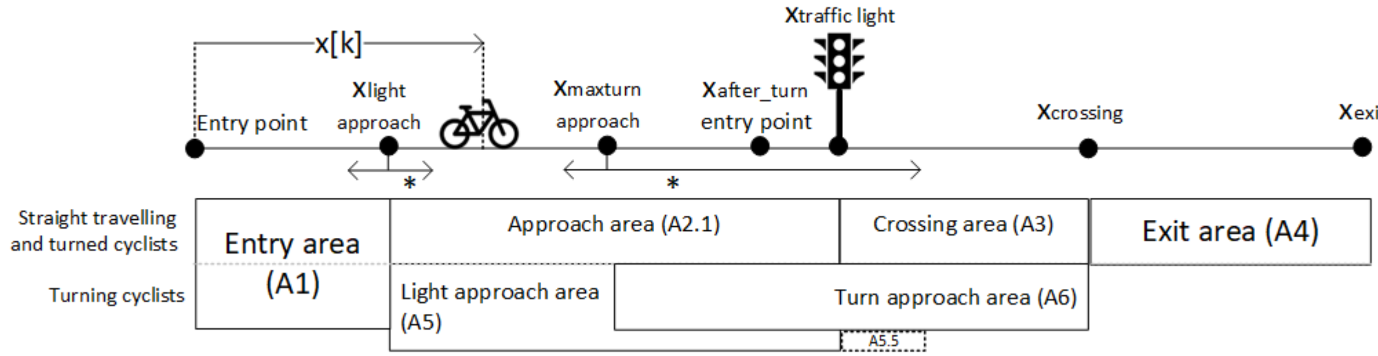


Figure 1: *System description of bicycle lane. The acceleration of a cyclist depends on what area (A1 to A6) he/she is located in. A straight travelling cyclist enters the system at the entry point and leaves the system at the exit point. Cyclists that make a left turn pass through two bicycle lanes. The first lane is entered at the entry point and exited at the crossing point. The second lane is entered at the after turn entry point and left at the exit point.*
** The location of these points is dependent on a cyclists personal characteristics*

traverse the lane to the exit point, behaving as a straight travelling cyclist. Similar to straight travelling and turned cyclists, the turning cyclist will in the basis aim to be travelling at its' preferred speed, following the basic acceleration equation 7. Their behavior diverges from straight travelling cyclist, when located in the turn approach area (A6). In A6, cyclists considering the turn they have to make.

When travelling faster than the turn speed, assumed to keep travelling at this speed up to the point that they need to start braking with d_{model}- to reach the crossing point with the turning speed. At this point, they will decelerate with d_{model} until arriving at the crossing point. When travelling slower than v_{turn}, the cyclist will accelerate in accordance with Equation 7, with target speed v_{turn}. A6 is bound by the crossing point and the maximum braking turn point, described in Equation **??**, which represents the point from which a cyclist, travelling at his preferred speed, must start braking - using the comfortable deceleration rate d^{cyc}_{model}- to reach the crossing point with the turning speed. Cyclists of whom the maximum turn approach point is located downstream of the traffic light will fist keep accelerating towards their preferred speed until they enter A6. This situation is visualized in Figure 1 as area A5.5.

$$x_{maxturnapproach} = x_{crossing} - \frac{v_{turn}^2 - v_{pref}^2}{2 * d_{constant}} \tag{10}$$

$$x_{braketurnmax} = x_{crossing} - \frac{v_{turn}^2 - v_{pref}^2}{2 * d_{constant}} \tag{11}$$

3.3 Mathematical model for car driver behavior

For simplicity sake and to stay within the applicability range of source model of Wen-xing, Jing-yu, and Ze-Rui, sorting lanes of the intersection are assumed to start at the system boundary and car drivers are assumed to enter the system on the correct lane designated for their destination, travelling at the speed limit v_{max}. The position and of cars is determined the same way as for bicycles, following Equation 4). Cars determine their new speed based on the current speed and acceleration, in accordance with equations 12 and 13. Acceleration is calculated based on a cars' current and optimal speed V_{opt}, which differs depending on a red or green traffic light.

$$v^{car}[k] = v^{car}[k-1] + a^{car}[k-1] * \Delta T \tag{12}$$

$$a^{car}[k] = 0.85(V(\Delta x^{car}(k)) - v^{car}[k]) \tag{13}$$

The optimal velocity for a vehicle following another vehicle is defined in equation 14. In this equation, $x_{car}[k-1]$ and $\Delta x_m[k-1]$ are the the position of the vehicle and the headway with its' predecessor in the previous time step. $v_{max} \in \{30, 50\}[km/h]$ represents the speed limit in turns and for straight parts of the road respectively. When facing a red traffic light, the first car between the upper (L_{up}) and lower (L_{low}) bounds for the influence of the traffic light starts braking in accordance with Equation 15. The upper and lower bounds are calculated following Equations 16and 17. Cars downstream of the lower bound pass the carry on at their current speed.

$$V(\Delta x_{car}[k-1]) = \frac{v_{max}}{2} * (\tanh(0.13(\Delta x_m[k-1] - 12.5) \\ -1.57) + \tanh(2.22) \tag{14}$$

$$V(\Delta x_{car}[k-1] = \frac{v_{max}}{2} * (\tanh(0.13(x_{light} - x[k-1] \\ -7.5) - 1.57) + \tanh(2.22 \tag{15}$$

$$L_{up}^{car} = \frac{\operatorname{arctan} h(\frac{2v_o}{v_{max}} - \tanh 2.22) + 1.57}{0.13} + 7.5 \tag{16}$$

$$L_{low}^{car} = -0.014 * v_o^2 + 1.022 * v_o - 0.017 \tag{17}$$

3.4 Definition of control objectives

For simplicity sake, only a subset of the desires of cyclists presented in Section 2.2 are included in the objective function. These two variables are the delay of cyclists and the number of stops cyclists have to make, to represent desires related to additional travel time and the additional required effort. The delay of car drivers is included to represent the desires of car divers. Delays are calculated following Equation 18, relating the total time spent (TTS) in the system with the time spent in the system at free flow speeds. The number of stops is calculated following Equation 19

$$\begin{aligned} D^{cyc} &= TTS^{cyc} - v_{pref} * x_{exit} \\ D^{car} &= TTS^{car} - v_{max} * x_{exit} \end{aligned} \tag{18}$$

$$N_{stops}^c = \begin{cases} N_{stops}^c + 1, & if v^c[k-1] < v_{stop} \leqslant v^c[k] \\ N_{stops}^c, & \text{if else} \end{cases} \tag{19}$$
$$\forall c \in C, \forall k \in K$$

4. Structure Free Genetic Control

A structure free controller is proposed that uses model based control (SFGA) to predict the effect of signal plans on the traffic state. A genetic algorithm is used to optimize the signal plan over a rolling horizon T_{RH}. Model based control is preferred over data driven control, because this allows for control over prediction errors in future work.

The signal plan of the first t_c seconds of the prediction horizon are already determined in the previous control window. This represents the time available for computation were the controller to be implemented in real life. Signal plans are created and evaluated by means of simulations that use the state of state of the main simulation at the start of the RH window as a starting point. The RH simulations are performed entirely independent of the main simulation and evaluate the effect of generated signal plans over the duration of T_{RH}. The first t_c seconds of the signal plan of the next control window are fixed to the signal plan of the best performing solution. The entire process then is repeated until the main simulation has ended.

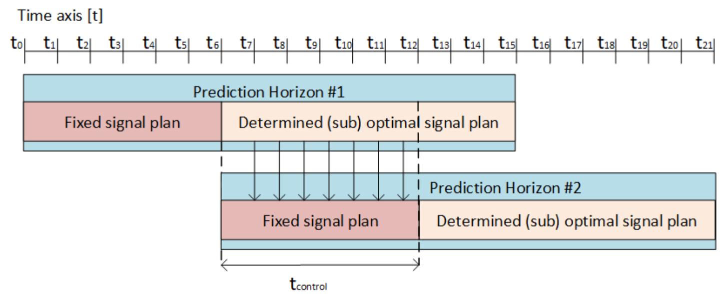


Figure 2: Rolling Horizon and control interval

The simulations are conducted in a Python environment. Scenarios for the main simulator are generated by means a seed that determines at what moment in time travellers are generated, the personal characteristics of these travellers and in which traffic lane they spawn.

The genetic algorithm functions as follows. At the start of each control moment, a fixed number N_{pop} (Population size) of random solutions (Signal plans S, composing of traffic signal states $s[i,k] \in S$ are generated. The effect of the solutions are evaluated by means of simulation using the traffic system model described in Section 3.. After evaluation, the N_{keep} with the lowest objective values are stored and are adapted with proposed mutation and crossover algorithms. This process is repeated for a fixed number of generations. GA parameter settings are determined by evaluating the resulting delay and convergence of successive generations. Used parameter settings are provided in Table 1.

Table 1: GA parameters

Variable	Value
Prediction horizon	20 [s]
Population size	25
Number of generations	10
Crossover probability	0.4
Mutation probability	0.4
Random solution probability	0.2
Stored best performing solutions	8

4.1 Solution generation

Random solution generation, two mutation algorithms and crossover algorithms are now discussed. The crossover algorithm is designed to combine signal plans, with the aim of determining the optimal sequence of traffic lights that show a green light. The mutation algorithms are designed to cause green time extensions and earlier ends of green, with the aim of determining the most optimal moment to switch between successive green periods, allowing as many travellers to cross before the light turns red and and avoiding unused green. All algorithms alternate between

All algorithms start with an signal plan S, of which the entries corresponding with the first t_c seconds are determined and the remainder is filled with NaNs. Then, the algorithms alternate between updating the matrix regard to minimum green time, conflicts, clearance time and yellow time (Equations 2 and 3) and selecting a new matrix entry $s[i, k]$ to be green. Updating the matrix with regard of these constraints is referred to as updating with system knowledge. This process is repeated until the entire matrix is filled.

Algorithm 1 shows the pseudo-code for the random solution algorithm. Algorithm 2 does the same for the crossover algorithms. Algorithms 3 and 4 describe the green time extension and green time reduction algorithms. Note that an extension of one green time results in a later start and green time reductions result in an earlier start of successive green periods of conflicting movements.

Algorithm 1 Random solution generator

Initialize sets:
  Empty spots E: $e(k, f) \in E$
  Set of ones and zeros: $o(k, f) \in O$, $z(k, f) \in Z$
  Discrete time steps up to G_{min}: $D \in \{0, 1, 2..G_{min}\}$
while $E \neq \emptyset$ **do**:
  for all $o(k, f) \in O$ **do**: ▷ Place ones based on G_{min}
    for all $d \in D$ **do**:
      $S(x, f) = 1$ for $x \in \{k, k{+}1...k{+}G_{min}{-}d\})$
      $S(X, f) = 1$ for $x \in \{(k + G_{min} - d), (k + G_{min} - d - 1), .., k$
  update E, O
  for all $o(k, f) \in O$ **do**:
    $s(k_2, f_2) = 0$ if $p(f, f_2) = 1$ ▷ Place zeros based on conflicts
    $s(k, f_2) = 0$ if $k_2 - k_1 < Cl(f, f_2)$ ▷ Place zeros based on clearance time
  update E, Z
  for all $f \in F$: ▷ Place zeros based on G_{min}
    for all $\Big(o(k_1, f_1), o(k_2, f_1)\Big) \in \begin{pmatrix} n \\ k \end{pmatrix}$:
      $s(k_1 : k_2, f) = 0$ if $S(k_1 : k_2, f) \in E$ and $k_2 - k_1 < G_{min}$
  update E
  $N =$ random index from E ▷ Generate a random empty location and place a one
  $e_n(k, f) \leftarrow 1$
  update E, O, Z

Algorithm 2 Crossover algorithm

Initialize:
  S_{parent_1}, S_{parent_2}
  $s_c(k, f) = \{0, 1\} \leftarrow S_{parent_1}(k, f)$ for k ¡ 6s ▷ Fix first six seconds of the solution
  update S_{child} with system knowledge, E ▷ Also update empty subset of S_{child}
  $N_{iterations} = 0$
while $E \neq \emptyset$ **do**:
  $S_{Options1} = \{(S_{parent1} \cap E\}$, $S_{Options2} = \{S_{parent2} \cap E\}$
  if $S_{Options1} \neq \emptyset$ and $S_{Options2} \neq \emptyset$ **do**:
    if $N_{iterations}$ is even $\vee$ $S_{Options2} = \emptyset$ **do**:
      $n(k_n, f_n) \in S_{Options1}$
    elif $N_{iterations}$ is uneven $\vee$ $S_{Options1} = \emptyset$ **do**:
      $n(k_n, f_n) \in S_{Options2}$
  else do:
    $n(k_n, f_n) \in E$ ▷ Select a random empty location
  $S_{child}(k_n, f_n) \leftarrow 1$
  update S_{child} with system knowledge, E

Algorithm 3 Green time extension mutation

Initialize:
  $s_p(k, f) = \{0, 1\} \in S_{parent}$
  $s_c(k, f) = e(k, f) \in S_{child}$
  $R = \big\{(k, f)$ if $s(k-1, f) * s(k, f) = 0 \wedge s(k, f) = 0 \wedge k > 6s\big\}$: ▷ Set of start of red time
  $n(k_n, f_n)$ ▷ Randomly chosen start of red
  $S_{child}(0 : (k_n - 1), f) \leftarrow S_{parent}(0 : (k_n - 1), f)$
  $S_{child}(k_n, f_n) \leftarrow 1$
for all $k_{copy} \in \{k_n + 1, k_n + 2, ...k_{max}\}$ **do**:
  update S_{child} with system knowledge, E
  $S_{child}(k_{copy}, f) \leftarrow S_{parent}(k_{copy}, f) \forall (k_{copy}, f) \in E$

4.2 Evaluation and selection

Each generation, all generated signal plans are simulated over a time horizon T_{RH} seconds to determine the effect of signal plans on the traffic system. Afterwards, a performance cost R_c for each solution is calculated following Equation 20, where D^{cyc}, N^{cyc}_{stop}, $*D^{car}$, $W_{cycdelay}$ W_{stop} and $W_{cardelay}$ represent the delay and number of stops of each cyclist and the delay of each car driver and the corresponding weighs respectively. The Equation also includes the parameters $N_{maxwaitingtime}$ and $W_{maxwaitingtime}$, representing the number of travellers that exceeded the maximum waiting time and the corresponding weight, which is orders of magnitude larger than all other weights.

Algorithm 4 Early end of green mutation

Initialize:
$s_c(k,f) = \{0,1\} \leftarrow S_{parent}$
$G_{end} = \{(k,f)\}$ if
$\big(s(k,f) = 1 \wedge k = k_{max}\big) \vee \big(s(k,f) * s_n(k+1,f) = 0 \wedge s(k,f) = 0\big)$
$k > 6[s]$ and
$s(k-6[s],f) = 1$ ▷ Set of end of green time
$n(k_n, f_n)$ ▷ Randomly chosen start of red
$S_{child}(k_n, f_n) \leftarrow 0$
$S_{child}(k,f) = e(k,f)$ if $p(f_n,f) = 1$ ▷ Clear entries based on conflicts
$S_{child}(k,f) = e(k,f)$ if $k_2 - k_n < Cl(f_n,f)$ ▷ Clear entries based on clearance time
while $E \neq \emptyset$ **do**:
$m(k_m, f_m)$ ▷ Place random one
$S_{child}(k_m, f_m) \leftarrow 1$
update S_{child} with system knowledge, E

$$R_c = \sum^{cyc} \big(W_{cycdelay} * D^{cyc} + W_{stop} * N^{cyc}_{stop}\big) + \sum^{car} W_{cardelay} * D^{car} + W_{maxwaitingtime} * N_{maxwaitingtime} \tag{20}$$

The N_{keep} best performing solutions are stored and used as input for the solution generation algorithms of the next generation. Duplicate solutions and different solutions with identical R_c values are distinguished with the overlap factor $O_f = \in [0,1]$ (Equation 21) is introduced, where a 0 indicates no overlap at all and a 1 indicates a fully identical solution. If the number of solutions with an identical R_c value and a different overlap factor result in more than N_{keep} solutions being stored, a random selection is made.

$$O_f(S_1,S_2) = \frac{\sum S_1 \odot S_2 + \sum (S_1 - 1) \odot (S_2 - 1)}{f_{max} * k_{max}} \tag{21}$$

5. Case study

A simulation based case study is performed to evaluate the performance of SFGA under different traffic demand levels. Performance is measured in terms of average values and spread of delay and delay by mode and the percentage of traffic light approaches that result in a full stop for cyclists. SFGA is benchmarked against Vehicle Actuated control (VA). For performance benchmark, the objective function of the controller weighs delay for car drivers and cyclists equally and W_{stop} is set to zero. Finally, the effect of using different weights in the objective function is investigated.

5.1 Experimental setup

The simulation environment is created in a Python environment, which allowed for multiple simulations to be run simultaneously on the DelftBlue Supercomputer [34]. Limited by computation time, simulations of 180 seconds are simulated The intersection layout is provided in Figure 3). Perfect prediction quality is assumed. In each scenario, the number of to be generated travellers is determined, from the the simulation duration and the traffic demand and mode split. Every traveller is assigned a time stamp at which they enter the system, following an uniform distribution, and a traffic modality, following probabilities in accordance with the modal split. Finally, all cyclists are distributed uniform over all cycle paths of the infrastructure layout and all car drivers are distributed uniform over all the car lanes. After generation, all travellers follow the traffic system model presented in Section 3..

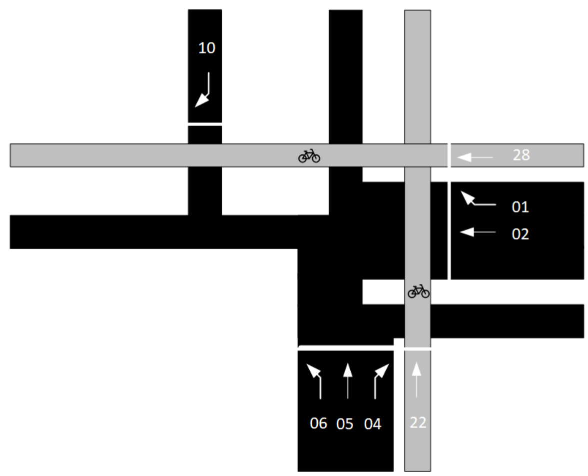


Figure 3: Intersection layout of the case study

To account for stochastic behavior in agent generation and cyclist heterogeneity, 14 scenarios are run for each combination of simulation parameters. The base value for modal split is Cyclist/Car $= 0.5$, based on the average modal split for trips between one and seven kilometres in a Dutch urban cores [35]. Cyclist heterogeneity is included by means of three different types of cyclists with different personal characteristics [32]. Thirty percent of the cyclists travelling in cycling path 22 (See Figure 3) are assumed to make a left turn.

The performance of both controllers is evaluated at three saturation rates, the percentage of the intersection capacity of approximately 7000 travellers per hour, divided roughly equal between cars and cyclists. Three equally spaced saturation rates (15%, 30% and 45% for both modalities) are used. Simulation of higher saturation rates provide unrealistic results, due to the assumption made in the traffic system model that cyclists do not interact with each other.

For the benchmark comparison, only the traffic saturation is varied. For the investigation of the effect of including different weights in the objective function of SFGA, the esimated values for VoT proposed in Section 2.3 $(1.7, 3.3, 5)$ are used. A value of W_{stop} equal to the equivalent of 0 and 15 seconds of car driver delay is used. Experimenting with different parameter values showed 15 to be a value that influences controller performance, without forcing the controller into always prioritizing cyclists over cars.

5.2 VA as comparison benchmark

The VA controller follows a fixed sequence of active combinations of traffic light, so called phases or blocks. The used control structure, one of the control structures with the lowest minimum cycle time generated by the VRIGen software for the intersection layout of Figure 3, is visualized in Figure 4. Algorithm 5 describes VA in pseudo-code.

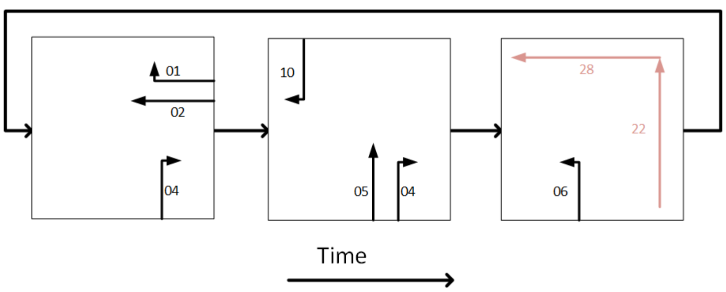


Figure 4: Control structure of benchmark VA control

Only traffic lights that are part of the current active phase are allowed to show green. If a traffic light has been green for less than the minimum green time, or if the controller detects traffic in this lane, green time is extended up to the maximum allowed green time. When the current phase has been active for the maximum allowed green time, or if no traffic is detected in any of the active traffic lanes, the next phase is activated. Conflicts related to yellow time and clearance time are enforced, similar to SFGA. The VA does not include flexibility, meaning no alternatives are included in the control structure that allow for an earlier start of one of the movements of the next phase, because this allows for a more universal benchmark, as the performance of VA is not influenced by choices on what alternatives are allowed.

Because this research considers the CE, traffic is not detected by means of induction loops, but instead instead VA is assumed to detect any traffic located between the traffic light and the start of the dilemma area. This area is the area in which travellers are assumed to make a stop and go decision. The start of dilemma area is located a distance equal to the yellow time multiplied by the maximum speed [36]. Because of the CE, VA considers personal characteristics of travellers and hence the distance from where the travellers are detected differs per traveller type. This is shown in Table 2.

Table 2: Detection distance of VAC upstream of the traffic light

Traveller	Detection range [m]
Slow cyclist	18.2
Average cyclist	28.9
Fast cyclist	42.0
Car	65.7

Algorithm 5 VA benchmark algorithm

Initialize system state:
  Active block B_a, active block duration B_d

for all $k \in \{k_0, k_1, k_2, ..., T_{max}/\Delta T\}$ **do**:
  update main simulator
  if k corresponds with multiple of 0.5 seconds:
    if B_d = 0 ▷ All red phase
      Activate random phase with detected travellers in dilemma zone. Update B_a and B_d
      If no travellers detected: $B_d = 0$
    if $0 \leq B_d \leq G_{max} - Gmin$
      Prolong green for i with $G_d < G_{min}$
      $i \in B_a$ with detected travellers: green
      $i \in B_a$ without detected travellers: red
      If all $i \in B_a$ red: activate next block
    if $G_{max} - G_{min} \leq B_d \leq G_{max}$
      i with $G_d < G_{min}$: prolong green
      $i \in B_a$ without detected travellers: red
      If all $i \in B_a$ red, activate next block

5.3 Results

The averaged delay per traveller over the 14 simulation runs is provided in Figure 5. The figure also shows the 75th percentile. The average delay of SFGA is a factor 1.8 lower than VA at 15% saturation, and 2.7 and 3.0 times lower for 30 and 45%. The average delay of VA increases more rapidly with higher traffic saturation than SFGA. This indicates that, at low traffic demand, the structure free controller is more flexible to accommodate additional travellers within its' signal plans. The delays of SFGA show less spread than VA, because SFGA controls for individual delays and therefore is inclined to allow travellers to cross if their delay grows larger. This contrary to VAC, where travellers have to wait until it is their turn to cross.

SFGA results in lower delays for car drivers and cyclists than VA. Delays of car drivers are similar to the combined average delays, but difference regard to cyclists are more profound (Figure 6). At 15% traffic saturation the controllers perform relatively similar, with 4.1s and 6.7s average delays for the SFGA and VA respectively, but at saturation rates the delay of VA increases to 12.0s and 22.3s, while for SFGA delays increase to 4.6s, only to be reduced to 4.0s at 45% satura-

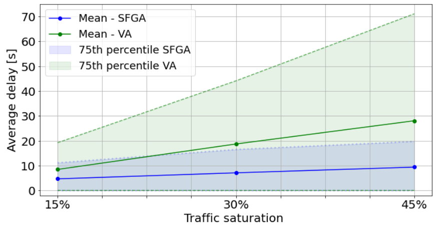


Figure 5: Delay of a traveller crossing the intersection

tion. In addition to lower delay for cyclist, the number of stop that are made by cyclists is also lower for SFGA.

The the lower delay and number of stops of SFGA compared to VA are attributed to differences in control mechanisms. The structure free controller considers the effect of its' control decisions on the delay of all travellers, thereby prioritizing traffic lanes with higher traffic densities. VA follows a fixed control sequence that can be accelerated by the absence of travellers in the currently active phase. For SFGA, this results in prioritization of movements with higher traffic densities. Higher traffic densities can be expected in bicycle lanes in urban areas, because of the smaller and higher saturation rate of bicycles. These density differences are unintentionally magnified by the choice of intersection layout. The prioritization of cyclists comes at the cost of car drivers, however average car driver delays do not get excessively long, because of the enforced maximum waiting time of 100s. If a car approaches this waiting time, the traffic light turns green and the cars waiting in this queue, can cross the intersection.

The relative (KPI_{SFGA}/KPI_{VA}) performance of the controllers is summarized in Table 3. At the lowest saturation rate, performance is the most similar between all metrics, with BSGC performing at most twice as good as VAC on all accounts. In absolute terms the difference is only a couple of seconds. With increased saturation levels the differences between the controllers increase in both relative and absolute terms. Only in terms of average car driver delay the relative performance is quite similar over all saturation levels.

Table 3: Performance ratios (BSGC/VAC)

	Saturation rate		
	15%	**30%**	**45%**
Average delay	1.8	2.6	3.0
Avg. delay - Cyclist	1.6	2.8	5.6
Avg. delay - Car driver	2.0	2.5	2.2
Full stops - Cyclist	1.9	2.3	3.1

The structure free controller is able to predict and choose the most effective signal plan for the current traffic state. This results in fewer people waiting for the traffic light and a larger share of travellers that is able to cross the intersection with a relatively short delay (Figure 7). On average, there are always fewer people in the dilemma area areas of BSGC than for VAC. Over time the number of travellers in the dilemma area remains relatively constant. This indicates that both controllers achieve a similar throughput of the intersection, however, in order to achieve this the VAC requires -on average- a higher number of travellers in the dilemma areas, waiting for the traffic lights, which results delay distributions that tend more towards low delays.

SFGA is able to accommodate a larger number of travellers that cross earlier because of two main reasons. Firstly, it is able to truncate green if even if there is traffic in proximity of the traffic light, allowing another movement with a larger number of travellers to cross. Secondly, it is able to use any non-conflicting combination of traffic lights that is most effective, instead of predefined combinations. Figure 8 shows SFGA truncates green more often when there are travellers in the dilemma area than VA, which is only able to do so if the maximum green time has passed. Note that inclusion of flexibility would provide VA with a larger degree of freedom as well, but including all alternatives in the control structure becomes increasingly difficult with a more complex intersection layout.

The ability of SFGA to choose the combination of traffic lights with the largest positive effect on delays is expected to result in a more effective use of green. However, on average, VA results in a slightly lower average crossing headway, indicating green time is used more effectively (Figure 9). This is because, if there is no conflicting traffic, SFGA allows a low number of travellers to cross, resulting in large crossing headways. VA forces these travellers to await their turn, allowing more time for queues to form, which in turn have a lower crossing headways when allowed to cross. This may be demonstrated by evaluating the total green time of both controllers, but SFGA gives green to a random movement without traffic, when there is nowhere else the green time would result in lower delays. Inclusion of a weight for total green time in the objective function, order of magnitudes smaller than any of the other weights, would prevent the controller from providing this unused green. Additionally, switching more often results in larger loss times which means it cannot be certain if the total green time would indeed be larger for SFGA.

Figures 10 to 13 the effect of explicitly prioritizing cyclists over cars on the delay of all travellers, the delay of both modalities and the percentage of traffic light approaches of cyclists resulting in a full stop. The inclusion of weights that prioritize cyclists results in choices of the controller on ending, extending or starting green time more often being made to the benefit of the cycle paths. Different relative weights for delay result in lower average delays and delay spread for cy-

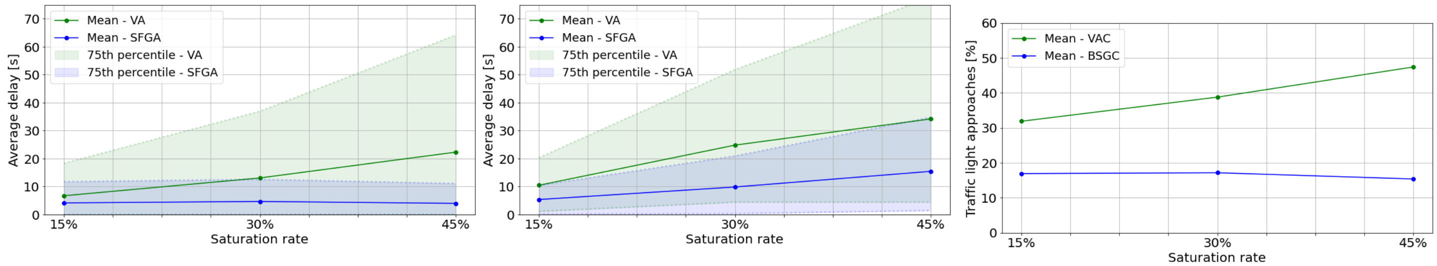
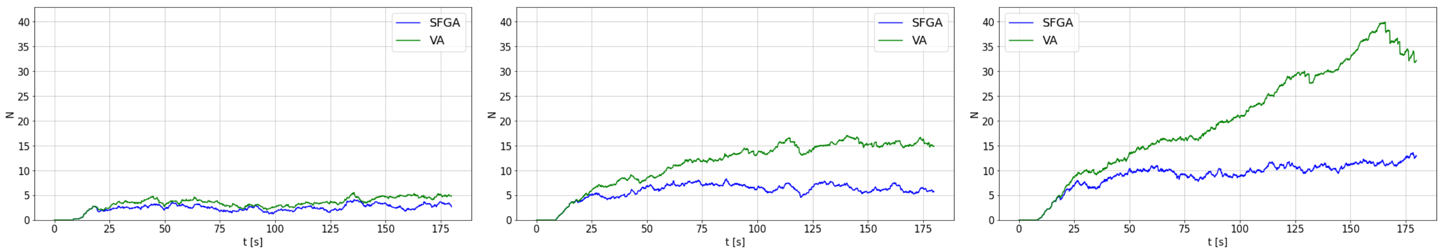
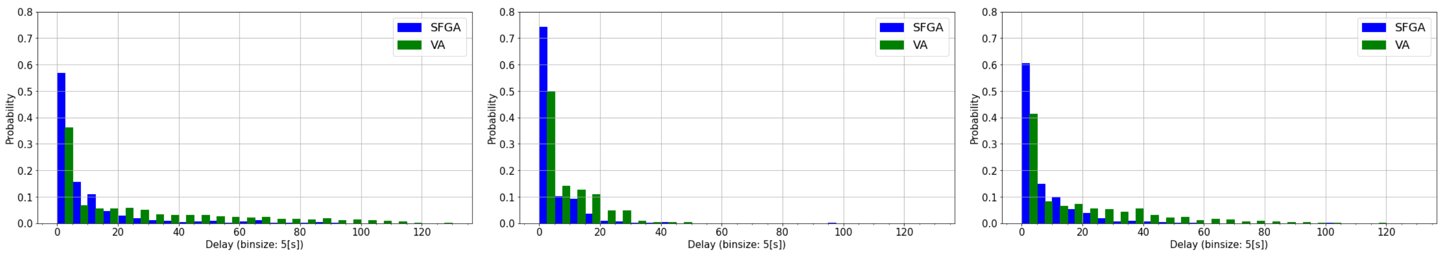


Figure 6: Impact of SFGA and VA on delay of cyclists (left), delay of car drivers (middle) and percentage of traffic light approaches of cyclists resulting in a full stop (right)



(a) 15% traffic saturation (b) 30% traffic saturation (c) 45% traffic saturation



(d) 45% traffic saturation (e) 15% traffic saturation (f) 30% traffic saturation

Figure 7: Average number of travellers in the dilemma area over time (top) and the corresponding delay distributions (bottom) for 15 (left), 30 (middle) and 45 (right) % traffic saturation

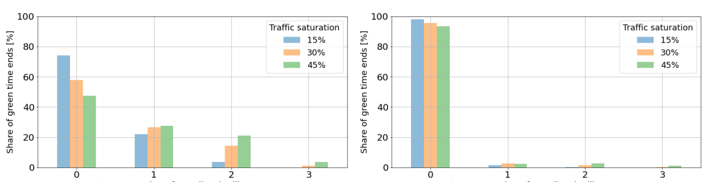


Figure 8: Share of green truncation given a number of travellers in the dilemma area for SFGA (left) and VA (right)

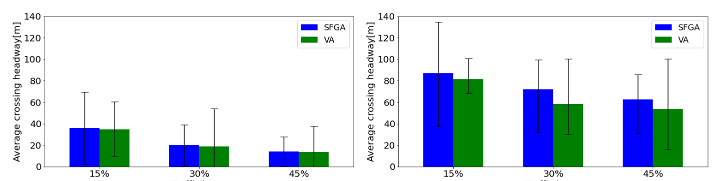


Figure 9: Average headways at the moment of crossing the stopping line for cyclists (left) and cars (right). A lower average headway indicates more effective use of green, as travellers follow each other more closely.

clists, but in disproportionately larger delays and spread for car drivers. At higher saturation rates the chance of a trade off resulting in a green light for any of the cars decreases because with more travellers in the system, total delays increase and the relative effects of the weights increase rapidly. The (small) improvements in cyclist delay therefore result in (larger) increases of car driver delay. Average delays for car drivers do not seem to increase to much more that 30 seconds. This is likely because of the imposed maximum waiting time of 100 seconds, which provides at least a green duration of the minimum green to this movement, allowing multiple cars to cross. This also means there is a maximum to what can be achieved by including weights for cyclists prioritization. At some points car drivers will be allowed to cross anyway.

Even though the relative delay weigh achieves a reduction in full stops for traffic lights, the constant weight is more effective in doing so. Regardless of the relative weight for delays, the effect of the weight for full stops on the average delay is fairly limited. This indicates that this weight does a better job at proportionally shifting delay from cyclists to car drivers.

However, with the high volumes of cyclists in this case study, resulting in already low cyclist delays for SFGA, it may be questioned whether explicitly cyclist prioritization is required. Prioritization may be better suited for scenarios in which cyclist volumes are low and prioritization is required for low cyclist delays.

6. Conclusion

This paper proposes proposed a structure free intersection controller based on a genetic algorithm, for an isolated intersection in an environment with connected cars and bicycles. The structure free controller uses simulation model based control to determine the effects of control decisions and a genetic algorithm to optimize for a combination of car driver delay, cyclist delay and full stops of cyclists. The controller tends to prioritize movements with the largest traffic densities, meaning the controller can prioritize cyclists in urban areas with large enough bicycle use. The weights in the objective function can be adapted to explicitly prioritize cyclists.

The results from the case study suggest that the controller outperforms the benchmark vehicle actuated control. In terms of average delay, the controller outperformed the benchmark by a factor 1.8, 2.7 and 3.0 for each of the evaluated saturation rates. The delay of the separate modalities and the percentage of cyclists that has to make a stop is also drastically reduced when compared to the benchmark.

The better performance of the structure free controller is attributed to the controller optimizing with a large degree of freedom, unlike vehicle actuated control that follows a predefined set of rules based.

Introducing any of prioritizing weights results in even better performance metrics for cyclists, but this comes at the cost of disproportionate increases of delays for car drivers. Whether or not this increase of delay of car drivers is acceptable is up for personal interpretation. A low delay priority factor or a cost for a full stop for cyclists is suggested to be the least intrusive method of providing addition priority for cyclists.

7. Future research recommendations

Further research is recommended on expansion of the scope of the controller and controller design. The controller should accommodate additional traffic modalities and more heterogeneity in personal characteristics. Solution generation algorithms can be improved to increase the share of feasible solutions and by by extension and reduction of green times with random lengths. The objective function should include a weight for total green time, orders of magnitude smaller than other weights, to avoid unused green time and the controller design should be evaluated and improved to function under non-perfect data and prediction quality.

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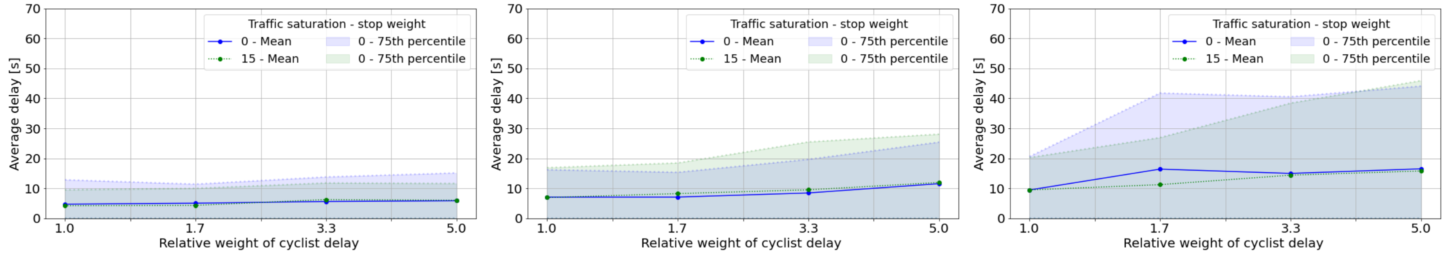

Figure 10: The average delay and the 75th percentile delay as a result of different relative weights (1.0, 1.7, 3.3, 5.0) for cyclist delay for each of the saturation levels

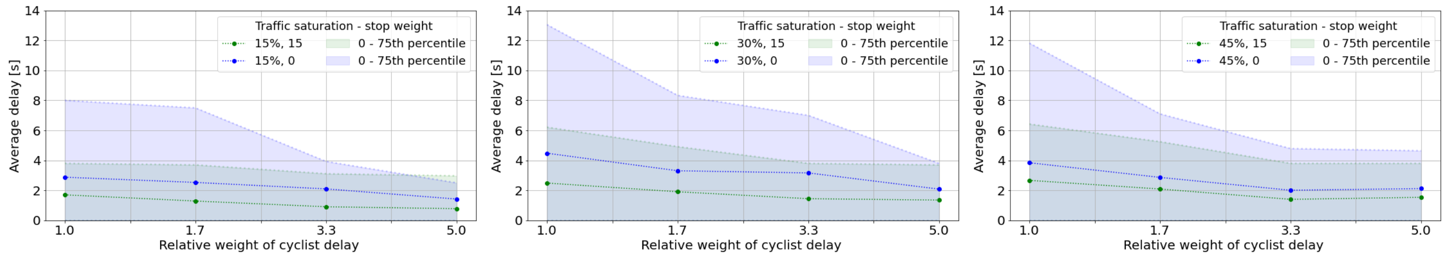

Figure 11: Average cyclist delay and the 75th percentile cyclist delay as a result of different relative weights (1.0, 1.7, 3.3, 5.0) for cyclist delay for each of the saturation levels

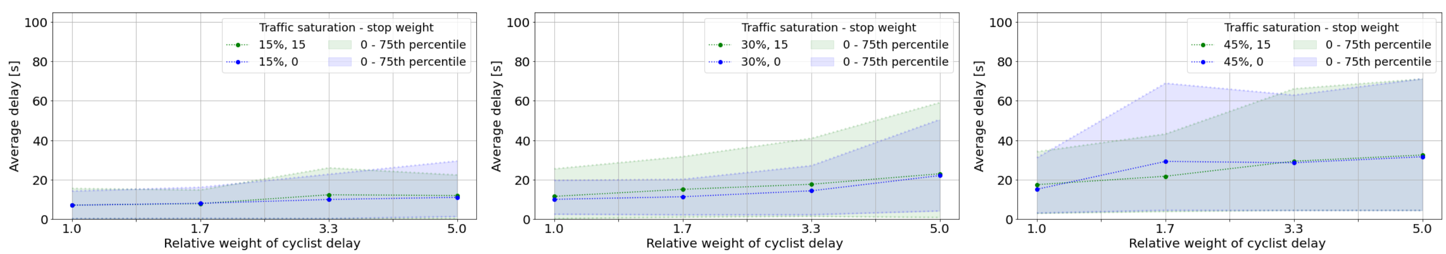

Figure 12: Average car driver delay and the 75th percentile car driver delay as a result of different relative weights (1.0, 1.7, 3.3, 5.0) for cyclist delay for each of the saturation levels

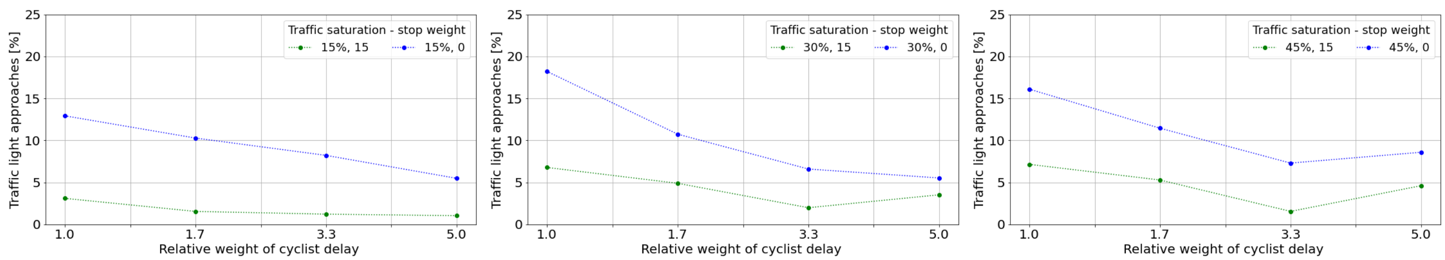

Figure 13: The percentage of traffic light approaches of cyclists resulting in a full stop as a result of different relative weights for cyclist delay for each of the saturation levels

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