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Resolving Interactions among Fully Automated Vehicles and Bicyclists in Complex Traffic Situations

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Executive Summary

Automated driving is regarded as one of the cornerstones of future mobility. Yet the integration of Automated Vehicles (AVs) in the mobility system and their acceptance by other road users is a significant challenge that automated driving has to overcome. Presently, AV research focuses on traffic safety related aspects of automated driving applications aiming to ensure safe interactions with other road users. Two of the key challenges for ensuring safe and continuous autonomy are the understanding and prediction of Vulnerable Road User (VRU) behavior and their respective interactions in traffic. Most research in this field is currently directed towards pedestrians, while the share of bicycles grows rapidly in urban networks mainly due to transport policy measures aiming to reduce the number of trips completed by motorized vehicles. As the importance of bicycle traffic for urban mobility systems increases, it is important to develop special automated driving functions that enable AVs to comprehend bicyclist behavior and ensure safe interactions.

Eventually the traffic safety aspects of AV operation will be mostly fully addressed. At the same time, city authorities, stakeholders and Human Road Users (HRUs) will move their attention into other areas and aspects of the AV operation. Efficient driving, continuous autonomy, acceptable driving behavior and the integration with traffic management will start to play an increasingly important role and will be the key differentiating features and the new area of competition among the different providers and fleet operators for the successful integration and acceptance of AV fleets in the mobility system. This dissertation proposes methods for resolving interactions among AVs and bicyclists. The novel methodological approach combines the development and evaluation of AV driving functions for supporting seamless and uninterrupted AV driving in the presence of bicyclists at unsignalized intersections with the development of a method for resolving AV and bicyclist interactions while improving traffic performance.

First, a deep learning model is developed that predicts the maneuver intentions of bicyclists at unsignalized intersection approaches. The model is based on Bidirectional Long Short Term Memory Networks (B-LSTMs) and predicts the intention of a bicyclist for a specific maneuver class (left-turn, right-turn, straight) at an intersection approach, before entering the intersection area. The behavioral data used for the prediction model was generated with a physical bicycle simulator through test subject studies. The best prediction performance results are achieved by combining features of the dynamic and operational bicyclist behavior with preclassified implicit and explicit gesture archetypes of the bicyclist communication behavior. This highlights the importance of the inclusion of the communication behavior features in human behavior prediction methods in the context of AV research.

The behavior of bicyclists in traffic is inherently unpredictable. Accurate uncertainty quantification and assessment are essential for the safe and efficient resolution of traffic interactions among AVs and bicyclists. In a second step, the deep learning model is expanded with a

method for quantifying the prediction uncertainty and for self-assessing its confidence using certain performance metrics.

The added information value gained through the prediction model is then integrated into a method that aims to resolve the interactions among bicyclists and AVs at a non-signalized intersection that ensures traffic safety and optimizes traffic efficiency. Specifically, a Mixed Integer Linear Programming (MILP) optimization framework is proposed that integrates the inherent bicyclist behavior uncertainty in the control actions taken to optimize traffic performance. The method considers the bicyclist individual behavioral characteristics by respectively adjusting the AV driving behavior and balances the requirements of the AV passengers. The proposed concept is integrated with the existing common traffic priority rules that regulate traffic at unsignalized intersections through the adaptation of the AV approach speed and the generation of acceptable time gaps for bicyclists of subordinate traffic streams to exploit.

Simulation evaluation results using Simulation of Urban Mobility (SUMO), where common traffic interaction scenarios are implemented, show that the proposed method consistently reduces delays and waiting times for bicyclists for moderate to high traffic demand compositions and outperforms the "Base" Scenario where priority is handled with the common traffic rules. The resulting delays for the superordinate AV traffic streams are minor and effectively not comparable to the significant gains for bicycle traffic. It is also found that the higher the complexity of the intended bicyclist maneuver at the intersection, the greater the bicycle traffic performance gains and the greater the significance and influence of the maneuver prediction confidence, while the performance of the proposed MILP optimization framework was poor or similar to the "Base" scenario for evaluated scenarios with low traffic demand. Thus, the proposed method proactively alleviates the automated driving task requirements for the interacting AVs by reducing the traffic situation complexity arising from the uncertain behavior of the increasing number bicyclists in the intersection area. This, further increases traffic safety and ensures continuous uninterrupted autonomy.

Zusammenfassung

Automatisiertes Fahren wird als einer der Eckpfeiler der zukünftigen Mobilität angesehen. Die Integration von automatisierten Fahrzeugen in das Mobilitätssystem und ihre Akzeptanz durch andere Verkehrsteilnehmer ist eine große Herausforderung. Derzeit konzentriert sich die Forschung im automatisierten Fahren auf verkehrssicherheitsrelevante Aspekte mit dem Ziel, sichere Interaktionen mit anderen Verkehrsteilnehmern zu gewährleisten. Einige der wichtigsten Herausforderungen für die Gewährleistung einer sicheren und kontinuierlichen Autonomie sind das Verständnis und die Wahrnehmung des VRU Verhaltens und der entsprechenden Interaktionen im Verkehrsgeschehen. Die Mehrheit der Forschung in diesem Bereich ist auf Fußgänger ausgerichtet, während der Anteil der Radfahrer in städtischen Netzen aufgrund verkehrspolitischer Maßnahmen zunimmt. Dabei ist es wichtig, spezielle automatisierte Fahrfunktionen zu entwickeln, die es den automatisierten Fahrzeugen ermöglichen, das Verhalten von Radfahrern zu verstehen und sichere Interaktionen zu gewährleisten.

Letztendlich werden in der Zukunft die Verkehrssicherheitsaspekte bei automatisierten Fahrzeugen größtenteils vollständig berücksichtigt. So werden städtische Behörden, Interessengruppen und die anderen Verkehrsteilnehmergruppen ihren Fokus auf andere Bereiche und Aspekte des automatisierten Fahrens lenken. Effizientes Fahren, kontinuierliche Autonomie, akzeptables Fahrverhalten und die Integration im Verkehrsmanagement werden eine immer wichtigere Rolle spielen und die wichtigsten Unterscheidungsmerkmale und neuen Wettbewerbsbereich zwischen den verschiedenen Anbietern und Flottenbetreibern für die erfolgreiche Integration und Akzeptanz von automatisierten Fahrzeugflotten im Mobilitätssystem darstellen. In dieser Dissertation werden Methoden zur Auflösung von Interaktionen zwischen automatisierten Fahrzeugen und Radfahrern festgelegt. Der neuartige methodische Ansatz kombiniert die Entwicklung und Bewertung von automatisierten Fahrfunktionen zur Unterstützung eines nahtlosen und ununterbrochenen automatisierten Fahrens im Mischverkehr mit Radfahrern an unsignalisierten Knotenpunkten mit der Entwicklung einer Methode zur Auflösung von automatisierten Fahrzeug- und Radfahrer-Interaktionen bei gleichzeitiger Verbesserung der Verkehrseffizienz.

Zunächst wird ein Deep-Learning-Modell entwickelt, das die Manöverabsichten von Radfahrern an unsignalisierten Knotenpunkten vorhersagt. Das Modell basiert auf B-LSTMs und prädiziert die Absicht eines Radfahrers für eine bestimmte Radfahrermanöverklasse (Linksabbiegen, Rechtsabbiegen, Geradeausfahren) an Knotenpunktzufahrten. Die verwendeten Radfahrerverhaltensdaten wurden mit einem physischen Fahrradsimulator im Rahmen von Probandenstudien erzeugt. Die besten Ergebnisse werden durch die Kombination von Merkmalen des dynamischen und operativen Radfahrerverhaltens mit vorklassifizierten impliziten und expliziten Gestenarchetypen des Kommunikationsverhaltens von Radfahrern erzielt. Dies unterstreicht die Bedeutung der Einbeziehung von Merkmalen des Kommunikationsverhaltens in die Methoden zur Vorhersage des menschlichen Verhaltens im Rahmen der automatisierten Fahrzeugforschung.

Das Verhalten von Radfahrern im Verkehr ist prinzipiell unvorhersehbar. Eine genaue Quantifizierung und Bewertung der Unsicherheit ist für die sichere und effiziente Auflösung von Verkehrsinteraktionen zwischen automatisierten Fahrzeugen und Radfahrern unerlässlich. In einem zweiten Schritt wird das entwickelte Deep-Learning-Modell um eine Methode zur Quantifizierung der Vorhersageunsicherheit und zur Selbsteinschätzung seines Vertrauens bei der Prädiktion anhand bestimmter Leistungsmetriken erweitert.

Der durch das Vorhersagemodell gewonnene Informationsmehrwert wird in einer Methode integriert, die darauf abzielt, die Interaktionen zwischen RadfahrerInnen und AVs an einer nicht signalisierten Kreuzung so zu lösen, so dass gleichzeitig die Verkehrssicherheit gewährleistet und die Verkehrseffizienz optimiert wird. Insbesondere wird ein MILP-Optimierungs-Framework entwickelt, das die Unsicherheit des Radfahrerverhaltens in die Steuerungsmaßnahmen zur Optimierung der Verkehrsleistung einbezieht. Die Methode berücksichtigt die individuellen Verhaltensmerkmale der Radfahrer, indem sie das automatisierte Fahrzeugverhalten entsprechend anpasst und die Anforderungen der Fahrgäste ausgleicht. Das vorgeschlagene Konzept wird in die bestehenden allgemeinen Verkehrsvorrangsregeln integriert, die den Verkehrsablauf an unsignalisierten Knotenpunkten durch die Anpassung der Anfahrgeschwindigkeit und die Generierung akzeptabler Zeitlücken für RadfahrerInnen der untergeordneten Verkehrsströme optimiert.

Die Ergebnisse der Simulationsauswertung mit SUMO, wobei typische Verkehrsinteraktionsszenarien berücksichtigt wurden, zeigen, dass die entwickelte Methode die Zeitverluste und Wartezeiten für Radfahrer bei mäßiger bis hoher Verkehrsnachfrage im Vergleich zum "Basis"-Szenario, bei dem die Priorität durch die üblichen Verkehrsregeln geregelt wird, reduziert. Die daraus resultierenden Zeitverluste für die übergeordneten Verkehrsströme sind geringfügig im Vergleich zu den signifikanten Gewinnen für den Radverkehr. Es wird auch festgestellt, dass je höher die Komplexität des beabsichtigten Radfahrermanövers am Knotenpunkt ist, desto größer sind die Leistungsgewinne für den Radverkehr und desto größer ist die Bedeutung und der Einfluss des Manövervorhersagevertrauens. Dabei ist die Leistung des MILP-Optimierungs-Frameworks schlechter oder gleich dem "Basis"-Szenario für bewertete Szenarien mit geringer Verkehrsnachfrage. Die vorgeschlagene Methode entlastet also proaktiv die technischen Anforderungen für die interagierenden automatisierten Fahrzeugen, indem sie die Komplexität der Verkehrssituation, die sich aus dem unsicheren Verhalten von mehreren Radfahrern im Knotenpunktbereich ergibt, reduziert. Dadurch wird die Verkehrssicherheit weiter erhöht und die ununterbrochene Fahrautonomie gewährleistet.

Contents

Chapter 1

Introduction

This chapter presents the Motivation (Section 1.1) and an overview of the State of the Art (Section 1.2) of the present research in the fields of bicyclist behavior modeling and intention prediction, Automated Vehicle (AV) cooperation and traffic flow optimization. Section 1.3 summarizes the methodology followed to accomplish the research objectives of this work, while section 1.4 lists the main scientific contributions of this dissertation.

1.1 Motivation

AVs are a key component of future mobility. It is expected that the introduction of AVs will improve traffic safety and traffic efficiency and enhance travel convenience. Although, AVs are regarded to be the future of mobility, they remain one component of the entire mobility system, that also includes public transport and *non motorized road users*. Especially, the share of non-motorized modes of transport, such as bicycles, grows rapidly in urban networks mainly due to transport policy measures aiming to reduce the number of trips completed with motorized vehicles. Such policy measures usually include the construction of bicycle infrastructure, traffic regulation measures for motorized traffic and the development of intermodal services.

Lately, *novel traffic control strategies* are also being developed that foster non-motorized traffic. While AVs are expected in the future to interact with bicyclists in mixed traffic situations without human supervision and intervention, they are currently not capable to handle and resolve several of these situations safely and efficiently, especially those that require communication among road users.

In contrast to a highway environment where currently low-automation level AVs are able to navigate autonomously under human supervision, urban streets have a higher degree of unpredictability and complexity when it comes to interactions among road users. In urban traffic environments, *understanding* of the common traffic scenarios, *cooperation* with other road users and handling of safety critical situations are some of the key elements that an AVs is required to possess in order to navigate safely and efficiently. Sometimes, such situations are even resolved by *priority negotiation* among road users or with slight deviations from the strict adherence to the traffic rules [Bogdoll et al., 2022]. AVs are therefore required to predict the behavior of other road users accurately, mitigate the effects of unpredictable situations and cooperate with other road users in order to resolve critical traffic situations with respect to traffic safety and traffic efficiency.

AVs are equipped with several different *sensors* that provide an abstract perception of their environment. This abstract information allows current experimental AVs to navigate in urban streets safely and handle simple common traffic scenarios. The utilized sensor inputs provide present AVs with very basic and mostly non-contextual information of their surroundings. Currently, AVs are not able to predict road user behavior for the long-term with high accuracy or differentiate in some cases among different types of road users. Especially under mixed traffic flow conditions non-motorized user behavior can be unpredictable, as the non-motorized user intentions are not known to the AV and due to the inherent movement flexibility of non-motorized users, their behavior and their actual influence on the vehicle's path cannot be easily foreseen. As technology continues to progress, new types of sensor and data sources become available that can be potentially utilized for the optimization of automated vehicle brain units, in order to comprehend traffic situations. As AV sensor technology improves, the comprehension of the road environment can become more accurate. Additionally, as in the future the number of AVs on the roads is expected to rise, *information exchange* and *cooperation* among AVs can also become a way of resolving critical traffic situations more efficiently.

As a further step, the understanding of basic non-motorized user communication patterns is essential in increasing vehicle autonomy. Currently road users often communicate their intentions to other road users through *implicit and explicit communication cues*. AVs are currently unable to comprehend or even detect most of these communication methods. In this context, an additional way to establish communication among AVs and other non-motorized road users can be through Human Machine Interfaces (HMIs) or mobile electronic devices such as smartphones or wearables. These can provide further insight into the non-motorized user intentions or by introducing special archetypes of gestures that convey a specific information or command to interacting AVs. However, the most important outcome is that for the first-time different types of road users finding themselves in the same traffic situation can exchange information on different channels. The biggest advantage of this *interconnection* comes from the data that is produced from all floating sources with high frequency rates and quality. The potential of the *utilization* of this data input and communication in urban intersections with mixed traffic flow conditions and the *fusion* of these data sources for resolving problematic traffic situations has not been thoroughly studied.

1.2 State of the Art

Automated driving will become an important part of urban traffic in the future. For automated vehicles, different levels of automation have been defined based on the applied technology as well as the degree of human involvement during driving. The most well-known are provided by the On-Road Automated Driving Committee (ORAD) [2021], the National Highway Traffic Safety Administration [NHTSA, 2013], and the Bundesanstalt für Straßenwesen [Gasser and Westhoff, 2012]. The automated driving classifications start from manual driving, proceed with assisted and partially automated driving where the vehicle takes over part of the vehicle control and move up to fully automated driving, where the vehicle takes over complete control. In full-automated driving mode, no human control is normally required. However, the driver must be ready to assume control in a short period of time to respond to a complex traffic situation that the vehicle control system cannot resolve on its own. The transition from fully automated to manual vehicle control can potentially be an overwhelming task for the drivers with potential drawbacks to traffic safety [Inagaki, 2006; Inagaki and

Furukawa, 2004], due to the fact that in fully automated driving the passenger is not required to supervise the vehicle driving operations and is allowed to perform other tasks. Thus, vehicle control algorithms and sensor technologies need to be optimized further in order to address traffic situations more safely and efficiently and eliminate the number and frequency of occurrences, where the control has to be handed over to the driver.

The prediction of road user intention has been the focus of extensive research in the fields of traffic safety, traffic control and automated driving. Especially AVs are required to interact with other human road users in interactive and cooperative decision-making processes. In this context, the intentions of other road users need to be deduced and integrated into a decision-making framework for AVs. Human Road Users (HRUs) (motorized and non-motorized human road users e.g. car and truck drivers, motorcyclists, pedestrians, bicyclists etc.) make use of different types of contextual information in their short-term and long-term decision-making process when interacting with other nearby road users. Sources of this type of information may include the dynamic, operational and tactical behavior features of nearby road users. Also, implicit (e.g. head movements, look direction, body posture) and explicit (e.g. hand gestures) communication features are often used by road users to indicate their intentions and are used both as a form of communication as well as subconsciously for decision making purposes. For example, bicyclists often utilize hand gestures to indicate a maneuver they will perform. Deceleration or acceleration processes can also hint a specific maneuver or driving action. Additionally, implicit communication cues such as head movements and eye contact are also part of the communication strategies often employed in traffic by road users to reveal their intentions to other road users, who in turn can use this information to forecast their behavior. For example, a pedestrian intending to cross the road would normally perform a visual check for oncoming vehicles before crossing the road. From the vehicle driver's perspective, this information is crucial as it serves as an indicator for forecasting the pedestrian's intentions.

In this context, special implicit and explicit characteristics of bicyclists' communication behavior may be used together with other behavioral features in forecasting their intentions in specific traffic situations. For human road users, such types of information may be understandable in a specific social and cultural context. However, for AVs, the understanding of bicyclist behavior is challenging in predicting the bicyclist intentions. Moreover, the behavior of bicyclists is inherently unpredictable and therefore the quantification and assesement of the prediction uncertainty is critical. AVs must be able to understand and predict the behavior of other road users with a certain degree of certainty in order to avoid safety critical situations and navigate safely in complex urban traffic environments. Additionally, resolving complex traffic interactions without passenger interaction with human-like behavior can further improve their acceptability among road users. Thus, the comprehension of the behavior of vulnerable road users such as bicyclists can play a crucial role for AVs in supporting their automated operation in urban road environments.

On the other hand, the social perception of automated driving will ultimately drive the acceptance of AV vehicles in traffic especially in urban areas where constant interactions with HRUs are expected. Pyrialakou et al. [2020] investigate the safety perception for automated vehicles from the perspective of drivers and Vulnerable Road Users (VRUs) (only non-motorized human road users, e.g. motorcyclists, pedestrians, bicyclists, e-scooter riders, etc.). Walking and cycling in shared spaces with AVs are identified as the most safety critical types of interactions with AVs with the latter being perceived as the most safety critical due to the higher bicycle travel speeds compared to walking and the increased the severity of potential incidents. The main traffic problem that road users have to resolve in shared spaces such as intersections or straight road sections originates from the competition for critical traffic resources at the Critical Sections (CSs), which are road sections where different traffic participant trajectories intersect [Zhang et al., 2013].

Present research on automated driving focuses primarily on resolving traffic situations for a singular vehicle with other motorized users or improving traffic efficiency at intersections or road sections though cooperation and communication with other AVs. At the same time, ongoing research on interactions among automated vehicles and non-motorized road users primarily focuses on improving detection technologies and methods and on the safer interaction with the non-motorized users. Little to none research has been found in the area of predicting bicyclist behavior and in resolving traffic situations with multiple bicyclists and AVs through cooperation and communication in shared space traffic environments.

The development of automated vehicle control algorithms that resolve traffic situations for AVs has already been undertaken by various researchers [Bouraoui et al., 2006; Brown et al., 2017; Colombo and Del Vecchio, 2012; K. Dresner and P. Stone, 2004; Furda and Vlacic, 2011; Grégoire et al., 2013; Zhang et al., 2013]. These methods leverage the sensors and technologies integrated in an AV for further optimizing traffic flow. As part of these approaches, AVs can potentially cooperate and resolve these traffic situations by negotiating priority among each other or by considering the non-motorized users at signalized intersections [Niels, Mitrovic, Bogenberger, et al., 2019; Niels, Mitrovic, Dobrota, et al., 2020; Niels, Bogenberger, et al., 2020; Kurt Dresner and Peter Stone, 2007] through reservation based and control optimization strategies.

A common element among these different methodologies, for optimizing traffic efficiency and safety is Vehicle-to-Everything (V2X) communication, which is a fundamental requirement for improving traffic efficiency in an automated vehicle environment [Tan, 2017]. At the same time, none of the existing scientific methodologies considers non-motorized road users at unsignalized intersections and mixed traffic flow conditions. Research on automated driving currently focuses primarily on the safety implications among AVs and non-motorized user interactions [Dixit et al., 2016; Gandhi and Trivedi, 2007; Gordon et al., 2016; Levinson et al., 2011; Litman, 2014] in shared spaces. In addition, communicating intentions among road users is important for resolving even common traffic situations, often relying in a mixture of a complex culturally guided series of interactions, including facial expressions and gestures. Thus, AVs are required to be able to comprehend and interpret this communication forms [Sandt et al., 2017]. Google prototype automated vehicles are able to detect and recognize bicyclists and respond to common riding behaviors that are observed on test tracks or on the road. Using machine learning, vehicles are taught to remember and recognize the bicyclists' explicit gestures and correlate them with specific bicyclist behavior [Google Inc., 2016; Kretzschmar and J. Zhu, 2015]. However, the proposed method makes use only of the explicit communication behavior of the bicyclists and specifically the hand gestures to adjust the vehicle driving behavior. It does not comprehend and consider implicit communication behavior features that potentially carry critical intention information. Eventually, bicyclists are not required to perform explicit gestures to communicate their maneuver intentions in traffic.

Additionally, no form of communication or collaboration with other AVs or the bicyclists is implied. Establishment of communication and collaboration among AVs and bicyclists can potentially provide the basis for improving traffic efficiency and safety on the traffic environment. SANTA et al. [2017] investigate the potential of integrating two wheelers (bicyclists and motorcyclists) within the future cooperative intelligent transportation system network. The embedded communication node for the two-wheelers includes software to warn the rider about the approaching of a vehicle through audio and visual notifications. Moreover, a counterpart for cars has also been developed. Based on the identified research gaps, the follwonig primary research question may be formulated that frames the scope of this disseration:

How can we resolve complex traffic situations at intersections among bicyclists and fully automated vehicles by optimizing traffic efficiency and utilizing information generated by automated vehicle sensors and bicyclists?

The primary research question can be further analysed and broken down into four research questions that define the framework for this present dissertation.

1. *How can we predict the bicyclist maneuver intentions?*
2. *How can we quantify and assess the confidence for the bicyclist intention prediction?*
3. *How can we resolve bicyclist interactions with AVs through cooperation?*
4. *How can we optimize mixed AV and bicycle traffic flow?*

1.3 Methodology

This section summarizes the methodology that will be followed in this work. Figure 1.1 presents the methodology steps followed. First a thorough review of related scientific work is undertaken. The scientific literature review will establish the basis for the development of the scientific methodology proposed to address the targets of the present dissertation topic and can be divided in three parts.

Section 2.1 will establish the framework for the present work from the AV perspective. It includes the definitions on the established AV automation levels and discusses the core components of the AV system architecture. Eventually, the methods that are developed as part of these work can be integrated with the respective core system components, assuming certain competences and limitations that are derived from the official automation level definitions.

The second part reviews the scientific literature investigating and modelling the behavior of VRUs and particularly bicyclists in the traffic environment. First, a review of related research on road user interactions is performed. The review will focus on identifying the most important aspects and characteristics of these interactions as well as the analysis of the behavior of road users, especially that of bicyclists. Additionally, a review of studies related to the road user communication strategies and behavior in the traffic environment will be performed to identify the key findings and characteristics related to explicit and implicit communication patterns and the methodologies applied to investigate and quantify explicit and implicit communication behavior by traffic participants. As the bicyclist data collection is performed using a bicycle simulator, a review of bicycle simulator research is undertaken. Here, the literature review will focus on the design and implementation of bicycle simulators of other institutions, the available software as well as the methodology for conducting simulator studies with test subjects. This section will also discuss the competences, properties and use cases of bicycle simulators in test subject studies, as well as their strengths and limitations in scientific research. Finally, a review of the approaches proposed in the scientific literature to model and predict the behavior of bicyclists and non motorized road users will be performed.

The third and final section of the literature review initially focuses on the investigation of related scientific research and present developments in AV technologies and methodologies developed for the cooperation among different agents focusing on solutions for human machine interaction. It highlights studies on the optimization of traffic flow at traffic intersections, the methodologies applied, the results and the evaluation tools utilized, especially with respect to solutions developed primarily for AVs or V2X technologies. An effort will also be made to include relevant research with respect to unsignalised intersections as well as methodologies developed for the optimization of mixed motor vehicle and/or bicycle traffic flow. The methodologies will be reviewed in order to examine the most common scientific approaches for optimizing the traffic flow at traffic intersections and to identify the most often utilized traffic efficiency indicators used in the development of such approaches.

Finally, based on the literature review a research needs assessment will be conducted to clearly define the research questions and the substantial contribution of the present doctoral thesis.

The findings of the literature review contribute in establishing the methodology followed to accomplish the research goals of the doctoral thesis. The target of this work is to develop a scientific solution for resolving complex traffic situations among fully automated vehicles and bicyclists through communication and information exchange among bicycles and fully automated vehicles. The scientific methodology will rely on the long-term prediction of the bicyclists' maneuver intention at the intersection's wider area. This prediction will be based on the information input by the vehicle sensors of fully automated vehicles and on common communication techniques used by bicyclists. Based on the maneuver intention prediction, a spatiotemporal model of the wider intersection area can be developed for predicting the short-term behavior of bicycles and fully automated vehicles. However, in contrast to the AV behavior, the bicyclist behavior is inherently uncertain. In order to quantify the prediction uncertainty, the prediction model is expanded with a method for assessing the prediction confidence. Given the identified traffic situation and the uncertainty quantification, an objective function is then optimized that utilizes information from all road users to implement the most optimal solution in terms of traffic efficiency that resolves the present traffic situation for any number and composition of bicycles and AVs at the intersection approaches. This method is governed by an established cooperation framework among bicycles and automated vehicles that regulates their interactions by conditionally prioritizing bicyclists on minor traffic streams over AVs on major traffic streams. A set of constraints and rules are also determined that ensure safe and conflict free interactions among all road users.

In this context, first a scientific method for the prediction of the bicyclist intentions at the intersection is developed. The scientific method will focus on identifying the bicyclist maneuver at the intersection area and the present traffic context. As the target is to improve the traffic efficiency, specific study cases at traffic intersections, where through cooperation among automated vehicles and bicycles, the traffic flow can be improved, are defined. For the use case of an unsignalized intersection, common traffic scenarios are modeled in a bicycle simulator [Andreas Keler, J. Kaths, et al., 2018], where test subjects are instructed to accomplish pre-specified maneuvers in the presence of other vehicles, while adhering to traffic rules. Specifically, the case study of a bicyclist performing the three most common maneuver types at an intersection (left turn, crossing, right turn) is selected and the complexity is reduced to the core question through assumptions and simplifications of the defining problem parameters. Under these assumptions, the broader critical traffic situation is reduced to more specific and clearly defined traffic scenarios involving different number of interacting vehicles and priority rules. The bicycle simulator allows the efficient, safe and cost-effective study of the behavior of multiple test subjects in a controlled environment with entirely identical traffic scenarios and without the influence of external environmental factors. Test subjects ride through the simulated traffic scenarios and generate trajectory data. Using an Intel® RealSense™ Depth Camera D435, skeleton data including hand gestures, body and head movements of the test subjects are recorded in parallel and classified into gesture archetypes. The scientific methodology for identifying the bicyclist intentions is then developed using the bicyclist trajectory data combined with the implicit and explicit communication data collected during the simulator studies. The proposed prediction model is subsequently coupled with a method for quantifying prediction uncertainty and assessing the prediction confidence.

As a second step, an operational framework for bicycle traffic and AV cooperation is developed using the knowledge gained from the scientific literature review and the developed scientific methodology for the prediction of the bicyclist intentions. The framework defines the behavior of the AV in cases of bicyclists and AV interactions at an unsignalized intersection and intents to improve traffic efficiency for all interacting road users. This work also discusses the communication tools for establishing a communication among the AVs and the bicyclists that will regulate the cooperation of the AVs and bicyclists in the selected study cases.

In particular a method is developed that can serve as a platform for analysing and forecasting the intersection traffic state and conditionally prioritizing bicyclists on minor traffic streams. Based on the traffic state estimation at the intersection approaches for the involved road users, the control strategy decides on the specific control actions at the intersection. The method includes functions for prioritizing bicyclists by creating acceptable gaps between a leading and a following AV for bicyclists to pass through or to merge in traffic. The decision-making process for the prioritization is formulated as a multi objective optimization problem for minimizing the expected delays and number of stops for all road users, based on the prediction probabilities for the intended maneuver of the incoming bicyclists for each traffic stream. Scenarios with varying information accuracy levels and traffic demand are compared and examined in order to assess the efficiency and sensitivity of the developed methodology at different deployment scenarios. The developed algorithm is then evaluated in simulation scenarios with simulated bicyclists in a fully automated vehicle simulation environment. Additional sensitivity studies may be undertaken in order to identify the limitations of the proposed solution.

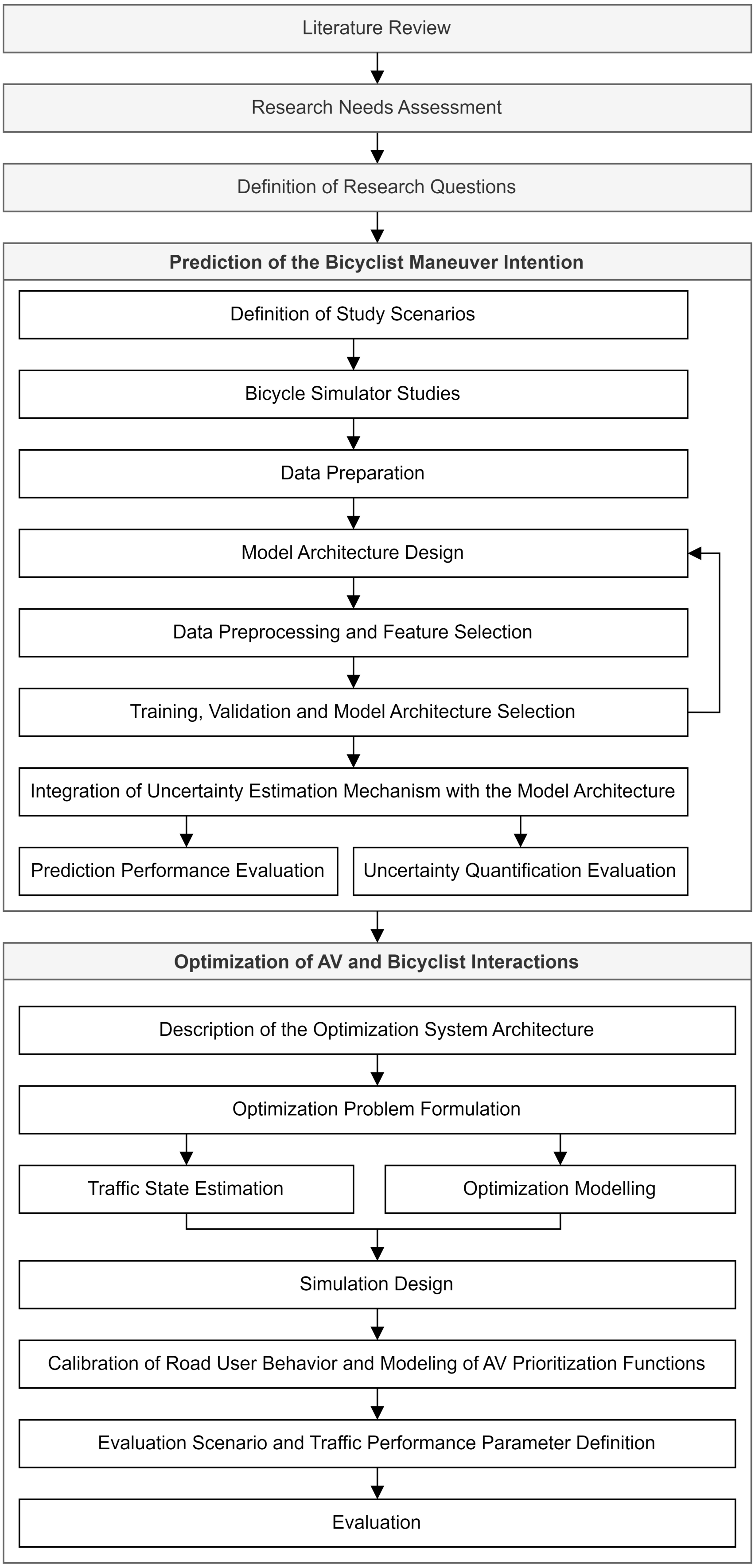


Figure 1.1: Methodology flowchart.

1.4 Contributions

The main goals of this work is first to develop a model that predicts the maneuver intentions of bicyclists at intersection approaches. The added information value gained through the prediction model is then integrated into a method that aims to resolve the interactions among bicyclists and AVs at an unsignalized intersection, while ensuring traffic safety and optimizing traffic efficiency. The following points summarize the key contributions of this dissertation for scientific research linked to the research questions defined in section 1.2.

1. This work introduces a novel deep learning model based on Bidirectional Long Short Term Memory Networks (B-LSTMs) that predicts the intention of a bicyclist for a specific maneuver class (left-turn, right-turn, straight) at an intersection approach and before entering the intersection area. The behavioral data used for the prediction model development was generated in a physical bicycle simulator through test subject studies. *(Research Question 1)*

2. The developed deep learning model with the best prediction performance results successfully combines features of the dynamic and operational bicyclist behavior with pre-classified implicit and explicit gesture archetypes of the bicyclist communication behavior. All evaluated model versions that used bicyclist communication behavior information performed significantly better than the evaluated model version that only utilized dynamic and operational bicyclist behavior features. This work demonstrates the importance of the inclusion of the communication behavior features in the prediction method. Therefore, the findings are transferable for the development of equivalent VRU behavior prediction models for automated driving research. *(Research Question 1)*

3. The deep learning model is expanded with a method for quantifying the prediction uncertainty. Therefore, the model is able to self-assess its confidence using certain performance metrics. This combined comprehensive novel approach for resolving the bicyclist maneuver prediction problem has not been previously presented so far (to the best of the author's knowledge) in any relevant scientific research in the fields of human action prediction or automated driving research. *(Research Question 2)*

4. The development of an optimization framework for resolving traffic interactions at unsignalized intersections among AVs and bicyclists, by improving traffic efficiency and considering traffic safety. The proposed method demonstrates the importance and the future potential, while identifying limitations for considering VRUs in shared spaces, in a fully automated vehicle traffic environment. *(Research Questions 3 and 4)*

Chapter 2

Literature Review

This chapter presents and discusses the most important and relevant contents of present scientific research that contributes to the aims of this scientific work. In this context, first section 2.1 outlines and defines the critical functions and system components of AVs and establishes the framework and limitations for the subsequently developed methods. Eventually the developed methods rely on the competences and properties of present AVs and can be potentially integrated in AVs as part of their core functions. Subsequently, sections 2.2, 2.3 and 2.4 present the most important developments in the fields of road user behavior analysis, communication behavior and methods for predicting road user behavior in the context of automated vehicle research. The review focuses primarily on bicyclists and additionally includes research that applies to other VRU types, as these findings are also deemed as relevant and transferable to the goals of this dissertation.

A novel approach in this work is the use of behavioral data from a bicycle simulator setup in order to develop a prediction method for bicyclist intentions. In this context, section 2.5 summarizes the most important work in the field of bicycle simulator research, presents the most recent and important bicycle simulators developed by researchers worldwide and discusses their key features, competences and limitations.

Subsequently, this work aims to resolve interactions among AVs and bicyclists. in this context, section 2.6 discusses the most important aspects in the fields of human machine co-operation and communication. Section 2.7 highlights the approaches followed for simulating the driving behavior of AVs and bicyclists. These findings are extensively used later on in the development of the simulation model for the evaluation of the proposed optimization framework. Section 2.8 presents the most important research in the field of traffic flow optimization in fully automated and connected traffic environments. Finally, section 2.9 summarizes and discusses the most important findings from the literature review, determines the research gaps and their implications for the development of the methodological approach and the aims of this dissertation.

2.1 Automated Vehicles

AVs will play a significant role in shaping and defining the future of mobility, logistics and urban transport. Automated vehicle research is expanding in the recent years in an effort to develop automated vehicle functions that increase traffic safety, accessibility, traffic efficiency and reduce environmental emissions and mobility costs. According to On-Road Automated Driving Committee (ORAD) [2021], six levels of driving automation may be defined from no driving automation (Society of Automotive Engineers (SAE) Level 0) to full driving automation (SAE Level 5). In the lower vehicle automation levels (SAE Level 1 and 2), the driver is required to monitor the driving environment and is assisted by the vehicle for performing either the lateral or longitudinal motion control actions (SAE level 1) or both (SAE level 2). In SAE level 3, the automated driving system performs all dynamic driving tasks but the driver should be ready to take control of the vehicle at any time. In SAE Level 4 and 5, the automated driving system performs all driving tasks in certain (e.g. in highways; SAE level 4) or in all conditions (SAE level 5). Therefore the different levels of automation define different sets of requirements and expectations for the automated vehicle manufacturers, driver, passengers and interacting HRUs. Figure 2.2 presents the descriptions of the different levels of vehicle automation as defined by the International Society of Automotive Engineers [On-Road Automated Driving Committee (ORAD), 2021]:

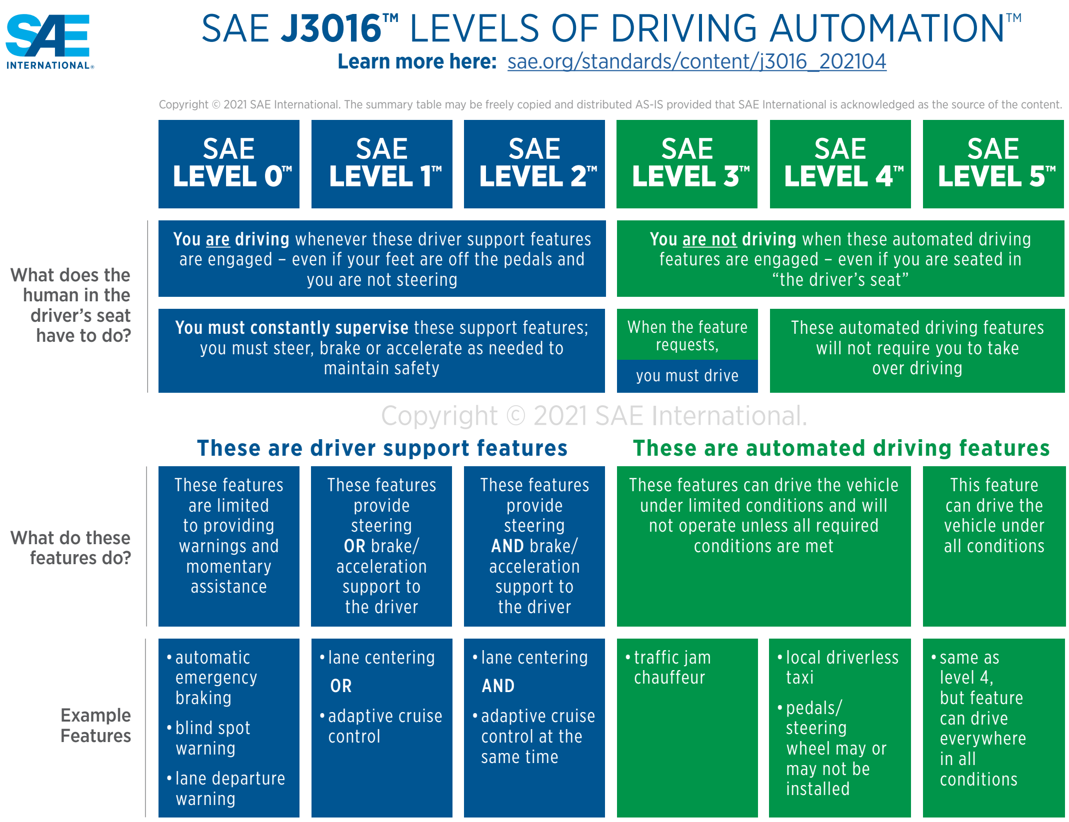


Figure 2.1: Levels of vehicle automation [On-Road Automated Driving Committee (ORAD), 2021].

Pendleton et al. [2017] defines three key functional elements for AVs: Perception, Planning, Control and presents their interrelations. Perception enables the AV to gather critical information from its environment through the fusion of information generated by multiple sensors. Typically, an AV is equipped with multiple sensors such as LIDAR, radar, cameras or ultrasonic sensors used to extract contextual information from its environment. The architecture and placement of these sensors on the vehicle body is of extreme importance for accurately capturing the vehicle's surroundings and detecting nearby road users [Katrakazas et al., 2015]. Especially in the case of VRUs such as pedestrians and bicyclists, AV vehicle sensors must be able to capture key features of the VRU dynamic and operational and communication behavior and predict their short-term intentions. The importance of this additional information source has already been highlighted in own past research [A. Keler et al., 2020; Malcolm et al., 2021].

In a second step, the information gathered from the sensors is transferred to the planning system component of the AV that performs decision making actions according to the vehicles higher objectives. AV decision making is a critical area in the automated driving research. Pendleton et al. [2017] defines three planning sub-components. The mission planner that considers high level objectives, the behavioral planner, which uses a predefined set of rules to make decisions on how to properly interact with other agents and in this process generates local objectives, and the motion planner that generates acceptable paths and/or sets of actions to achieve local objectives. Eventually these problem formulations are typically reduced into a generalized problem description on how to reach a certain position while avoiding possible collisions.

Most AV research focuses on how to resolve the path generation problem based on scenario oriented approaches. De Beaucorps et al. [2017] propose a human-like decision-making algorithm for navigating at unsignalized intersection approaches in the presence of another vehicle. The algorithm is trained using human driver recordings and is based on reference speed profiles for certain interaction scenarios. Wang [2020] suggest an AV decision making framework for identifying the right of way at unsignalized intersections and adjusting the vehicle driving behavior for crossing the intersection area efficiently and safely. Hang et al. [2021] present a decision making framework based on the Stackelberg game and grand coalition game approaches optimized through model predictive control Model Predictive Control (MPC) for the scenario of motion planning in an unsignalized roundabout. Németh and Gáspár [2021] present an optimization method that is based on a reinforcement learning approach that handles the motion of an AV at an unsignalized intersection with other vehicles. The optimizer is trying to minimize the difference between the control input and learning control, while considering constraints regarding acceleration and deceleration, safe distance keeping and collision free motion. Deshmukh et al. [2022] present in their review more sophisticated approaches based on deep learning methods for training an AV to learn driving policies using the Waymo dataset in specific driving scenarios. Finally, the Control component executes the actions decided by the planning component for the vehicle. Figure 2.2 presents the typical components of an automated vehicle system [Pendleton et al., 2017].

Campbell et al. [2010] and Pendleton et al. [2017] additionally highlight a fourth component: "Communication" that has the potential to further improve the performance of the basic three AV system components through the sharing of perception information and cooperation with other road users by communicating the decisions of planning and the state control actions. Also Katrakazas et al. [2015] identify communication and the incorporation of transport engineering aspects in planning as a promising area for further optimizing and improving AVs functions. It is a fact, that already for HRUs, even common traffic scenarios

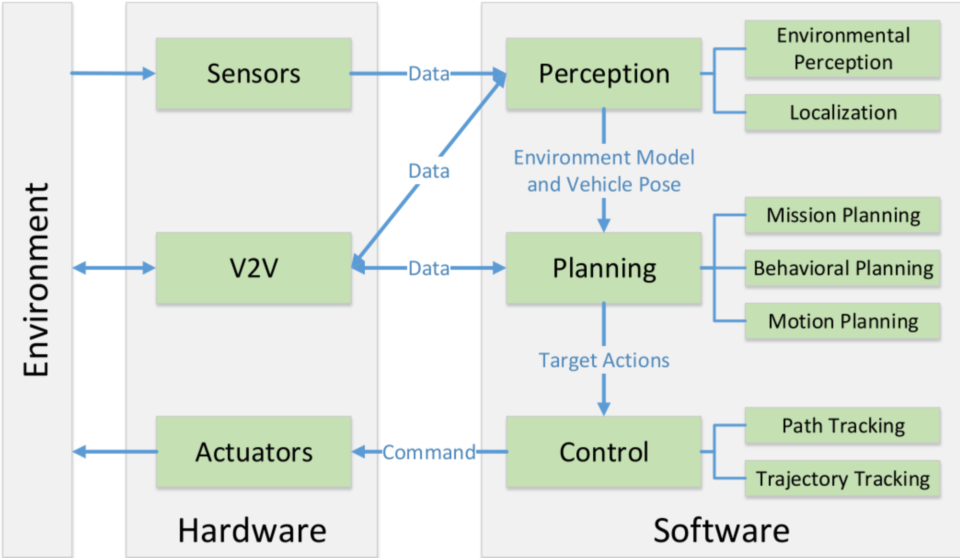


Figure 2.2: Overview of the typical automated vehicle system components and their interdependencies by Pendleton et al. [2017].

can be highly complex to resolve as they are required to adjust their behavior according to different often contradicting factors such as their goals, traffic rules and the intentions of other road users. Perdomo Lopez et al. [2017] propose a methodology for AVs to establish a scenario interpretation by defining primary situations, which in turn are based on potential conflicts with other road users. In their methodology they define a set of critical tasks, among which are the intention prediction of other road users and handling occlusions. Fulfilling both of these tasks comes with uncertainty especially as due to occlusion of other road user or other critical elements, the AV might not have accurate estimation of the traffic state.

Communication and cooperation with other AVs in such situations through information sharing offers a solution to handling traffic situation estimation uncertainties and improving the perception and behavior planning of AVs. Hussein et al. [2018] assessed the added benefits of Vehicle-to-Vehicle (V2V) and Pedestrian-to-Vehicle (P2V) communication and cooperative information sharing between two AVs (leader and follower) in a conflict scenario with a VRU. In all study cases with communication active, the AVs demonstrated more efficient driving behavior as the VRU detection was faster while the braking decision was also faster and less aggressive. The utilization of multiple sensor inputs and a collaborative resolution of detection, mapping and the path and motion planning problems for a group of AVs has a also been proposed by Schweizer et al. [2019]. Hubmann et al. [2018] propose a method for reducing the uncertainty of path planning for AVs that profits from V2V communication, where robots do not always opt for the collision free path but rather assume the cooperation of humans in the efficient resolution of the motion planning problem.

In conclusion, methods developed in this work, need to be seamlessly integrated within the existing typical AV system modules, while leveraging the available sensors and technologies. Requirements are also established with respect to the autonomy and human supervision and intervention are established. Maintaining the automated status in critical traffic situations is a driving factor for increased traffic safety and social acceptance. AV Communication and cooperation with other road users is also identified as a critical system component for the future adoption and integration of AVs in urban traffic.

2.2 Road User Behavior and Interactions at Traffic Intersections

The decision making of road users in traffic is largely influenced by the traffic rules according to the German Traffic Regulations (Straßenverkehrs-Ordnung) (StVO) [Bundesministerium für Verkehr und digitale Infrastruktur, 2013]. Based on the StVO, an analysis of the legal driving behavior and the interaction with the surrounding road users and the right-of-way regulations at unsignalized intersections is carried out. According to the traffic regulations of the StVO, different priority orders of right-of-way are defined for individual traffic streams. Due to the hierarchy of the right-of-way, each subordinate traffic stream has to consider one or more superordinate traffic streams. The designation and classification of the traffic streams is presented in the following figure for a unsignalized intersection. For bicycle traffic flows on the roadway, the respective designations of the vehicle flows apply.

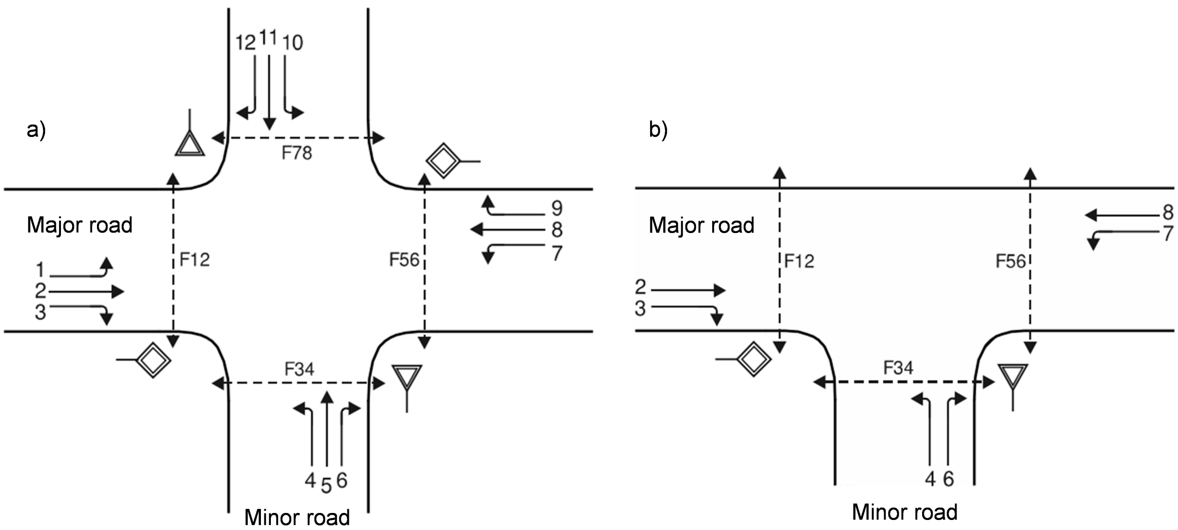


Figure 2.3: Official designation of traffic streams according to the German Highway Capacity Manual (HBS) [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015] at a) an unsignalized intersection with right-of-way signs, b) an unsignalized entry with right-of-way signs. Pedestrian streams are marked with F.xx. Figure adapted from [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015].

Based on Figure 2.3, the hierarchy of superordinate (major) and subordinate (minor) traffic streams can be defined. The ranking of the respective traffic streams indicates how priority is assigned. Based on this hierarchy, interaction scenarios and priority rules between bicyclists and motorized vehicles may be defined. The scenarios can be defined depending on the respective participating traffic streams and are divided into interaction scenarios within a traffic stream and interaction scenarios among different traffic flows.

Table 2.1: Official priority ranking of traffic streams according to the German Highway Capacity Manual (HBS) [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015] at a) an unsignalized intersection with right-of-way signs, b) an unsignalized entry with right-of-way signs.

Maneuver	**Intersection**		**Entry**	
	Traffic Stream	Rank	Traffic Stream	Rank
Straight on the major road	2, 8	r = 1	2, 8	r = 1
Right turn from major into the minor road	3, 9	r = 1	3	r = 1
Left turn from major into the minor road	1, 7	r = 2	7	r = 2
Right turn from minor into the major road	6, 12	r = 2	6	r = 2
Straight on the minor road	5, 11	r = 3	-	-
Left turn from minor into the major road	4, 10	r = 4	4	r = 3

The StVO as well as the corresponding traffic regulations in the respective countries might provide the basic framework and ruleset with which interactions among road users are formally handled. Yet in real traffic, different factors associated with the operational and tactical behavior or road users co-influence their behavior and actions. Especially in the case of VRUs, this problem becomes even more complex due to their inherent flexibility in space and their ability to change infrastructure, compared to motorized users. For example a bicyclist might have multiple path options when crossing an intersection. Depending on the available road infrastructure, the bicyclist may choose to perform the crossing maneuver using an available bicycle lane or using the pedestrian sidewalk and the pedestrian crossing. Given the immense variability of traffic scenarios, the variability of traffic infrastructure and personal and social factors large number of possible outcomes and choices for the same fundamental traffic scenario can be observed.

Twaddle and Busch [2019] studied the behavior of bicyclists at signalized intersections. They identified 43 independent features describing situational factors, strategic behavior and prior tactical choices and associated them to specific bicyclist maneuver types observed at signalized intersections. Based on these features tactical behavior choices of bicyclists such as rule breaking behavior, infrastructure selection and maneuver type might can be predicted using regression models.

For the case of crossings at unsignalized intersections a probabilistic framework (based on discrete choice theory) is proposed that models the decision making process of a driver to yield for an incoming bicyclist. For this problem formulation the estimated time of arrival at the conflict point, the vehicle speed and the proximity of the bicyclist to the conflicting zone are the most important factors for modeling the decision process [Silvano et al., 2016]. In another study, traffic infrastructure, bicycle volume and traffic control related factors are also found to be associated with bicycle accidents [Saad et al., 2019].

Therefore, it becomes apparent that the road user behavior during interactions is probabilistic and is accompanied with an inherent lower or, depending on the situation, higher level of uncertainty. Traffic regulations in this case serve not only as a fundamental framework for handling these interactions but also define the probability for specific behavior outcomes of the road users, assuming a universal compliance with the respective traffic rules. Still the behavior of road users in the traffic space remains probabilistic and complex traffic situations often arise.

One method to navigate through and resolve complex traffic situations, is the collaboration with other road users and the communication of road user intentions. Road users communicate their intentions with others in such situations using various informal nonverbal communication cues such as adjusting their dynamic driving behavior (e.g., speed adjustment, acceleration/deceleration) and forms of explicit or implicit gestures (e.g., eye contact, hand movements, head movement) in order to, coordinate joint actions and resolve the traffic situation. For example, bicyclist hand gestures are acknowledged as a formal gesture by the German Traffic Regulations [Allgemeine Verkehrsregeln, 2019]. However, the effects of informal communication on road user decisions are not yet fully understood. One relevant study analyzed pedestrian-driver interactions inside a parking area. Results highlighted the importance of non-verbal communication during road user interactions as the use of the head movement and head direction, the use of vehicle-based signals were bevioral features used for negotiating priority among the different user groups. The absence of established non-verbal communication was linked to the driver proactively slowing down [Uttley et al., 2020]. This finding clearly illustrates how the absense of communication may lead to the delayed or not optimal-resolution of a traffic interactions.

Thus, the development of automated driving functions has to take into account these informal nonverbal communications with surrounding road users. This is expected to have a positive impact on overall traffic safety and efficiency in mixed traffic with AVs, as well as increasing the level of automation in AVs. Taking into account the communication-based decision making of road users in relevant situations, AVs also need to communicate their intentions. To achieve this goal, it is first important to understand how informal nonverbal communication cues influence road users' decisions and trust, and in which traffic scenarios they occur. In the context of this work, the development of a cooperation framework among AVs and bicyclists need to be able to understand the bicyclist intentions. As interactions with bicyclists are inherently probabilistic, the development of a method that predicts the bicyclist intentions and reduces or quantifies the uncertainty in their future behavior is a crucial component in the context of this work.

2.3 Road User Communication Behavior in Traffic

One of the main causes of safety critical interactions between motor vehicle and bicycle traffic is the lack of cooperation. Cooperation is defined as a joint action in which two or more parties work together for a common benefit or goal. In the case of road transport, this goal describes an accident-free process. In the UR:BAN research project, Dotzauer et al. [2018]

attributes this to bad experiences with the other of these two road users and the mutual power struggle in traffic.

In addition to official traffic regulations, informal rules and communication among road users result improve traffic safety [Fuest et al., 2017]. Road users use informal and formal means of nonverbal communication that can indicate an intent for a specific action. Informal means of communication are unofficial signals, which result from the shared experience of the road users and the prevailing social norms. These may include "looking around", eye contact or driving dynamics [Bruder and Winner, 2019]. Additionally, nonverbal means of communication can be separated into explicit and implicit behaviors [Fuest et al., 2017]. Informal means of communication are unofficial signals, which result more from experience and the prevailing social norms [Portouli et al., 2014]. Figures 2.4-2.7 present typical examples of implicit and explicit communication behavior of cyclists as manually selected from video data collected at traffic intersections in Freiburg and Munich, Germany as part of past research [Georgios Grigoropoulos, Khabibulin, et al., 2021; Georgios Grigoropoulos, Leonhardt, et al., 2022]. The images showcase typical examples of bicyclist communication behavior revealing their intentions with respect to their planned maneuver.

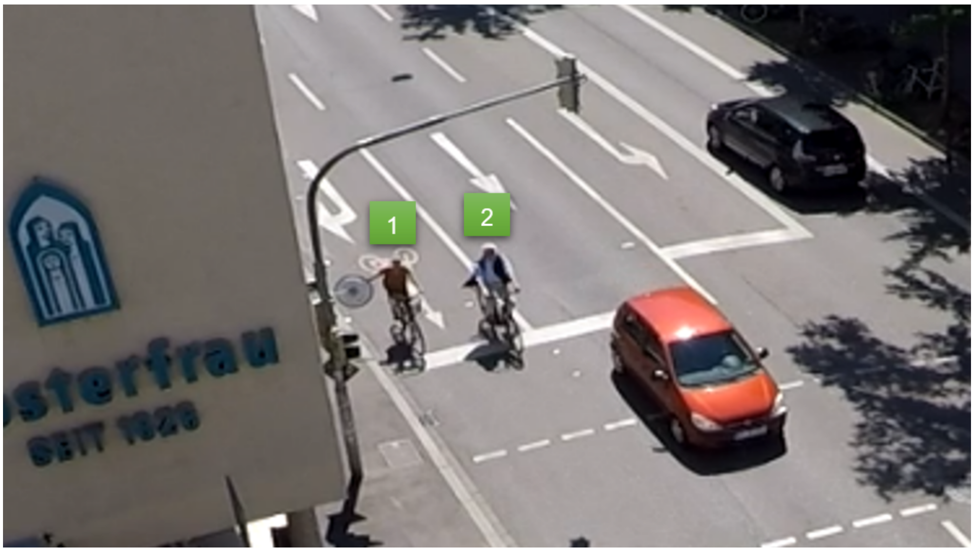


Figure 2.4: Study intersection Eschholz-/ Lehenerstraße (Freiburg im Breisgau, Germany) Bicyclist right arm hand gesture (explicit communication) (1) Bicyclist head rotation (implicit communication) (2).

Figure 2.5: Study intersection Oberanger / Rosental / Rindermarkt (Munich, Germany) Bicyclist left arm hand gesture (explicit communication) combined with a stop inside the intersection area for a conditionally compatible left turn maneuver (1).

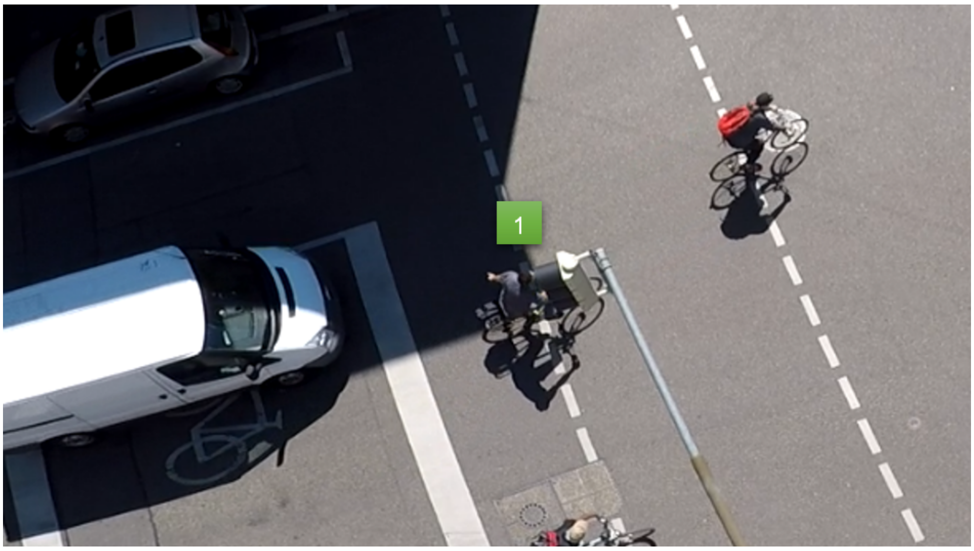


Figure 2.6: Study intersection Eschholz-/ Lehenerstraße (Freiburg im Breisgau, Germany) Bicyclist left arm hand gesture (explicit communication) before moving from the right side to the left side of the lane and perform a left turn maneuver at the intersection (1).

Figure 2.7: Study intersection Eschholz-/ Lehenerstraße (Bicyclist left arm hand gesture (explicit communication) combined with a left overshoulder look (implicit communication) while performing a lane changing maneuver combined with road infrastructure change (bicycle lane to motor vehicle traffic lane) (1).

So far, there is still too little work that specializes in communication methods of bicyclists [Stanciu et al., 2018]. However, this topic is becoming increasingly important in relation to automated driving. The long-term goal is to completely hand over the communication and the interaction resolution task to the AV, so that the passenger(s) are no longer required to either supervise or intervene during the driving process. In order to be able to develop such systems, it is important to understand the interaction between bicyclists and AVs beforehand and be able to predict the intentions of the bicyclists [Dotzauer et al., 2018]. Human prediction of intent is largely based on a single strong indicator, e.g. that the bicyclist makes a clear head movement or a certain hand gesture. Several weaker features, which combined could serve as a strong indicator, are likely overlooked or too complex to be handled by humans in real time. Six implicit communication instructions are decisive for the prediction of the bicyclist's behavior: head movement, speed, speed adjustment, leaning, position and pedaling behavior [Hemeren et al., 2014].

Several scientific studies have determined that hand gestures [Drury and Pietraszewski, 1979; Stanciu et al., 2018; Vasardani et al., 2016; Walker, 2005; Walker and Brosnan, 2007], eye contact and head movements [Stanciu et al., 2018; Hemeren et al., 2014; Walker, 2005; Walker and Brosnan, 2007; Westerhuis and De Waard, 2017] can be decisive explicit and implicit communication cues that reveal a bicyclists intentions and therefore they can be used for developing a method for predicting the behavior of the bicyclists. Additionally, a patent has been filed for predicting the behavior of bicyclists through the analysis of their implicit and explicit communication cues [Kretzschmar and J. Zhu, 2015]. The communication cues can be extracted from the bicyclist using a skeleton-based detection and tracking algorithm [Deng et al., 2018; Yagi et al., 2019]. How drivers interpret implicit and explicit communication cues of bicyclists to predict their behavior has been the focus of some studies [Drury and Pietraszewski, 1979; Y. M. Lee and Sheppard, 2016; Walker, 2005].

These studies suggest that implicit and explicit communication cues can be used for the prediction of road user behavior. In the case of executing maneuvers, bicyclists often perform hand gestures to indicate their intended movement direction. As a part of the execution of a maneuver, a bicyclist might execute a sequence of implicit and explicit communication cues. These cues can fall into any of the categories defined by Wilbrink et al. [2018] and can be different cues for different traffic situations and road users. Table 2.2 summarizes a classification of past scientific publications according to specific features of implicit and explicit communication. These features, as defined in scientific research, are the main behavioral features that bicyclist use to reveal their intentions and can be potentially associated with the prediction of bicyclist behavior. In conclusion, the communication behavior of bicyclists in traffic has the potential to provide an additional source of information in predicting their long-term intentions. Moreover, a cooperation framework among AVs and bicyclists that relies on these inherent behavioral traits and does not require from bicyclists any sort of explicit special communication gestures or the use of equipped devices by the bicyclists has the potential to be more accessible and acceptable by all road users.

Table 2.2: Previous research on the definition of explicit and implicit features of bicyclist communication behavior.

Feature	**Communication Feature Type**	**References**
Hand gesture	explicit	Vasardani et al. [2016], Drury and Pietraszewski [1979], Walker [2005], Walker and Brosnan [2007], Stanciu et al. [2018], Deng et al. [2018], Yagi et al. [2019], Hou et al. [2020], Malcolm et al. [2021], Andreas Keler, Malcolm, et al. [2021], and Robert [2021]
Bicycle direction	implicit	Meijer et al. [2017]
Eye contact	implicit	Walker [2005], Walker and Brosnan [2007], Stanciu et al. [2018], Hemeren et al. [2014], Westerhuis and De Waard [2017], Chaloupka-Risser and Füssl [2017], and Robert [2021]
Head movement	implicit	Walker [2005], Walker and Brosnan [2007], Hemeren et al. [2014], Westerhuis and De Waard [2017], Deng et al. [2018], Hou et al. [2020], Malcolm et al. [2021], and Andreas Keler, Malcolm, et al. [2021]
Leaning	implicit	Hemeren et al. [2014] and Malcolm et al. [2021]
Lane position	implicit	Hemeren et al. [2014]
Pedalling behavior	implicit	Hemeren et al. [2014]
Speed	implicit	Hemeren et al. [2014] and Meijer et al. [2017]
Speed adjustement	implicit	[Hemeren et al., 2014; Westerhuis and De Waard, 2017; Meijer et al., 2017]

2.4 Road User Behavior Prediction

The prediction of road user intention has been the focus of extensive research in the fields of traffic safety, traffic control and automated driving. Especially AVs are required to interact with other human road users in interactive and cooperative decision-making processes. In this context, the intentions of other road users need to be deduced and integrated into a decision-making framework for AVs. HRUs make use of different types of contextual information in their short-term and long-term decision-making process when interacting with other nearby road users. Sources of this type of information may include the dynamic, operational, and tactical behavior of nearby road users. Also, implicit and explicit communication are often used by road users to indicate their intentions and are used both as a form of communication as well as subconsciously for decision making purposes. For example, bicyclists often utilize hand gestures to indicate a maneuver they will perform. Deceleration or acceleration processes can also hint a specific maneuver or driving action. Additionally, implicit communication cues such as head movements and eye contact are also part of the communication strategies often employed in traffic by road users to reveal their intentions to other road users, who in turn can use this information to forecast their behavior. For example, a pedestrian intending to cross the road would normally perform a visual check for oncoming vehicles before crossing the road. From the vehicle driver's perspective, this information is crucial as it serves as an indicator for forecasting the pedestrian's intentions.

In this context, special implicit and explicit characteristics of bicyclists' communication behavior may be used together with other behavioral features in forecasting their intentions in specific traffic situations. For HRUs, such types of information may be understandable in a specific social and cultural context. However, for AVs, the understanding of bicyclist behavior is challenging in predicting the bicyclist intentions. AVs must be able to understand and predict the behavior of other road users in order to avoid safety critical situations and navigate safely in complex urban traffic environments. Additionally, resolving complex traffic interactions without passenger interaction with human-like behavior can further improve their acceptability among road users. Thus, the comprehension of the behavior of VRUs such as bicyclists can play a crucial role for AVs in supporting their automated operation in urban road environments.

Several approaches have been proposed for the intention prediction of human actions in the area of automated driving and road user behavior research. Most proposed approaches address either the trajectory and sequence prediction problem or the classification problem of specific actions that will be performed by road users in a future time horizon. Most recent scientific work on this topic relies on Ensemble Methods, Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs) and Long Short Term Memory Network (LSTM) based models or combinations of these approaches tailored to address different properties and limitations of the respective research question. Pool et al. [2019] propose a RNN network for bicyclist path prediction trained on a dataset that includes 51 tracks of a bicyclist approaching an intersection with the possibility to perform a left turn or continue straight. They also utilize the bicyclist hand gestures as an additional feature and achieve an average prediction error of 33 cm when predicting the future position one second into the future. Random forest classifiers in conjunction with functional discretization have been used to analyze the trajectories of cars approaching an intersection and predict the intended maneuver [Barbier et al., 2017]. Their dataset is a hybrid of real (20%) and simulated data (80%). Results show an 82% prediction accuracy in longitudinal maneuver classification and 80% accuracy on driving direction classification. Schneegans and Bieshaar [2018] develop a Deep Residual Neural Network (ResNet) model (ResNet expands the standard CNN) for predicting bicyclist initial movement classes (waiting, starting and moving) using accelerometer and gyroscope inputs from the bicycle sensors/ They achieve a mean f1-score of 95% for the classification of the respective classes.

Several researchers propose LSTM based methods for human action prediction and classification. LSTM models have proven successful in learning and generalizing properties found in sequential data. An approach is proposed by Losing et al. [2017] for the bicyclist start intention detection utilizing their head trajectories based on LSTM cells able to handle sequences of different lengths. In their work, 206 cases of stop and move actions of bicyclists are investigated and with an input sequence length of 1.0 s, an f1-score of 96.2% on average is achieved 0.680 s after the first movement of the bicycle.

A B-LSTM and a LSTM with two stacked layers that use bicyclists' sequential positions data to predict their future trajectories is proposed in [Saleh et al., 2018]. The researchers evaluate their approaches using 130 trajectories from the Tsinghua-Daimler Cyclist Benchmark (TDC Benchmark) dataset for two prediction horizons (5 or 15 steps ahead) of the bicyclists' trajectories as well as against baseline approaches. Results show significant gains over the tested baseline approaches with more than 50% in mean error score averaged over all the tested bicyclists' trajectories.

An intention prediction model for pedestrians based on a CNN for the pose estimation and a LSTM for the intention recognition is proposed in [Fang and A. M. Lopez, 2019]. The f1-score for pedestrian intention recognition on stopping and crossing classes ranges from 71% and 72% to 87% and 85% for the prediction horizon 1/16 second and 1 second respectively.

Z. Huang et al. [2021] propose a LSTM framework, that uses bicylist motion input along with information on the bicyclist interactions with the road and other users to predict the bicyclist trajectory. The proposed method manages to reach an average prediction error of 0.41m, while the prediction error is 0.86m for a 2.4 second prediction horizon.

The NGSIM Dataset is used by Benterki et al. [2020] to train a hybrid approach for an automated vehicle that integrates maneuver classification using ANNs and trajectory prediction using LSTM networks to identify the future positions of nearby vehicles. The proposed approach can predict driver intention to change lanes on average 2.2 seconds in advance. Three maneuver classes are defined, Lane Change to the Right (LCR), Lane Change to the Left (LCL) and Lane Keeping (LK). The classification accuracy is 86.2%. for 3s sequences and reach up to 97.49% for 6s sequences.

Xu et al. [2017] combine a LSTM temporal encoder with a fully convolutional visual encoder to predict discrete and continuous driving actions. For predicting the discrete driving action classes straight, stop, left turn, right turn, they test different model architectures and types and size of data input and reach a maximum prediction accuracy of 84.6% for the temporal convolution as the temporal fusion mechanism (TCNN9). The CNN-LSTM approach also achieves a comparable performance as TCNN9 (84.5%).

Finally, a LSTM-based model is presented by Khairdoost et al. [2020] that predicts driver maneuvers. They utilize driver cephalo-ocular behavioral information (driver gaze information, head movements, etc.) and vehicle dynamics as features to train their model. The model demonstrates 84.2% and 82.9% precision and recall accuracy respectively for the prediction of five maneuver classes.

In summary, the scientific approaches found in the literature are not easily comparable with each other in terms of their performance. All approaches are addressing different prediction or classification problems. They are also developed tailored to their given dataset, where depending on the data input type specific types of neural networks are preferred. In the case of image or video data input, CNN or CNN-LSTM based models are proposed, while in the case of trajectory data input mostly LSTM based models are proposed. However, most of the found scientific approaches are based partially or entirely on LSTM models or their variations. Also, performance comparisons against other proposed models show that LSTM based architectures outperform other common types of neural networks in the classification and prediction of human behavior. Additionally, none of the reviewed models include a method that addresses the uncertainty problem of the prediction estimation. These literature review findings are important for the further development of the AV and bicyclist cooperation framework as they support the use of artificial neural network types that are capable of handling sequential data for predicting road user intentions. Additionally, they identify significant research gaps in the present scientific research in the field of bicyclist behavior prediction for automated driving solutions, as the topic of the long term prediction of the bicyclist maneuver intention has not been sufficiently addressed, whereas similar problem definitions do not fully consider the bicyclist communication behavior features.

2.5 Review of Bicycle Simulator Research

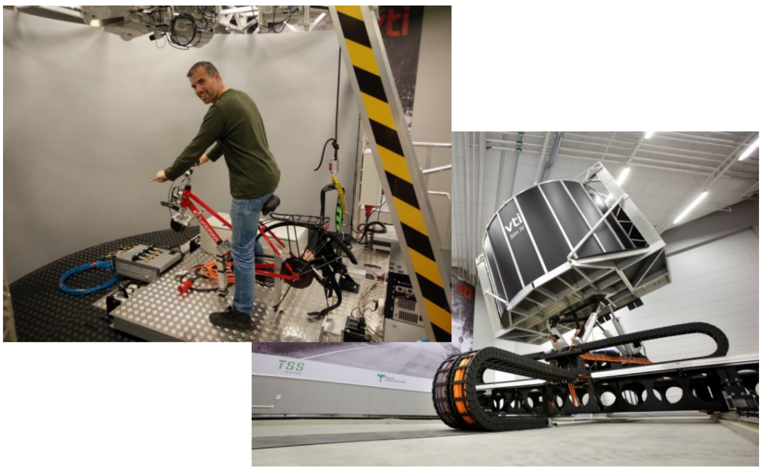
This section presents the most important findings on present research regarding bicycle simulators. In comparison to field observations and experiments, simulator studies have the potential to research human behavior efficiently, consistently and systematically in safe, repetitive, and controlled environments. Specifically bicycle simulators can be used for reveal insights on the bicyclist behavior, assessing traffic infrastructure, evaluating communication concepts and testing traffic control solutions. Based on the targets and research focus objectives of the respective researchers, bicycle simulators can have a variety of properties and special features used explicitly to model or gather data on specific areas of bicyclist behavior.

A starting property of differentiation among the different bicycle simulators is their ability to simulate bicycle stabilization dynamics and physics. Typical examples are the KAIST Interactive Bicycle Simulator [Kwon et al., 2001] and the the DLR bicycle simulator [Martinez, 2021].

The KAIST Interactive Bicycle Simulator integrates a motion generation system that integrates a Stewart platform, that consists of 6 linear actuators and upper and lower platforms. It provides 6 degrees of freedom motion to the bicycle, handle and pedal resistance systems which are attached to the handlebars and the rear wheel. A dynamics module calculates the location and the velocity of the bicycle and reactive forces. The visual and motion cues and reactive forces are then fed back to the test subject [Kwon et al., 2001]. Similarly, Bruzelius and Augusto [2018] designed a bicycle simulator on top of a motion platform with 8 degrees of freedom. The motion platform provides motion feedback that replicates the experience of a real bicycle ride. Martinez [2021] use a simpler approach, where a stationary bicycle frame is mounted on a motion platform with two degrees of freedom that reproduces the pitch and roll movement. Here the main purpose is to simulate road inclination, lean angle, external forces acting on the bicycle and different road surfaces. A headwind simulator is integrated in this setup that creates wind airflow for immersion while riding at different velocities. Figure 2.8 presents a selection of simulators with integrated bicycle dynamics and physics simulation capabilities.

(a) The KAIST Interactive Bicycle Simulator [Kwon et al., 2001]

(b) The DLR Bicycle Simulator [Martinez, 2021]



(c) The VTI Bicycle Simulator [Bruzelius and Augusto, 2018]

Figure 2.8: Typical examples of bicycle simulators focusing on the simulation of bicycle dynamics and physics.

These simulators are able to capture and replicate bicycle dynamics in high detail, however they remain highly complex. Most bicycle simulator research focuses on traffic safety, bicyclist behavior in traffic and the evaluation of bicycle infrastructure, where the integration of bicycle dynamics is not regarded of high importance with respect to the study objectives [Schramka et al., 2017; Huemer et al., 2022; Andreas Keler, J. Kaths, et al., 2018; Cobb et al., 2021; X. Guo et al., 2022]. Such simulators are more modular comprising of a physical bicycle mounted on a trainer [Schramka et al., 2017; Huemer et al., 2022; Andreas Keler, J. Kaths, et al., 2018; X. Guo et al., 2022] or a stationary platform [Cobb et al., 2021], where sensors are attached to the front wheel and the rear wheel in order to extract information on the speed and riding direction of the bicyclist. A special additional attribute of the bicycle simulator by X. Guo et al. [2022] is that an adaptive, real-time indoor bicycle grade simulator is attached to the front fork of the bicycle that inclines the bicycle body front depending on the simulated road grade. Such bicycle simulator setups are in turn easier and more cost-efficient to design and operate as they do not rely complex mechanical modules and setups that are necessary for simulating bicycle dynamics.

When it comes to the simulation environment, most simulators rely on well established open-source 3D graphics platforms such as Unity or Unreal Engine. Kwon et al. [2001] however use their own developed visual engine, while Andreas Keler, J. Kaths, et al. [2018], Cobb et al. [2021] and Huemer et al. [2022] utilize commercial solutions. Certain deviations are identified in the case of the simulation of road user behavior. Respectively, simulators either rely on scripting and predefining the behavior of other road users or some integrate and couple with microscopic traffic simulation software such as PTV Vissim [Schramka et al., 2017] or Simulation of Urban Mobility (SUMO) [Andreas Keler, J. Kaths, et al., 2018]. However, Schramka et al. [2017] uses PTV Vissim to model only the surrounding traffic and infrastructure, while there is no consideration for modeling interactions realistically between the test subject and other road users. Unless the behavior of other road users is not scripted, road users won't interact with the test subject.

In contrast, the bicycle simulator by Andreas Keler, J. Kaths, et al. [2018] integrates this additional feature as other road users are controlled by SUMO, while the bicycle simulator inputs are communicated to SUMO via the Traffic Control Interface (TraCI) which allows for realistic and unscripted interactions between the simulated road users and the test subject. Thus, it is possible to model complex traffic situations with multiple road users as that may have a variety of different outcomes depending on the personal characteristics of each test subject.

Finally, the visualization and the feedback of the 3D environment back to the test subject typically relies on the use of monitors [Andreas Keler, J. Kaths, et al., 2018; Huemer et al., 2022; Cobb et al., 2021; Sun and Qing, 2018], projection screens [Kwon et al., 2001; Sun and Qing, 2018; Bruzelius and Augusto, 2018], head mounted display Kwon et al. [2001] or VR glasses [Schramka et al., 2017; Kwon et al., 2001; Sun and Qing, 2018; Bruzelius and Augusto, 2018; Martinez, 2021; X. Guo et al., 2022]. Sun and Qing [2018] are also able to vary the visualization component depending on the research objectives. Figure 2.9 presents a selection of examples of the 3D simulation environments used by bicycle simulators.

(a) The OSU Bicycle Simulator 3D Environment using SimCreator [Cobb et al., 2021]

(b) The DLR Bicycle Simulator 3D Environment using Unreal Engine 4 [Martinez, 2021]

(c) The ETH Bicycle Simulator 3D Environment using Unity [Schramka et al., 2017]

(d) The Bicycle Simulator by Andreas Keler, J. Kaths, et al. [2018] 3D Environment using DYNA4 coupled with SUMO

Figure 2.9: Examples of bicycle simulator simulation environments.

So far bicycle simulators have been used in a variety of studies that are mainly assessing bicycle infrastructure, traffic safety and study bicyclist behavior in specific traffic situations. The OSU bicycle simulator [Cobb et al., 2021] has been deployed in several simulator studies. It has been used to quantify the factors influencing bicyclist perceived level of comfort with varying surrounding traffic conditions M. G. Abadi and Hurwitz [2018]. Cobb et al. [2021] used the bicycle simulator to study the effect of traffic infrastructure on bicyclist behavior using the speed, horizontal displacement, and physiological responses tracked by a Shimmer3 GSR + Sensor. In another study Jashami et al. [2022] measured the bicyclist physiological response and eye tracking at vehicle loading zones of varying dimensions in order evaluate alternative engineering design alternatives and propose solutions for the dimensioning of vehicle loading zones. Scott-deeter et al. [2022] assessed different intersection traffic engineering treatments (bike box, mixing zone, bicycle signal control) for defining which solution is the most effective at mitigating turning vehicle-bicycle collisions at signalized intersections. Their analysis was based on several parameters including the lateral position in lane, eye-tracking fixations, level of stress as well as questionnaire survey results.

Nazemi et al. [2021] used the ETH bicycle simulator [Schramka et al., 2017] to assess the perceived level of safety on bicycle infrastructure with different types, dimensions and color treatments depending on varying ambient pedestrian and motor vehicle traffic volume in an effort to understand the needs of existing and potential bicyclists. Huemer et al. [2022] used their simulator to evaluate different types of on-street markings for road sections with and without bicycle lanes adjacent to longitudinal parking lanes.

Thorslund and Lindström [2020] used the VTI bicycle simulator [Bruzelius and Augusto, 2018] in order to study the behavior of bicyclists crossing an intersection and coming into confict with right turning vehicles. In the bicycle simulator study, they varied the vehicle type, the lane markings and lane width, in order to understand how different traffic and infrastructure rleated characteristics affect the behavior of bicyclists and their perceived safety and comfort. For that they analyzed the test subjects trajectories, speed and positioning along the lane.

Lindner, Georgios Grigoropoulos, et al. [2022] used their coupled AV-bicycle simulator [Lindner, Andreas Keler, et al., 2022] to assess a mobile application-based communication concept for resolving bicyclist and AV interactions at intersections using a smartphone for the bicyclist and an Internal Human Machine Interface (iHMI) for the AV passenger. The aim of the study was to increase safety at interaction points with AVs and increase acceptance and trust towards AVs in real traffic. The bicyclist would turn left at the intersection, while the AV would approach from the opposite direction. The bicyclist then receives instructions from the AV when approaching the intersection area regarding the right-of-way regulation. The AV state and decision is also communicated to the AV passenger (another test subject) via the iHMI. In certain scenarios the AV passenger is also prompted to use iHMI and decide how the priority should be handled. Overall the application increased the perceived safety when interacting with an AV.

The bicycle simulator of Andreas Keler, J. Kaths, et al. [2018] has been also deployed in several studies for investigating bicyclist behavior as well as assessing bicycle infrastructure treatments. H. Kaths, Andreas Keler, J. Kaths, et al. [2019] used the bicycle simulator to assess the trajectories from the test subjects and compare them with real trajectories from video observations. H. Kaths, Andreas Keler, Georgios Grigoropoulos, et al. [2021] also evaluated different dimensions and designs for urban bicycle highways using the bicycle simulator. In a follow-up study, they used the bicyclist trajectory data from H. Kaths, Andreas Keler, Georgios Grigoropoulos, et al. [2021] to calibrate the Wiedemann 99 car-following model for bicycle traffic [H. Kaths, Andreas Keler, and Bogenberger, 2021] as collecting this type of data in reality is extremely difficult. Malcolm et al. [2021] have used the bicycle simulator to analyze the bicyclist communication behavior in common traffic situations. Table 2.3 summarizes the most important properties of bicycle simulators found in the scientific literature.

In conclusion, bicycle simulators have been extensively used for studying bicyclist behavior efficiently, consistently and systematically in safe, repetitive, and controlled environments. In contrast field tests or real traffic observations are complex and cost-intensive, while their outcomes might not be representative depending on the research aims. As part of this research a model that predicts the bicyclist maneuver intention needs to be developed. Thus, the generation of a bicyclist behavior dataset is an important step towards the development of a data driven model for the bicyclist behavior prediction. Equivalently to the controlled field experiments that are often used in the context of AV research in the generation of data and the development of of automated vehicle functions, a bicycle simulator can provide the opportunity for the generation of a high detail dataset through safe, repetitive, controlled and cost-efficient experiments. Also in contrast to field experiments, bicycle simulator test subjects will have to opportunity to experience identical traffic scenarios, without external environmental factors influencing their behavior. Finally, the laboratory setup will enable the extraction of highly accurate behavioral data, free from sensor noise and environmental effects as would be the case in real world experiments.

Table 2.3: Bicycle simulators in scientific research.

Type	Simulation Software	Visualization	Research Objectives	Special Features	Reference
Physical Bicycle Simulator	SILAB 6.0	2 x 3 monitors	bicycle infrastructure	5.1 surround sound system	Huemer et al. [2022]
Physical Bicycle Simulator	ZouSim	projection screens with projectors, virtual reality (VR) goggle, large screen monitors, stereoscopic 3D monitors	bicycle infrastructure, bicycle traffic control, traffic safety	Multiple display options depending on research objectives	Sun and Qing [2018]
Physical Bicycle Simulator	Unity coupled with PTV Vissim	VR glasses	bicycle infrastructure	Resistance unit for modelling slopes and other physical forces	Schramka et al. [2017]

Table 2.3: Bicycle simulators in scientific research.

Type	**Simulation Software**	**Visualization**	**Research Objectives**	**Special Features**	**Reference**
Physical Bicycle Simulator	Different versions have been implemented: DYNA4, DYNAanimation, CARLA (Unreal Engine), Unity. All versions are coupled with SUMO for simulating road user behavior	1 to 4 monitors	Bicycle infrastructure, traffic control infrastructure, traffic safety, bicyclist behavior in traffic	Depth camera for communication behavior detection, non-scripted realstic simulated user behavior and interactions using SUMO, a large variety of available simulation environments	Andreas Keler, J. Kaths, et al. [2018]
Coupled AV-Bicycle Simulator	Unity	1 monitor	AV-Bicyclist interaction, HMI evaluation	Coupled AV-Bicycle Simulator, depth camera for communication behavior detection, mobile device interconnection	Lindner, Andreas Keler, et al. [2022]
Physical Bicycle Simulator	Kitten Visual Simulator (self-developed)	Beam Projector or Head Mounted Display	Bicycle Dynamics Simulation	Full motion generation and force reaction system	Kwon et al. [2001]

Table 2.3: Bicycle simulators in scientific research.

Type	**Simulation Software**	**Visualization**	**Research Objectives**	**Special Features**	**Reference**
Physical Bicycle Simulator	Not defined	VR glasses	Road infrastructure design, traffic safety	-	HERN et al. [2017]
Physical Bicycle Simulator	SimCreator Software	1 monitor	Road infrastructure design, traffic safety, bicyclist behavior and physiological responses	Surround sound speakers, Galvanic Skin Response (GSR) sensor integration	COBB et al. [2021]
Physical Bicycle Simulator	VTI SimIV	Projection screen	Bicycle Dynamics Simulation, road infrastructure design, traffic safety, bicyclist behavior	Motion platform with 8 degrees of freedom	BRUZELIUS and AUGUSTO [2018] and THORSLUND and LINDSTRÖM [2020]
Physical Bicycle Simulator	Unreal Engine 4	VR glasses	Bicycle Dynamics Simulation, road infrastructure design, traffic safety, bicyclist behavior	Motion platform, VR gloves, head-wind simulator	MARTINEZ [2021]

Table 2.3: Bicycle simulators in scientific research.

Type	Simulation Software	Visualization	Research Objectives	Special Features	Reference
Omni-Reality and Cognition Lab Bicycle Simulator	Unity	VR glasses	Bicyclist behavior and physiological responses	Front body inclination, eye tracker, headwind simulator	X. Guo et al. [2022]

2.6 Human-Machine Communication and Cooperation

This section summarizes and presents results from the literature review on human-machine cooperation. It is assumed that for vehicles in full-automated driving mode, no human control is required [Inagaki, 2006; Inagaki and Furukawa, 2004]. Therefore in the context of this research, the AV is responsible to interact, cooperate and resolve the traffic situation presented with other HRUs (human drivers, pedestrians, bicyclists). Present research in the field of human-machine cooperation and automated driving focus in two main research areas. The first area of research adresses the development of cooperation frameworks among humans and robots or AVs and the modeling of human machine interactions. The second research field is directed towards the development and evaluation of solutions that enable human-machine communication. These are implemented through the use of HMIs that either reveal the intentions of the AV in certain interaction scenarios or relay a message to the human interacting with the AV for undertaking a specific action. Finally, the literature review in this section aims to present the most important research in the fields of human and robot or AV and findings on HRU and AVs communication through the use of HMI concepts and solutions. In this effort, the review will not only focus on bicyclists as not sufficient research has been found that can fully cover the respective research areas. Especially, research in the fields of human and machine collaboration and the development of cooperation frameworks is not generalized for humans without differentiating in different types or categories. Also some research findings in the areas of HRU and AVs communication are transferable for bicyclists as in their core they involve human and AV interactions.

Lichtenthäler and Kirsch [2016] present a comprehensive literature review of findings, assumptions and methods for developing legible robot behavior. They define robot behavior as legible if a human observer or "interactor" is able to comprehend the robot's intentions, which means that a human can predict the robot's objective, its trajectory and the meaning of a communication gesture or message. Secondly, the robot behavior should meet the expectations of the human observer or "interactor". The motion and actions of a robot are also considered legible when they are human-like, stereotypical, efficient, as visible as possible, and take into account social constraints and human preferences. These definitions can be expanded to AVs, as they are essentially robots interacting with HRUs in a shared space environment.

According to Kruse et al. [2010], the generation and execution of action plans for human and robot collaboration imposes additional challenges with respect to social rules and legibility and differentiates in domains with static and moving humans. In their work they present the concept of optimistic planning by adding cost functions in predictive human motion planning so that a robot does not identify humans in the vicinity as static obstacles. Therefore, in their motion planning solutions, robots do not always opt for the collision free path but rather assume the cooperation of humans in the efficient resolution of the motion planning problem. They finally propose the use of explicit communication for communication the robot's intentions in possible deadlock situations.

Saleh et al. [2017] consider the behavior of VRUs as unpredictable and highlight the importance of facilitating trust in their interactions with AVs. They proceed to propose a framework for the trust modeling of VRUs that is integrated in a typical AV system architecture. The most important components of their model are the short-term and long-term intent prediction of the VRUs that is used to understand their goals, the behavioral executive component that decides behavior of the vehicle in the given situation and the intent communication interface that relays the decision of the vehicle to the VRUs through a suitable interface. Using this workflow, trust is established among the relevant parties based on a shared intent understanding. HRU intent recognition and prediction is therefore an important component in facilitating AV and HRU collaboration. The significance of explicit auditory and visual communication from the AV to the HRU and the recognition of HRU detection for different AV driving behavior states is also highlighted by Merat et al. [2018].

Based on the work of Kruse et al. [2010] and the discussed principles on human and robot cooperation an example for a communication and cooperation framework for resolving AV and bicyclist interactions at complex traffic situations is described in Figure 2.10.

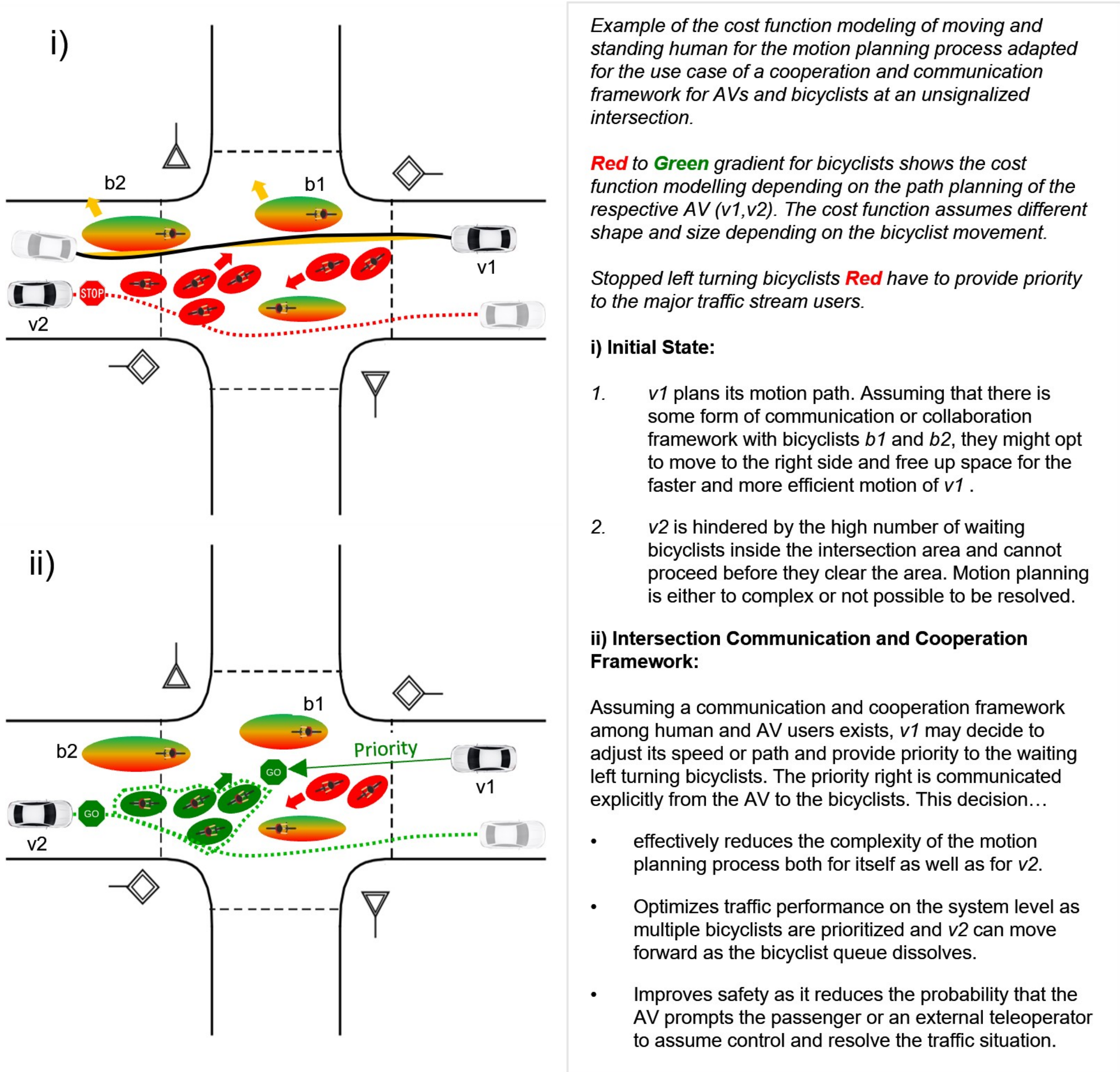


Figure 2.10: Presentation of an AV-bicyclist cooperation and communication framework for resolving the motion planning problem for AVs. Figure partially adapted from KRUSE et al. [2010].

FUEST et al. [2017] present in their work a taxonomy for traffic situations, for assessing communication and cooperation solutions between AVs and HRUs. They identify a series of features that have a significant influence on the communication among the relevant counterparties. These include the driving speed, the right-of-way, the intentions of the AVs and the HRUs regarding the right-of-way, the HRU type, the lateral and longitudinal distance between the interacting parties, the travel speed, the AV driving direction, the AV perspective, the state of attention of the HRU during the interaction and the impairment of the perception of the HRU. Most importantly, in their taxonomy, they identify the right-of-way as a negotiation parameter between AVs and HRUs, while they consider speed as an attribute that affects the understanding of the HRUs of the situation. In this sense a degree of cooperation is expected among HRUs and AVs in traffic. Another research suggests that in scenarios, with right-of-way negotiation, the AVs should initiate the communication, communicate the right-of-way explicitly and implicitly through their dynamic behavior while not changing their maneuver to ensure safety and increase efficiency. The combination of implicit and explicit communication was rated as highly comprehensible, increased traffic safety during the interactions, increased traffic efficiency and reduced decision time [Rettenmaier, Dinkel, et al., 2021].

Finally, addressing the correct road user group in a cooperation scenario is also significant. Hübner et al. [2022] investigated the safety, efficiency and legibility in a multi-agent road crossing simulator scenario where an AV addressed a human driver and a pedestrian. The communication concept of the automated vehicle consisted of combined implicit communication by using the speed profile and lateral offset within the traffic lane, and explicit communication an External Human Machine Interface (eHMI). They identified a learning effect for pedestrians, when distinguishing the correctly addressed partner (themselves or the human driver). This did not apply to the human drivers as they did not detect the pedestrian in time and felt misaddressed. Misaddressed pedestrians on the other hand, proceeded to cross the road which led to safety critical interactions. Finally, traffic efficiency parameters improved for test subjects with correct behavior sequences. Results, highlight the importance that HMI design characteristics should integrate solutions for addressing the correctly intended users. All users should first understand that they are not being addressed and subsequently can imply and predict the behavior of all users in a given scenario.

Vinkhuyzen and Cefkin [2016] highlight the importance that AVs should interact and collaborate with HRUs in socially acceptable manners. They additionally signify the importance of contextual information during the driving task. For example, a human driver driving on an empty road with kids playing in the surrounding might preemptively reduce the vehicle's speed. They also discuss the social acceptability that in certain traffic situations formal driving rules have to be partially breached or overlooked in order to resolve traffic situations in a socially acceptable manner. They conclude that the integration of social practices and contextual information into automated driving algorithms is a required step towards the social acceptance of automated driving. The social perspective of human and AV interactions are also explored by Robert [2021]. Context information, the adoption of social norms, the consideration of individual characteristics should be considered together with rule and guideline compliance in AV design.

When it comes to facilitating the communication and collaboration of HRUs and AVs, the majority of recent research focuses on development of solutions based on eHMIs [Kass et al., 2020]. Vinkhuyzen and Cefkin [2016] proposed an eHMI concept named the Intention Indicator that uses a blue light strip running along the sides and front of the car, as well as a display in the window that are used to display the intention of the AV in traffic interactions. Hou et al. [2020] developed a series of interface designs for assisting AV-cyclist interactions. These interfaces include a laser projection on the pavement in front of the interacting bicyclist, a car window screen, a bicycle Heads-Up Display (HUD), a helmet verbal audio, a helmet nonverbal audio, and handlebar vibration. They identified that such interfaces can improve the bicyclist confidence during lane merging scenarios. The laser projection and HUD interfaces had the highest confidence and usefulness scores. However they also found that bicyclists relied on the communication cues instead of visual interpretations of the vehicle behavior to make merging decisions, which might result in safety critical situations in mixed traffic. The developed interface concepts for bicyclist and AV communication are presented in Figure 2.11.

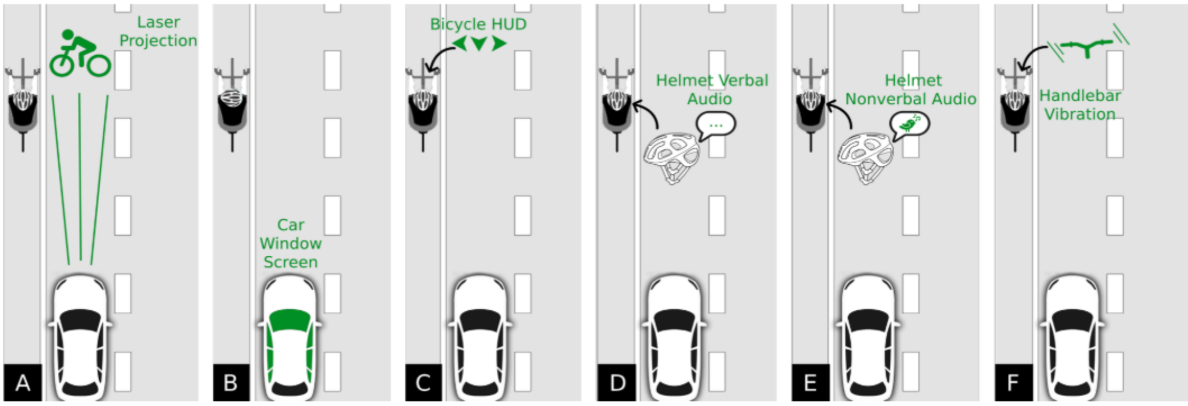


Figure 2.11: Interface concepts that were implemented and tested in the virtual reality bicycle simulator study conducted by Hou et al. [2020]: (A) Laser Projection, (B) Car Window Screen, (C) Bicycle Heads-Up Display (HUD), (D) Helmet Verbal Audio, (E) Helmet Nonverbal Audio, (F) Handlebar Vibration.

eHMIs are found to increase the efficiency of HRU and AV interactions [Papakostopoulos et al., 2021]. In a field experiment with an AV equipped with an eHMI, pedestrians crossed the road faster with a higher speed than when the vehicle was not equipped with an eHMI. They also rated higher their ability to infer the yielding behavior of the vehicle. Song et al. [2018] studied different eHMIs types used to communicate the intention to give right-of-way to pedestrians through an online survey. Results suggested slight tendencies within the eHMI types and significant differences were identified between implicit (no eHMI) and explicit (with eHMI) communication in the crossing frequency and the reaction time of the survey participants.

Joisten et al. [2021] proceeded a step further and focused their research additionally on the investigation of intercultural aspects in the efficiency of eHMIs for AV and pedestrian interactions. In an online video survey they introduced a German (N = 126) and Chinese (N = 79) group of participants and evaluated their response to a crossing scenario with an interacting yielding AV. They concluded that the "walking person" eHMI had more consistent effects in improving crossing willingness and trust against AVs for both samples compared to a "smiling face" sign and a no eHMI symbol. Similar results are presented by Bazilinskyy et al. [2022]. In their study they investigated the decision making of a bicyclist to cross or to brake in the presence of an automated on human driven vehicle, at different Time-to-Collision (TTC) levels and with or without an eHMI. In the presence of the eHMI with the "GO" sign on the vehicle rooftop, a significant majority of study participants decided not to break proactively in contrast to all scenarios without the eHMI.

At the same time Winter and Dodou [2022] argue whether eHMIs are crucial for the the efficient and safe interaction among HRUs and AVs. They present a comprehensive review of present scientific research as well as the results from research projects and conclude on a series of main argument point against and in favor of the use of eHMIs. Among other arguments they highlight the fact that vehicle movement actually communicate the intentions of the vehicle and, overreliance, that there is a great variation of eHMI concepts that lead to confusion. On the other hand, positive traits of eHMIs include that they complement implicit communication as it can also be not understood and lead to confusion and most importantly they can communicate the level of automation or the automation status of the AV, which can set the framework for trusted and safe interactions with HRUs. KASS et al. [2020] focused their research in assessing whether eHMIs are useful for supporting AV and bicycle interactions. In a bicycle simulator study 20 test subjects encountered different interaction scenarios with an AV. Results showed that the eHMI increased efficiency for bicyclists when the AV braked. However, the eHMI also provoked safety-critical behavior during some interactions, where the vehicle continued to drive.

Some studies have therefore focused on solely using the vehicle dynamic behavior for developing implicit communication strategies for resolving HRU and AV interactions. ACKERMANN et al. [2019] used the deceleration and speed of the vehicle as a form of informal implicit communication cue. Significantly shorter reaction times for higher deceleration rate and lower speed are observed. They propose that future communication among AVs and pedestrians can be based on the vehicle dynamic driving behavior by applying a smooth and early deceleration. BENGLER et al. [2020] define this as the Dynamic Human Machine Interface (dHMI) and suggest that such behavior can be part of both external and internal communication. Conventional driving dynamics and specially designed trajectories may be used to communicate the intentions of the vehicle. RETTENMAIER and BENGLER [2021] developed and tested solutions for yielding the right-of-way or to taking over the right-of-way using only the vehicle dynamics. Specifically in a driving simulator study in bottleneck scenarios with an AV and a human driver, they adjusted the AV speed (maintain speed, one-step deceleration, two-step deceleration) and the lateral offset of the AV (no offset, close offset, distant offset) to indicate whether the AV will yield or maintain the right-of-way. Results showed that test subjects had a better anticipation of the AV intention and its future behavior due to the change in the lateral offset. They also evaluated the lateral offset as significantly more comprehensible than speed adjustment, while the absence of the lateral offset resulted in less comprehensible AV movements.

Literature findings from the field of human-machine communication and cooperation highlight the importance of considering human factors in the design of automated driving functions. Cooperation and communication solutions among AVs and HRUs have to rely on the assumption that not only the vehicle but also the interacting human will cooperate in resolving a complex interaction often to the AV's benefit. In this context the AV behavior has to be legible in the context of the respective traffic interaction. Additionally, the AV state and intention has to be communicated accurately to the respective road user group. According to previous research, communication from the side of the AV should optimally rely on an appropriate combined eHMIs and dHMIs solution. These findings are important considerations for the development of a cooperation framework for AVs as the solution design has to consider these factors for the definition of the specific AV functions as well as for the rules and assumptions that will regulate the AV and bicyclist interactions. These will ultimately result in requirements and limitations for the proposed method.

2.7 Simulation of Road User Behavior

2.7.1 Simulation of Automated Vehicles

With the ever increasing scientific interest and development of automated vehicle technologies, the simulation of AVs and their functions is an essential step towards accelerating the development and the evaluation of new automated vehicle technologies as well as measuring and understanding the effects of the future introduction of AVs in real traffic. A variety of methodologies have been adopted by researchers in the fields of AV research, intelligent transportation systems and traffic engineering in an effort to simulate and develop models of automated vehicles to simulated automated vehicle functions. Two comprehensive literature review studies present and discuss the different approaches [Gora et al., 2020; Do et al., 2019]. It is found that the method selection for the simulation and modeling of AVs and their functions primarily relies on the requirements regarding the level of accuracy in the representation of AV functions and modules as well as the use case for which the model is developed for. Do et al. [2019] highlight that as no adequate empirical data of the use of AVs in real traffic are available, the calibration of the AV parameters in simulation models is mostly relying on assumptions. As there is a lack of standardized methods and real world datasets that can be used to model automated vehicle functions both papers highlight the difficulty in comparing results from different scientific studies, the importance of method standardization and creating repositories with real-world that can be used to develop and benchmark AV functions [Gora et al., 2020; Do et al., 2019]. Therefore, the scientific approaches that are found in the literature for simulating automated vehicles can be grouped in two main categories:

1. Approaches that couple vehicle simulator models such as vehicle dynamics simulation software (e.g. CARLA, CarSim, CarMaker) or specially designed and dedicated for automated driving simulation environments with traffic simulation software.

2. Approaches that rely on scripting automated vehicle functions in traffic simulation software and/or modifying/calibrating the car-following and lane changing behavior parameters in existing traffic simulation models for replicating the AV behavior.

Tettamanti et al. [2018] present a Vehicle-In-the-Loop (VIL) test environment that couples the microscopic traffic simulation software SUMO with a test vehicle equipped with AutoBox a tool for using the dSPACE real-time system. Signals from the test vehicle are transmitted via CAN bus and Matlab to SUMO using TraCI that simulates surrounding traffic and infrastructure. Subsequently, these model inputs are transmitted back to AutoBox using CAN messages. The framework architecture is a typical example for coupling a simulation environment with an external component that can be either a physical vehicle or device, a physical simulator or another simulator environment. In this example, Matlab serves as the common interface of communnication between the CAN bus of the test vehicle and TraCI as it is able to both translate and create CAN messsages as well as to convert them in understable inputs for SUMO using the TraCI API.

Similarly CARLA, the open-source simulator for automated driving research, that is used to develop, train and assess automated driving systems [Dosovitskiy et al., 2017] has been coupled with SUMO and PTV Vissim, in order to enable users to benefit from both simulators. CARLA comes with pre-installed simulation models for automated vehicle detector technologies, vehicle dynamics and models for simulating different environmental conditions, while SUMO includes microscopic models for simulating the behavior of road users and traffic infrastructure. Also, the Python Interface in CARLA and in SUMO TraCI allows for the combined integration and the modeling of automated vehicle functions in development such as V2X and V2V communication. For example, AOKI et al. [2020] additionally integrated a CNN object classifier and use the simulator environment to train, test and evaluate their occlusion and cooperative perception method for detection reliability and compare it against a baseline protocol. In a similar approach, C. WU et al. [2022] first developed FLOW a modular learning framework , which uses deep reinforcement learning to address complex traffic dynamics and coupled it with SUMO. They proposed this method in order to develop data driven control models for AVs that learn and adopt control laws through traffic simulation scenarios.

Methodologies that couple existing dedicated automated vehicle simulators with microscopic simulation software provide advantages primarily for the development and evaluation of methods integrated in the sub-microscopic level of automated vehicles, such as object detection methods, decision making modules and motion planning algorithms. They are less complex and more efficient for testing specific automated vehicle functions independent of other vehicle modules. They can also be used for data generation and data augmentation for designing, training and testing models and methods for detection and motion planning, as they can be sued to reproduce and replicate scenarios and situations that are not easily observable in real traffic. KLISCHAT et al. [2019] coupled their software framework CommonRoad with SUMO to test motion planning of automated vehicles in an effort to efficiently test their approach without integrating it into typical vehicle simulator software that covers the whole vehicle workflow and physics.

Despite the high accuracy and detail that coupled simulation methods provide, they still remain highly complex. In cases where the microscopic, mesoscopic and macroscopic effects of AVs and automated vehicle functions on traffic networks are assessed or control strategies for optimizing the AV traffic flow are developed, researchers mostly proceed to model automated vehicle functions in traffic simulation software using scripting tools and interfaces and/or adjust the behavior parameters of the motor vehicles for replicating the AV behavior.

Typically in microscopic traffic simulation software such as AIMSUN, SUMO and PTV Vissim road user behavior is simulated using different components (models) for the longitudinal and lateral motion behavior. In AIMSUN the longitudinal behavior is modeled using the Gipps car following model [PETER G GIPPS, 1981], which is a safety distance model. In PTV Vissim, the longitudinal behavior is modeled using the psycho-physical car-following models of Wiedemann (versions 74 and 99) [WIEDEMANN, 1974] [PTV AG, 2016]. SUMO [P. A. LOPEZ et al., 2018] utilizes the car following model of KRAUSS et al. [1997] which is also a safety distance model. However SUMO also integrates a variety of other car following models [P. A. LOPEZ et al., 2018] including the Wiedemann models (versions 74 and 99), the Intelligent Driver Model (IDM) [TREIBER and HELBING, 2002] and Adaptive Cruise Control (ACC) models [MILANÉS and SHLADOVER, 2014; XIAO et al., 2017] that can also be used to model car following behavior.

Excluding the ACC models, the car-following models used typically in microscopic traffic simulation rely also on stochastic or probabilistic behavior parameters in order to account for the human drivers' imperfection during driving. MAHMASSANI [2016] defines two main factors for modeling the car-following behavior of AVs: First, their ability to constantly monitor other vehicles in their vicinity, which should result in a deterministic behavior in dealing with other road user behavior; and secondly their ability to react instantaneously to any changes in the driving environment. Therefore, the stochasticity of car-following models has to be eliminated so that they can be used to model AV car-following behavior.

PTV Vissim lane chaning behavior is modeled based on the model of SPARMANN [1978] with modifications and enchancements [WEYLAND et al., 2021]. Aimsun uses the lane changing model proposed by Gipps [PETER G GIPPS, 1986; P G GIPPS, 1986] that models the user's lane chaning behavior as an objective driven decision making process. Similarly to AIMSUN, SUMO [P. A. LOPEZ et al., 2018] models the lane changing behavior as a hierarchical decision making process by defining: the strategic, cooperative, tactical change and regulatory lane change decision layers [ERDMANN, 2015]. This model version is referred to as LC2013. Subsequently an expanded version of the LC2013 model, referred to as SL2015, is used to support sublane changing behavior in SUMO, [SEMRAU and ERDMANN, 2016]. The SUMO Sublane Model was developed in an effort to support research in Advanced Driver Assistance Systems (ADAS) and extends the lateral resolution of a traffic lane in SUMO so that multiple vehicles may use the same lane on the lateral dimension (e.g. drive side by side). The Sublane model expands the modelling capabilities of SUMO, as it more accurately simulates the co-existence of different road users of different dimensions in the same traffic lane, the overtaking maneuvers on the same lane for bicyclists and the lateral road user dynamics. The respective model parameters can be modified by the user to a great extend [P. A. LOPEZ et al., 2018].

When it comes to simulating road user behavior at intersections, intersections in PTV Vissim are modeled by creating connections among the corresponding intersection links. The intersection points between these connections are then identified by the software and the user is required to setup and adjust the respective priority rules and the gap acceptance parameters that will apply to the road users at each intersection point seperately [PTV AG, 2016]. In SUMO the intersection model creation is in comparison faster as the user is only required to join the edges that form the intersection area. The intersection and the respective traffic stream connections are then generated automatically by SUMO using preset parameters. This enables the fast and automated modeling of intersections as the user is not required to manually define all connections and then establish the conflict and priorirty rules for each intersect position. The SUMO junction model subsequently defines behavioral parameters for the simulated road users for adjusting their behavior at the intersection. Priority rules and other attributes, such as for example the stop position for subordinate traffic streams and the connection form can be further adjusted and more accurately defined by the user in NETEDIT [P. A. LOPEZ et al., 2018; GEORGIOS GRIGOROPOULOS, LÜCKEN, et al., 2019]. However, in contrast to PTV Vissim, SUMO does not allow for the individual adjustment of priority rules and intersection behavior for each intersect point between the junction connection.

Scripting and the modification of the running traffic simulation is possible in AIMSUN, SUMO and PTV Vissim through their respective scripting interfaces. AIMSUN uses the using the Python-based AIMSUN API, PTV Vissim uses the COM Interface, while SUMO relies on the TraCI interface [WEGENER et al., 2008]. SUMO provides the highest degree of freedom when modifying the simulation, as the majority of the behavior of SUMO elements can be retrieved and adjusted online. PTV Vissim in comparison is more limited, especially when it comes to modifying road user behavior. Both software solutions have been used extensively in the evaluation of the effects of automated driving in traffic. Aria et al. [2016] used PTV Vissim to assess the effects of AVs on driver behavior and traffic performance. They modeled high automated vehicle behavior using findings from their literature review. The modified parameters in PTV Vissim included setting adjusting the headway time (CC1) to $0.3s$, defining the distribution of the maximum speed to a narrow value range of $\pm 2km/h$ and activating cooperative lane change for both left and right sided overtaking.

Müller et al. [2016] used AIMSUN to evaluate their Mixed Integer Linear Programming (MILP) intersection control strategy for AVs traffic. However, they did not make major adjustments to the respective vehicle behavior models and used the default values provided by the software. The parameters that were modified were ultimately only the parameters that controlled the behavior of the vehicles at intersections and the parameters that were part of proposed control method. Therefore, they only proceeded to adjust the minimum transversal headway h_T to $0.6s$ and the longitudinal headway as h_L to $1.2s$, while the maximum acceleration and deceleration values were set to $a_{max} = 3m/s^2$, $a_{min} = -4m/s^2$ respectively. Makridis et al. [2018] used the Gipps Model in AIMSUN combined with the Aimsun API to deploy the Cooperative Adaptive Cruise Control (CACC) model by Mahmassani [2016]. Subsequently, for modeling the cooperation component between the leader and the follower the CACC algorithm decided using a set of constraints if the cooperation should be established, while at all times the CACC was not responsible for changing the lateral driving behavior. Otherwise, the default Gipps model was used to model the car-following behavior. In terms of adjusted behavior parameters for the connected vehicles, a $0.3s$ reaction time was used in comparison to $0.8s$ for human drivers and $0.5m$ for the minimum safe gap. The maximum comfortable deceleration and acceleration was set to $a_{min} = -3m/s^2$ and $a_{max} = 2m/s^2$ respectively based on literature review findings. A common characteristic between the studies by Müller et al. [2016] and Makridis et al. [2018] is that both studies simulated only specific automated functions in their models, while the rest aspects of the vehicle behavior were governed by the default AIMSUN models. Additionally they adjusted only the relevant behavior parameters, while they used the default model parameters of values from past research for all remaining behavior properties that were not part of the evaluated functions.

Lu et al. [2020] used SUMO to assess the effect of AVs on urban traffic network capacity. The modified the Krauss car following model to replicate AV driving behavior. In comparison, to their non-automated vehicle parameters, they set the minimum gap value to $0.5m$, and the time headway to $0.6s$ instead of $0.9s$ under the assumption that AVs in contrast to human drivers, should be able to drive closer to one another. Respectively as the AV driving control function are assumed to perfectly steer and control the vehicle the sigma parameter of the Krauss model that defines driver imperfection was set to 0. Fernandes et al. [2010] also used SUMO to develop solutions for cooperative and automated communication-enabled vehicles, with platooning capabilities modifying the integrated IDM car-following model and vehicle driving behavior using TraCI. However, in their work, they do not specify the adapted vehicle behavior parameters.

Olstam et al. [2020] used PTV Vissim to model the behavior of different AV automation classes (basic, intermediate and advanced). Each class differentiates in terms of operational design and driving aggressiveness, while adapting its behavior with respect to the driving environment complexity: driving on a motorway, on an arterial, on an urban street or a shared space. They proceeded to implement the driving logics in PTV Vissim by by adjusting the Wiedemann 99 behavioral model parameters. Most importantly they turned off the implicit stochasticity of the driving behavior and assume perfect deterministic automated driving, narrow speed distributions at the speed limit, no reaction time, cooperative lane changing and advanced merging. They proceed to provide reference values for all Wiedemann 99 car-following and lane changing parameters (CC0 – CC9) depending on the automation level.

Overall, it is found that the method selection for the simulation and modeling of AVs and their functions primarily relies on the requirements regarding the level of accuracy in the representation of AV functions. In the context of this research, the aim is to evaluate the effects of a cooperation framework for AVs and bicyclists on the system level of the unsignalized intersection. Therefore, the appropriate approach would include the modeling of the respective functions in a microscopic traffic simulation software. Finally, the proposed AV behavior parameters for microscopic models found in scientific research provide an ideal basis for modeling the AV in the context of this work.

2.7.2 Simulation of Bicyclist Behavior and Evaluation of Traffic Performance

Microscopic traffic simulation tools are developed to model the behavior of road users in traffic and provide a method for the evaluation of traffic measures and the effects of using transport infrastructure. The modeling of bicycles in microscopic traffic simulation tools relies on modified motor vehicle or pedestrian models [P. A. Lopez et al., 2018; Twaddle, Schendzielorz, et al., 2014]. Thus, most of the scientific research in the field strives to provide extensions to current models and software for the replication of bicyclist behavior. Efforts focus primarily on the description of the tactical behavior of bicyclists [L. Huang and J. Wu, 2009; Schönauer et al., 2012; Twaddle and Busch, 2019], the modeling of bicycle infrastructure [Georgios Grigoropoulos, Lücken, et al., 2019] in microscopic traffic simulation tools, as well as the modeling of the dynamic characteristics of bicycle behavior [Andresen et al., 2014; Haifeng et al., 2013; Twaddle and Georgios Grigoropoulos, 2016; G. Grigoropoulos et al., 2019].

The bicyclist tactical behavior includes the decision of bicyclists to perform short-term maneuvers in order to resolve specific traffic situations, such as the bicyclist path in traffic and stop positioning [Michon, 1985]. Bicyclists are found to adapt their behavior according to their intended maneuver, the traffic state [Angenendt et al., 2005; Twaddle and Busch, 2019] and the bicycle infrastructure state and dimensions [Kuller et al., 1986; Alrutz et al., 2009; Georgios Grigoropoulos, Leonhardt, et al., 2022].

The bicyclist operational behavior, comprises of subconscious actions to control the bicycle within the environment, including speed control, acceleration, deceleration, gap acceptance, and spacing [Michon, 1985]. Several studies address the definition of the bicyclist desired speed as a function of the respective traffic infrastructure used by the bicyclist and its dimensions. The bicyclist desired speed is found to be affected by the type and dimensions of the bicycle facility [Opiela et al., 1980; Alrutz et al., 2009; Schleinitz et al., 2017; Twaddle and Busch, 2019; Georgios Grigoropoulos, H. Kaths, et al., 2020; Georgios Grigoropoulos, Leonhardt, et al., 2022]. Results across all these studies suggest that bicyclists travel with a higher speed on on-road bicycling facilities, such as bicycle lanes and in mixed traffic, while the lowest speeds observed on sidewalks. These findings provide a basis for the calibration of the bicyclist speed choice in microscopic traffic simulation models as they define the bicyclist desired speed as a function of the respective available infrastructure.

The same applies to the modeling of gap acceptance for bicyclists in microscopic traffic simulation, where empirical findings are also transferable. When crossing a prioritized traffic stream, bicyclists are found to accept time gaps of 3 – 4 seconds on average [Kwigizile et al., 2017; Opiela et al., 1980]. Motor vehicle drivers crossing a prioritized bicycle traffic stream are found to accept average time gaps of 6 – 7s between crossing bicyclists [Petzoldt et al., 2017]. Gap acceptance is a critical parameter for accurately modeling bicyclist and vehicle interactions at intersections as the accurate definition of the gap acceptance behavior for both motor vehicles and bicyclists has a major influence in the respective estimation of the Level of Service (LOS) for the intersection traffic streams.

The design of microscopic traffic models often combines the use of both empirical data and data from past research for the model calibration and validation. The relevant bicycle behavior parameters are extracted from empirical data and used for the calibration and validation of microscopic traffic simulation models. Specifically, the bicycle traffic behavior is calibrated by adjusting the car-following and lane-changing model attributes. This methodology is introduced primarily as part of research focusing on the assessment of new types of infrastructure [Georgios Grigoropoulos, Lücken, et al., 2019; Georgios Grigoropoulos, Hosseini, et al., 2021], the effect of new categories of bicyclists such as cargo bikes and e-bikes on traffic flow [Georgios Grigoropoulos, Hosseini, et al., 2021] or the development of models for quantifying the effects of bicycle traffic flow [Georgios Grigoropoulos, Leonhardt, et al., 2022] for traffic scenarios that are not easily or at all observable in real traffic.

Bicycle traffic disrupts the movements of partially conflicting streams of motor vehicles [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015] and is therefore decisive for estimating the LOS for motorized traffic. The LOS for non-motorized traffic is based on the maximum waiting time for the complete crossing of an intersection approach. For modeling these effects both the German Highway Capacity Manual (HBS) [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015] and the American Highway Capacity Manual (HCM) [National Research Council, 2016] use adjustment factors which are a function of the expected occupancy duration of the conflict zone among vehicular and bicycle traffic streams.

J. Chen et al. [2014] developed a platoon width model and a polynomial regression model, which can be used to generate the adjustment factor for the saturation flow rate calculation in the HCM for left-turning motor vehicles. [X. Chen et al., 2009] proposed a methodology for calculating capacity considering the influence of bicycle blockage, waiting bicyclists in partially conflicting streams, traversing bicyclists and bicyclists waiting inside the intersection. A similar approach in which models are developed to quantify the effects of bicycle traffic on the saturation flow rate of the turning vehicles by defining different stages of bicycle movements is proposed by Y. Guo et al. [2012]. The HCM [National Research Council, 2016] uses a LOS for non-motorized traffic based on multiple parameters describing the traffic performance and intersection characteristics. This method is limited to intersection approaches with less than a 2 % gradient.

Additionally, bicycle traffic delay is calculated and assessed independently of the LOS score and applies only for dedicated bicycle facilities. It is assumed that bicycles in mixed traffic experience the same delay as vehicular traffic. As a result, no dedicated thresholds for bicycle traffic LOS are provided for unsignalized intersections. Also these models are developed for specific use cases and consider only specific evaluation parameters. Therefore they are limited in their application with respect to large variety of interactions that exist among vehicular and bicycle traffic flow.

In conclusion, sufficient research is already available for the calibration of bicyclist behavior in microscopic traffic simulation. Additionally, relevant traffic performance indicators for bicycle traffic are identified. In the context of this work it is important not only to consider these factors for the evaluation of the proposed cooperation framework but also integrate them in the proposed approach as critical factors for the interaction optimization. Eventually, these factors are already being utilized by traffic authorities for dimensioning and evaluating traffic performance in existing road networks. Therefore, the integration of these factors as part of the cooperation framework is aligned with our overarching goal of providing an acceptable and integrative solution for resolving bicyclist and AV interactions.

2.8 Traffic Flow Optimization at Intersections with AVs

This section discusses scientific methods that have been proposed to optimize the traffic flow and traffic performance at controlled or uncontrolled intersections with AV traffic. In contrast to HRU traffic, the anticipated future introduction and expansion of AVs in urban traffic unveils a significant potential in introducing novel traffic control solutions that take into advantage the controlled and predictable driving behavior of AVs, while assuming a sufficient level of interconnectivity and cooperation among all agents. In HRU traffic, the control and regulation of traffic flow relies primarily on traffic signals, traffic signs and sets of common traffic rules that regulate the priority of different traffic streams along traffic lanes and at intersections. However, this type of control takes place on the traffic stream level, meaning that rules or control signals apply for all road users belonging to a certain stream and it is assumed that all road users follow the given rules without exceptions. Considering the predictable and pre-regulated driving behavior of the AVs it is possible to further control and optimize the traffic flow by controlling and micro-managing the driving behavior aspects of individual users on the agent-level. Gholamhosseinian and Seitz [2022] categorizes AV traffic intersection control architecture Vehicle-to-Infratructure (V2I) and V2V and a hybrid mode where one vehicle undertakes the intersection control for the short-term.

Kurt Dresner and Peter Stone [2006] review Connected and Automated Vehicles (CAVs) traffic control methods and describe the most promising methodological approaches for addressing the multiagent optimization problem for Autonomous Intersection Management (AIM). They propose the development of reservation based systems based on the segregation of the intersection area in reservation tiles, with the intersection manager optimizing the allocation of the tiles to the different agents based on the First Come First Serve (FCFS) concept. The minimization of the delay and of the tile allocation cost should be the core objective of the multi-agent optimization problem. In their follow up work Kurt Dresner and Peter Stone [2007] propose solutions for the integration of HRUs in AIM by combining the input from the normal traffic lights with the FCFS policy and regulating traffic using lane-based signal policies for each traffic lane direction. The proposed method requires that a single dedicated lane is assigned to each travel direction and a signal head is then assigned to each lane communicating the control state of the lane to the HRUs. Connections between lanes are then successively given dedicated green phases for accommodating the HRUs, while CAVs are reserving space and connections using the FCFS policy. Figure 2.12 presents the control approach Kurt Dresner and Peter Stone [2007] for integrating HRUs in AIM.

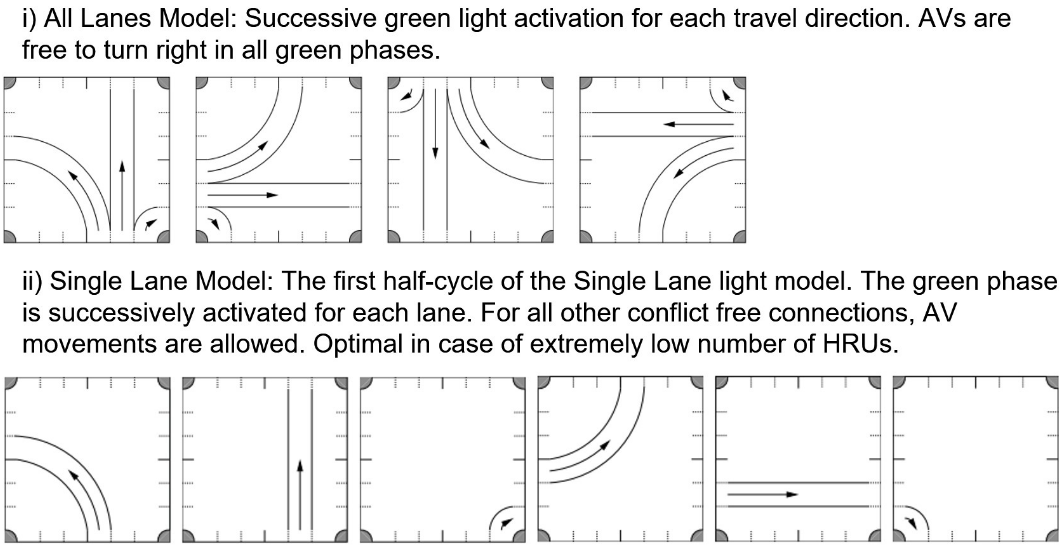


Figure 2.12: Description of the Light Model Control Method. Figure adapted from Kurt Dresner and Peter Stone [2007].

Y. Wu and F. Zhu [2021] proceed to evaluate the FCFS policy for intersections and roundabouts and compare it against the typical traffic control methods: signal control and priority rule based traffic regulation respectively. it is found that intersections with signal control have the largest capacity in comparison to FCFS based approaches, however this is highly dependent on the acceptable safety gaps that are defined for the FCFS policies. Also the unsignalized FCFS policies outperform signal based control in low traffic demand. In terms of capacity, the roundabout coupled with FCFS outperforms all other on signalized FCFS policies. Thus, in future FCFS control policy implementations for CAVs, roundabout setups should be considered instead of intersection layouts.

Most of the present scientific work focuses on the optimization of traffic flow with (connected) AVs at signalized or unsignalized intersections and roundabouts. With respect to unsignalized intersections different control concepts for CAVs have been proposed. Typically, traffic control in unsignalized intersections relies on established traffic rules and traffic signs, that basically regulate the traffic flow for conflicting traffic streams. (Connected) AV control approaches start with remodeling the intersection area for control operations. The remodeling is performed following different methods. In the case of the spatio-temporal reservation the intersection area is divided into a set of tiles that can be spatially and time based reserved for vehicle passage. In the case of the trajectory planning approach, specific trajectories linking the intersection approaches are defined for all vehicle streams. Vehicles use the pre-defined trajectories to cross the intersection [GHOLAMHOSSEINIAN and SEITZ, 2022].

Solutions assume communication among vehicles and rely on cooperative resource reservation that relies on time- and tile- based FCFS intersection area reservation policies, virtual traffic lights that basically emulate the signalized intersection control framework on an agent level and vehicle trajectory planning [L. CHEN and ENGLUND, 2016]. Vehicle trajectory planning is then performed following with different approaches. Vehicle trajectories are planned and scheduled simultaneously if they do not come into conflict (safe pattern), by identifying vehicle paths and adjusting vehicle speed profiles to avoid collisions path (priority graph) and by formulating a maximal robust controlled invariant set problem for collision avoidance (collision region) [L. CHEN and ENGLUND, 2016].

Furthermore, the majority of research also considers primarily intersections and control scenarios with only CAV traffic. They do not consider the presence of HRUs, with the exception of the work by NIELS, MITROVIC, BOGENBERGER, et al. [2019], NIELS, MITROVIC, DOBROTA, et al. [2020], and NIELS, BOGENBERGER, et al. [2020] that study and integrate pedestrians and bicyclists in novel control methods for signalized intersections with CAVs. QIAN et al. [2017] suggest the inclusion of bicyclists and pedestrians in AIM only through dedicated crossing time slots. Nonetheless VRUs are only considered as part of traffic safety and not as part of traffic performance optimization solutions [L. CHEN and ENGLUND, 2016].

CAI et al. [2014] present an unsignalized cooperative optimization control method based on speed adaptation and information exchange among agents. They use the vehicle delay and the number of stops as their optimization objectives. They proceed to optimize the traffic flow by generating virtual green time windows for the different traffic streams and thus emulating the control concept of a signalized intersection. They manage to achieve significant improvements in average delay, stops, queue length and speed across different traffic flow scenarios in comparison to actuated control. However, their study case and the developed control concept can closely be related to a signalized intersection.

Game theory approaches have also been developed for coordinating traffic at uncontrolled intersections. ZOHDY and RAKHA [2012] present a game theory solution for regulating CAV traffic at an uncontrolled intersection that significantly reduces delays in comparison to stop sign control. In another work ELHENAWY et al. [2015] suggest a game-theory-based algorithm for controlling CAV motion at uncontrolled intersections. The approach is based on the chicken game and assumes that all vehicles follow the Nash equilibrium solution. The method achieves an average travel time delay reduction of 49% and 89% delay reduction compared to the all-way stop sign unsignalized intersection. Both presented approaches assume connection and cooperation among the agents, while player actions are translated into inputs in the CACC system. ZOHDY and RAKHA [2012] and ELHENAWY et al. [2015].

MAVROGIANNIS et al. [2020] propose a method for regulating traffic flow and resolving traffic interactions at an unsignalized intersection through a decentralized planning algorithm that generates actions aimed at reducing the uncertainty of the multi-agent behavior. The method collectively rejects unsafe intersection crossings and assumes no communication among the agents. Each agent trajectory is predicted using a probabilistic model that relies on spatio-temporal braids. The resolution of the collision free agent passage is provided by a decision-making mechanism that reduces overall uncertainty based on a set of actions. Although in their approach they significantly reduce detected collisions and reduce overall uncertainty, the travel time is increased as agents take on safer actions. In another work, researchers propose a decentralized navigation function for coordinating approaching and intersecting CAVs at intersections based on the vehicles' Estimated Time of Arrival (ETA), speed and desired speed. Their evaluation is based on energy consumption, which is improved compared to the control scenario [Makarem and Gillet, 2012].

T. Wu et al. [2020] propose a reinforcement learning approach based on the multi-agent reinforcement learning algorithm. Specifically, they expand the Multiagent Deep Deterministic Policy Gradient (MADDPG) to account for non static environments and cooperation among agents. MADDPG is an adaptation of actor-critic methods which considers action policies of other agents and can learn policies that require complex multi-agent coordination. T. Wu et al. [2020] adjust the gradient of the expected return to account for uncertainty and the cooperative effects among the different agents and through the selection of the largest impact vehicles according to their space distance, where only the closest interacting vehicles are considered. Their method reaches a 39.28% improvement in travel times compared to a reference method.

Niels, Mitrovic, Bogenberger, et al. [2019] adopt suggestions from the work of [Kurt Dresner, 2008] and present reservation based control strategies that consider pedestrians as part of AIM based on FCFS control and showcase that such strategies already have the potential to improve traffic performance for pedestrians. The pedestrian(s) either reserve the entire intersection or the respective crossing legs. Results show that pedestrians benefit from the proposed control strategies. For the CAVs results indicated that they benefited from AIM compared to the base scenario with two-phase signal control with a fixed cycle. They proceed to expand their work by also considering dynamic lane reassignment for vehicles approaching the intersection. traffic performance results are better for CAVs across all traffic demand scenarios (low to high) when compared to the base scenario of actuated signal control. Pedestrian waiting times are similar for scenarios of low to medium traffic demand compared to the basis scenario with actuated signal control. However pedestrian waiting times improve in the case of the high demand scenario [Niels, Mitrovic, Dobrota, et al., 2020]. This suggests that their approach expands the potential gains for pedestrians primarily in high traffic demand situations. Niels, Mitrovic, Bogenberger, et al. [2019], Niels, Mitrovic, Dobrota, et al. [2020], and Niels, Bogenberger, et al. [2020] additionally argue that optimization based control can further improve the traffic efficiency in comparison to FCFS control.

Niels, Bogenberger, et al. [2020] applied similar strategies only for bicyclists at a signalized intersection. Here they additionally consider the problem of the bicyclist maneuver intention in two separate control scenarios. In the first control scenario they implement the all-directions-green strategy for bicyclists. In the second scenario signal control detects the bicyclists but is unaware of the bicyclist maneuver intention. They proceed to resolve this uncertainty by assigning both a crossing and a left turning phase to the bicyclists. In the third scenario they assume full and certain knowledge of the bicyclist maneuver intention. Overall, results are mixed with respect to the improved performance for the different road user types across all control scenarios and vehicle demand variations. It is found that the knowledge of th bicyclist intention leads to better performance for the vehicle traffic as there are no unnecessary activations of the left turn phase. Specifically for bicyclists, traffic performance improves with the first two control scenarios, while with the third control scenario bicyclist waiting times increase.

Optimization based approaches have been extensively used to optimize CAV traffic flow. J. Lee and Park [2012] formulate the intersection control as a constrained nonlinear optimization problem for coordinating the vehicle trajectories by minimizing the overlapping of all conflicting vehicles. Conflicts are derived from a phase conflict map mapping all conflicting intersection maneuvers. Their approach is evaluated using PTV Vissim and motor vehicle travel times are reduced by 33% compared to the base scenario of actuated traffic control. A great reduction of 99% is observed for total waiting stop time as the optimizer schedules the vehicle arrivals and the vast majority of vehicles are therefore not required to come to a full stop. Mirheli et al. [2018] present an algorithm for maximizing intersection throughput, by minimizing the vehicle ETA to the destination over the planning horizon. They also proceed to use the Monte Carlo tree search in order to reduce the solution state space. Significant reductions in travel time in comparison to fixed-time (-59.4%) and fully-actuated control (-83.7%) are observed.

In the context of optimization methods, MILP approaches are also quite popular in resolving the CAV intersection control. Müller et al. [2016] presents a MILP approach for intersection control with CAVs using vehicle delay as the minimization target for the objective function. In their approach they schedule the vehicle arrivals at the intersection by calculating their ETA and subsequently adjusting their speed profiles in order to minimize their exit time after the intersection and thus resolving the motion planning problem for all CAVs. Results suggest a significant reduction in vehicle delays. Fayazi and Luckow [2017] and Fayazi and Vahidi [2018] in turn formulate the CAV arrival scheduling problem with a cost function by minimizing the latest access time assigned to a crossing vehicle, while constraining the vehicle delays through the definition of an individual maximum arrival time. Safety gaps between vehicles and the maximum acceleration rate and the speed limit are defined as constraints of the optimization problem. Results show significant reductions in average travel time and stop delay time per vehicle. Ashtiani et al. [2018] in a follow up work expanded their approach for multiple intersections.

Overall, scientific literature findings indicate that MILP optimization based approaches are highly efficient in for CAV traffic optimization solutions. Also the majority of research considers primarily intersections and control scenarios with only CAV traffic, without integrating HRUs in their approach. In the few exceptions found, important topics for consideration in the development of integrative CAV-HRU cooperation frameworks are discussed. The importance to tackle the problem of uncertainty and unpredictability of human intentions is highlighted. Although, in the context of signalized intersections this issue is partially or fully resolved by assigning dedicated CAV or HRU routes, while estimating the HRU intentions through external devices or their traffic lane position, this cannot be the case in mixed traffic flow at unsignalized intersections which is the focus area of this dissertation. Nevertheless, the combined findings and conclusions from sections 2.1-2.6 provide a solid basis for the path towards the development of a cooperation framework for resolving AV and bicyclist interactions at unsignalized intersections with mixed traffic conditions.

2.9 Research Needs Assessment

This section highlights and discusses the key findings from the literature review and bridges them with the scientific goals of the present dissertation. The development of technologies that will enable future AVs to operate autonomously without human supervision or intervention remains a vivid area of research, where steady and continuous progress is made. Nevertheless, as the overarching goal of automated driving is the introduction of AVs in urban traffic, the safe and efficient interaction with VRUs is critical for their acceptance and adoption. So far research focuses mostly on one-to-one interactions between an AV and a VRU, whereas most of the research focuses on the prediction of pedestrian behavior, as well as the interaction, cooperation and communication between a AV and a pedestrian. In comparison, little research is found, that considers bicyclists in the context of their interactions with AVs. With the future introduction of AVs in urban traffic, AVs will have to share the road and interact with bicyclists mixed traffic conditions. Bicycle traffic is a significant part of daily urban traffic in Europe and in Asia, where it is often not segregated from motor vehicle traffic with dedicated infrastructure.

In this context, first, the intention comprehension and prediction bicyclist behavior is crucial for AVs for adjusting their driving behavior and ensuring safe and efficient interactions. Bicyclists and VRUs behavior in general, is inherently and up to a certain extend unpredictable. However, certain features of their dynamic, operational and communication behavior can be used and exploited in order to derive a assumptions for their behavior and their future intentions. Especially, dynamic operational features have been used extensively for predicting VRU behavior in the context of automated driving research, however only for short-term trajectory predictions and not long-term intention prediction problem formulations. Despite the significant amount of research in the analysis of the communication behavior of bicyclists (see Table 2.2), little scientific work is found that considers bicyclist communication behavior for the prediction of their future behavior in traffic [Google Inc., 2016; Kretzschmar and J. Zhu, 2015; Pool et al., 2019]. Additionally, in their work, researchers only consider explicit bicyclist communication behavior (hand gestures) for predicting the bicyclist behavior. Implicit communication behavior features were not considered so far in any prediction method. Yet, as discussed in section 2.3, implicit and explicit communication features have the potential to provide an additional significant source of information for more accurately estimating bicyclist intentions. A model based on LSTM neural networks has the potential to provide a solution towards the long-term prediction of the bicyclist intentions and can also be seamlessly integrated with the existing AV system component setup while leveraging typical AV sensor technologies. ***(Research Question 1)***.

With respect to interactions with VRUs, present AV research predominately considers interaction scenarios with pedestrians and little research is found for bicyclists. In urban traffic, VRU and AV interaction scenarios will be common. In these cases a certain form of cooperation and communication among all agents will be required. However, these studies are contacted primarily in simple mostly one-to-one scenarios, where the main focus of the study lies on evaluating the communication method, in terms of safety, acceptance, comprehensiveness and compliance from the VRU perspective. In terms of communicating to VRUs, eHMIs are found to serve this role adequately, while the simultaneous changes in the dynamic vehicle behavior also carries information for the VRUs (dHMI) and its combination with an eHMI is ideal for successfully conveying specific message to VRUs. Nevertheless, the effects of such cooperation and communication concepts on the traffic system have not been evaluated, as these studies typically consider one-to-one interactions. the aggregation of these effects on other road users or on the traffic performance on the urban network section, where these interactions take place are mostly not being considered in present research ***(Research Question 3)***.

At the same time issues arise as to which VRU(s) are addressed and how the system can verify compliance and should react in case of non-compliance. In any case, VRU is not controllable and therefore VRU behavior always carries a level of uncertainty. VRU intention cannot be accurately derived as no steady exchange on information exists. In the case of bicyclists, previous research considers the use of mobile devices and wearables [Hou et al., 2020; Lindner, Georgios Grigoropoulos, et al., 2022] as a means for facilitating communication and cooperation between bicyclists and AVs. However it is safe to assume, that such devices are optional for users, while in no case will bicyclists be required to equip such devices for interacting with AVs. As in present human driven motor traffic, AVs will be solely responsible for correctly detecting and interacting with VRUs. Specifically, for bicyclists and in the context of this research, the estimation of the confidence for the prediction of the bicyclist behavior is crucial, first in terms of traffic safety and secondly in terms of efficiency and acceptance from the AV perspective. Therefore, in the context of this research, the bicyclist maneuver prediction model must be fully integrated with a mechanism that quantifies and evaluates the uncertainty of the predicted bicyclist behavior. Additionally, the proposed cooperation framework has to consider the inherent behavior unpredictability of bicyclists through limitations and rules that are easily comprehensible and legible by the interacting bicyclists. ***(Research Questions 2 and 3)***.

Additionally, the limitations deriving from the uncertainty of the VRU behavior and its proper consideration in any method for optimizing traffic flow at intersections are also not being properly considered during the development of such methods. Especially in urban areas, traffic at unsignalized intersections can often be chaotic and complex interactions may arise. In contrast to pedestrians, that typically use the sidewalk, bicyclists will have to share the road and interact with AV, especially in areas with no bicycle infrastructure. In ensuring the seamless integration of AVs in the urban transportation system, it is crucial to develop methods and solutions that ensure the safe, proper, unsupervised and uninterrupted autonomy of such vehicles, as well as their acceptance from other HRUs, such as bicyclists, especially in shared spaces and in mixed traffic ***(Research Question 2, 3 and 4)***.

AVs can leverage their equipped sensors and communication technologies for innovative approaches that can potentially improve traffic conditions for all road users. In contrast to human driven motor traffic, AVs are fully controllable and will be able to communicate and share among each other crucial information for their surroundings. This includes information on the intended behavior of other road users, the traffic state, as well as the possibility to coordinate their driving actions in order to resolve traffic situations and improve traffic performance. As highlighted in section 2.8, most of the present research, considers exclusively AVs. VRU requirements are not substantially considered. Only few solutions for the VRU integration and consideration in a AV traffic environment are proposed, with the exception of the work by Niels, Mitrovic, Bogenberger, et al. [2019], Niels, Mitrovic, Dobrota, et al. [2020], and Niels, Bogenberger, et al. [2020], who consider VRUs at signalized intersections with AV traffic. Still no scientific work yet considers bicyclists at unsignalized intersections with AV traffic. In this context, MILP based optimization models have proven to be robust in supporting methods for the optimization of AV and VRU traffic flow ***(Research Questions 3 and 4)***.

Chapter 3

Prediction of the Bicyclist Maneuver Intention at Unsignalized Intersections

Parts of this chapter have been published as part of the following authors' publications, but are further expanded here.

Georgios Grigoropoulos, Patrick Malcolm, Andreas Keler, Heather Kaths, et al. [2021]. "Bicyclist Maneuver Type Prediction using Bidirectional Long Short-Term Memory Neural Networks". In: *TRB 100th Annual Meeting*. Washington DC, USA, (virtual, poster presentation only)

Georgios Grigoropoulos, Patrick Malcolm, Andreas Keler, and Fritz Busch [2022]. "Predicting Bicyclist Maneuvers using Explicit and Implicit Communication". In: *8th Road Safety and Simulation Conference*. Athens, Greece: National Technical University of Athens Road Safety Observatory (NRSO)

3.1 Overview

This section presents a method to address the problem of predicting the maneuver intention of a bicyclist at an unsignalized intersection. Based on the literature review, methods that have already been proposed in this field mostly focus on resolving the problem of the short-term trajectory prediction of a bicyclist. This is sufficient for traffic safety applications, as well as for the safe motion planning of AVs. However this is not the case for traffic flow optimization applications, as the optimizer needs a longer sufficient time interval to react and communicate its decisions to all critical road users.

Additionally, it is found that most developed approaches do not fully consider the bicyclist communication behavior. The combination of the explicit and implicit communication cues with other bicyclist behavioral features, may add an additional valuable source of information for predicting the bicyclist intentions. Also, the added value deriving from the inclusion of the communication behavior has not been assessed, and no evaluation of which implicit and explicit communication cues are important to consider as part of a prediction model has been performed.

3.2 The Bicycle Simulator Setup at the Chair of Traffic Engineering and Control

In order to study the behavior of bicyclists in traffic, a bicycle simulator introduced at the Chair of Traffic Engineering and Control at the Technical University of Munich is used [Andreas Keler, J. Kaths, et al., 2018]. The bicycle simulator has the purpose of collecting trajectories of test subjects experiencing traffic scenarios and interacting with other simulated road users and transport infrastructure. Based on the targets and research focus objectives of the respective researchers, simulators can have a variety of properties and special features used explicitly to model or gather data on specific areas of bicyclist behavior.

The bicycle simulator consists of a physical bicycle fitted with speed and steering sensors connected to a microcontroller, which sends the measurements to a model (MATLAB Simulink) within the driving simulation software DYNA4 from the company TESIS (now part of Vector Informatic GmbH, the corporate merger was completed at the end of 2020). Other road users in the simulator environment are simulated using the microscopic traffic simulation software SUMO [P. A. Lopez et al., 2018] via a bridge module between SUMO and DYNA4. Since SUMO is used to model the simulated road users, the test subject can experience realistic traffic interactions in the simulator [H. Kaths, Andreas Keler, J. Kaths, et al., 2019], as the simulated road user behavior is not scripted and is governed over the respective SUMO simulation modules and functions. This provides an additional advantage over real traffic studies where multiple external factors and the complex nature of traffic interactions can heavily influence the outcome of traffic scenarios so that road users can rarely experience the exact same traffic situation unfolding more than once. The test subject riding the physical bicycle experiences the simulation and interacts with the simulator environment over four 50-inch monitors. Three monitors are positioned on the left side, center and right side in front of the test subject and provide a 180° degree front view of the simulation environment. The fourth monitor is positioned in the back, adjacent to the front left side monitor. This configuration enables the test subject to have a left overshoulder view of the surrounding simulation environment. The test subject can the use this monitor in order to check for incoming traffic from the back before performing an overtaking or lane changing maneuver.

An Intel® RealSense™ Depth Camera D435 is used to collect the implicit and explicit communication behavior features as well as the body movements and posture of the test subject. PoseNet [Papandreou et al., 2017] is used for extracting the skeleton of the test subjects. Arm gestures (left arm gesture, right arm gesture) are detected and classified using k-means classification. Head movements are detected using a helmet marker and the head movements (right glance, left glance, left over shoulder glance) are then classified using a threshold value method. The experimental setup is presented in Figure 3.1.

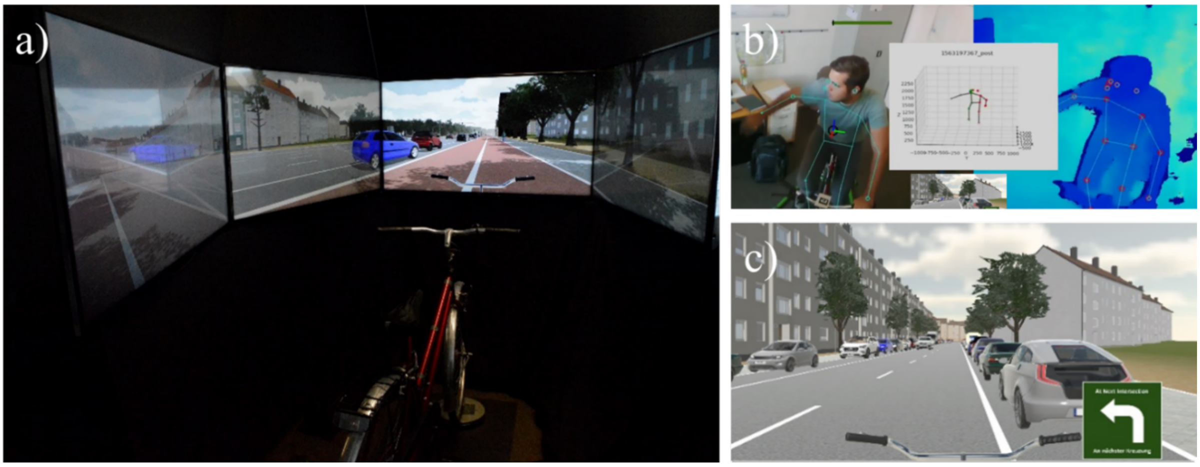


Figure 3.1: a) Bicycle simulator setup, b) skeletal points extraction and depth field detection, c) 3D simulator environment.

3.3 Experimental Design

The bicycle simulator at the Chair of Traffic Engineering and Control is deployed in order to study the bicyclist behavior during the execution of typical bicyclist maneuvers at an itersection approach. In comparison to field observations and experiments, simulator studies have the potential to research human behavior efficiently, consistently and systematically in safe, repetitive, and controlled environments, in contrast to field test or real traffic observations where it is extremely complex, difficult and cost-intensive to replicate the exact same research conditions. Additionally, the simulator setup enables the extraction of high precision implicit and explicit communication features of the test subjects which is currently not possible reach in real world experiments.

The bicycle simulator study consists of six scenarios, which require test subjects to perform the three typical maneuver types at an intersection approach of a four-arm intersection: 1) left turn, 2) straight and 3) right turn. Scenarios are varied according to the priority assignement for the bicyclist, the presence of surrounding vehicle traffic and the positioning of the bicyclist at the intersection approach before performing a left turn maneuver. The aim for the variations is to study and consider the influence of these factors on the dynamic, operational and communication behavior of the bicyclist and retrieve a reliable dataset for the further model development. Three scenarios are examined for left turns, two scenarios for the crossing and one scenario for right turns. In all the scenarios, the test subject approaches a four-way intersection of two-lane roads, at which traffic must follow the right-before-left rule. Each traffic lane is 3.3 meters wide. No special markings or dedicated traffic lanes are provided for turning traffic. Adjacent to the traffic lanes, a 2-meter-wide parking lane and then a 3-meter-wide sidewalk are placed. The speed limit on all the streets is set to 30 km/h. The infrastructure layout and traffic lane widths at each intersection were established based roughly upon those at the intersection of Oberanger and Rosental in the city center of Munich.

The simulation of the behavior of the other road users is facilitated using SUMO [P. A. Lopez et al., 2018]. The simulated road user traffic flow and behavior are controlled using the TraCI Application Programming Interface (API) [Wegener et al., 2008]. Instructions are given to the test subjects using on-screen messages appearing at the bottom right corner of the front screen. Each message graphic appears when the test subject is 200m away from the intersection and disappears when they are approximately 100m away of the intersection.

Table 3.1: Test scenarios.

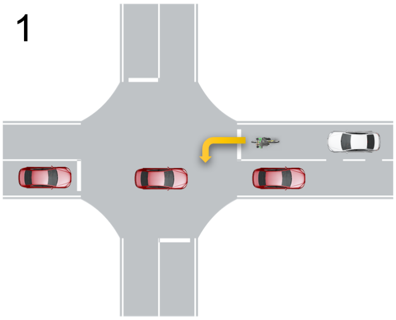
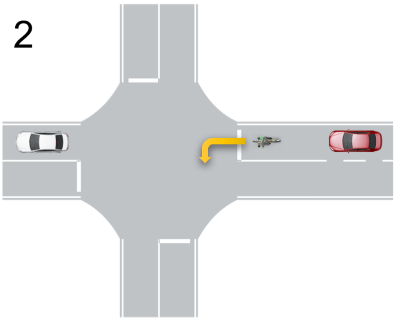
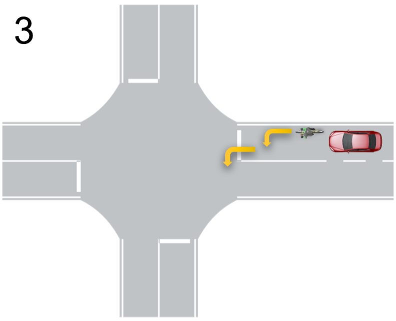
Bicycle Maneuver	**Description**	**Scenario Setup**
Left turn	Test subject is impeded by several vehicles driving straight in the opposite direction and therefore must yield to them and wait to proceed	1 
Left turn	Test subject is not impeded by any other vehicles	2 
Left turn	Test subject must perform a left turn preceded by lane change from right side of approach lane to left side, with a vehicle following behind	3 

Table 3.1: Test scenarios.

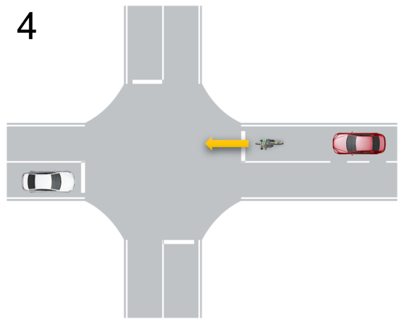
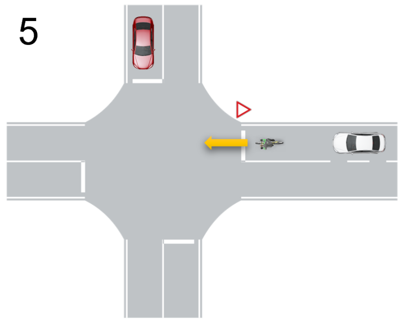
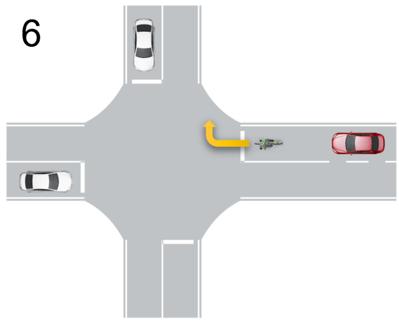
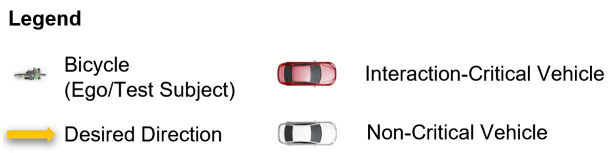
Bicycle Maneuver	Description	Scenario Setup
Straight	Test subject is not impeded by any other vehicles	
Straight	Test subject is impeded by a vehicle approaching from the right with the right-of-way and therefore must yield to them	
Right turn	Test subject is not impeded by any other vehicles	

Table 3.1: Test scenarios.

Bicycle Maneuver	**Description**	**Scenario Setup**



3.4 Data Collection and Preprocessing

Thirty-one test subjects participated in the simulator study (Male = 21, Female = 10). From these, two were under the age of 18, one between the ages of 18 and 24 and three over the age of 60. The rest of the subjects were between 25 and 59 years old. The sample size is sufficient according to the work of FAULKNER [2003] and NIELSEN and LANDAUER [1993] who estimate that a test subject sample sizes greater than 20 are sufficient for high certainty outcomes. Additionally a test subject sample size equal or greater than 30 fullfills the Central Limit Theorem, as the sampling distribution of the mean approaches a normal distribution [ROSENBLATT, 1956; KWAK and KIM, 2017]. All test subjects were informed about the objective of the simulator study. Test subjects were instructed to behave as they would in real traffic. They were also explicitly informed about the bicycle simulator setup capabilities of detecting gesture and communication behavior. At the beginning of the simulator study, the test subjects are asked to cycle a test track in the simulated environment to familiarize themselves with the simulator. At the end of the simulator test, all test subjects completed an online questionnaire, where they also evaluated the experimental study. Among other questions, test subjects evaluated how "immersive" or "realistic" various aspects of the simulator were. Results are presented in Figure 3.2.

Most of the test subjects evaluated different aspects of the bicycle simulator as “completely” to “somewhat” immersive/realistic. Negative evaluations of the bicycle simulator immersiveness remain under 26% for all the evaluated aspects. The overall simulation was assessed as "very" immersive/realistic by 53% of the test subjects. Results suggest that most of the test subjects are confident that the bicycle simulator can simulate traffic situations at a high level of realism and that the test subjects felt immersed in the simulation during the study. All test subject behavior data are treated equivalently in the further steps of this research, regardless of the respective individual test subject simulator evaluation.

The lateral and longitudinal coordinates, speed and front wheel angle of the test subjects, lateral and longitudinal coordinates, speed and driving angle of the simulated motor vehicles are recorded with a 0.1s resolution from SUMO. The lateral and longitudinal coordinates and angles are transformed and projected into a new singular coordinate system. The explicit

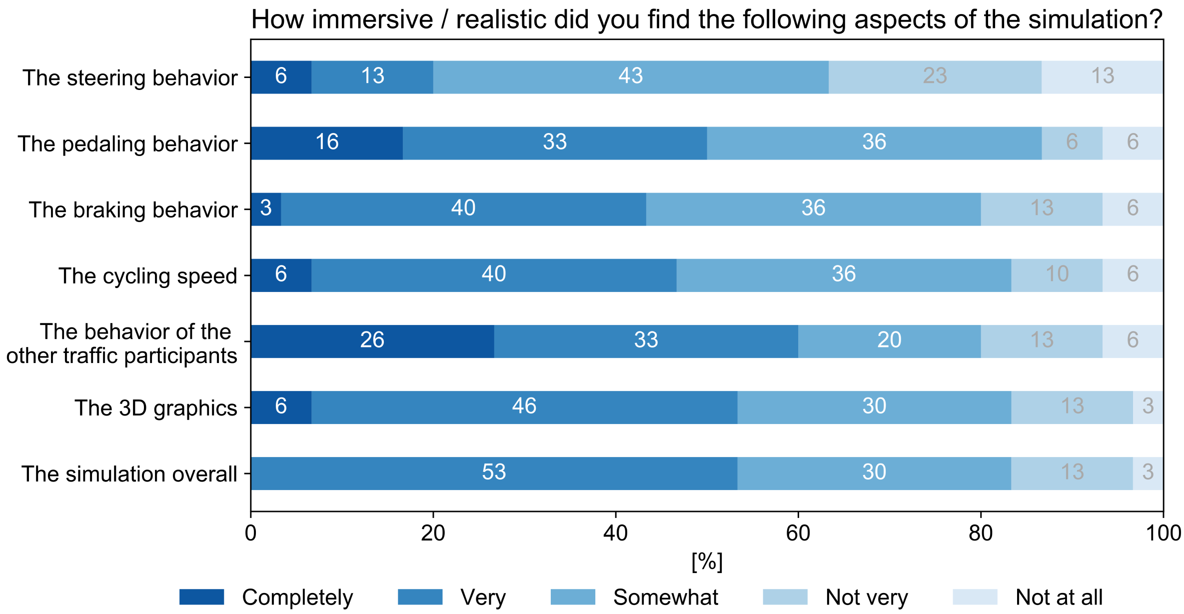


Figure 3.2: Evaluation of the bicycle simulator immersiveness by the test subjects [Malcolm et al., 2021].

and implicit communication cues of the test subjects are recorded in parallel using the depth camera. With respect to the skeleton detection of the test subjects, the right and left arm longitudinal and lateral angles, the right and left elbow angles, the shoulder twist angle and the body lateral and longitudinal angles are processed and extracted as independent skeleton joint angle metrics. With respect to the head movement, the head yaw angle is extracted via helmet marker detection. A total of 411 implicit ($n = 357$, 86.9%) and explicit ($n = 54$, 13.1%) gestures are detected using the k-means classifier for the hand gestures and body posture and threshold values for the head movement respectively. The explicit gesture classes include the left and right arm signal, and the implicit gesture classes include the left, right and left-over shoulder look and the forward, back, left and right body lean. In the driving maneuvers performed, explicit gestures with an average frequency of less than 2 gestures per test subject are given before turning maneuvers are carried out, however not all test subjects perform explicit gestures in the corresponding scenarios. Non-mutually exclusive implicit and explicit communication cues might also take place at the same time. In no case was an incorrect hand gesture (e.g. arm gesture during crossing maneuver, left arm gesture during right turn) performed. An average number of 5.2 implicit and/or explicit communication cues were performed by the test subjects in every scenario. The resulting driving data from SUMO, the extracted skeleton features and the implicit and explicit communication cues are merged into a single dataset using the respective timestamps. In a final processing step, all entries at 20m away from the respective intersection approach stop line and immediately after the stop line are filtered out in line with the purposes of the prediction. A total of 154 (46% left turns, 16% right turns and 38% crossing maneuvers) distinct sequences are extracted and can be used for the model building process.

A more extended and detailed analysis of the bicyclist implicit and explicit communication behavior as part of the bicycle simulator study is part of a joint publication [Malcolm et al., 2021].

3.5 Prediction of the Bicyclist Maneuver Intention at Unsignalized Traffic Intersections

3.5.1 Model Architecture Design

The bicycle simulator study dataset is used to develop, train and validate a model for the prediction of the type of maneuver a bicyclist intends to perform at an unsignalized four-arm intersection and explore the potential of using the additional information coming from the implicit and explicit communication behavior alongside the detected dynamic and operational bicyclist behavior. Every bicyclist exhibits a unique set of behavioral patterns in traffic scenarios. In addition, not all bicyclists use explicit communication cues to reveal their future behavior, however implicit communication cues may have the potential along with other data sources to hint the bicyclists' intent. The development of such a model may prove beneficial for the behavioral and motion planning layers of AVs and for avoiding deadlock situations where a passenger or a remote human controller may have to intervene. It can also improve traffic safety and control at intersections where computer vision-based technologies for traffic monitoring purposes are installed.

LSTM models have proven to be a robust approach for learning and generalizing properties of temporal sequential data and they have been extensively used in motion prediction und human action recognition applications [Benterki et al., 2020; Saleh et al., 2018; Viktor Kress et al., 2019; Xu et al., 2017]. LSTM is considered to be a superior type of RNN architecture capable of memorizing long-term dependencies [Hochreiter and Schmidhuber, 1997]. In contrast to the simple cell structure of RNNs, where information is conveyed over a single network layer, an LSTM cell contains four interacting layers, the cell state layer c_t, the forget gate layer f_t, the input gate layer, with the i_t ($sigmoid$) and $\tilde{c}_t$ ($tanh$) subgates, and the output gate layer o_t. The cell state conveys information across all the cells of the LSTM layer. The three gate layers or gates are responsible for controlling the cell state in each cell. The gates decide which information to pass forward to the next LSTM cells (important information) and which information must be dropped (not important information). The gates are composed of $sigmoid$ and $tanh$ activation layers for regulating the information inflow and outflow.

Figure 3.3 presents the LSTM architecture based on the work of Hochreiter and Schmidhuber [1997].

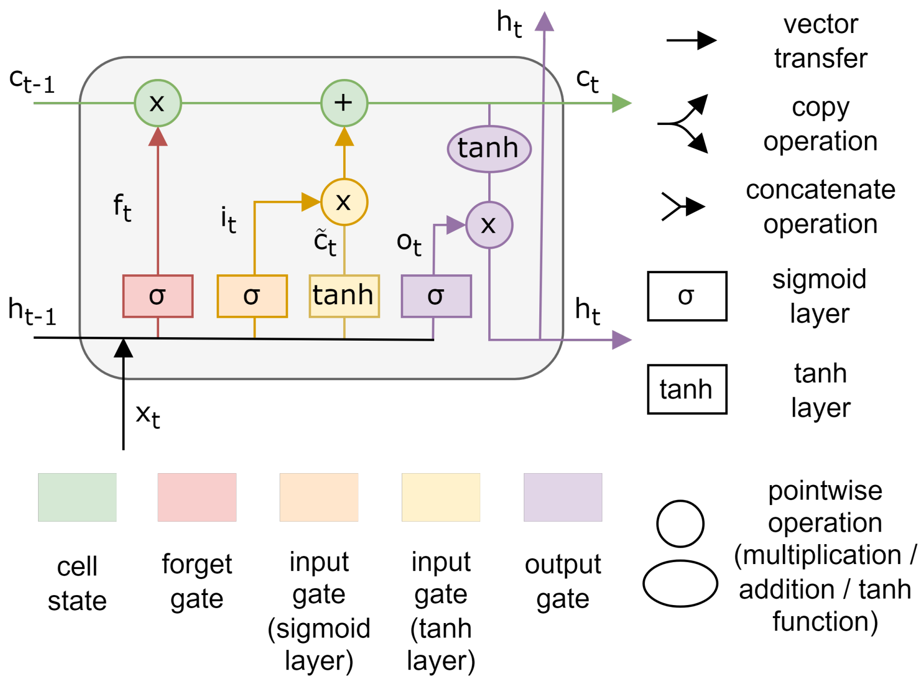


Figure 3.3: The LSTM architecture adapted from Olah [2015].

The respective *sigmoid* and *tanh* activation functions are presented in equations 3.1 and 3.2.

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{3.1}$$

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} = \frac{1-e^{-2x}}{1+e^{-2x}} \tag{3.2}$$

Equations 3.3–3.8 are based on Hochreiter and Schmidhuber [1997], Olah [2015], and Graves [2013] and describe the operation of the LSTM cell in the hidden layers as defined by the LSTM architecture in Figure 3.3 for each input time step t.

For a given LSTM cell, its cell state c_t and output h_t are determined as a function of the previous hidden state output h_{t-1}, previous cell state c_{t-1} and input x_t by the sequence of the following operations.

First, the previous hidden state output h_{t-1} and current input x_t are processed by the forget gate layer f_t using a *sigmoid* neural layer that decides which input information is irrelevant and does not need to be considered for the current (new) cell state c_t. Equation 3.3 defines the output of the forget gate, where W_{xf} and W_{hf} are the respective weight matrices for the given states and b_f is the variable bias vector.

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \tag{3.3}$$

In a second step, the input gate (see Figure 3.3) determines which information from the previous hidden state output h_{t-1} and current input x_t is important for the current cell state c_t. The input gate consists of two sub-gates that perform different functions, i_t ($sigmoid$)

and $\widetilde{c}_t$ $(tanh)$. First the i_t gate defines how much new information from previous hidden state output h_{t-1} and current input x_t will be passed to the new cell state. Secondly, the hidden state output h_{t-1} and current input x_t are passed through the $tanh$ function to determine which candidate values will be added to the new state cell state c_t by creating the new vector $\widetilde{c}_t$. Equations 3.4 and 3.5 define output functions of the two sub-gates i_t and $\widetilde{c}_t$ that form the input gate, where W_{xi}, W_{hi}, W_{xc} and W_{hc} are the respective weight matrices for the given states and b_i and b_c the respective bias vectors.

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + b_i\right) \tag{3.4}$$

$$\widetilde{c}_t = tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right) \tag{3.5}$$

The current cell state c_t is then composed by dropping the not important information from the previous cell state c_{t-1} using the forget gate output c_t and adding the most important information as determined by the input gate through the i_t and $\widetilde{c}_t$ outputs (Equation 3.6).

$$c_t = f_t c_{t-1} + i_t \widetilde{c}_t \tag{3.6}$$

The previous two steps are performed for updating the current cell state c_t. The current hidden state output h_t of the LSTM cell is finally determined by combining the output from the output gate o_t with a filtered version of the current cell state c_t. The output gate decides which information may be passed directly forward to the hidden state h_t from the previous h_{t-1} and current input x_t using a $sigmoid$ function. Equation 3.7 defines the output gate o_t, where W_{xo} and W_{ho} are the respective weight matrices for the given state vectors and b_i and b_c the respective bias vectors.

$$o_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + b_o\right) \tag{3.7}$$

Finally, the current cell state c_t is passed through a $tanh$ function and is combined with the output gate o_t to define the final current hidden state output h_t of the LSTM cell ((Equation 3.8). The current hidden state output h_t is passed forward together with the current cell state c_t to the subsequent LSTM cell (t+1). Additionally, the hidden state output h_t is passed to the subsequent neural network layer.

$$h_t = o_t tanh\left(c_t\right) \tag{3.8}$$

In conventional LSTMs, also known as Unidirectional Long Short Term Memory Networks (U-LSTMs), information is processed only in the forward direction. B-LSTMs are a variation of U-LSTMs that can process information in positive and negative time directions and are thus more capable in understanding their input information [Schuster and Paliwal, 1997].

Based on the conclusions of previous research, the model is developed using stacked B-LSTM layers for the advantages it provides over stacked unidirectional LSTM and taking advantage of the long-term memory, an inherent weakness of RNN layers. However, in the context of this research work, additional versions of the proposed architecture with unidirectional and bidirectional layers and different types of neural network layers (LSTM,Gated Recurrent Unit (GRU),RNN) will be assessed. This investigation is performed in order to identify whether the use of bidirectional neuron layers provides an increased performance over a unidirectional approach. Additionally, GRUs are a more recent and simplified version of LSTMs that may possibly provide better results compared to the latter. Simple RNN layers are also used primarily to assess the importance of long-term correlations in the bicyclist behavior data.

The novel neural network is built using TensorFlow [M. Abadi et al., 2016]. All tested versions of the model based on unidirectional and bidirectional versions of the LSTM, GRU and RNN layers use the respective default classes defined by the TensorFlow Keras layers API. Scikit-learn [Varoquaux et al., 2015] is used for supporting operations.

3.5.2 Data Preprocessing and Feature Selection

The input to the model is the sequential positional bicyclist data and speed, the sequential skeleton joint metrics derived from the skeleton detection, the explicit arm gestures, the head movement and the body pose of the bicyclists. As the dataset consists of differently scaled features, one hot encoding is applied on all categorical features and min-max normalization on the continuous features to improve the training process efficiency of the model. The features used for training and the output classes are described in Table 3.2.

Table 3.2: Input features (dependent variable) and output (independent variable).

Input variable	**Feature type**	**Feature class**
X (m)	Continuous	Dynamic
Y (m)	Continuous	Dynamic
Speed (m/s)	Continuous	Dynamic
left hand gesture (-)	Boolean	Gesture archetype (explicit)
right hand gesture (-)	Boolean	Gesture archetype (explicit)
left look (-)	Boolean	Gesture archetype (implicit)
left overshoulder (-)	Boolean	Gesture archetype (implicit)
right look (-)	Boolean	Gesture archetype (implicit)
back lean (-)	Boolean	Gesture archetype (implicit)
forward lean (-)	Boolean	Gesture archetype (implicit)
left lean (-)	Boolean	Gesture archetype (implicit)
right lean (-)	Boolean	Gesture archetype (implicit)
lateral left arm angle (°)	Continuous	Skeleton joint metric
longitudinal left arm angle (°)	Continuous	Skeleton joint metric
left elbow angle (°)	Continuous	Skeleton joint metric
lateral right arm angle (°)	Continuous	Skeleton joint metric
longitudinal right arm angle (°)	Continuous	Skeleton joint metric
right elbow angle (°)	Continuous	Skeleton joint metric
shoulder twist angle (°)	Continuous	Skeleton joint metric
head yaw angle (°)	Continuous	Skeleton joint metric
lateral body angle (°)	Continuous	Skeleton joint metric
longitudinal body angle (°)	Continuous	Skeleton joint metric
Output variable	**Type**	**Output class**
Left turn	Boolean (One-Hot encoding)	Maneuver archetype
Right turn	Boolean (One-Hot encoding)	Maneuver archetype
Straight	Boolean (One-Hot encoding)	Maneuver archetype

Additionally, as different sets of features are available for training, the effect that the use of these different features can have on the prediction performance is investigated. Most similar approaches found in the literature use only dynamic data for the prediction task, while a few also incorporate pose detection data. However, no analysis is performed that investigates the added value that the inclusion of pose detection can have on the prediction performance. Therefore, the performance of alternative versions of the proposed model are investigated, where along with the bicyclist dynamic data, either the descriptive classes (archetypes) of explicit and implicit communication or only the skeleton joint metrics are used as features. A final test case is also investigated where only the pre-classified skeleton poses and the skeleton joint metrics are used to predict the maneuver type. These comparisons are performed in order to assess the added value that the bicyclist skeleton joint metrics and the pre-classified explicit and implicit communication cues provide towards performance. Finally, the added value of the pre-classification of explicit and implicit communication archetypes over the use of skeleton joint angle values as descriptive features for the bicyclist explicit and implicit communication behavior is also assessed. The five test cases are listed in Table 3.3.

Table 3.3: Model Training and Testing Feature Group Cases.

Case Number	**Case Name**	**Features Combination Description**	**Number of Features**
1	Bike Positions + Speed	Bike XY coordinates, bike speed (Base comparison scenario)	3
2	All Features	Bike XY coordinates and bike speed, pre-classified body posture archetypes, hand gesture archetypes, head direction archetypes, skeleton joint angles	22
3	Bike Positions + Speed + Skeleton Joint Metrics	Bike XY coordinates, bike speed, skeleton joint angles	13
4	Bike Positions + Speed + Classified Skeleton Poses	Bike XY coordinates, bike speed, pre-classified body posture archetypes, hand gesture archetypes, head direction archetypes	12
5	Classified Skeleton Poses + Skeleton Joint Metrics	Pre-classified body posture archetypes, hand gesture archetypes, head direction archetypes, skeleton joint angles	19

3.5.3 Training, Validation and Model Architecture Selection

The training dataset is split into $k = 5$ equal subsets using stratified k-fold cross validation. We then proceed on training and validating our model using the k-fold samples. First, we need to investigate and determine the optimal model architecture and hyperparameter values. Due to the different sets of features used in the different test cases the optimal network architecture and hyperparameter values may vary depending on the input features. Thus, the optimal model settings for all cases are separately investigated

Different model architectures are tested, where starting from one and up to four B-LSTM layers are progressively stacked together to determine the optimal network architecture. A fully connected layer follows the B-LSTM layers and outputs the prediction probabilities for our multi-class classification problem. One downside when designing and training LSTM networks is the required fixed shape and size of the data input which must be defined in advance and remains constant during training and prediction. It is found that the optimal batch size is 128. Dropout [Mele and Altarelli, 1993] is used as the regularization strategy and the position of dropout layers and dropout probability value are investigated. It is found that the optimal performance is achieved by inserting a dropout layer between each set of two consequent neural network layers. The optimal dropout probability value is 0.5. With respect to activation functions, the default $sigmoid$ and $tanh$ for the B-LSTM layers and the $softmax$ function for the fully connected layer, that converts the output into a probability distribution are utilized as it is appropriate for multi class classification tasks. The Adam optimizer with a learning rate of 0.0005 is used for training the model and updating model weights, as during training it produced better performance in comparison to the Stochastic Gradient Descent (SGD) optimizer that was also tested.

Finally, categorical cross entropy is the optimal loss function for classification task. The network architecture with the best performance for test cases 1,4,5 is presented in Figure 3.2. For test cases 2: All Features and 3: Bike Positions + Speed + Skeleton Joint Metrics the best prediction results are produced using 512 (2x256) instead of 256 (2x128) units in theB-LSTM layers. This is attributed to the increased data complexity resulting from the inclusion of the raw skeletal joint metrics in the feature set. All other hyperparameters and network architecture were found to remain identical to the rest test cases.

In order to assess the model performance and select the optimal model architecture, appropriate evaluation metrics have to be used. in the context of the given model case *Accuracy* (Equation 3.9) assesses the ability of the model to classify the validation sample maneuvers correctly and is the ratio of correctly classified maneuvers (both true positives and true negatives) to all predicted maneuvers. *Precision* (Equation 3.10) is the ability of the model to correctly classify a specific bicyclist maneuver in a class over all classified bicyclist maneuvers of that same class. On the other hand, *Recall* (Equation 3.11) is the share of correctly classified bicyclist maneuvers of a specific class out of all bicyclist maneuvers actually belonging in that same class.

Thus, *Precision* is the preferred performance metric when the costs of false positives is high, whereas *Recall* is the preferred performance metric when the cost of false negatives is high. The *f1-score* (Equation 3.12) is a measure of relative performance between *Precision* and *Recall* that summarizes the two performance measures into a single metric. It is computed using the harmonic mean of *Precision* and *Recall*, which means that the *f1-score* weighs more lower values and therefore can be used as the single performance metric as both the cost of false positives and false negatives is equally high for this classification task. Thus, the model evaluation will be based on the *f1-score* and the *Accuracy* score metric.

$$accuracy = \frac{Tp + Tn}{Tp + Tn + fp + fn} \tag{3.9}$$

$$precision = \frac{Tp}{Tp + fp} \tag{3.10}$$

$$recall = \frac{Tp}{Tp + fn} \tag{3.11}$$

$$f1 - score = \frac{2 * precision * recall}{precision + recall} = \frac{2 * Tp}{2 * Tp + fp + fn} \tag{3.12}$$

where:

y_i = The true value of the i-th test sample.

$\widehat{y}_i$ = The predicted value of the i-th test sample.

Tp = The sum of correctly classified (predicted) test instances $\widehat{y}_i$ in a maneuver type.

Tn = The sum of classified (predicted) test instances not belonging to a maneuver type that are correctly classified.

fp = The sum of incorrectly classified (predicted) test instances $\widehat{y}_i$ in a maneuver type.

fn = The sum of classified (predicted) test instances belonging to a maneuver type that are incorrectly classified.

3.5.4 Uncertainty Estimation Methods in Deep Learning

Machine learning models will always provide a prediction independently of the quality of the provided input data. Thus, the proposed model will always consider the maneuver with the highest prediction probability as the "True" predicted maneuver. If a correlation with a human were established, in any given prediction task a human would always be able to provide a prediction output together with a self-defined subjective level of certainty for the provided prediction. The quantification of prediction uncertainty and the utilization of uncertainty assessment metrics for deep learning models is part of present research primarily in the scientific fields of image classification, Natural Language Processing (NLP) and computer vision for medical applications [Abdar et al., 2021]. One exception is the work of Hoel et al. [2020], who integrated uncertainty in AV decision making through a bayesian reinforcement learning method. Simulation results in SUMO showed that trained agent can quantify the uncertainty of its decisions and identify unacceptable actions. Also the trained agent outperformed the agent trained with a standard reinforcement learning method (Deep Q-Network).

In the proposed bicyclist maneuver prediction model, problems with the input data might include unseen bicyclist behavior during model training, the absence of bicyclist behavior input data due to external factors limiting the detection or contradicting bicyclist behavior (e.g. raising the left arm indicating a left turn but moving straight or turning right). In an ideal scenario when it comes to model uncertainty, the probability difference among classes might be small, indicating high uncertainty. However, an evaluation metric or threshold is still required to assess the prediction certainty. Deep learning tools are not able to capture and quantify model uncertainty on their own [Gal and Ghahramani, 2016].

Different methods have been proposed in order to assess the uncertainty for prediction tasks in deep learning applications. Monte Carlo Dropout (MC Dropout) is a regularization method that approximates training a large number of neural networks with different architectures in parallel. The key idea is to randomly drop units (along with their connections) from the neural network during training. This prevents units from co-adapting excessively on the training data [Mele and Altarelli, 1993]. In MC Dropout, dropout is used as a Bayesian Approximation. The neural network with arbitrary depth and non-linearities, with dropout applied before every layer, is mathematically equivalent to an approximation of a probabilistic deep Gaussian process [Damianou and Lawrence, 2013; Gal and Ghahramani, 2016]. Therefore, MC Dropout estimates the predictive mean and predictive uncertainty by collecting the results of N stochastic forward passes through the trained model.

In a second step, the prediction uncertainty for each bicyclist trajectory has to be quantified. The quantification of prediction uncertainty is part of current research, especially in the field of image classification and computer vision for medical applications. In the scientific literature, three metrics are primarily used to quantify forecast uncertainty of deep neural network models [Shadman Roodposhti et al., 2019; Zaragoza et al., 1998; Combalia et al., 2020]. The relative entropy or Kullback-Leibler Divergence (KL Divergence), quantifies the distance between two discrete probability distributions defined on the same probability space. This is the primary metric used in scientific literature for uncertainty quantification. The closer the distribution of probabilities P to a uniform distribution Q, the smaller the prediction confidence.

$$D_{\mathsf{KL}}(P \parallel Q) = \sum_{i=1}^{N} p_i \log\left(\frac{p_i}{q_i}\right) \tag{3.13}$$

The Bhattacharyya coefficient is a measure of the amount of overlap between two statistical samples or populations. It can be used to measure the separability of two classes in classification tasks.

$$BC(P \parallel Q) = \sum_{n=1}^{N} \sqrt{p_i q_i} \tag{3.14}$$

The prediction variance of the N predictions for each class, and the mean-variance of the probabilities over all prediction classes. The higher the variance of a class probability distribution p the higher the uncertainty.

$$\sigma^2\left(p_N\left(x\right)\right) = \frac{1}{N}\sum_{i=1}^{N}\left(p_i(x) - p_N\left(x\right)\right)^2 \tag{3.15}$$

The final proposed model architecture for the bicyclist maneuver prediction coupled with the application of MC Dropout at an intersection approach is presented in Figure 3.4.

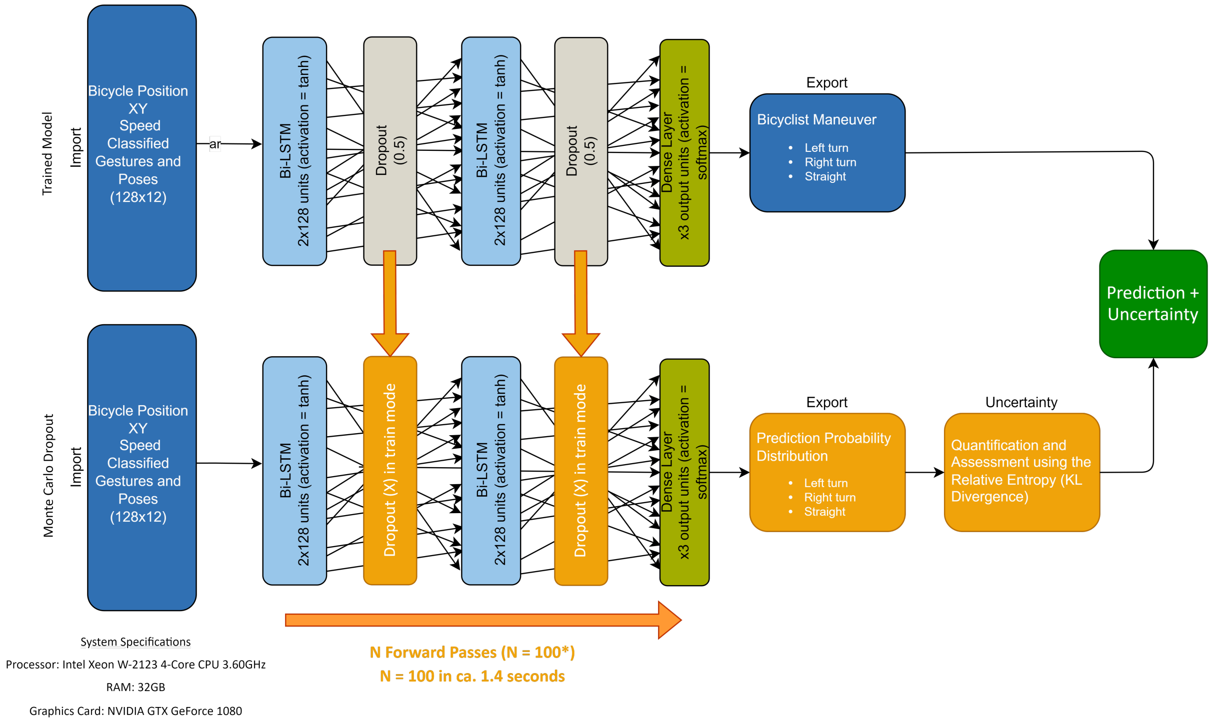


Figure 3.4: The Bidirectional LSTM model architecture coupled with the application of MC Dropout respectively for the bicyclist maneuver prediction and uncertainty evaluation of the estimated classification probabilities of the maneuver classes.

3.5.5 Model Performance Results

The best model results are achieved using feature group Case 4: Bike Positions + Speed + Classified Skeleton Poses combined with B-LSTMs. The results in Figure 3.5 present the comparison for all neural layer types evaluated only for Case 4: Bike Positions + Speed + Classified Skeleton Poses, as this feature combination produced the best prediction performance results. Here it is important to mention that Bidirectional Gated Recurrent Units (B-GRUs) almost reach the same performance as the B-LSTM model version. This is not a surprising outcome, as the GRUs is a newer and more simplified version of the LSTM. Additionally, the LSTM version significantly profits from the bidirectional information processing in comparison to the GRU version. The unidirectional GRU version significantly outperforms the unidirectional LSTM version, which exhibits comparable performance to the Bidirectional Recurrent Neural Networks (RNNs) version. In any case, it is also apparent that long-term memory networks are superior to the simple RNNs that suffer from the short-memory problem for the examined problem formulation.

Figure 3.6 shows the performance of all model cases using the average accuracy scores and f1-scores only for the case of B-LSTMs. As the f1-score penalizes false classifications based on the harmonic mean between model's precision and recall metrics, the f1-score values are smaller than the accuracy score values across all model cases. Results suggest that the best performance for the prediction of the bicyclist maneuver type is reached with Case 4:

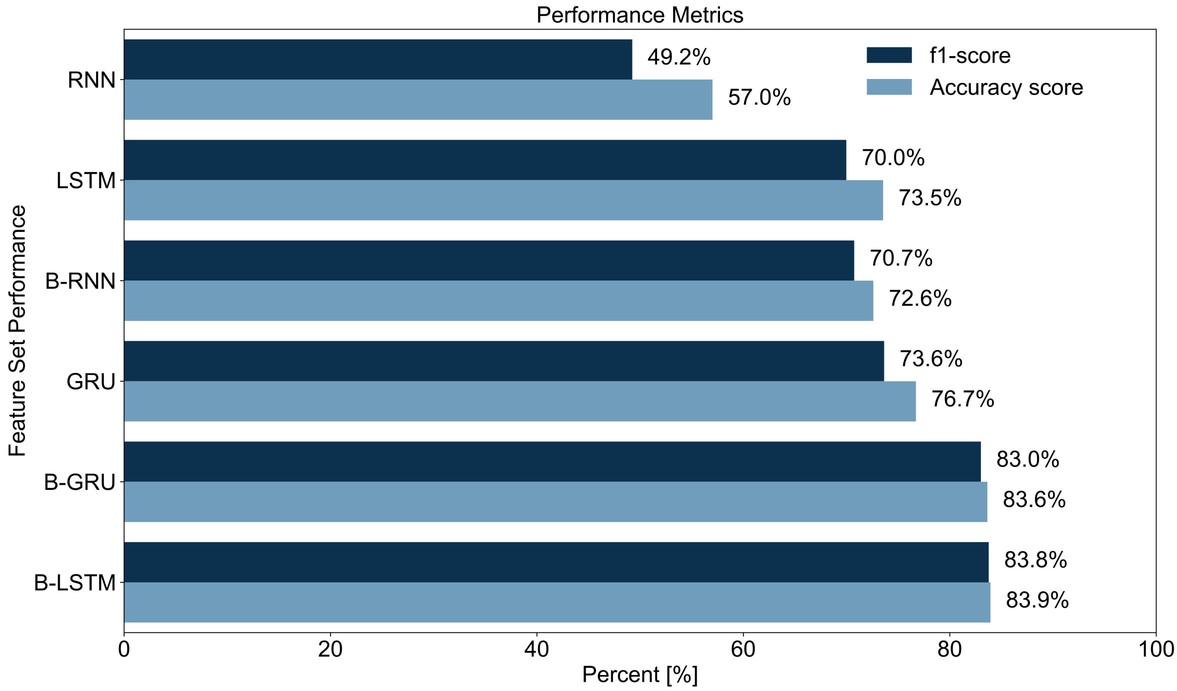


Figure 3.5: Average f1-scores and accuracy scores across all k-folds for all different neural network layer types for feature group case 4: Bike Positions + Speed + Classified Skeleton Poses.

Bike Positions + Speed + Classified Skeleton Poses (f1-score 83,8%). The result is also consistent and comparable with results from the scientific work presented in the literature review section, where comparable classification tasks are addressed. The fact that the f1-score is almost equal to the accuracy-score (83,9%) showcases that the number of fp type and fn type classifications across all maneuver types is almost the same. Case 1: Bike Positions + Speed performed the worst compared to all other cases (f1-score 56,7%), which illustrates the high added value that the inclusion of bicyclist pose information has in predicting the maneuver at the intersection approach. All model cases used exclusively data collected before the intersection stop line. Depending on the characteristics of future applications, it might be possible to increase the data collection window and include bicyclist data collected after the stop line. In such case it is expected that the additional bicyclist dynamic data collected will increase the performance for model Case 1 or even provide an equivalent performance compared to other model cases.

Case 5: Classified Skeleton Poses + Skeleton Joint Metrics also achieved a better performance over Case 1, which shows that scientific models developed for the bicyclist maneuver intention prediction should also rely on bicyclist pose detection data. Case 2: All Features had the second-best performance (f1-score 78.6%). This shows that the increased data complexity and the added noise coming from the inclusion of skeleton joint metrics in the feature set reduces the model performance as the model fails to generalize on the added information from the skeleton joint metrics, whereas only the inclusion of pre-classified archetypes of implicit and explicit communication behavior and skeleton poses reduces the data complexity and simplifies the classification task for the B-LSTM network.

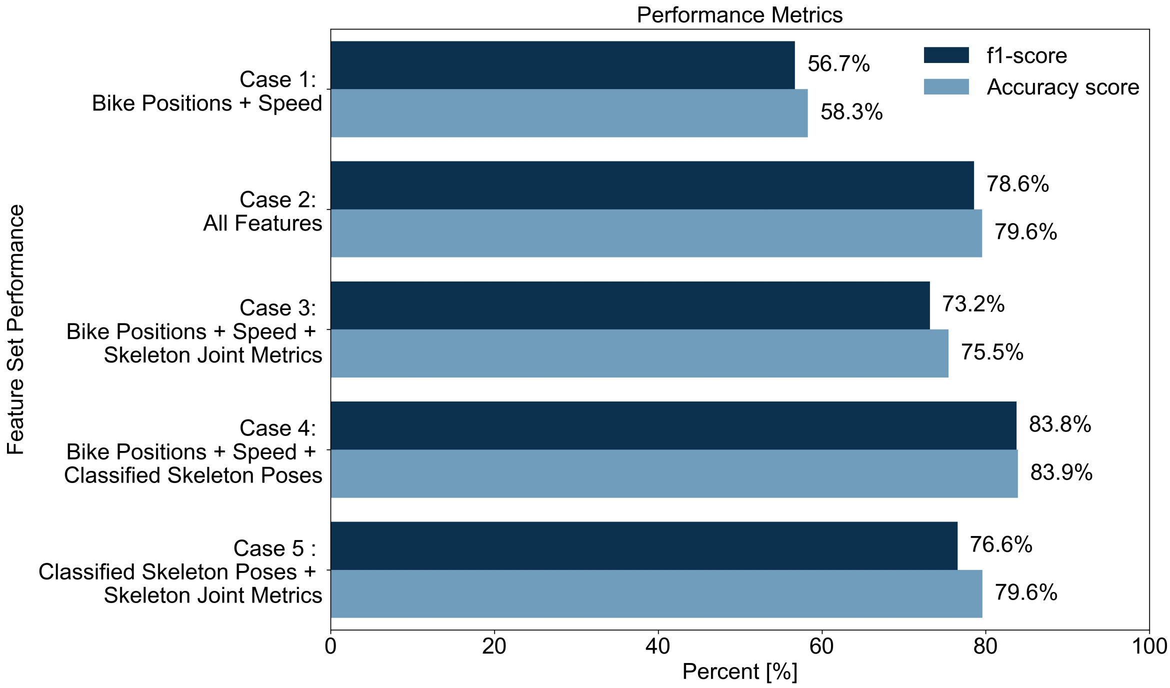


Figure 3.6: Average f1-scores and accuracy scores across all k-folds for all model cases.

Figure 3.7 presents the confusion matrices for all examined model cases. Model Case 4: Bike Positions + Speed + Classified Skeleton Poses demonstrates overall similar accuracy values (>82%) for all maneuver types for the classification task. Additionally, the model can differentiate between the two turn maneuver types with a high degree of accuracy, as 1.5% of left turns are incorrectly classified as right turns and 4.0% of right turns are classified as left turns. All other incorrectly classified left and right turn maneuvers are then classified as a straight maneuver (13.2% and 12% respectively). A similar pattern can be observed for straight maneuvers, as 13.8% of straight maneuvers are incorrectly classified as left turns in comparison to only 3.4% being classified incorrectly as right turns. Also, in Case 5, the accuracy results are similar to those in Case 4 for left turns and straight maneuvers, while the model performed very poorly in the classification of right turns, showing that added information from the bicyclist dynamic data is important for the prediction of bicyclist right turns. This statement is also supported by the fact that the classification accuracy of right turns in model Case 5 is higher than that of model Case 1, where only bicyclist dynamic data were used for the classification task. For all other maneuver types, model Case 1 had by far the worst performance compared to all model cases. Finally, model cases 2 and 3, where skeleton joint metrics are used alongside the bicyclist dynamic data, demonstrate the highest classification accuracy for left turns (91.2% and 94.1% respectively), however this is attributed to the fact that both model cases are susceptible to predicting left turns over right turns and straight maneuvers. This is also supported by the fact that 34.5% and 31% of straight maneuvers are incorrectly classified as left turns, while the same rate is only 13.8% for model Case 4.

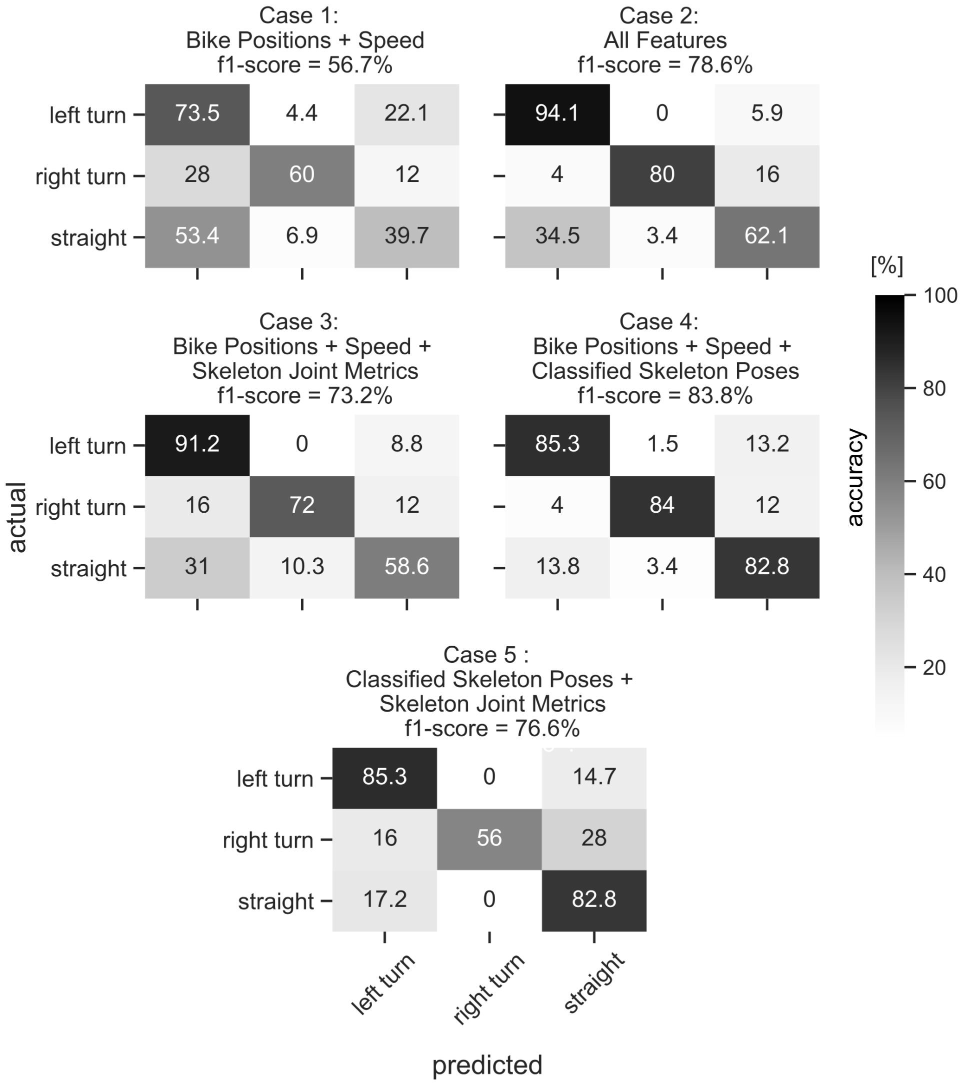


Figure 3.7: Confusion matrix results for all examined model cases. For each model case, the respective confusion matrix depicts the prediction accuracy (predicted maneuver, x-axis) for each maneuver class (actual maneuver, y-axis).

3.5.6 Uncertainty Quantification Results

This section presents a selection of results from the test dataset where MC Dropout was implemented in order to quantify model uncertainty. For this part only predictions for each test sample are compared to the true maneuver classes in an effort to better understand the behavior of the uncertainty quantification metrics and suggest possible approaches and thresholds for differentiating between certain and uncertain predictions. Therefore, three bicyclist trajectories are selected from the test dataset to demonstrate the implementation and usability of MC Dropout for quantifying the uncertainty of the bicyclist maneuver prediction task. In

Figure 3.8 and Figure 3.9, the respective examples present a bicyclist trajectory where the model predicted the bicyclist maneuver correctly. Figure 3.8 presents the case with high prediction confidence and Figure 3.9 presents the case with a lower prediction confidence but still sufficient to qualify for a high certainty. In Figure 3.10, the example is from an incorrect bicyclist maneuver prediction, where also the model confidence is low. The aim of the evaluation is to better understand and evaluate the implementation of the prediction uncertainty quantification procedure. The prediction probability and the corresponding metrics for quantifying the prediction uncertainty are presented for the entire duration of the trajectory acquisition (Step: 0-127). These metrics include the distribution of the prediction probabilities of the MC Dropout (N=100) forward passes through the neural network, the respective variance of the prediction probabilities for all maneuver classes, the respective results for the Bhattacharyya coefficient and the relative entropy.

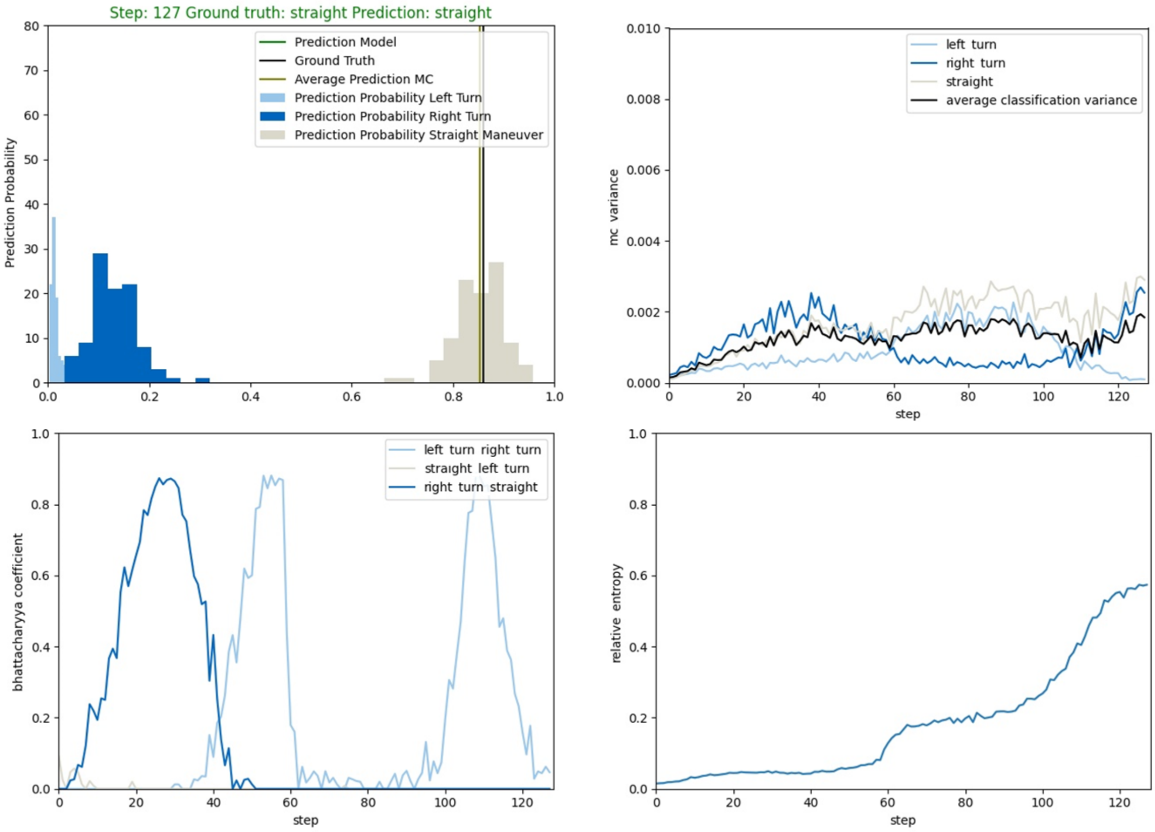


Figure 3.8: Example: Correct model prediction with increasing prediction confidence for the three maneuver classes Left Turn, Right Turn, Straight. (Top left: Distribution of prediction confidence across all maneuver classes, Bottom Left: Results of quantifying prediction uncertainty using the Bhattacharyya coefficient, Top Right: Results of quantifying prediction uncertainty using the prediction probability variance, Bottom Right: Results of quantifying prediction uncertainty using relative entropy).

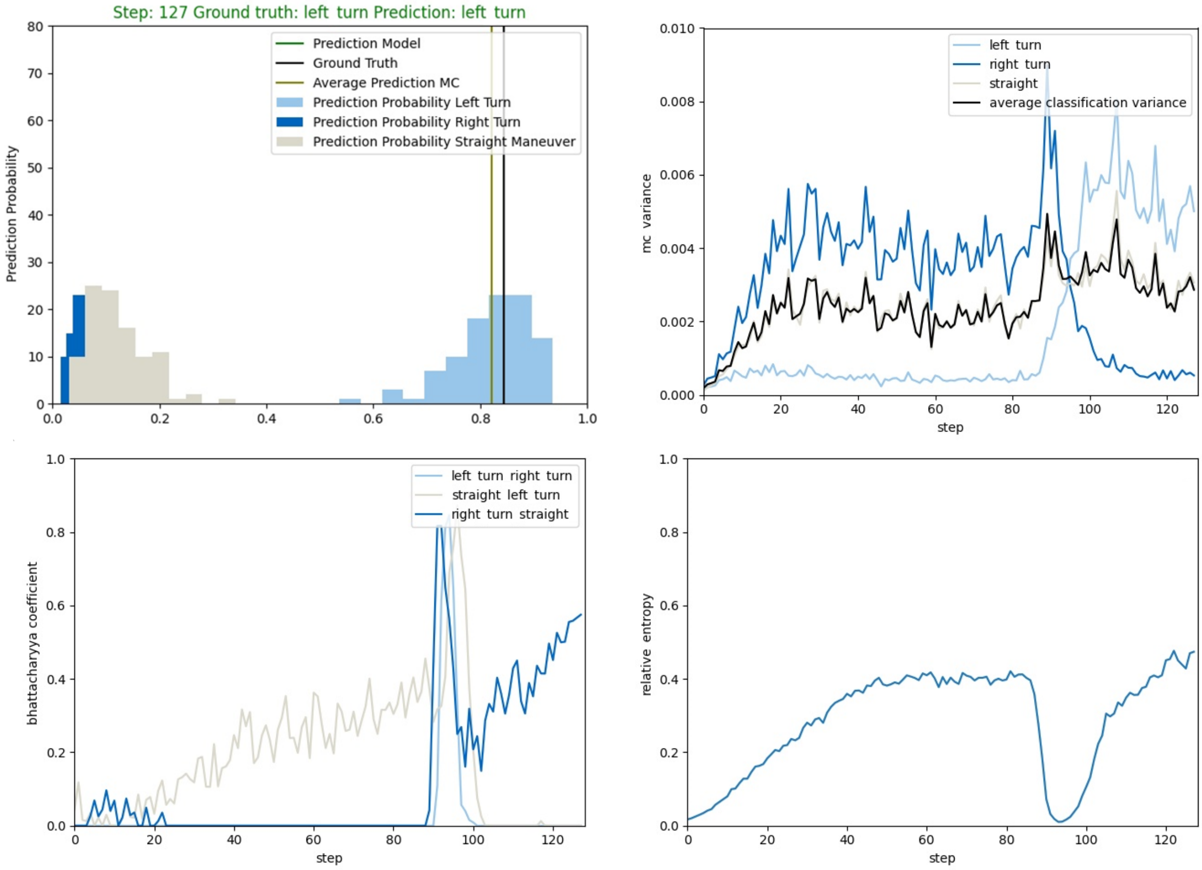


Figure 3.9: Example: Correct model prediction with low prediction confidence for the three maneuver classes Left Turn, Right Turn, Straight. (Top left: Distribution of prediction confidence across all maneuver classes, Bottom Left: Results of quantifying prediction uncertainty using the Bhattacharyya coefficient, Top Right: Results of quantifying prediction uncertainty using the prediction probability variance, Bottom Right: Results of quantifying prediction uncertainty using relative entropy).

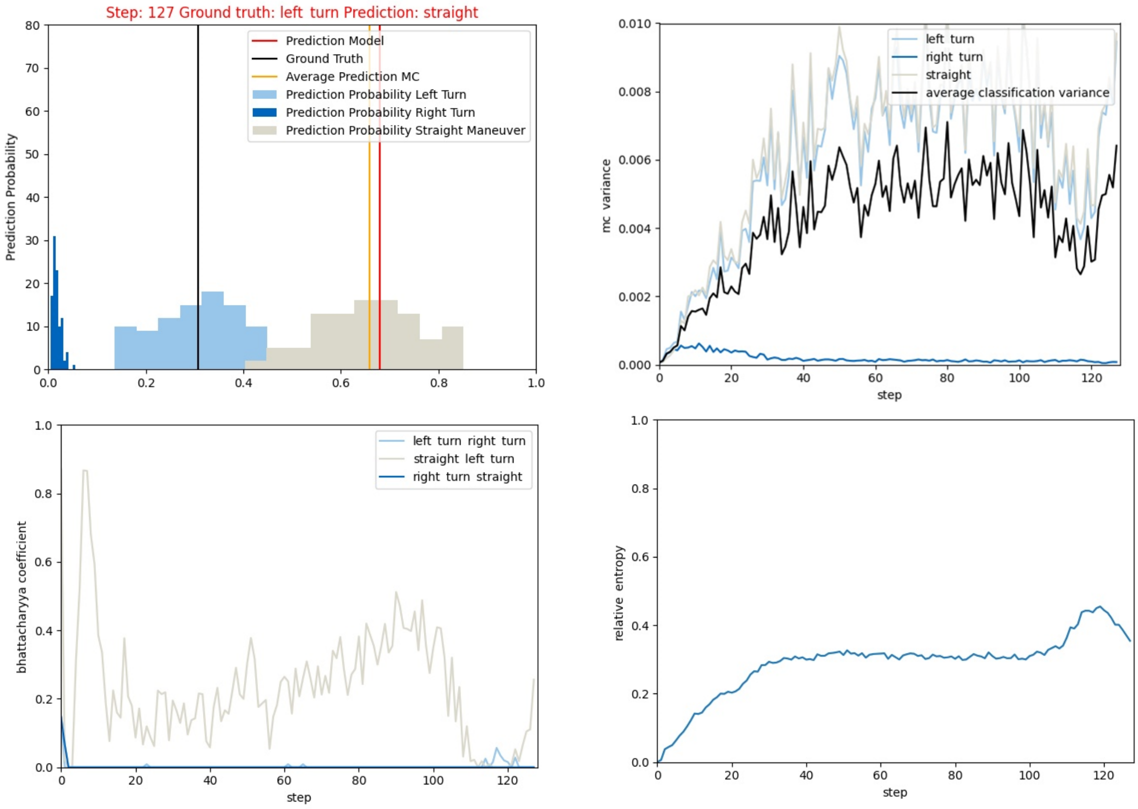


Figure 3.10: Example: Incorrect model prediction with low prediction confidence for the three maneuver classes Left Turn, Right Turn, Straight. (Top left: Distribution of prediction confidence across all maneuver classes, Bottom Left: Results of quantifying prediction uncertainty using the Bhattacharyya coefficient, Top Right: Results of quantifying prediction uncertainty using the prediction probability variance, Bottom Right: Results of quantifying prediction uncertainty using relative entropy).

The comparison of the results among Figure 3.8, Figure 3.9, and Figure 3.10 suggests that high prediction uncertainty is linked to higher values of variance and relative entropy. Both the average variance and relative entropy provide a meaningful quantification and assessment of the model's predictive uncertainty. The variance evaluation of the different maneuver classes can additionally be used to evaluate the predictive uncertainty for the final prediction. Additionally, the Bhattacharyya coefficient offers the option to compare the probability distributions of two prediction classes and to evaluate their overlap. Thus, it becomes possible to conclude or exclude certain maneuver classes through the Law of Non-Contradiction (LNC). For example, examining the Bhattacharyya coefficient values together with the variance of the prediction confidence in Figure 3.10, it can be concluded that despite the high model uncertainty, the right turn maneuver can be safely excluded as a possible prediction class, due to the small overlap among the respective distributions and the small Bhattacharyya coefficient and variance values.

The combined assessment of the individual uncertainty quantification metrics has therefore the potential to further improve the usability of the predictions for the respective maneuver classes especially when the respective predictions are used from the AV for adapting its driving behavior in response to the intentions of bicyclists. The exclusion of certain maneuver classes has the potential to further increase the efficiency of AVs as well as the traffic safety during AV and bicycle interactions. For example, in a scenario where a right turn bicyclist maneuver is excluded as a probable maneuver intention, AVs approaching the intersection from the opposite direction might still drive with a slower speed in anticipation of a probable crossing left turn maneuver.

Subsequently, the question of how to determine the threshold between a "certain" and an "uncertain" prediction arises. Based on the results of the uncertainty quantification in the test dataset, a statistical analysis is performed and the samples of the corresponding metrics for correct and incorrect classification are evaluated for each test trajectory. The results are presented in Figure 3.11. The analysis shows differences in the distributions of both the relative entropy and the average variance values between the "correct" and "incorrect" classified test samples. From the analysis, it can be observed that even correct predictions can be classified as "uncertain". Accordingly, by quantifying the prediction uncertainty, the quality of the model for bicyclist maneuver prediction increases. Thus, it is possible to define threshold values for both metrics for differentiating among "high certainty" and "low certainty" predictions. However, the application of such thresholds should still remain an area of future research and dependent on the criticality of the respective prediction in a case by case assessment.

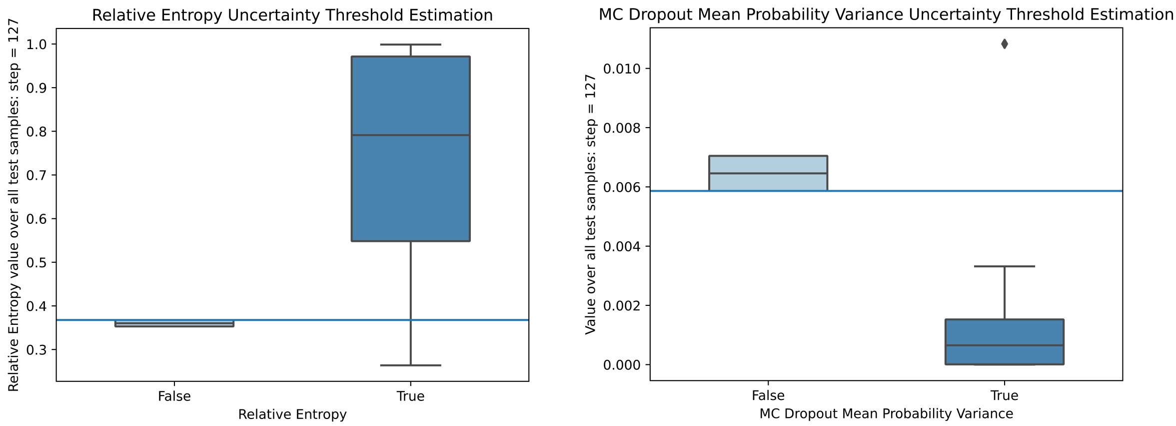


Figure 3.11: Determination of the limits for the evaluation of the confidence of the model prediction. The blue line represents a possible boundary of the prediction uncertainty depending on the corresponding minimum (Variance) and maximum (Relative Entropy) value of "incorrect" predictions.

3.5.7 Discussion

A bicycle simulator is used to study the behavior of bicyclists and to collect data for developing a B-LSTM model that predicts the bicyclist intended maneuver type before an intersection approach. First the bicyclist dynamic behavior and the explicit and implicit communication behavior is recorded. Features describing the bicyclist behavior are extracted and associated with the respective maneuver types. A deep learning model based on B-LSTM is trained on behavioral data from the bicycle simulator dataset. The performance of the proposed model architecture is evaluated using different sets of descriptive features. Five different model cases are investigated in order to identify the optimal input feature set and evaluate the added value from the inclusion of the bicyclist explicit and implicit communication behavioral data in the classification task. A maximum average f1-score value of 83.8% is reached with Model Case 4: Bike Positions + Speed + Classified Skeleton Poses, where preclassified archetypes of implicit and explicit communication behavior are used together with the bicyclist dynamic behavior data for the maneuver type prediction. The result is also comparable to other research found in the scientific literature in the field of human action classification and prediction in traffic environments. In comparison to the relatively poor performance of the Model Case 1: Bike Positions + Speed, where only bicyclist dynamic data are used, the results of the present research illustrate the importance of the inclusion of bicyclist body pose information in the development of predictive approaches for bicyclist behavior. Also the preclassification of bicyclist body poses has the potential to further improve model performance as the input data complexity is reduced. Possible application areas of the proposed model may include, but are not limited to, the expansion and support of existing models and functions in the field of automated driving and the improvement of traffic efficiency and safety through real-time monitoring and forecasting of bicyclist behavior at traffic intersections.

The deep learning model is developed using data from bicycle simulator studies. Overall, most test subjects evaluated the bicycle simulator positively. The biggest advantages of the experimental setup are the increased safety in contrast to real world experiments, the reduced cost in comparison to real traffic experiments and observations and that all test subjects experienced the same traffic situations with no other environmental factors affecting the scenario evolution over time other than the individual test subject's behavior. The model performance results are also comparable to the results of similar approaches found in the literature in the field of road user behavior prediction and classification that were trained on both naturalistic and simulated data. Future work may focus on expanding the simulator dataset with naturalistic data gathered in real traffic conditions or at test sites and investigating potential of the inclusion of simulator data in the methodological approaches for designing, training and testing of models in the fields of automated driving and human behavior prediction.

Finally, in the scope of this dissertation, the proposed model for the bicyclist maneuver prediction coupled with the mechanism for the uncertainty quantification and assessment can be used as a critical function that supports the development of an optimization method for resolving AV and bicyclist interactions at unsignalized intersections and adresses research questions 1 and 2 as they were defined in section 1.2. The proposed model can reveal the intended maneuver of a bicyclist before entering the intersection area with a measure for the prediction confidence. This information is not only valuable for motion planning and for adjusting the driving behavior of individual AVs but also for coordinating and optimizing the AV and bicyclist traffic flow at unsignalized intersections and resolving their interactions on the system level.

Chapter 4

Optimization of AV and Bicyclist Interactions at Unsignalized Intersections

4.1 Overview

As the share of bicycle traffic grows rapidly in urban networks, novel methods for resolving interactions among AVs and bicyclists in mixed traffic need to be developed. It can be expected that a significant number of such interactions will take place at unsignalized intersections in urban areas. In signalized intersections, only acceptable or conditionally acceptable traffic streams are served during each phase and therefore conflicts among traffic streams are efficiently regulated and resolved. However, in unsignalized intersections road users are individually responsible for following traffic priority rules, which, in turn, may lead to more complex and safety critical interactions. In this context, present research on intelligent traffic control focuses primarily on leveraging the potential of the introduction of AVs in traffic, through the exploitation of vehicle integrated sensor and communication technologies, for controlling the conflicting traffic streams not on the traffic stream level as the case is currently with HRUs but rather on the road user level through scheduling and controlling the vehicle driving paths at the intersection area. These approaches mostly assume full communication and cooperation among the AVs and full compliance with the control actions.

Apart from some exceptions [Niels, Mitrovic, Bogenberger, et al., 2019; Niels, Mitrovic, Dobrota, et al., 2020; Niels, Bogenberger, et al., 2020] most research primarily focuses on AV intersection control and assumes no mixed traffic or interactions with VRUs. With respect to VRUs (bicyclists and pedestrians) Niels, Mitrovic, Bogenberger, et al. [2019], Niels, Mitrovic, Dobrota, et al. [2020], and Niels, Bogenberger, et al. [2020] consider signalized intersections, where still the VRU traffic streams make use of dedicated signal controllers, signal phases and infrastructure. However, bicyclists in urban areas often travel in mixed traffic sections with motorized vehicles, where no bicycle infrastructure is present. In contrast to an AV, their driving intentions are mostly unpredictable, unless explicitly communicated. In Chapter 3, a deep learning model for predicting the maneuver intention of a bicyclist at an intersection approach is proposed. Additionally, a method for self-quantifying the prediction uncertainty is incorporated within the model architecture. This adresses the requirements for the developement of a method for resolving the interactions among bicyclists and AVs as described in the research questions 1 and 2 (section 1.2). Given that the bicyclist maneuver intention is coupled with an uncertainty measure, it is possible, in a further step, to exploit this information for optimizing the traffic interactions of AVs and bicycle traffic at unsignalized intersections. The proposed model can thus be integrated into a method for resolving the interactions among bicyclists and AVs through cooperation (research question 3 section 1.2), while optimizing mixed traffic flow at an unsignalized intersection (research question 4 section 1.2). Such a method has the potential to improve traffic performance and contribute to the acceptance and seamless integration of AVs in urban traffic.

In contrast to signalized approaches, where a protected phase for VRUs is provided, in the case of mixed traffic flow and unsignalized intersection control, bicyclists have to adhere to certain traffic rules, exhibit different riding behaviors and are limited by their competences due to their individual traits and characteristics. Bicyclists in subordinate traffic streams have to provide priority to road users on superordinate traffic stream(s), unless a sufficient time gap between the prioritized road users is available. This time gap is different for each bicyclist [Opiela et al., 1980]. The travel time for a bicyclist through the intersection cannot be accurately estimated as it relies on both the bicyclist desired speed and the current traffic situation. Also, there is the chance of observing bicyclists impeding superordinate road users for several reasons. These may involve false interpretation, misjudgment and estimation of the superordinate user behavior and speed from the bicyclists or intentionally impeding superordinate users due to impatience or the given traffic state at the intersection. In the case of AVs, the possibility of exploiting AVs by impeding their path exists. Bicyclists may always assume that priority will be handed over to them in any situation or that the AV will anyway stop or decelerate in order to avoid a collision. This is highly problematic, especially given the fact that the intersection layout, infrastructure and dimensions are defined and assessed according to the expected traffic flow given a set of priority rules that also considered as part of this process Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV) [2015] and National Research Council [2016].

Additionally, it can be assumed that bicyclists will be present along all intersection approaches at any given time and therefore any measure that assigns priority to a certain group of bicyclists or a bicycle traffic stream, has to always consider possible conflicts with other bicyclists on the higher rank traffic streams. As a result an additional question arises as to how to communicate to bicyclists the fact that they are allowed transverse through the intersection safely. At signalized intersections, this task is performed by the signal heads. At unsignalized intersections, bicyclists comply with the traffic signs and general traffic rules. However, here the aim is to regulate the priority among bicycles and AVs in order to optimize their interactions. Thus, special functions have to be developed for AVs that allow them to safely communicate and interact with bicyclists and adjust their behavior in order to resolve traffic interactions.

Therefore a method for resolving interactions among AVs and bicycle traffic at unsignalized intersections has to be able to address all the aforementioned challenges in the areas of behavior prediction, confidence quantification, traffic state estimation, communication, cooperation and safety. This chapter proposes a MILP based optimization method for optimizing the traffic flow of interacting bicyclists and AVs. The method considers the aforementioned challenges, by conditionally activating and deactivating prioritization functions in AVs that adjust their driving behavior, based on the estimated traffic conditions. Specifically, in the case of bicyclist prioritization, AVs try to form acceptable time gaps for bicyclists to pass through the conflict points. First the developed method is presented in detail together with solutions with respect to the integration of the proposed method in the AVs system architecture. Also suggestions for the possible communication of the AVs system state to bicyclists are presented. Figure 4.1 presents the key properties and components of the proposed optimization framework.

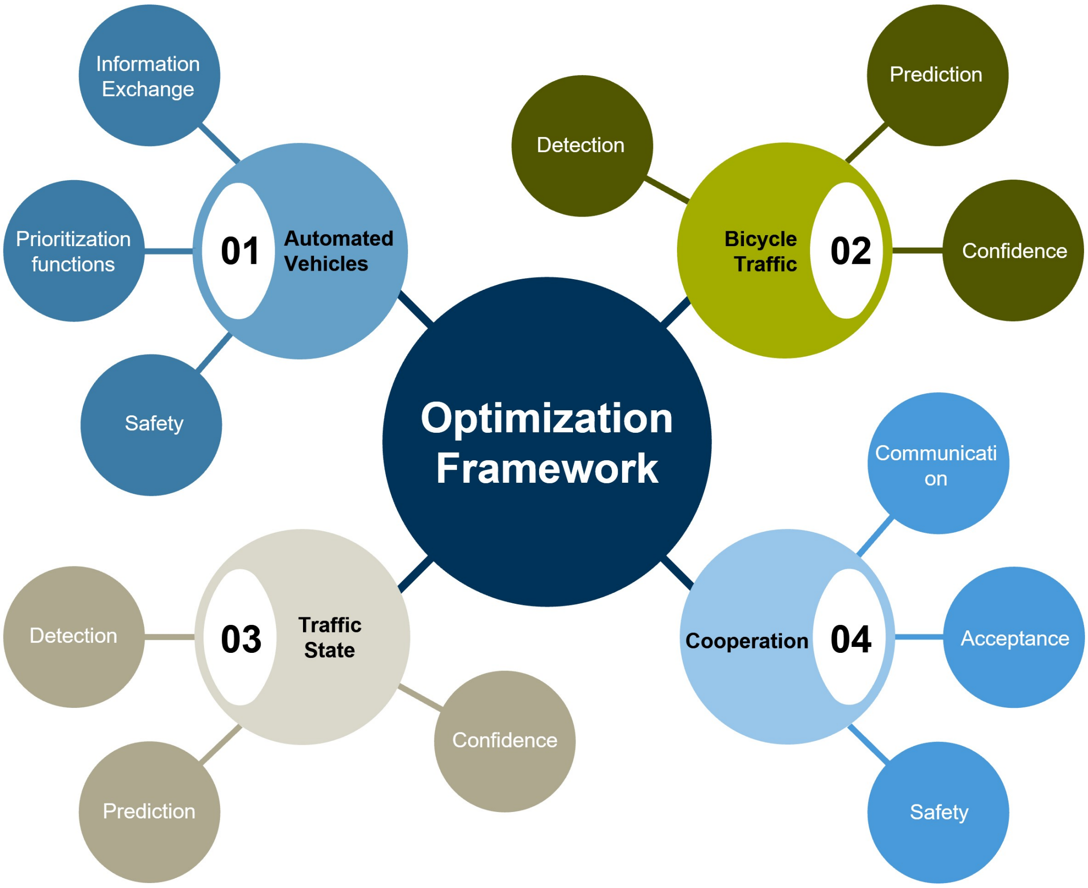


Figure 4.1: The key properties and components of the proposed optimization framework.

In a second step, the proposed method is evaluated using the SUMO microscopic traffic simulation software. In this context, the approach for the modeling and integration of the optimization method, the AV prioritization function in SUMO are thoroughly described. Also details regarding the calibration of the AV and bicycle behavior in SUMO are provided.

In a final step, evaluation scenarios are defined for assessing the proposed optimization method against the "Base" scenario of without optimization, while considering different aspects including the traffic demand composition as well as the average bicycle maneuver prediction certainty. Finally, results are analyzed and discussed in the respective sections of this chapter.

4.2 Methodology

4.2.1 Description of the Optimization System Architecture

This section describes the proposed method for resolving AV and bicyclist interactions at unsignalized intersections. As discussed, the method has to address certain challenges that arise, due to the fact that the behavior of bicyclists is inherently unpredictable and, in contrast to AV vehicle behavior, cannot be fully controlled. Nevertheless, the method has to incorporate functions that communicate the control decisions to the respective road users. Finally, the optimization objectives have to be defined and an approach estimation for the respective optimization variables has to be defined.

4.2.1.1 Context

The proposed method addresses the optimization of the traffic flow at an unsignalized four-arm intersection with mixed traffic, a typical example of an unsignalized intersection for urban areas in Germany, according to the Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV) [2015]. With respect to traffic priority rules, these are defined according to Figure 2.3 and Table 2.1 for a four arm intersection. Despite that the proposed method aims to regulate the traffic flow, still a baseline of right-of-way rules has to be in place, primarily for regulating interactions among HRUs, especially when AVs are not present. Additionally, right-of-way rules in unsignalized intersections play a significant role during dimensioning and for the evaluation of traffic performance [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015]. The proposed method does not aim to completely substitute the common methods of right-of-way assignment due to the presence of HRUs, as this would be equal to transforming the unsignalized traffic control to signalized traffic control. The proposed method instead works in the middle ground between signalized and unsignalized traffic control.

4.2.1.2 Definition of Road User Types

The proposed method considers two types of road users: The AVs and the bicyclists. With respect to the AVs, it is assumed that they are SAE level 5 vehicles with full automation therefore can drive without a human present in the vehicle. The AVs fully comply with the traffic rules, are interconnected, exchange information and cooperate to resolve traffic situations. Given that there is full information exchange, all AVs at the intersection have a detailed overview of all road users present at the intersection at all times together with their intentions and future actions. Finally, they are equipped with the prediction model presented in Chapter 3 and can predict the intentions of nearby bicyclists with a certain level of confidence. Bicyclists ride on conventional bicycles are assumed to fully comply with traffic rules and that they do not impede users on a higher priority traffic stream. Here, bicyclists on special types of bicycles, such as cargo bicycles are not considered, as these exhibit different dynamic, operational, communication and tactical behavior that was not part of the research undertaken in Chapter 3 and therefore were not considered during the prediction model training and testing.

4.2.1.3 Prioritization Concept

At unsignalized intersections traffic performance is limited due to the reduced capacity of subordinate traffic streams. Aside from the dimensions and type of the traffic infrastructure at the intersection approaches, right-of-way rules play a significant role in the estimation of the LOS at intersections, as the capacity of the subordinate streams is further reduced due to the traffic flow on superordinate traffic streams Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV) [2015]. Eventually the right-of-way rules define how the occupation rights and time of the intersection points is allocated among different traffic streams. The higher the rank of a traffic stream the greater the right and the probability that it occupies the intersection points. Therefore, the problem of resolving the interactions can be viewed as a problem of optimal resource allocation, where the resource in this context is the time that a traffic stream can occupy the respective intersection points (space). The mechanism for distributing the allocation of the occupancy time is the prioritization of a traffic stream over the other. In present research, this problem has been addressed so far, only for the case of AV traffic, through scheduling the arrival time and speed of the road users and therefore creating conflict free paths for each road user. However, in the context of this research, bicyclists are being considered as a new user group. Their behavior cannot be fully controlled and thus may be unpredictable.

The proposed prioritization concept aims to integrate bicycle traffic into a method for optimizing traffic flow in a AVs traffic environment. The concept relies in its core on the present traffic and right-of-way rules as defined by the StVOs, that are assumed to be known and acceptable by both bicyclists and AVs and define the hierarchy of prioritization among the different traffic streams. Given that the priority rules are established for all users, the prioritization concept uses the base situation for estimating the traffic state. It assumes that both user groups will comply with the default priority rules, while interacting with each other. Users on subordinate traffic streams will provide priority and won't impede road users of superordinate traffic streams. Users on subordinate traffic streams will make use of acceptable time gaps between users on super ordinate traffic streams to drive through the intersection. In this process, the interacting road users are identified and a prediction for their future behavior is derived.

In a second step the prioritization concept evaluates the possibility to provide priority to subordinate traffic stream(s) over superordinate traffic stream(s) based on future traffic state estimations. The estimation of the future traffic state however is difficult due to the uncertainty in the behavior of bicyclists. Even with the maneuver prediction in place, that resolves the problem of allocating a bicyclist to a specific traffic stream, still their behavior cannot be predicted with high certainty. Bicyclists also exhibit inherently a great variation of desired travel speeds, acceleration reaction times and gap acceptance due to their personal traits. Therefore a state estimation for bicyclists can only be derived based on certain assumptions. It is therefore assumed that:

- **User paths and intersection point definition and prediction**: Based on the maneuver prediction intention, incoming users are assigned to a typical path for their intended maneuver that intersects with the typical path of other road users. It is important to note here that in the context of this dissertation no special method for predicting the bicyclist path is proposed or used. In the context of this research it is assumed that this functions is already integrated with AVs. In a real world implementation separate paths with a given prediction confidence would be generated for each arriving bicyclist. However, still this prediction currently takes place only for the short-term time horizon (<2s) as discussed in Section 2.4. Therefore, it is safe to assume that the long term path prediction will still rely on a typical trajectory.

- **Bicyclist ETA at intersection points of two traffic streams**: Bicyclists will maintain their current speed as detected at any time step until arriving at the respective intersection point. It is assumed that no external factors or other road users influence this procedure. In real traffic, road users interact in multiple directions with each other. Especially bicyclists can freely navigate the traffic space without restrictions in contrast to motor vehicles that typically occupy a traffic lane to its entire width. Tracking the effect of these chaotic interactions is not entirely feasible neither in the simulation nor in reality. The methodology therefore only accounts for two-way, pairwise interactions between two road users each time (the AV and the bicyclist). It won't base estimations based on the effects of other users on the two-way interaction under investigation.

- **Bicyclist Gap Acceptance**: Bicyclists of subordinate traffic streams will accept only time gaps equal or greater than 4 seconds [OPIELA et al., 1980] and will never impede higher priority road users forcing the latter to decelerate. This value is fixed for all bicyclists regardless of their personal traits.

- **Bicyclist behavior during prioritization**: In case of prioritization, bicyclists are considered to make use of their assigned priority right and pass trough the intersection point with the higher priority stream, while accelerating to their desired speed. Influences from other road users are not considered as part of this research. Speed adjustment by bicyclists aiming to ride through the intersection point without coming to a conflict with an oncoming user or to a stop after another higher priority user has passed through are also not considered. Bicyclists riding past the intersection point are assumed to ride past the intersection area, while accelerating to their desired speed.

Figure 4.2 presents the user paths and intersection point definition and prediction modeling.

The respective assumptions simplify the problem of traffic state estimation both for bicyclists and for AVs given the uncertainty of the bicyclist behavior. The decision making process of bicyclists is far too complex to model especially in the context of multiple interactions and influences with other road users.

Given the proposed assumptions, a function has to be developed that eventually decides on the prioritization of certain traffic streams given the estimated traffic state. The decision making process can be therefore formulated as a MILP optimization problem, with the objective to improve traffic efficiency. Subsection 4.2.2 presents and discusses the optimization problem in detail. The Optimizer regulates which traffic streams will gain priority over the others by comparing the estimated traffic state in the case of no prioritization against the case of prioritization.

In the context of the integration of bicycle traffic certain aspects need to be addressed. The first aspect, is how the prioritization of a bicycle stream should take place. It is proposed that

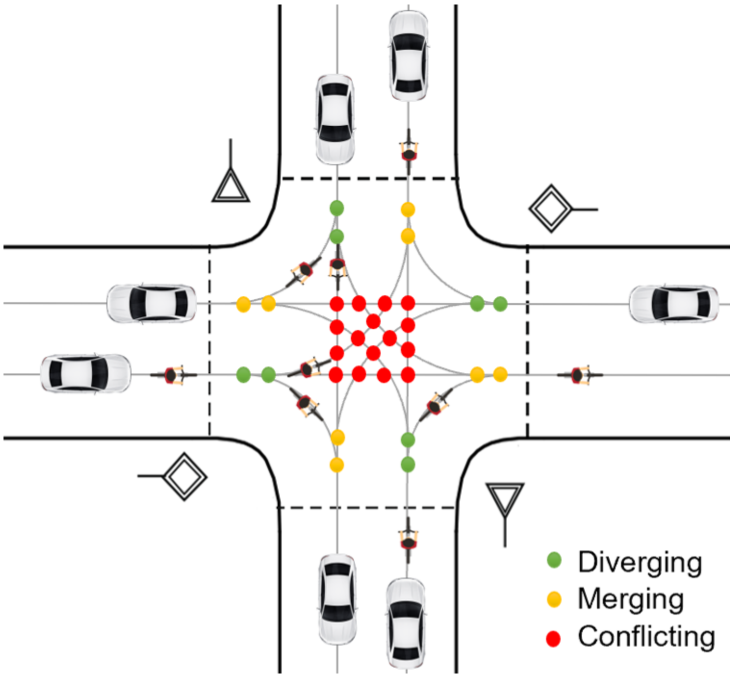


Figure 4.2: User path modeling and intersection point definition. Figure adapted from: Federal Highway Administration [2004].

in the case of prioritization, AVs form acceptable, bicycle-friendly time gaps so that bicyclists can safely drive through the superordinate traffic stream. The size of the acceptable time gap is set to $6s$ which is $2s$ greater than 4 seconds estimated by Opiela et al. [1980]. The additional $2s$ are added to ensure that bicyclists accelerate conveniently to their desired speed and that also slower moving bicyclists are being considered. The concept for the generation of acceptable time gaps for bicyclists on the minor traffic stream is presented as a graphical representation in Figure 4.3. The decision for this approach lies on multiple reasons:

- **Subordinate bicyclists already make use of acceptable time gaps for driving through a superordinate traffic stream in the present traffic context**. It is also important to mention here that present research on the effects of AVs on traffic performance Aria et al. [2016], Müller et al. [2016], Makridis et al. [2018], Lu et al. [2020], and Olstam et al. [2020] as presented in subsection 2.7.1 consider very small car-following time gaps between AV traffic (smaller than 1s). These time gaps are unacceptable for bicyclists [Opiela et al., 1980] let alone for other motor vehicles. In the case of high AV traffic flow on the super ordinate traffic stream, it will become even more difficult for bicycles to pass through. The proposed method therefore ensures that given the traffic state and bicycle traffic demand at an intersection, bicycle-friendly time gaps can be formed if necessary. As a result, the proposed approach does not require for existing traffic rules to be altered or for special training from the bicyclist side and is easy to comprehend.
- **AVs are not required to come to a full stop at the intersection approach and steady uninterrupted traffic flow on the super ordinated traffic stream in most**

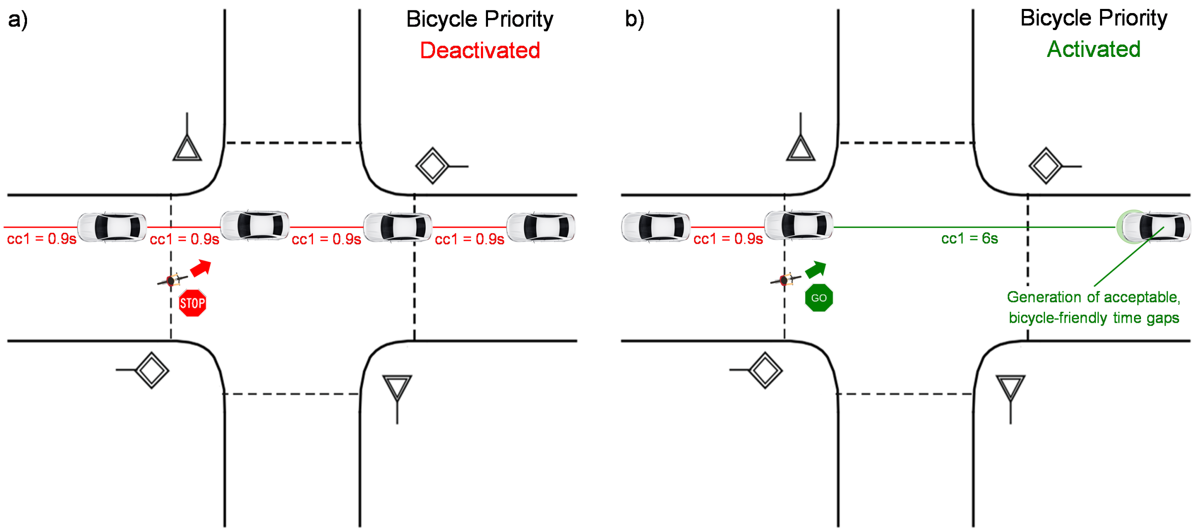


Figure 4.3: Graphical representation of the proposed prioritization concept based on the generation of acceptable, bicycle friendly time gaps between AVs on the super ordinated traffic stream. a) Deactivation of the prioritization (default state), b) activation of the prioritization.

situations is guaranteed. This ensures the acceptance or tolerance of the specific strategy from the AV passenger side and limits the expected negative efficiency effects on the super ordinate traffic stream as AVs continue to flow. From another perspective it additionally accounts for the uncertainty in the bicyclist intentions. Inherently, the evaluation of traffic performance following the HBS [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015] or the HCM [National Research Council, 2016] considers that superordinate traffic streams require more capacity due to the increased traffic flow. The interruption of the traffic flow on a superordinate traffic stream will negatively affect LOS to the point that a different evaluation methodology for the LOS needs to be implemented. The proposed method aims to assist bicyclists in their interactions with superordinate traffic streams and improve their traffic efficiency without significantly deteriorating the traffic conditions for AV traffic flow.

- **The possibility that the priority state can be exploited by bicyclists in the expense of AVs is reduced while ensuring steady traffic conditions.** It forces the bicyclists to either accept or deny a small but convenient time frame for them to pass through the intersection point. This is a more flexible and optimal solution in contrast to signal controlled approaches where bicyclists eventually have the possibility to react later to the signal head state as they are given a certain long green time period to pass through. This approach also limits oncoming bicyclists from riding with a slower speed knowing that they will pass through the intersection point. Such an implementation would actually be equivalent to introducing a form of "signalized control" at an unsignalized intersection and is out of scope of the present research.

Another aspect that needs to be addressed is how to resolve the interactions between bicyclists of conflicting bicycle streams in the context of prioritization. As the bicyclist behavior cannot be controlled, bicyclists are unaware of the intentions of other bicyclists in the intersection. Therefore, in the case that bicyclists are present on the superordinate traffic stream, it is not possible to prioritize bicyclists of a subordinate intersecting traffic stream in order to avoid possible collisions and critical interactions among bicyclists. This restriction eventually limits the activation time of the prioritization concept especially at intersections with high bicycle traffic flow, however it ensures safe and acceptable interaction among all road users.

A final aspect that needs to be addressed is the consideration of the bicyclist intention uncertainty. The primary problem for the optimization function is to correctly assign the involved road users in the correct traffic stream. In this case it is decided to introduce the bicyclist intention uncertainty as a weight factor for the respective traffic state estimation for each bicyclist belonging to a certain bicycle traffic stream. The higher the prediction confidence the greater the effect of the respective user estimated traffic state on the optimizer. At the same time, the weight factor is introduced for AV and is set equal to 1.0 as it is assumed that the AV driving direction is known. This ensures that AVs higher confidence of maneuver intention consistently outweighs lower confidence.

4.2.1.4 AV Prioritization Functions

In order to enable the prioritization of bicyclists, AVs have to be equipped with special functions that adapt their driving behavior in order to generate the respective time gaps for bicycle traffic. In this process, AVs will form acceptable time gaps between each other or decelerate for prioritizing bicyclists. Given the predefined restrictions that traffic flow on the superordinate traffic stream should not be interrupted, AVs should not come to a full stop but rather maintain a minimum driving speed while driving towards the intersection point with the subordinate traffic stream. Additionally, only bicyclists that are past the intersection approach are considered by the optimizer as only for these bicyclists, a maneuver prediction is made. Therefore if the bicyclists indeed accept the provided time gaps and pass through the intersection point in time, the optimization needs to be deactivated. The same applies for the case where the maneuver prediction is false and bicyclists drive towards another direction.

However, as the acceptance of the time gap is not guaranteed, the prioritization has to remain active until the bicyclists have passed through the intersection point. This means that possibly bicyclists are going to accept a time gap by a following AV. Also, while prioritization is active, bicyclists will still be arriving at the intersection. It is therefore possible given that bicyclist travel with different speeds, that by the time the bicyclists are close to the intersection point, additional bicyclists have caught up and pass through the intersection. This means that in case of high traffic demand, bicyclists may eventually bring oncoming superordinate AVs to a stop as a long queue of bicyclists passes through the intersection.

Also, from the AV perspective it can be the case that by the time the prioritization is activated for the respective stream, the AV is so close to the intersection point that it can no longer safely and comfortably decelerate in time for the prioritization state. In such case, the AV needs to continue driving past the intersection point and the following AV has to prioritize the bicycle traffic. Therefore depending on AV position, speed, distance to the intersect point, and time gap to the leader AV different AV states need to be defined that describe how the

AV has to adjust its behavior depending on the traffic state. The decision making process for the respective AV, when the prioritization is activated is described below:

In case the optimizer activates the prioritization for bicycle traffic then, depending on the state of the AV on the traffic stream, each AV on the relevant route decides:

- Whether to create an acceptable gap to its leader AV.
- Whether to slow down and decelerate in order for the interacting bicycle(s) to pass through in case the AV is the leader of the platoon or the leader AV is past the intersection point.
- Whether to not adjust its behavior as it is not possible to create the time gap in time with a safe and comfortable deceleration rate.

In this context, supportive functions need to be developed that do not only adapt the AV driving behavior but also map the interactions with bicyclist of the minor traffic stream. Given the assumptions described in subsection 4.2.8, for the bicyclist and AV approach speed, AVs have to classify the interacting bicyclists and AVs based on the nature of their interaction. For each vehicle (AV / bicyclist) or *ego vehicle*, its *intersecting vehicle(s)* are defined in each simulation time step t. The pairwise mapping and classification of interactions takes place from the ego vehicle perspective for all vehicles of all intersection traffic streams depending on their maneuver prediction. Therefore AVs are considered at all times as their maneuver intention is known. Bicyclists are considered as soon as they arrive at the intersection area as the model for the prediction of the bicyclist maneuver intention has concluded its operation. All *intersecting vehicles* are assigned to a class depending on the type of their intersecting relationship to the *ego vehicle*. As a result all relationships among all road user pairs are mapped. The intersecting class defines if the two road users will come into an interaction while maintaining their current speed and by calculating their ETA to the intersect point. The classification considers the following properties:

- **Priority traffic stream:** This information is important in order to define the exact relationship between the vehicle pairs at the intersection points for the accurate estimation of the traffic state in case of activation and deactivation of the prioritization.
- **Stop status:** In case the lower priority vehicle is already stopped, it cannot be assumed that the vehicle will travel past the intersection point with its present speed. Therefore, the acceleration process towards the intersection point to its desired speed needs to be considered.
- **Time gap to leader for vehicles in higher priority traffic streams:** The investigation of interactions takes place pairwise for each two interacting road users. The size of the time gaps between vehicles on the higher ranked stream has to be considered as they might not be acceptable by the lower priority vehicles and therefore platoons are formed.

Based on these considerations, a pairwise investigation of the interaction of the *ego* user to all possible *int* (intersecting) users is performed. The investigation uses as basis their common intersect points *i*. The respective ETA of the *ego* user to each intersect points *i* in the users path is estimated using Equations 4.1 to 4.8:

As the main interest in the interaction analysis is to identify based on the default priority rules, until when a user will occupy each intersect point *i* and hinter the respective *int* subordinate users, the *ego* user has to cover a distance s_i^u that is given by Equation 4.1:

$$s_i^u = d_i^u + l_u \tag{4.1}$$

where:

$d_i^u \in \mathbb{R}^+ =$ The present distance of user u to intersect point i.

$l_u \in \mathbb{R}^+ =$ The length of user u.

The *ego* user has to cover the distance s_i^u in order to first occupy and subsequently free intersect point *i*. The arrival of the user is a function of its travel speed towards the intersect point *i*. Given the complexity and the high uncertainty in accurately predicting the long-term position of road users that is also influenced by external factors, certain assumptions have to be made in order to proceed forward with the ETA estimation. At any given time *t* each road user travels with a speed v_t^u and an acceleration rate a_t^u. It is assumed that the user will always strive to approach the intersect point *i* with its desired or maximum allowed speed v_{max}^u. Given this assumption, the distance s_i^u is consists of two separate parts: the acceleration part and the stable speed part, as defined in Equation 4.2:

$$s_i^u = s_a^u + s_s^u \tag{4.2}$$

where:

$s_a^u \in \mathbb{R}^+ =$ The acceleration distance of user u to its maximum allowed or desired speed towards intersect point *i*.

$s_s^u \in \mathbb{R}^+ =$ The stable speed distance of user u with its maximum allowed or desired speed towards intersect point *i*.

while based on Equation 4.2, the conditions in Equation 4.3 apply:

$$s_i^u = \begin{cases} s_a^u & s_a^u \geq d_i^u + l_u \\ s_a^u + s_s^u & s_a^u < d_i^u + l_u \end{cases} \tag{4.3}$$

The current acceleration of user u that will be used for the subsequent estimation of the ETA to the intersect point *i* at time step t is decided based on the conditions defined in Equation 4.4.

$$a_c^u = \begin{cases} a_t^u & v_t^u > 0 \\ a_{max}^u & v_t^u = 0 \end{cases} \tag{4.4}$$

where:

$a_c^u \in \mathbb{R}$ = The current selected acceleration rate of user u.

$v_t^u \in \mathbb{R}^+$ = Speed of user u at time step t.

$a_t^u \in \mathbb{R}$ = Acceleration rate of user u at time step t.

$a_{max}^u \in \mathbb{R}^+$ = The maximum or desired acceleration rate of user u. It is assumed that if user u is stopped, the user intends to accelerate to the intersect point i with its maximum or desired acceleration rate.

In the pairwise investigation no contextual knowledge on the detected road user behavior is considered. Therefore, given the detected acceleration or deceleration rate it is not possible to accurately predict the intended target speed of user u. In the context of this approach, it is therefore assumed that in case of deceleration user u intends to come to a full stop (target speed = 0) and in case of acceleration user u intends to reach its desired or maximum allowed speed v_{max}^u. For the investigation of the acceleration distance s_a^u, first t_a^u, which is the time spend for user u accelerating or decelerating from its current speed $v_c^u = v_t^u$ to its target speed, has to be determined (Equation 4.5).

$$t_a^u = \begin{cases} -v_c^u / a_c^u & a_c^u < 0 \\ (v_{max}^u - v_c^u)/a_c^u & a_c^u \geq 0 \end{cases} \tag{4.5}$$

where:

$a_c^u \in \mathbb{R}$ = The current selected acceleration rate of user u.

$v_c^u \in \mathbb{R}^+$ = The current speed of user u.

$v_{max}^u \in \mathbb{R}$ = The maximum or desired speed of user u.

Given the estimation for t_a^u, s_a^u is calculated using Equation 4.6.

$$s_a^u = v_c^u t_a^u + \frac{1}{2} a_c^u t_a^{u2} \tag{4.6}$$

where:

$v_c^u \in \mathbb{R}^+$ = The current speed of user u.

$t_a^u \in \mathbb{R}^+$ = Time spend for user u accelerating or decelerating from its current speed v_c^u to its maximum allowed or desired speed v_{max}^u.

$a_c^u \in \mathbb{R}$ = Current acceleration or deceleration rate of user u.

In case that $s_a^u < s_i^u$ and $a_c^u < 0$ the result of Equation 4.6 suggests that user u will come to a full stop before the intersect point i. In the context of this approach, it is assumed that the ego user u will first decelerate to a full stop during time period t_{ds}^u and then accelerate again past the intersection point i. Thus, $t_a^u \rightarrow t_{ds}^u$, while Equation 4.2 is transformed to Equation 4.7:

$$s_i^u = s_{a,new}^u + s_{s,new}^u + s_{ds}^u \tag{4.7}$$

where:

$s_{a,new}^u \in \mathbb{R}^+$ = The new acceleration distance of user u to its maximum allowed or desired speed towards intersect point *i* from the previous stop position.

$s_{s,new}^u \in \mathbb{R}^+$ = The new stable speed distance of user u with its maximum allowed or desired speed towards intersect point *i* from the previous stop position.

$s_{ds}^u \in \mathbb{R}^+$ = The deceleration distance of user u to a stop before intersect point *i*.

$t_{ds}^u \in \mathbb{R}^+$ = Time spend for user u decelerating to a stop before intersect point *i*.

Subsequently, a new investigation that additionally considers the intermediate stop of user u need to take place for the accurate estimation of the ETA to the intersect point i using Equation 4.7 and then Equations 4.3-4.6 assuming that user u comes to a stop at distance s_{ds}^u and then immediately accelerates to its maximum allowed or desired speed v_{max}^u with its desired acceleration rate a_{max}^u. Finally, the estimated total travel time t_s^u, user u requires to travel distance s_i^u is defined using Equation 4.8.

$$t_s^u = \begin{cases} \frac{-v_c^u \pm \sqrt{{v_c^u}^2 - 2a_c^u s_i^u}}{a_c^u} & s_a^u \geq s_i^u \text{ or } s_{a,new}^u + s_{ds}^u \geq s_i^u \\ \frac{s_s^u - s_a^u}{v_{max}^u} + t_a^u & s_a^u < s_i^u \text{ and } a_c^u > 0 \\ \frac{s_{s,new}^u - s_{a,new}^u}{v_{max}^u} + t_{a,new}^u + t_{ds}^u & s_a^u < s_i^u \text{ and } a_c^u < 0 \text{ and } s_{a,new}^u < s_i^u \end{cases} \tag{4.8}$$

where:

$v_c^u \in \mathbb{R}^+$ = The current speed of user u.

$t_a^u \in \mathbb{R}^+$ = Time spend for user u accelerating or decelerating from its current speed v_c^u to its maximum allowed or desired speed v_{max}^u.

$a_c^u \in \mathbb{R}$ = Current acceleration or deceleration rate of user u.

$s_s^u \in \mathbb{R}^+$ = The stable speed distance of user u with its maximum allowed or desired speed towards intersect point *i*.

$s_a^u \in \mathbb{R}^+$ = The acceleration or deceleration distance of user u to its maximum allowed or desired speed.

Respectively the following classes for mapping the nature of the interactions between two pairs of vehicles, the *ego vehicle* and the *intersecting vehicle*, are defined based on the comparison of their traffic stream rank and their respective ETA, following time gaps and position. to their common intersect point(s) *i*.

- **Irrelevant:** Both vehicles find themselves on intersecting routes, however they won't interact at the intersect position, while maintaining their current speed.

- **Critical:** The *ego vehicle* will interact with the *intersecting vehicle*. The *ego vehicle* is on the higher priority route and the *intersecting vehicle* has to provide priority.
- **Intersecting Critical:** The *ego vehicle* will interact with the *intersecting vehicle*. The *intersecting vehicle* is on the higher priority route and the *ego vehicle* has to provide priority.
- **Critical leader:** This class is assigned to the *Critical* higher priority *ego vehicle* that is the first vehicle to obstruct the movement of the lower priority *intersecting vehicle*. As multiple vehicles may approach the intersection point with the lower priority vehicle, several of them might individually obstruct the maneuver of the lower priority vehicle, as their following time gaps are not acceptable by the lower priority vehicle. This information is used upon activation of the prioritization by the decision making functions in the AVs on how to adapt their driving behavior.

Figure 4.4 presents an example for the assignment of the defined interaction classes.

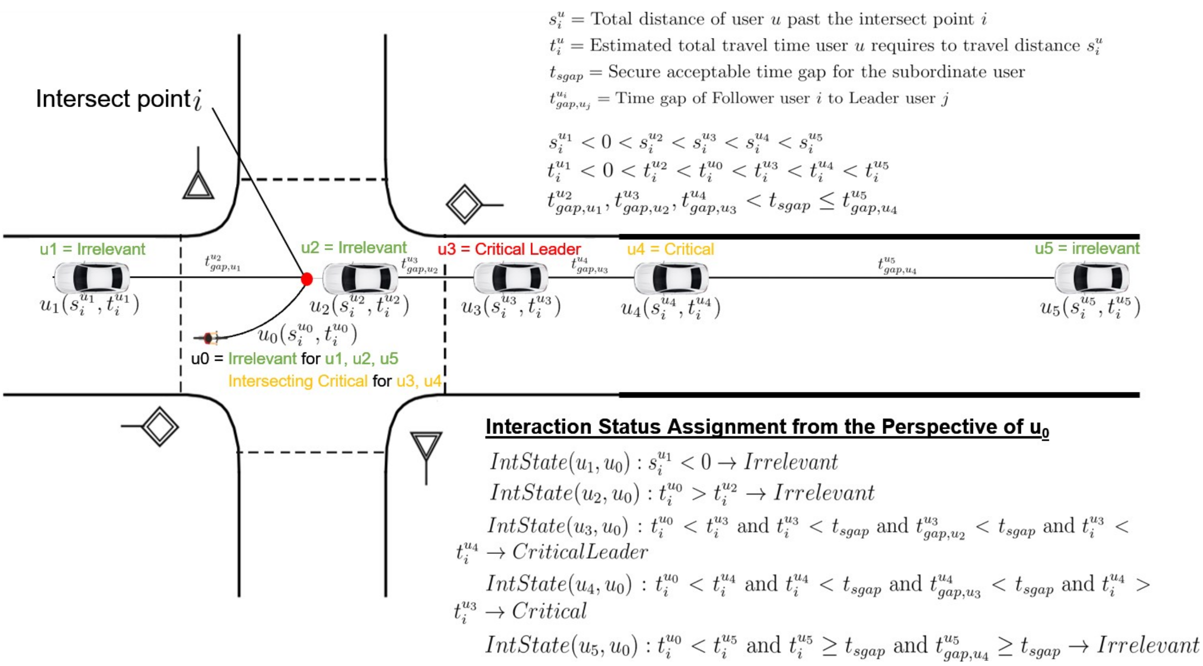


Figure 4.4: Example for the assignment of the defined interaction classes for users on subordinate and superordinate traffic streams.

Based on the intersecting classes, the traffic state estimation for all traffic streams is derived once for activation and once for deactivation (default state) of the prioritization. Depending on the decision of the optimizer, if prioritization is activated, then acceptable time gaps for the subordinate traffic stream are created. However, the activation takes place on the traffic stream level for all AVs. The previous mapping of the pairwise interactions enables the AVs to individually assess how to adapt their driving behavior. Based on the pairwise interaction classes, only AVs on the higher ranked stream that have been assigned the interaction class *Critical leader* or *Critical* may have to adjust their driving behavior to create the time gaps.

However, this requires further investigation, as the prediction of the traffic state still relies on multiple assumptions and there is uncertainty in the gap acceptance behavior of bicyclists. Also, additional bicyclist(s) might be riding past the intersection approach, as soon as the previous bicyclist(s) considered by the optimizer, pass through their intersection points. A possible sudden deactivation of the prioritization might lead to confusion and safety critical situations.

The *Critical Leader* may be the AV that by default will be prioritizing certain bicyclist(s). However, as the interactions are mapped pairwise multiple *Critical Leaders* might be found on the super ordinate AV traffic stream depending on the position and speed of the respective bicyclist(s) on the subordinate traffic stream. Also, the *Critical Leader* might not be able to decelerate safely and comfortably in order to create an acceptable time gap. Therefore, the prioritization task has to be undertaken by the next following AV upstream. Given these considerations, the following states of AV driving behavior are defined for the activation of the prioritization state on a traffic stream.

- **Active prioritization ($ActivePrio$):** This state is assigned only to AVs mapped as a *Critical Leader* or *Critical* based on the estimated ETA to the intersect point. The AVs will adjust their speed down to a minimum velocity $v_{prio}^{MIN} = 10km/h$ and create the acceptable time gap for its the subordinate interacting bicyclist(s). AVs will continue to travel with this speed until they arrive at a distance of 2m before the intersect point, until all their interacting bicyclist(s) are past the intersect point or until the prioritization is deactivated.

- **Deactivated prioritization due to small ETA ($OffPrioETA$):** This state is assigned only to an AV mapped as *Critical Leader* or *Critical* during the pairwise interaction investigation. Based on the estimated ETA to the intersect point i the AVs might not be able to safely and comfortably decelerate in time in order to create the acceptable time gap. In this case the AV needs to accelerate again to its desired speed and clear the intersection in order to reduce delays for both subordinate traffic and AVs upstream of its position.

- **Passive prioritization ($PassivePrio$):** This state is assigned only to AVs mapped as *Critical* during the pairwise interaction investigation. Based on the estimated ETA to the intersect point the AVs start slowing down and try to form acceptable gaps to their leader AV with a lower deceleration rate. In case of continuous high demand on both on the superordinate and the subordinate traffic stream AVs arriving at the intersection will have already created acceptable time gaps to their leaders.

- **Deactivated prioritization (default state) ($OffPrio$):** This is the default driving state for all approaching and exiting AVs. This state is also assigned to AVs with only *Irrelevant* interaction classifications to other bicyclists or when the prioritization is terminated for the AV traffic stream. It is assigned to AVs that are downstream of the intersect point with the subordinate traffic stream and therefore irrelevant for the Optimizer.

Figure 4.5 presents the logic for assigning the AV prioritization status for each AV on the superordinate traffic stream, for which the Optimizer has activated the prioritization.

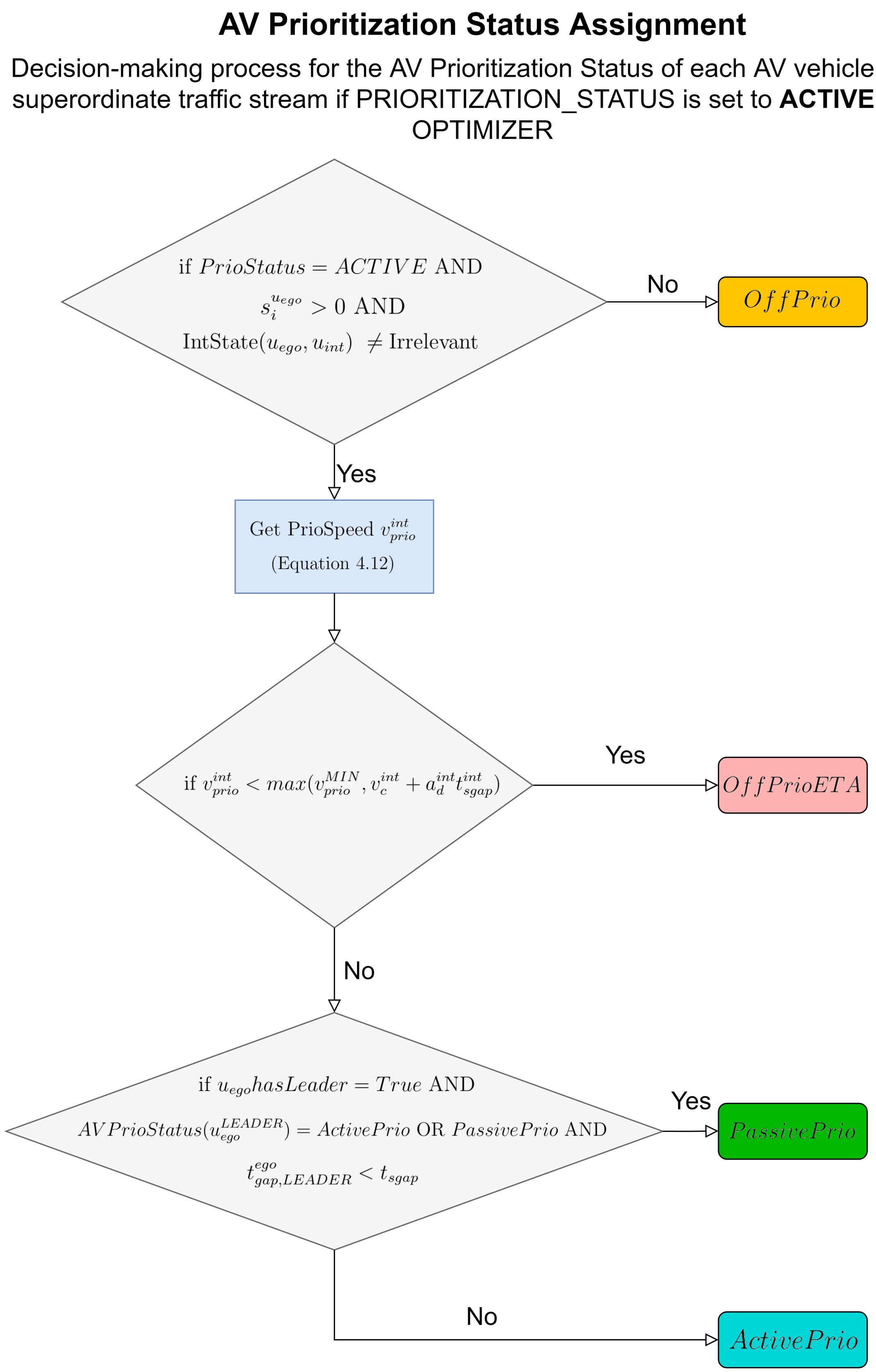


Figure 4.5: AV prioritization status assignment flowchart.

Figure 4.6 presents an example of the AV prioritization status assignment logic based on the interaction state identification in Figure 4.4

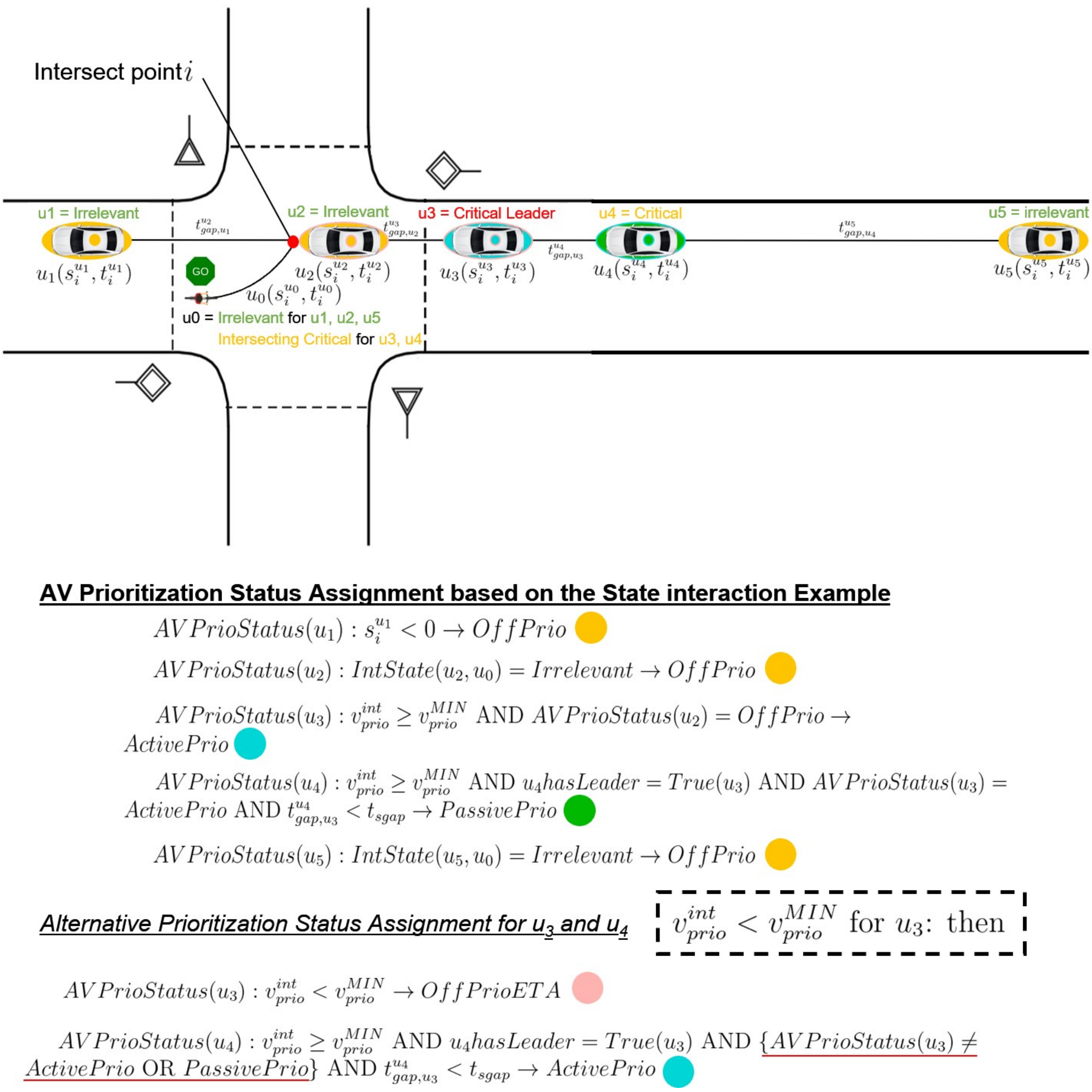


Figure 4.6: Example of the AV prioritization status assignment logic.

4.2.1.5 Suggestions for AV State Communication to Bicyclists

This section presents suggestions for the communication of the AV prioritization state to the bicyclists. The evaluation of the proposed interaction concept is out of scope of the present work. Here, upon prioritization, the bicyclist gap acceptance relies only on the personal bicyclist traits. A comfortable time gap to the intersection point is created by the AV that is $6s$ in duration and is therefore $2s$ bigger than the average $4s$ average time gap that is accepted by bicyclists interacting with motor vehicles as previous research suggest [Opiela et al., 1980].

It is proposed that the communication concept should rely primarily on an eHMI solution combined with the respective adjustments in the dynamic state of the vehicle as previous research finds this combination to be optimal in communicating the intentions of an AV to VRUs [Winter and Dodou, 2022; Kass et al., 2020; Rettenmaier and Bengler, 2021]. The communication concept may be supported by sound indications during the prioritization state changes, in order to reduce th continuous dependence on the eHMI state for the bicyclist. Thus, bicyclists should not be addressed as individual users and are not individually requested to perform certain actions, as this might lead to confusion, safety critical situations and increase interaction complexity [Hübner et al., 2022]. Instead, only the information on the AV state and behavior is provided. Bicyclists are free to choose their action depending on their personal characteristics. In this way, interactions remain simple and familiar to the default interactions when no prioritization is active and the common traffic rules apply. Also AVs are not required to verify the bicyclist(s) actions or force the bicyclist(s) to perform a specific actions, as there is high uncertainty both in the actions of existing bicyclists in the intersection area and the actions of incoming bicyclists [Niels, Mitrovic, Bogenberger, et al., 2019; Hubmann et al., 2018]. Finally, the communication concept may optionally integrate mobile handheld devices for the bicyclists supporting the communication with the AVs as such a concept has been evaluated positively by bicyclists for negotiating priority with an AV at an unsignalized intersection [Lindner, Georgios Grigoropoulos, et al., 2022].

Therefore, each AV priority state needs to be communicated explicitly with a specific eHMI message to the bicyclists. The respective acceleration and deceleration processes during the respective deactivation and activation of the prioritization function can be combined with the eHMI change of status to further communicate the AV intentions through the vehicle's dynamic behavior (dHMI). These communication functions can be optionally supported by sound indications and the bicyclist mobile devices (iHMI).

4.2.2 Optimization Problem Formulation

4.2.2.1 Problem Description

Given the intersection, the road user types and the automated vehicle functions described above, it is important to establish a method for deciding the activation or deactivation of the prioritization for specific road user types, while considering the discussed limitations. The problem can be formulated as a MILP optimization problem, given the linear objective functions mixed with integer variables and and the integer constraints. MILP is a robust approach used extensively for scheduling AV arrivals, resolving the path planning problem for AVs and optimizing traffic flow at intersections [Müller et al., 2016; Fayazi and Luckow, 2017; Fayazi and Vahidi, 2018; Ashtiani et al., 2018]. The optimization problem is described through objective functions and constraints. Finally, the problem is modeled using the Gurobi Solver which is a solver for numerical programming tasks, including MILP [Gurobi Optimization, LLC, 2022].

4.2.2.2 Traffic State Estimation

The main goal of the proposed efficiency is to optimize traffic performance at the unsignalized intersection for both AVs and bicyclists and assist bicyclists on subordinate traffic streams to pass through the intersection. Therefore, first it is important to define the goal of the objective function. The goal definition should rely on specific relevant traffic parameters that are critical traffic efficiency indicators. Here the delay is selected as the critical traffic efficiency parameter for both AVs and bicyclists as it accurately maps the effects of the prioritization state for both road user types. In the case of prioritization activation, AVs will travel with a speed less than the speed limit, which will result in greater travel times. Similarly, bicyclists providing priority at the superordinate AV traffic stream will have to decelerate to the intersection point, wait for the intersection point to clear and then accelerate and exit the intersection. The delay parameter can map these processes in detail.

Secondly, the number of stops are defined as a second optimization parameter only for bicyclists. Stops are considered in the context of the design and evaluation of bicyclist prioritization measures as critical performance indicators [Georgios Grigoropoulos, Twaddle, et al., 2018; Georgios Grigoropoulos, Hosseini, et al., 2021]. Additionally, stops serve as an indicator for bicyclist presence inside the intersection area. Especially in the case of queuing bicyclists it is possible that multiple stops for the same bicyclist might occur before passing through the intersection. In this context, the consideration of bicyclist stops introduces both a traffic safety and a comfort aspect consideration in the optimization process.

In a second step, the values of the already defined parameters have to be estimated both for the case of the prioritization activation and deactivation. Given the method for mapping of interactions among AVs and bicyclists (see 4.2.1.4), only the critically interacting road users are considered and assigned into their respective traffic streams. The traffic streams are defined in Figure 2.3, however as the prioritization is activated only for bicyclists, it is important to distribute the road users into user type specific traffic streams. For the type-specific traffic streams the base traffic rules defined in Figure 2.3 and priorities Table 2.1 apply. The predicted delay and number of stops are then derived for each road user pair once for the case of priority activation and once for the case of priority deactivation. The methodology described in the next paragraphs applies for the case where the ego vehicle (bicycle or AV) belongs to a lower rank traffic stream s and the $intersecting$ (AV) vehicle belongs to a higher rank traffic stream s.

Given an ego vehicle that belongs to a lower rank traffic stream s and an $intersecting$ vehicle that belongs to a higher rank traffic stream s that will interact at intersect point i, the expected incurred delay for the ego vehicle is determined using Equation 4.10. $t^{ego}_{i,MaxSpeed}$ is calculated using Equation 4.9 if $v^{u}_{c} > 0$ to account for the time it would actually take the ego vehicle to reach the intersection point i in free flow conditions and consider this in the actual delay estimation $d^{ego}_{i,expected}$.

$$v^{ego}_{c} > 0 \rightarrow t^{ego}_{i,MaxSpeed} = \frac{s^{ego}_{i}}{v^{ego}_{max}} \tag{4.9}$$

If $v^{ego}_{c} = 0$ then the ego vehicle is stopped. $t^{ego}_{i,MaxSpeed}$ is defined using the investigation methodology defined by Equations 4.1-4.8 assuming that the ego vehicle approaches the intersect point i from a full stop.

where:

$v_c^{ego} \in \mathbb{R}^+$ = The current speed of the ego vehicle.

$v_{max}^{ego} \in \mathbb{R}^+$ = The maximum allowed or desired speed of the ego vehicle.

$s_i^{ego} \in \mathbb{R}^+$ = The distance the ego vehicle needs to travel to get past the intersect point i.

$$d_{i,p}^{ego} = \begin{cases} t_i^{int} - t_{i,MaxSpeed}^{ego} + d_{t-1}^{ego} & \text{if no prioritization is activated for } ego \text{ against the } int \text{ vehicle} \\ t_i^{ego} + d_{t-1}^{ego} & \text{if prioritization is activated for } ego \text{ against the } int \text{ vehicle} \end{cases} \tag{4.10}$$

where:

$d_{t,p}^{ego} \in \mathbb{R}^+$ = Total predicted delay of the ego vehicle at time step t due to the priority of int vehicle.

$t_{i,p}^{int} \in \mathbb{R}^+$ = Predicted time spend for int vehicle traveling past the intersection point i as defined using Equation 4.8.

$t_{i,p,MaxSpeed}^{ego} \in \mathbb{R}^+$ = Predicted time spend for int vehicle traveling to the intersection point i from its current position using its maximum desired or allowed speed.

$d_{t-1}^{ego} \in \mathbb{R}^+$ = Total accumulated delay of the ego vehicle at time step $t-1$.

$t_{i,p}^{ego} \in \mathbb{R}^+$ = Time the ego vehicle requires from its current speed v_c^{ego} to travel past the intersection point i as defined using Equation 4.8.

Based on the identification of the respective interactions it is assumed that the subordinate ego vehicle will come to a full stop before the intersect point i in case of no prioritization and will not stop in case of prioritization. Equation 4.11 determines the prediction of the number of stops of the ego vehicle.

$$h_{i,p}^{ego} = \begin{cases} 1 + h_{t-1}^{ego} & \text{If no prioritization is activated for } ego \text{ against the } int \text{ vehicle.} \\ 0 + h_{t-1}^{ego} & \text{If prioritization is activated for } ego \text{ against the } int \text{ vehicle.} \end{cases} \tag{4.11}$$

where:

$h_i^{ego} \in \mathbb{I}_0^+$ = Predicted stop(s) of the ego vehicle due to the priority of int vehicle.

$h_{t-1}^{ego} \in \mathbb{I}_0^+$ = Accumulated stop(s) of the ego vehicle at time step $t-1$.

For the prediction of the traffic state of the $intersecting$ vehicle both in the case of prioritization and in the case of no prioritization a similar methodology is applied. First it is important to mention the fact this prediction applies only for $intersecting$ AVs. The prediction is redundant for bicyclists according to the **second constraint** (see: 4.2.2.4), which ensures that no prioritization is activated if bicyclist traffic is found on the superordinate traffic stream at time t.

In case of prioritization, it is assumed that the $intersecting$ AVs will actively participate in the prioritization of its bicyclist(s). However, it remains uncertain whether, when and which bicyclist(s) will accept the created acceptable gaps. Also the prioritization activation will remain active according to the **fifth constraint** (see: 4.2.2.4) in case of bicyclists present in the considered bicyclist traffic stream. Possible incoming bicyclist(s) will still need to make use of the available time gaps or the AVs will need to readjust their speeds either due to the fact that existing bicyclists did not accept the provided time gap of the leading vehicle, or because possibly incoming bicyclists need to be serviced. These delays cannot be quantified accurately in advance due to the inherent uncertainty of the bicyclist behavior. Also, although the *critical leading* AV will be the one prioritizing bicyclist(s) still delays for following AVs will incur.

In order to account for such effects, the prediction of the expected delays for the AVs needs to consider the worst case scenario with the maximum incurred delay for each AV. This assumption considers each incoming AV that is able to adjust its speed safely in time to provide priority will do so for each assigned incoming bicyclist(s). Thus, it does not consider that only the leading AV will prioritize the incoming bicyclist(s) but it considers both the possibility of additional incoming bicyclists as well as the probability that the considered incoming bicyclist(s) do not accept the first available time gap. The proposed approach is very conservative in the prioritization activation as it ensures that the prioritization will be activated only if the gains for the bicyclist prioritization outperform the losses for the AV streams for their worst case efficiency scenario.

According to these considerations, the predicted delay for the $intersecting$ AVs is calculated based on the investigation of its new prioritization speed v_{prio}^{int} that is determined using Equation 4.12.

$$v_{prio}^{int} = \frac{s_i^{int}}{t_{sgap}^{int}} + \frac{1}{2} a_d^{int} t_{sgap}^{int} \tag{4.12}$$

where:

$v_{prio}^{int} \in \mathbb{R}^+$ = The required travel speed of the int vehicle to provide the secure gap t_{sgap}.

$s_i^{int} \in \mathbb{R}^+$ = Distance of the int vehicle to the intersect point i.

$a_d^{int} \in \mathbb{R}^-$ = Desired deceleration rate of the int vehicle.

$t_{sgap} \in \mathbb{R}^+$ = Secure gap for the ego vehicle.

According the result of Equation 4.12, it is necessary to investigate whether a prioritization activation is indeed possible for the int vehicle given the resulting v_{prio}^{int}. Based on this result and the prioritization activation state, the predicted delay for the int vehicle is found using Equation 4.13.

$$d_{i,p}^{int} = \begin{cases} t_{i,MaxSpeed}^{int} + d_{t-1}^{int} & \text{If no prioritization is activated} \\ t_{i,MaxSpeed}^{int} + d_{t-1}^{int} & \text{If prioritization is activated} \\ & \text{and } (v_{prio}^{int} < 0 \text{ or} \\ & max(v_{prio}^{MIN}, v_c^{int} + a_d^{int} t_{sgap}^{int}) \geq v_{prio}^{int} \geq v_{MaxSpeed}^{int}) \\ t_{sgap}^{int} + t_i^{ego} + d_{t-1}^{int} & \text{If prioritization is activated} \\ & \text{and } v_{prio}^{int} \geq 0 \text{ and} \\ & max(v_{prio}^{MIN}, v_c^{int} + a_d^{int} t_{sgap}^{int}) < v_{prio}^{int} < v_{MaxSpeed}^{int} \end{cases} \tag{4.13}$$

where:

$d_{t,p}^{int} \in \mathbb{R}^+$ = total predicted delay of the int vehicle at time step t due to the expected interaction with the ego vehicle.

$t_{i,MaxSpeed}^{int} \in \mathbb{R}^+$ = Predicted time spend for int vehicle traveling past the intersection point i with its maximum allowed or desired speed.

$d_{t-1}^{int} \in \mathbb{R}^+$ = total accumulated delay of the int vehicle at time step $t-1$.

$t_{sgap} \in \mathbb{R}^+$ = Secure gap for the ego vehicle.

$t_i^{ego} \in \mathbb{R}^+$ = Time the ego vehicle requires with its current speed v_c^{ego} to travel past the intersection point i as defined using Equation 4.8.

The respective stop states for the int vehicle are defined using Equation 4.13.

$$h_{i,p}^{ego} = \begin{cases} 0 + h_{t-1}^{ego} & \text{If no prioritization is activated} \\ 1 + h_{t-1}^{ego} & \text{If prioritization is activated} \end{cases} \tag{4.14}$$

where:

$h_i^{int} \in \mathbb{I}_0^+$ = Predicted stop(s) of the int vehicle due to the interaction with the ego vehicle.

$h_{t-1}^{int} \in \mathbb{I}_0^+$ = Accumulated stop(s) of the int vehicle at time step $t-1$.

Respectively, as the bicyclists are considered in the prioritization only if they belong to the subordinate traffic stream and the AVs activate priority only if they are on a superordinate traffic stream, the maximum delay and stop value against all critically interacting AVs is assigned to each bicyclist in the case of priority deactivation and the minimum delay and stop value against all critically interacting AVs is assigned to each bicyclist in the case of priority activation. The same applies for AVs, where the maximum delay value against all critically interacting bicyclists is assigned to each AV in the case of priority activation and the minimum delay value against all critically interacting bicyclists is assigned to each AV in the case of priority deactivation. The stop values are not considered for AVs as the prioritization concept restricts the AVs from coming to a full stop during the prioritization state. Eventually one delay value and one stop value is assigned to each road user for each prioritization state. The respective values are aggregated for each road user type specific traffic stream for each prioritization state.

4.2.2.3 Definition of the Objective Functions

The problem is formulated into a multi-objective optimization problem for minimizing total delay for the respective intersection and minimizing bicycle stops. The minimization of the total delay is set as the highest priority objective, as it equally considers both the AVs and the bicyclists. The minimization of the number of bicyclist stops is set as the second priority objective. Following the hierarchical approach, a priority is defined for each objective. The optimization solver then considers only solutions that would not degrade the objective values of the higher-priority objectives.

The 1^{st} priority objective minimizes the expected delay for all road user type specific traffic streams at the intersection. The uncertainty quantification is used as an average weight factor c_{u_s} for the estimated delay during activation and deactivation for each traffic stream. The 1^{st} objective function for minimizing the total delay is defined in 4.15:

$$Minimize \quad D = \sum_{s \in streams} \left[c_{s_s} * \sum_{u \in users} \left[d^a_{u_s} * 1_{a_{s_s}} \right] + c_{s_s} * \sum_{u \in users} \left[d^d_{u_s} * 1_{d_{s_s}} \right] \right] \tag{4.15}$$

The activation and deactivation of prioritization is described respectively by the boolean variables according to 4.16 and 4.17:

$$1_{a_{s_s}} = \begin{cases} 1 & \text{If priotization on traffic stream } s_s \text{ is active} \\ 0 & \text{If priotization on traffic stream } s_s \text{ is not active} \end{cases} \tag{4.16}$$

$$1_{d_{s_s}} = \begin{cases} 0 & \text{If priotization on traffic stream } s_s \text{ is active} \\ 1 & \text{If priotization on traffic stream } s_s \text{ is not active} \end{cases} \tag{4.17}$$

For equations 4.15, 4.16 and 4.17 applies:

$c_{s_s} \in [0,1]$ = Average prediction confidence weight factor for all users on traffic stream s (-).

$d^a_{u_s} \in \mathbb{R}^+_0$ = Total expected time delay for user u on traffic stream s on prioritization activation (in seconds).

$d^d_{u_s} \in \mathbb{R}^+_0$ = Total expected time delay for user u on traffic stream s on prioritization deactivation (in seconds).

$s_s \in \mathbb{I}^+ \cap [1,12]$ = s_s in AV and bicycle traffic streams.

The 2^{nd} priority objective minimizes the expected number of stops for all bicyclist traffic streams at the intersection given a relative tolerance of 0.2 for degrading the 1^{st} priority objective. The uncertainty quantification is used as a weight factor c_{u_s} for the estimated number of stops during activation and deactivation for each bicyclist. The 2^{nd} objective function for minimizing the total number of bicyclist stops is defined in 4.18:

$$Minimize \quad S = \sum_{b_s \in bicycles} \left[c_{b_s} * \sum_{u \in users} \left[h^a_{u_s} * 1_{a_{u_s}} \right] + c_{b_s} * \sum_{u \in users} \left[h^a_{u_s} * 1_{d_{u_s}} \right] \right] \tag{4.18}$$

The activation and deactivation of prioritization is described respectively by the boolean variables according to 4.19 and 4.20:

$$1_{a_{b_s}}(x) = \begin{cases} 1 & \text{If priotization on bicycle stream } b_s \text{ is active} \\ 0 & \text{If priotization on bicycle stream } b_s \text{ is not active} \end{cases} \tag{4.19}$$

$$1_{d_{b_s}}(x) = \begin{cases} 0 & \text{If priotization on bicycle stream } b_s \text{ is not active} \\ 1 & \text{If priotization on bicycle stream } b_s \text{ is active} \end{cases} \tag{4.20}$$

For equations 4.18, 4.19 and 4.20 applies:

$c_{b_s} \in [0,1]$ = Average prediction confidence weight factor for all users on bicycle traffic stream s (-).

$h^a_{u_s} \in \mathbb{I}^+_0$ = Total expected number of stops for user u on traffic stream s on prioritization activation (-).

$h^d_{u_s} \in \mathbb{I}^+_0$ = Total expected number of stops for user u on traffic stream s on prioritization deactivation (-).

$b_s \in \mathbb{I}^+ \cap [1,12] = b_s$ in bicycle traffic streams.

4.2.2.4 Definition of Constraints and Threshold Values

Constraints are defined that limit the optimal solution range for the objective function in order to ensure safe traffic operations, while supporting the prioritization concept. Constraints are applied for the activation of the prioritization only on the respective superordinate AV and bicycle traffic streams. Although, no prioritization activation takes place on bicyclist streams, the boolean variables serve the role for considering the traffic performance effects in the objective functions.

The **first constraint** ensures that there is not a concurrent activation and deactivation status on the same traffic stream. Equation 4.21 defines the constraint for the boolean activation and deactivation variables, for all intersection traffic streams s_s, based on the equations 4.16 and 4.17:

$$1_{a_{s_s}} + 1_{d_{s_s}} = 1 \tag{4.21}$$

where:

$s_s \in \mathbb{I}^+ \cap [1,12] = s_s$ in AV and bicycle traffic streams

Taking inspiration from the work of Kurt Dresner and Peter Stone [2007], the **second constraint** ensures the safe and conflict free prioritization of a subordinate bicycle traffic stream b_s over a superordinate traffic stream s_s by restricting the prioritization activation only for situations where no bicycle traffic is detected on the superordinate traffic stream s_s. In this way, the priority of bicyclists on the superordinate traffic stream is guaranteed, while the base traffic rules continue to apply. Equation 4.22 defines the constraint for the boolean activation variables, for all intersection traffic streams s_s, based on the equations 4.16, with no bicycle traffic demand on the superordinate bicycle traffic stream b_s:

$$1_{a_{s_s}} + 1_{D_{b_s}} \leq 1 \tag{4.22}$$

The presence of bicycle traffic on the superordinate traffic stream b_s is represented using a boolean variable as defined in equations 4.23:

$$1_{D_{b_s}}(x) = \begin{cases} 0 & \text{If demand for bicycles on bicycle traffic stream } b_s \text{ is detected} \\ 1 & \text{If demand for bicycles on bicycle traffic stream } b_s \text{ is not detected} \end{cases} \tag{4.23}$$

Where:

$b_s \in \mathbb{I}^+ \cap [1, 12] = b_s$ in bicycle traffic streams.

The **third constraint** ensures that under no circumstances will a prioritization state be activated for bicycle streams of rank 1 according to Figure 2.3 and Table 2.1, as they already have priority over all other traffic streams. Equation 4.24 defines the constraint for the boolean activation variables of equation 4.16:

$$1_{a_{B_1}} = 0 \tag{4.24}$$

where:

$B_1 \in b_2, b_3, b_8, b_9 =$ rank 1 bicycle traffic streams.

The **fourth constraint** is defined for all traffic streams of rank 2, 3 and 4 according to Figure 2.3 and Table 2.1. It ensures that a prioritization activation for a lower rank traffic stream is always paired with the activation in all intersecting bicycle and AV streams as pairs together with superordinate traffic streams. In this way, safe and conflict free interactions are guranteed as all superordinate AV traffic streams are required to provide priority.

Equations 4.25 to 4.28 define the prioritization activation pairs for 2^{nd} rank traffic streams:

$$1_{a_{b_1}} \rightarrow 1_{a_{av_8}} \tag{4.25}$$

$$1_{a_{b_6}} \rightarrow 1_{a_{av_2}} \tag{4.26}$$

$$1_{a_{b_7}} \rightarrow 1_{a_{av_2}} \tag{4.27}$$

$$1_{a_{b_{12}}} \rightarrow 1_{a_{av_8}} \tag{4.28}$$

Equations 4.29 and 4.30 define the prioritization activation pairs for 3^{rd} rank traffic streams:

$$1_{a_{b_5}} \rightarrow 1_{a_{av_2}} \wedge 1_{a_{av_7}} \wedge 1_{a_{av_8}} \wedge 1_{a_{av_9}} \tag{4.29}$$

$$1_{a_{b_{11}}} \rightarrow 1_{a_{av_1}} \wedge 1_{a_{av_2}} \wedge 1_{a_{av_3}} \wedge 1_{a_{av_8}} \tag{4.30}$$

Equations 4.31 and 4.32 define the prioritization activation pairs for 4^{th} rank traffic streams:

$$1_{a_{b_4}} \rightarrow 1_{a_{av_1}} \wedge 1_{a_{av_2}} \wedge 1_{a_{av_7}} \wedge 1_{a_{av_8}} \wedge 1_{a_{av_{11}}} \tag{4.31}$$

$$1_{a_{b_{10}}} \rightarrow 1_{a_{av_1}} \wedge 1_{a_{av_2}} \wedge 1_{a_{av_5}} \wedge 1_{a_{av_7}} \wedge 1_{a_{av_8}} \tag{4.32}$$

For equations 4.25 to 4.32 applies:

$b_s \in \mathbb{I}^+ \cap [1, 12] \quad = b_s$ in bicycle traffic streams.

$av_s \in \mathbb{I}^+ \cap [1, 12] = av_s$ in AV traffic streams.

The **fifth constraint** is defined through a dynamic timer threshold value that keeps the prioritization active if bicycle demand is still detected on the subordinate bicycle stream for a maximum time duration. Here the threshold value is set to 30s. As the Optimizer calculates a new solution for each simulation step, this constraint ensures that the prioritization is not switching on or off randomly due to new incoming road users that alter the intersection traffic state. This step is performed before the optimization starts, where the activation variable of the respective bicycle traffic stream is fixed to 1. The prioritization will only be deactivated in case there is no longer any bicycle traffic detected on the subordinate bicycle traffic stream.

Algorithm 1: Fifth Constraint: Timer-based Prioritization Activation for Bicycle Traffic Streams

```
Result: Fixes the activation variables for bicycle traffic streams before optimization at
        each simulation time step
ActivationTimerThreshold = 30;
for s in BicycleTrafficStreams do
    if PreviousStepActivations[s] == 0 or BicycleDemandCheck[s] == 0 then
        ActivationTimerDuration[s] = 0;
        ActivationTimerState[s] = 0;
    else if PreviousStepActivations[s] == 1 then
        ActivationTimerDuration[s] += SimulationStepSize;
        ActivationTimerState[s] = 1;
    if ActivationTimerState[s] == 1 and ActivationTimerDuration[s] ≤
     ActivationTimerThreshold then
        ActivationTimerDuration[s] = 0;
        ActivationTrafficStream[s] = 1;
end
```

4.2.3 Simulation Model Design

The developed optimization method will be assessed using in the SUMO microscopic traffic simulation software. SUMO is chosen primarily due to each open source nature as well as due to the fact that the TraCI API provides the user with a significant level of freedom in extracting simulation state parameters and controlling the behavior of simulated road users. TraCI is also using Python and thus it can effortlessly integrate and communicate with the Gurobi Python interface.

The following subsections describe in more detail the design setup of the simulation model, the integration of the optimization method with SUMO, the modeling of the AV prioritization functions and the simulation studies design. A simple fictional unsignalized intersection is designed in SUMO. The layout is based on the intersection dimensions used for the bicycle simulator study in Chapter 3. Each intersection approach consists of a two-way road with one traffic lane per travel direction. Each traffic lane has a 3.30m width, an adjacent parking lane of 2.0m width and a sidewalk with 3.0m width. Motor vehicle and bicycle traffic are allowed to travel only on the traffic lane. Nevertheless, the parking lane and the sidewalk are included to account for more realistic intersection area dimensions. The speed limit for vehicles is set to 30 km/h which is typical for unsignalized intersections in urban areas in Germany. With respect to traffic priority rules, these are modeled according to Figure 2.3 for a four-arm intersection. The east and west intersection arms are part of the major road, while the north and south arms are part of the minor road. The priority rules are handled by the SUMO Junction Model using the intersection model connection geometry. This is generated by the SUMO network editor (NETEDIT) automatically. Here, no adjustments are made neither to the connections' geometry nor to the default control point positions that are used by the SUMO Junction Model to identify the stop positions for users on the minor connections that have to provide priority. Figure 4.7 presents the intersection model layout.

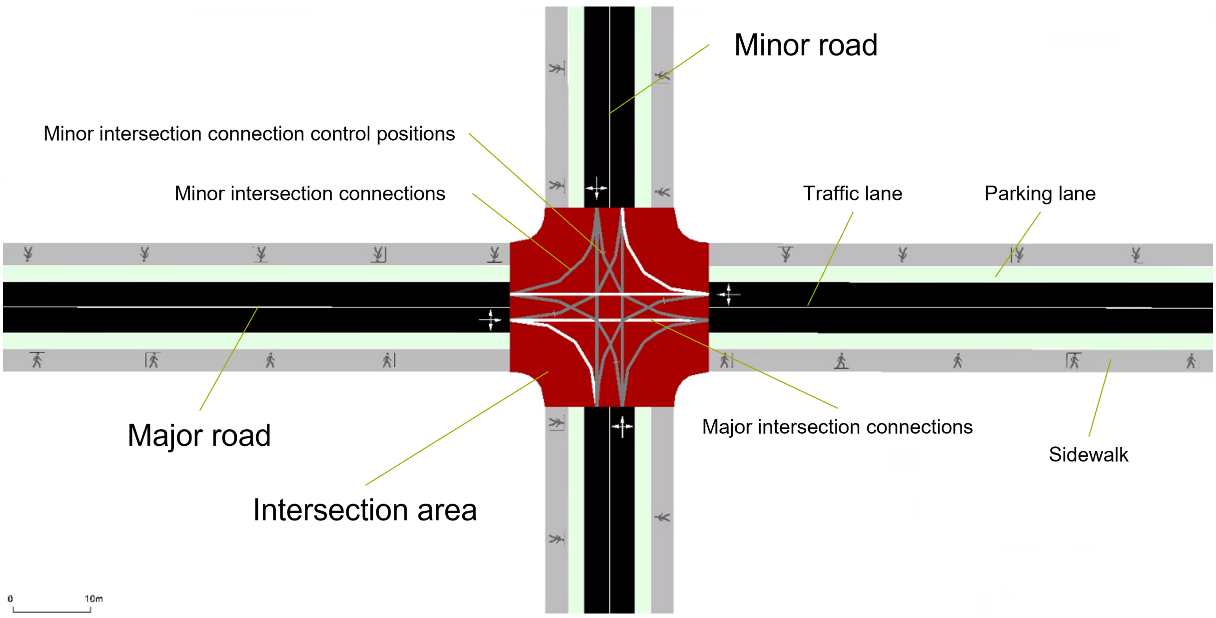


Figure 4.7: SUMO intersection model layout.

4.2.4 Integration of Optimization System Architecture with SUMO

In order to evaluate the proposed optimization method, it is essential to integrate it with SUMO. As the the Gurobi Solver provides a Python interface for modeling the problem formulation, it is possible to use the SUMO TraCI API for the integration. TraCI can also be used to derive important simulation properties and adjust the road user behavior based on the results of the optimizer.

However TraCI is not able to inherently provide access to all the necessary simulation parameters. First, with respect to the connections in the intersections, it is not possible to derive directly the intersection points and the polyline connection lengths. Thus, an additional function is necessary to estimate conflict events. Secondly, although it is possible for each road user to derive a list for all its surrounding road users at each time step, it is not possible to know the nature of their interaction or how they will interact in the future time steps. Thus, for interactions at the intersection it is not possible to directly extract the information on whether a road user will yield for another user or how the driving behavior will change so that conflicts are avoided. Finally, as the optimization method relies on the proposed vehicle prioritization functions, these need to be explicitly modeled in SUMO as well. This task involves the definition of several functions using TraCI. Figure 4.8 presents the core modules that are developed for facilitating the integration of the optimization method in SUMO. The architecture consists of eight different modules.

- **Scenarios**: Defines the simulation setup for each SUMO scenario. This includes the traffic demand for each traffic stream, the number of simulation runs and the activation of the *Optimizer* for the entire simulation (whether to run the "Base" scenario or the "Optimization" scenario)
- **Demand**: It receives the input from the *Scenarios* module and creates the traffic demand for each simulation.
- **Vehicle Types**: It defines the driving behavior parameters for all road users.
- **Control**: It is responsible for initiating the SUMO simulation and transferring information between the simulation and the other modules.
- **SUMO**: The SUMO simulation instance. It communicates with the *Control* module via TraCI.
- **Methods**: It includes all the necessary functions for identifying the intersection points between different intersection connectors and for assigning them to specific traffic routes as well as assigning vehicle objects to their respective network elements. It includes all the functions that are necessary to identify the interactions between all road users and provides estimations with respect to the optimizer interaction parameters for both the activation and deactivation scenarios of the prioritization states at each simulation step. These are then returned to the respective vehicle object parameters and ultimately processed by the *Optimizer* module.

- **Vehicles**: It defines the vehicle class. The vehicle class is initiated each time a new vehicle enters the simulation. The vehicle class is the same for both AV and bicycle users and enchances their properties through new parameters and functions that are important for the integration with the *Optimizer*. It includes parameters for all user types that describe the type and predicted effects for the interactions with all relevant road users as identified by the *Methods* module. For bicycle users it also includes the parameters for the uncertainty estimation of the maneuver prediction. For AV users, it includes the required functions for deciding the appropriate prioritization state for each vehicle based on the input received by the *Optimizer* module.
- **Optimizer**: It includes the optimization model modeled for the Gurobi Solver using the Python API. It includes supporting functions for deriving the traffic demand state for each route and identifying the relevant road users at each traffic stream that will be considered for the optimization at each simulation step. It finally communicates the optimization results back to SUMO through the *Vehicles* module.

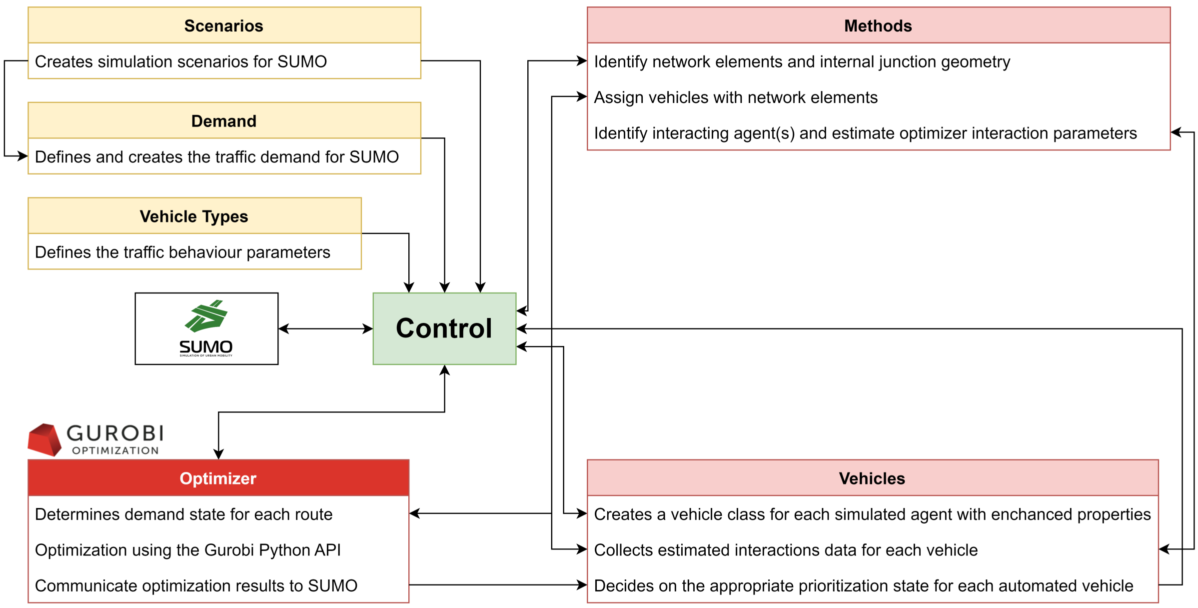


Figure 4.8: Integration of Optimization System Architecture with SUMO.

4.2.5 Modeling Uncertainty for the Bicyclist Maneuver Prediction

As discussed in 3.5.6, the definition of an appropriate threshold value for differentiating between high and low certainty in bicyclist maneuver predictions can be part of future research and is dependent on the use case of the respective uncertainty quantification method. Nevertheless, the introduction of the uncertainty measure as a weight factor in the proposed optimization method, requires the definition of a certain methodology as part of the simulation evaluation for defining the uncertainty threshold. Here, the relative entropy will be used as the measure for quantifying uncertainty as with a single metric, an estimate for the prediction uncertainty across or maneuver classes is reached. Also, based on the meta-analysis on the test sample

Figure 3.11, it is possible to define a "hard" threshold value in the range between 0.38 and 0.55 that mark the upper and lower 75% percentile bounds between the "False" and "True" classifications respectively. Lower threshold values will result in the inclusion of lower certainty predictions in the objective functions, while a higher threshold value will result in a more conservative and safety-biased consideration. Still the inclusion of a hard threshold in the optimization method may generate additional problems. Firstly, bicyclists arriving at the intersection with prediction confidence values under the threshold won't be considered at all by the Optimizer. As the intersection is by no means the end destination of the bicyclists, in cases of high traffic demand this will lead to extreme delays. Also for subordinate bicycle traffic streams entering the major road, a prioritization activation for the 3^{rd} and 4^{th} rank streams will involve anyway the activation of the prioritization for multiple superordinate AV streams on the major road. Eventually the consideration of a "soft" threshold of the confidence prediction factor will lead to slower reactions of the optimization function as the bicyclists will need to accumulate significant delays in order to get prioritized. This also includes the case where multiple bicyclists arrive at the intersection simultaneously with a low prediction confidence. In that way, the method still considers bicyclists with low prediction confidence in the long term and does not penalize them for the failure of the prediction method to reach a high prediction confidence value.

Additionally, the integration of the deep learning model in the proposed simulation architecture in 4.2.4, is an unnecessary step for the evaluation as it adds in complexity without significant gains for the future analysis. Also, mapping the trajectories and gesture metrics from the bicycle simulator test subjects in the simulation is questionable as in the simulations multiple concurrent bicyclists have to be simulated while the users have to interact with one another. This would result in changes in the bicycle simulator trajectories and gesture behavior that cannot be realistically replicated in the simulation.

Accounting for these different aspects and trade-offs, the 0.5 value of the relative entropy is selected as the threshold for differentiating between certain and uncertain predictions. With the initiation of the vehicle class for the vehicle type *Bicycle*, the prediction uncertainty value is selected randomly using a continuous uniform distribution. The bicyclist route prediction assigned to the highest prediction confidence class is considered within the optimization functions. The probability density function is defined in 4.33:

$$p(x) = \frac{1}{c_{max} - c_{min}} \tag{4.33}$$

where:

$c_{min} \in [0, 1] =$ Minimum value of the confidence value range as set by the user.

$c_{max} \in [0, 1] =$ Maximum value of the confidence value range as set by the user.

The *Optimizer* module is unaware of the bicyclist maneuver prediction true value. It classifies and considers the bicyclists according to their artificially-generated predicted maneuver, using the respective parameter of the *Vehicles* class. The threshold is used only for differentiating between high and low prediction confidence simulation scenarios. The soft consideration of the confidence factors in the optimization method will allow the proposed method to react in the long-term to bicyclists accumulating increasing delays with a low prediction confidence. In SUMO, rings are used to visualize the true maneuver only for the external observer.

4.2.6 Simulation of Road User Behavior

The bicyclist behavior is calibrated based on the behavior parameters of previous own research work, based on simulation models in SUMO [Georgios Grigoropoulos, Lücken, et al., 2019; Georgios Grigoropoulos, Hosseini, et al., 2021] and PTV Vissim [Georgios Grigoropoulos, Leonhardt, et al., 2022], where the bicyclist behavior is calibrated and validated through empirical data. The AV behavior is calibrated using the behavior parameter provided by Olstam et al. [2020]. In their work, behavior parameter values are provided for calibrating the AV driving behavior by adjusting the respective parameter of the Wiedemann 99 model. Based on their suggestions, the Wiedemann 99 is adjusted for the advanced AV class with the normal driving logic for the urban street environment as it considers the case of unsignalized at-grade intersections.

The prioritization functions and states are modeled in SUMO given the specifications provided in paragraph 4.2.1.4. In SUMO the *setSpeed* function is used for the respective activation and deactivation of the prioritization in each simulated SUMO. The passive prioritization state is simulated using the *openGap* function of the TraCI Vehicle Class. This function changes the vehicle's desired time headway to its leader smoothly to a new value defined by the user. The corresponding input value for the desired time headway is set to $6s$, which is the predefined convenient bicyclist time gap. Figure 4.9 presents an example of the AV speed and acceleration profile during prioritization in the SUMO simulation. Finally, Figure 4.10 presents an example of the successive deactivation and activation of the prioritization status in SUMO and the respective transitions between the AV states.

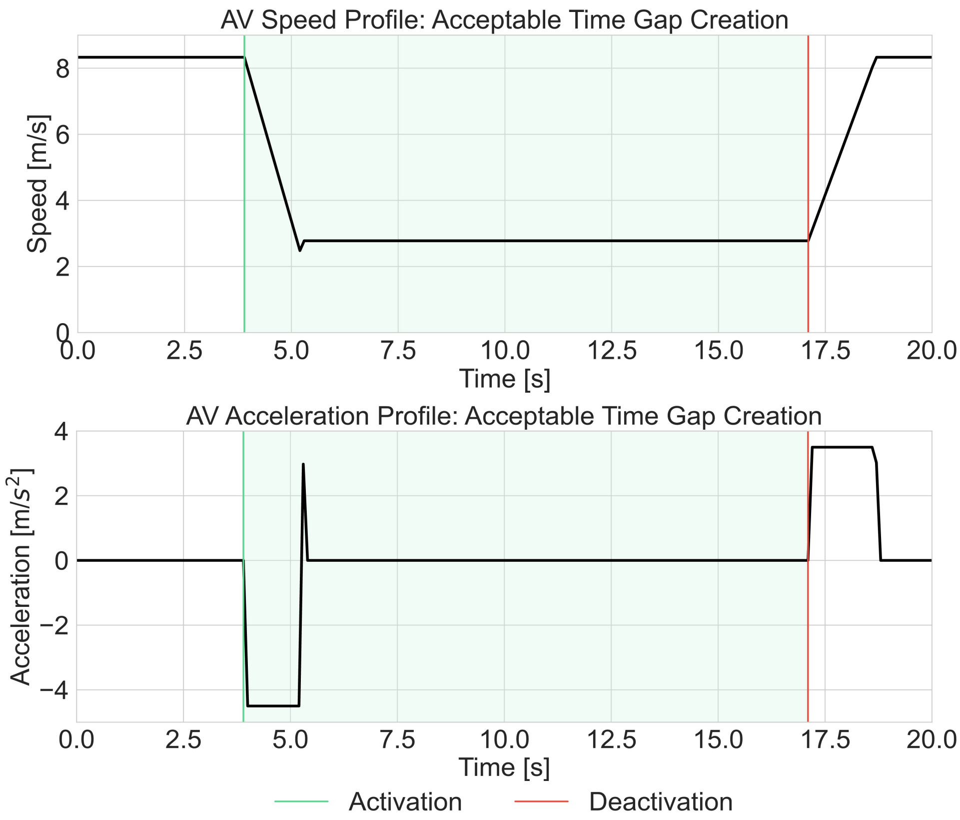


Figure 4.9: Example speed and acceleration profile of an AV in SUMO during the activation and subsequent deactivation of an acceptable time gap.

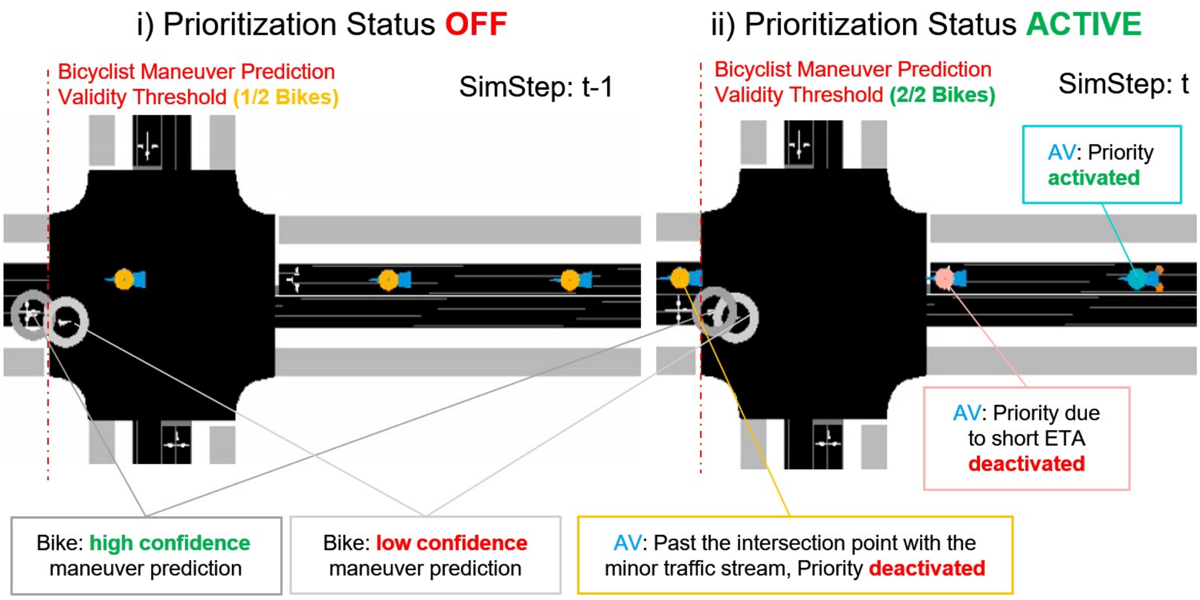


Figure 4.10: Example of the successive deactivation and activation of the prioritization status in SUMO and the respective transitions between the AV states.

4.2.7 Simulation Scenario Definition

In order to assess the proposed method and analyse its effects and performance, specific traffic scenarios need to be defined. The principle function of the proposed method is that it prioritizes bicyclists of subordinate traffic streams over AVs on superordinate traffic streams. The decision for prioritization is a function of the estimated traffic state on the AV and bicycle traffic stream, the uncertainty evaluation of the bicyclist intentions and the bicycle demand on the superordinate traffic stream. As part of the evaluation, it is important to assess how these factors influence the performance of the proposed method and how that compares to the base scenario without prioritization. Thus, it is decided to evaluate traffic scenarios with both AV and bicyclist traffic allocated on specific intersection traffic streams that define typical and clear prioritization scenarios in order to better understand the performance effects without the influence of complex user interactions.

Finally, with respect to the traffic composition during the evaluation scenarios, it is important to assess the performance of the proposed method during varying demand scenarios for both bicyclist and AV traffic and better assess for which traffic conditions, an optimal traffic performance is reached. Thus, for each road user type an increasing traffic volume is defined and variations of each scenario with low to high traffic demand are simulated.

4.2.7.1 Scenario 1: Prioritization of left turning bicycle stream on main road

A common traffic situation on unsignalized intersections involves bicyclists, that want to perform a left turn maneuver from the major road into the minor road, having to provide priority to the crossing traffic stream on the opposite driving direction. As a result bicyclists have to stop inside the intersection area and wait for the opposing traffic stream to clear the intersection point. This in turn may lead to critical traffic situations with other road users on the rest traffic streams. In the case of high bicycle traffic, the queuing left turning bicyclists will eventually become a bottleneck fro crossing traffic on the major road. This scenario aims to assess the performance of the proposed method considering different traffic compositions for the AVs and the bicyclists. The traffic volume for each AVs and bicycle traffic stream will be gradually increased separately, from 100 veh/h to 700 veh/h with a step of 200 veh/h. All intermediate combinations for the traffic demand are assessed for both traffic streams. As a result, it will ve possible to analyse the effects of the proposed method, in the cases of lower to higher bicycle demand against higher to lower AVs traffic demand and derive for which combinations the application of the proposed method maximizes performance. Figure 4.11 presents the setup properties for Simulation Scenario 1a: Prioritization of left turning bicycle stream on main road without concurrent bicycle traffic on the main road.

Simulation Scenario 1b expands Scenario 1a. It includes bicycle traffic on the superordinate traffic stream in order to assess the sensitivity of the proposed method against the predefined constraints, where prioritization is not activated in the case of bicycle traffic demand on the superordinate traffic stream. This analysis is performed for all traffic volume combinations of Scenario 1a, by additionally including a 50 bicycles/h volume on the major traffic stream. it is expected that the prioritization method won't be activated in these scenarios resulting in traffic performance that is closer to the base scenario without prioritization. Figure 4.12 presents the setup properties for Simulation Scenario 1b: Prioritization of left turning bicycle

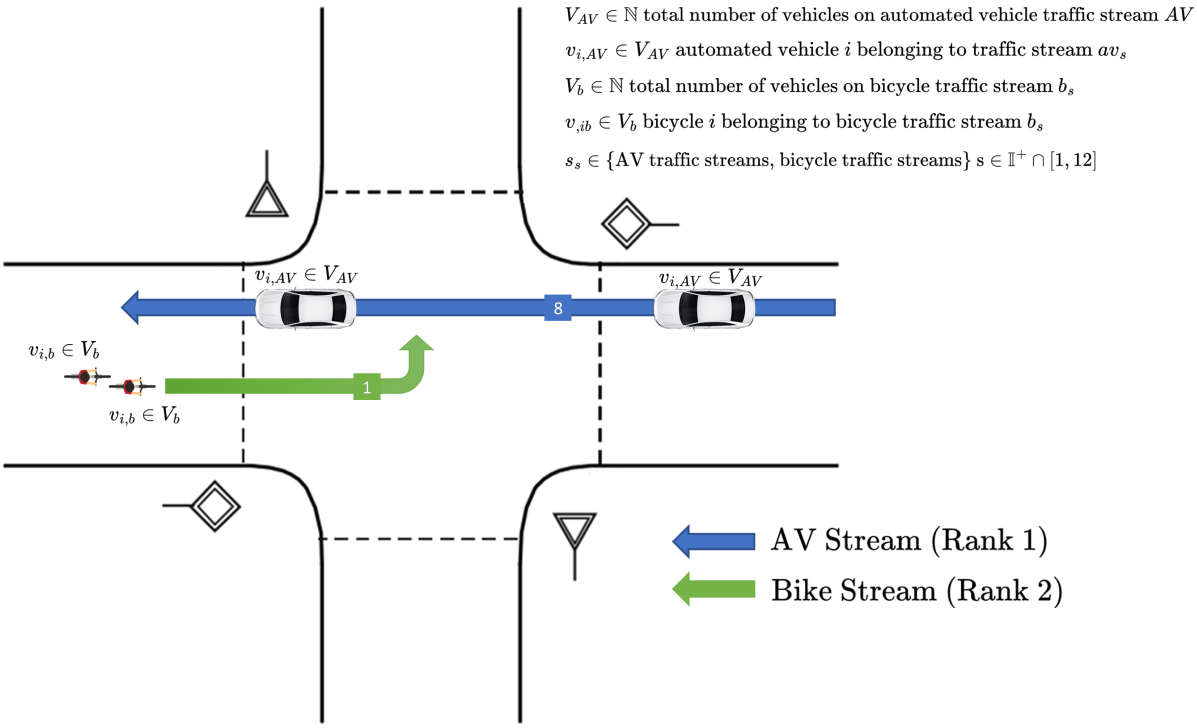


Figure 4.11: Simulation Scenario 1a: Prioritization of left turning bicycle stream on main road without concurrent bicycle traffic on the main road.

stream on main road with concurrent bicycle traffic on the main road.

4.2.7.2 Scenario 2: Prioritization of a crossing bicycle stream from the minor road

This scenario analyses the performance of the prioritization method for assisting bicyclists, traveling on the minor road, while crossing the major road. In cases of high traffic demand this task is highly stressful and safety critical for bicyclists as they have to simultaneously cross two superordinate motor vehicle traffic streams. The proposed method aims to create secure and acceptable time gaps for bicyclists to cross. Hoewever, as the proposed method tries to balance the traffic performance gains among the AV and bicycle traffic streams, the difficulty for activating the prioritization method increases in this scenario as AV traffic is found in two traffic streams instead of only one (Scenario 1). The traffic volume for both AV traffic streams and the single bicycle traffic stream will be gradually increased, from 100 veh/h to 500 veh/h with a step of 200 veh/h. All intermediate combinations for the traffic demand are assessed for both user groups. As a result, it will be possible to analyse the effects of the proposed method, in the cases of lower to higher bicycle demand against higher to lower AV traffic demand and derive for which combinations the application of the proposed method maximizes performance. Figure 4.13 presents the setup properties for Simulation Scenario 2a: Prioritization of a crossing bicycle stream from the minor road without concurrent bicycle traffic on the main road.

Simulation Scenario 2b expands Scenario 2a. It includes bicycle traffic on the superordinate

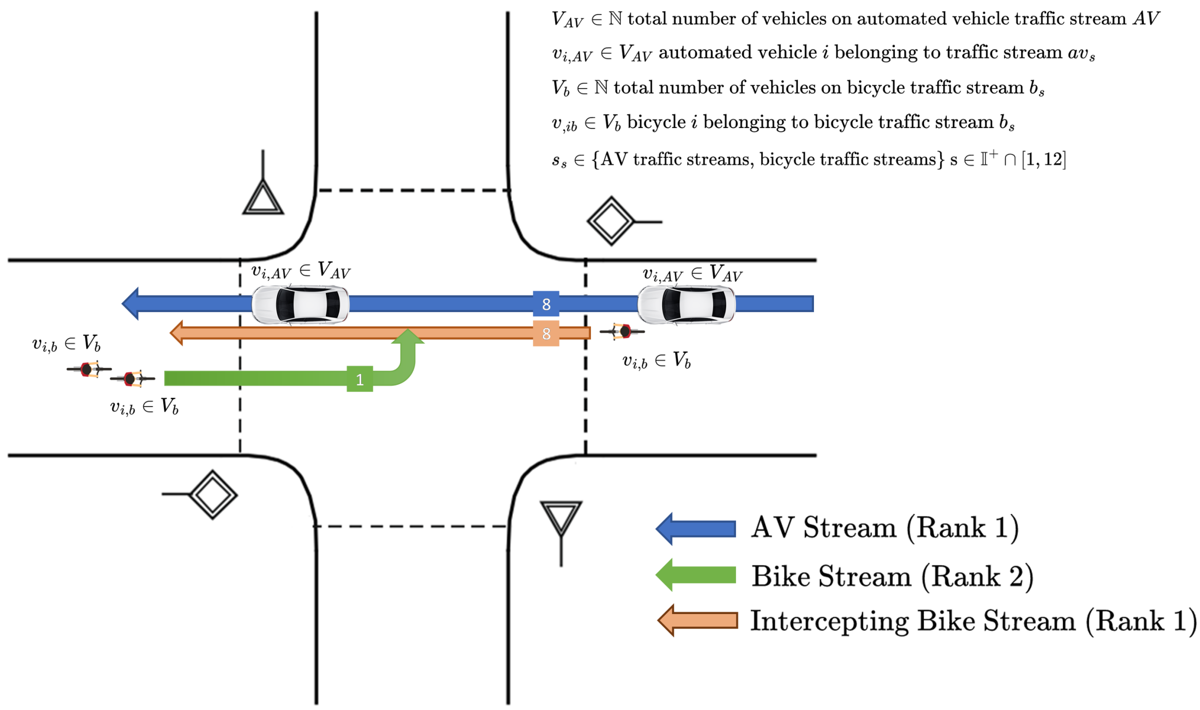


Figure 4.12: Simulation Scenario 1b: Prioritization of left turning bicycle stream on main road with concurrent bicycle traffic on the main road.

traffic stream in order to assess the sensitivity of the proposed method against the predefined constraints, where prioritization is not activated in the case of bicycle traffic demand on the superordinate traffic stream. This analysis is performed for all traffic volume combinations of Scenario 2a, by additionally including a 50 bicycles/h volume for each AVs traffic stream on the major road. it is expected that the prioritization method won't be activated in these scenarios resulting in traffic performance that is closer to the base scenario without prioritization. Figure 4.14 presents the setup properties for Simulation Scenario 2b: Prioritization of a crossing bicycle stream from the minor road with concurrent bicycle traffic on the main road.

4.2.7.3 Sensitivity Analysis of the Uncertainty Quantification

Here the influence of the uncertainty quantification during the optimization is assessed for Scenarios 1a and 2a. As the novel introduction of the uncertainty metric in the estimation of the traffic state eventually influences the decision of the Optimizer, it is important to conduct a sensitivity analysis in order to quantify its influence on the objective function. In a real world implementation, it is expected that due to occlusion of sensors, sensor inaccuracy or failure, the prediction confidence might deteriorate in certain situations. 4.33 is adjusted in the respective scenarios within the range 0.1–0.6 to account for the situation where more than 50% of the bicyclist maneuver predictions have a low certainty value and are below of the confidence threshold as defined in 4.2.5. The uncertainty factor is still set to 1.0 (high certainty) for all AVs.

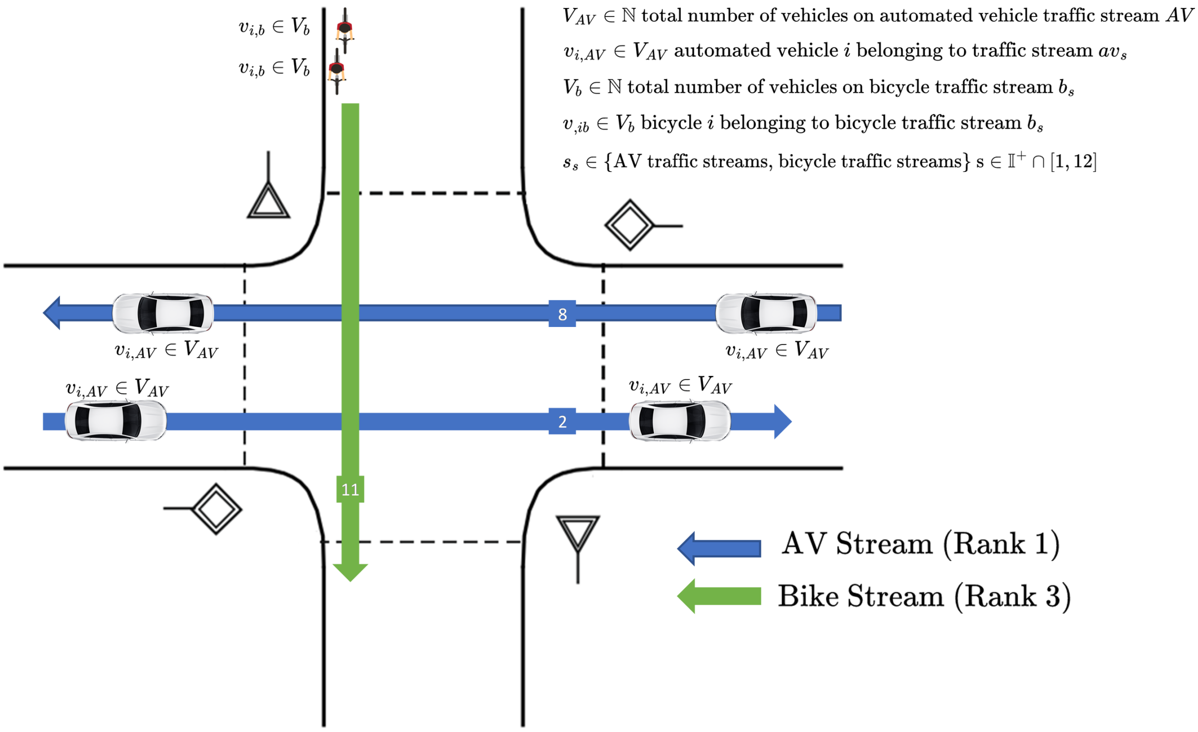


Figure 4.13: Simulation Scenario 2a: Prioritization of a crossing bicycle stream from the minor road without concurrent bicycle traffic on the main road.

4.2.8 Definition of Traffic Performance Parameters

The proposed method is evaluated based on three key typical traffic performance parameters, the delay, the waiting time and the number of stops. These parameters can be conveniently extracted for each road user from SUMO using TraCI. Both the estimations of delay and the number of stops are parameters use by the 1^{st} and 2^{nd} objective functions respectively by the proposed optimization method. However, as already defined in , both parameters are estimated using assumptions for their future state. The derivation of these parameters through SUMO after the respective road user exited the simulation will provide the basis for a more balanced and accurate evaluation, as it will additionally consider the influence of other external factors. Additionally, the waiting time is also introduced as it considers only the time spend in a stop by a road user. The delay considers the entire time spend by road users below their desired speed for bicyclists and the desired speed or the speed limit by AVs. The definition of the waiting time is therefore much closer to how the evaluation of the LOS is performed in both the HBS and the HCM. Finally, incidents where AVs have to come to a full stop cannot be excluded in case of high bicycle demand during queue dissipation. Therefore the waiting time will provide an additional insight for AVs on the average duration of these time periods. The evaluation parameters are defined below based on the SUMO documentation [P. A. Lopez et al., 2018]:

- **Delay:** The time lost due to driving below the ideal speed. (slowdowns due to intersections etc. incur time loss, scheduled stops do not count) (in seconds).

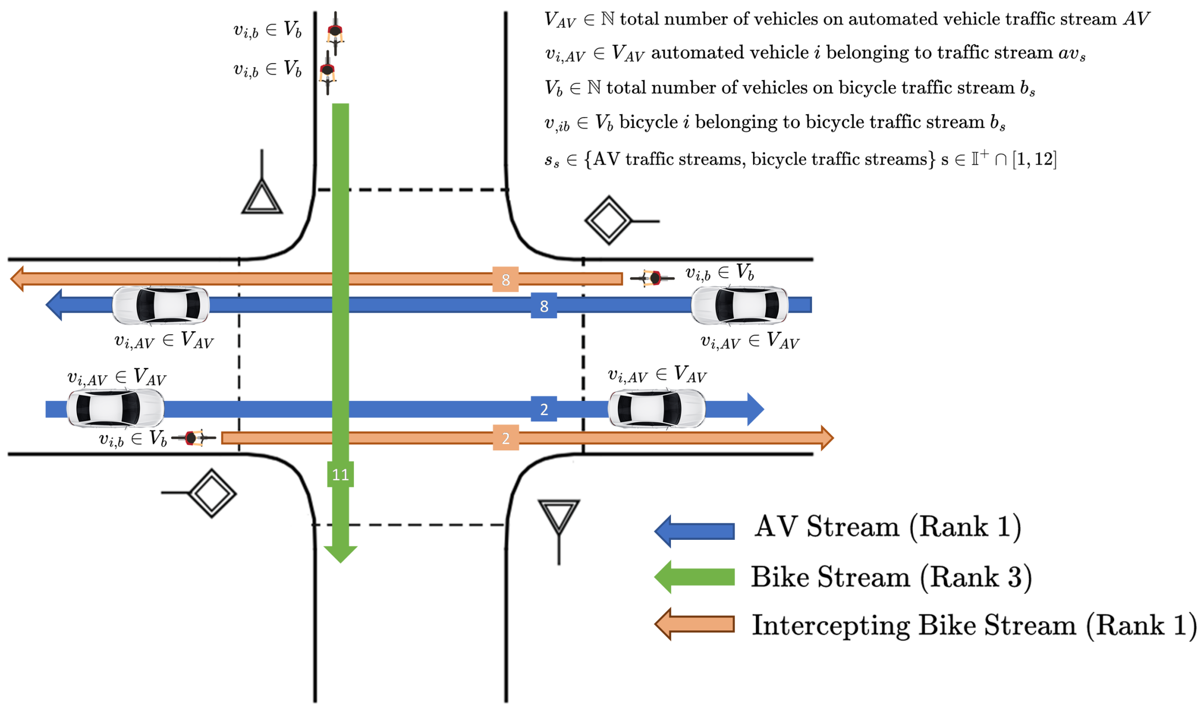


Figure 4.14: Simulation Scenario 2b: Prioritization of a crossing bicycle stream from the minor road with concurrent bicycle traffic on the main road.

- **Waiting Time:** The time spent with a speed below 0.1m/s since the last time it was faster than 0.1m/s (in seconds).
- **Stops:** The occurrence of driving with a speed below 0.1m/s since the last time it was faster than 0.1m/s. (-)

4.2.9 Simulation Studies Setup

For the traffic performance analysis a sufficient number of simulation runs is required for each scenario variation in order to account for the randomness of the simulation. The required number of simulation runs is iteratively defined by applying the methodology proposed by Dowling et al. [2004]. As there is no past knowledge in simulating the specific scenarios, it is necessary to identify the minimum number of simulation runs through iteration. Here simulations are executed until the estimated number of simulation runs matches the number of required simulation runs assumed when looking up the t statistic. s is the standard deviation of the selected performance parameters resulting after each iteration. The minimum number of simulation runs is defined using:

$$CI_{1-a\%} = 2t_{(1-\frac{a}{2}),N-1} \frac{s}{\sqrt{N}} \tag{4.34}$$

where:

$CI_{1-a\%}$ = is the confidence interval for the true mean as defined by the user, where a equals the probability of the true mean not lying within the confidence interval.

$t_{(1-\frac{a}{2}),N-1}$ = is the Student's t-statistic for the probability of a two-sided error summing to a with $N-1$ degrees of freedom, where N equals the number of repetitions. Here, the 95% confidence interval is used for determining the minimum number of simulation runs.

s = is the standard deviation of the resulting model performance parameters.

Each simulation run consists of 200s warm up time, so that the relatively small simulation network is filled with traffic and an additional 1800s of simulation time, where simulation data is recorded will be considered for the evaluation. In total 2000s of simulation time is executed per scenario variation. Following the methodology of Dowling et al. [2004] the required number of simulation runs is found to be 10, hence 12 simulation runs are chosen to be performed for each scenario variation. To account for the comparability among the different scenario variations between the Base Scenario and the Prioritization Scenario, 12 simulation seed numbers are randomly selected. The same seed numbers are used for each simulation run during the simulation initiation in SUMO. Thus, the differences in the analysis of the traffic performance parameters cannot be later on attributed to simulation randomness.

The traffic demand for each scenario variation is defined in SUMO using the *Scenarios* module. In order to ensure that road users are randomly inserted in the simulation, their flows are modeled using the Bernulli process, for which a vehicle will be emitted randomly with the given probability each second until the specified number is reached P. A. Lopez et al. [2018]. Thus, road users do not arrive at the intersection at a steady rate, but demand fluctuates depending on the set probability.

4.3 Results and Analysis of Traffic Performance Indicators

This section discusses the simulation results for the selected traffic performance indicators for both simulation scenarios including their variations. The traffic performance indicators are aggregated over each road user type for each simulation scenario. Each figure presents the results for one traffic performance indicator for the "Base" scenario, where no prioritization concept is activated and for the "Optimization" scenario where the prioritization concept is activated using the proposed prioritization method. For each scenario variation, the respective average indicator value per road user type is presented over all simulation runs. The vertical line over the mean value for each scenario variation defines the standard deviation of the respective sample of indicator values over all simulation runs. The y-axis of defines the traffic performance indicator values. The x-axis defines the range of bicycle traffic volume variations. The grayscale color scale for each line defines the respective AV traffic volume value. Results are presented separately for bicycle traffic and AV traffic, for the average delay, average number of stops and average waiting times.

Finally, the analysis is based on statistical testing. The statistical test will determine if the differences between the mean values of the "Base" and "Optimization" scenarios are significant. First the Levene test is used on the simulation results of the traffic performance indicators to evaluate the equality of variance between the two populations ("Base" and "Optimization"). The Levene test is more robust in comparison to the F-test as it does not assume distribution normality. Based on the acceptance or rejection of the null hypothesis for the Levene Test (p-value < 0.05), the t-Test or the Welch-Test is applied respectively to determine if the hypothesis of equal means must be rejected. The null hypothesis of equal means in both populations is rejected if the p-value is smaller than 0.05. In all tables, the, mean traffic performance indicators values of the "Optimization" are compared against the "Base" scenario. For each scenario variation of combined traffic volumes, the (%) difference to the "Base Scenario" is found on the top of each table cell and the corresponding p-value on the bottom of each table cell. Improvements in the traffic performance indicators are marked with a **Green** color, while the deterioration of the traffic performance indicators is marked with a **Red** color. Statistically significant differences (rejection of the null hypothesis H_0) between the means are additionally indicated with bold letters and color filling (**Green** for improvement and **Red** for deterioration).

4.3.1 Simulation Results

4.3.1.1 Simulation Scenario 1a: Prioritization of left turning bicycle stream on main road without concurrent bicycle traffic on the main road

4.3.1.1.1 Bicycle traffic (Subordinate Traffic Stream) Figures 4.15 ,4.16 and 4.17 present the traffic performance indicator results for the average delay, average number of stops and average waiting time. The respective results of the statistical analysis are presented in Tables 4.1 ,4.2 and 4.3.

It is found that in both the "Base" and the "Optimization" scenarios the average delay (Figure 4.15) for bicyclists increases as a function of increasing bicycle and AV traffic volume. Results, suggest that the "Optimization" scenario does not outperform the "Base" scenario for AV traffic volumes equal or less than 500 veh/h. Results for these scenarios are mixed, however the differences between the means are not statistically significant. The "Optimization" consistently reduces the average bicyclist delays significantly for the AV traffic volume of 700 veh/h and outperforms the "Base" scenario, with the exception of the highest bicycle traffic demand scenario (700 bicycles/h) (Table 4.1).

In the other scenario variations, due to low traffic demand as well as due to the fact that bicyclists have to pass through only a single intersection point, it is possible that bicyclists find acceptable gaps fairly easily between superordinate AVs and thus prioritization is not activated. Respectively as, bicyclists need to cross a single intersect point estimated delays remain small in comparison to AVs. These results are expected from a traffic performance perspective, as under low traffic conditions, priority rules outperform active control measures [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015; National Research Council, 2016] in terms of traffic performance.

Also, it is possible that the prioritization activation effectively reduces the delay for a bicyclist group, however as AVs in turn decelerate they form small platoons with incurred increasing delays per vehicle. Bicyclists upstream arriving at the intersection may no longer be prioritized due to the AV delay carrying on from the previous prioritization activation. This forms a repetitive pattern where, eventually one group always arrives with smaller delays than the other road user group and prioritization is activated and deactivated respectively depending on which group has the highest delay upon arrival.

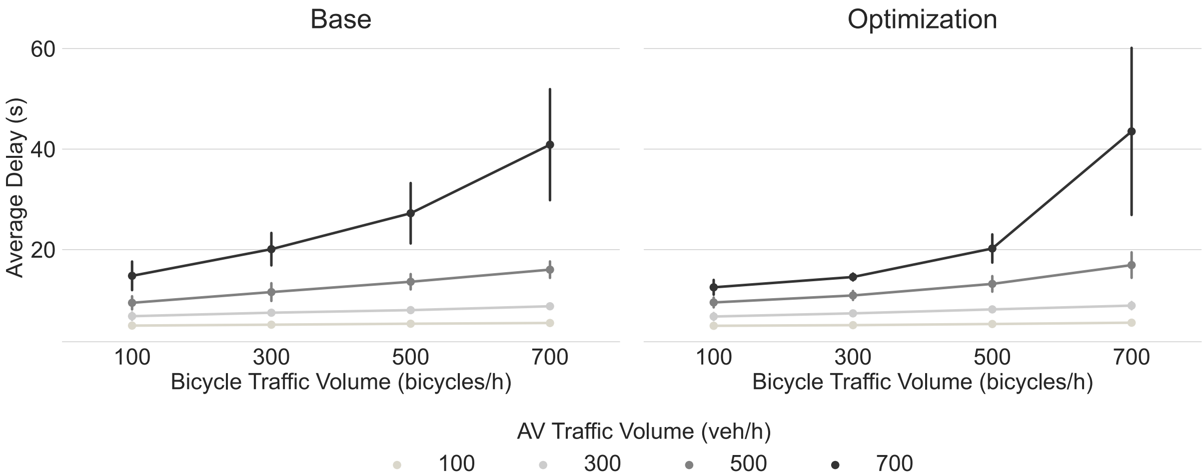


Figure 4.15: Simulation Scenario 1a: Bicycle traffic (minor stream) average delay.

Table 4.1: Simulation Scenario 1a: Bicycle traffic (minor stream) average delay. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)**			
	100	300	500	700
100	-0.755% 0.827	-1.777% 0.516	-1.045% 0.624	1.041% 0.653
300	-0.969% 0.838	-1.697% 0.513	1.840% 0.624	1.512% 0.631
500	0.780 0.883	-5.826% 0.272	-3.142% 0.522	5.706% 0.327
700	**-15.463%** 0.027	**-27.559%** 0.000	**-25.750%** 0.002	6.463% 0.665

With respect to the number of stops and the waiting time (Figure 4.16 and Figure 4.17) results provide further insights on the behavior of the optimization method and its effects on bicycle traffic. Interestingly, the optimization method manages to consistently reduce the waiting times for bicyclists in the majority of all traffic volume compositions, however only improvements for the high AV traffic demand are found to be statistically significant (Table 4.3). At the same time, the average number of stops per bicyclist increases for the large majority of all traffic demand compositions. Here an interesting exception is the AV low traffic demand scenario variation, where mostly the number of bicyclist stops are reduced, however still this difference is not found to be statistically significant. Nevertheless, only for high bicycle and AV traffic demand compositions the increase in number of stops is statistically significant.

As the waiting time is accumulated only during a stop, results suggest that the average number of stops per bicyclist has increased, however as a trade-off the average stop duration per bicyclist has decreased. This is consistent with the hierarchical definition of the objective functions as the delay that includes the waiting time, is the first decisive minimization objective. Additionally, these results hint that the optimization method may be slow to react as by the time bicyclists enter the intersection area, AVs still occupy the common intersection point or cannot decelerate in time to form an acceptable time gap. However, this is a restriction of the proposed bicyclist maneuver prediction model as the prediction certainty increases significantly close to the intersection area, where the most decisive bicyclist communication and dynamic behavior actions that reveal the bicyclist intentions occur.

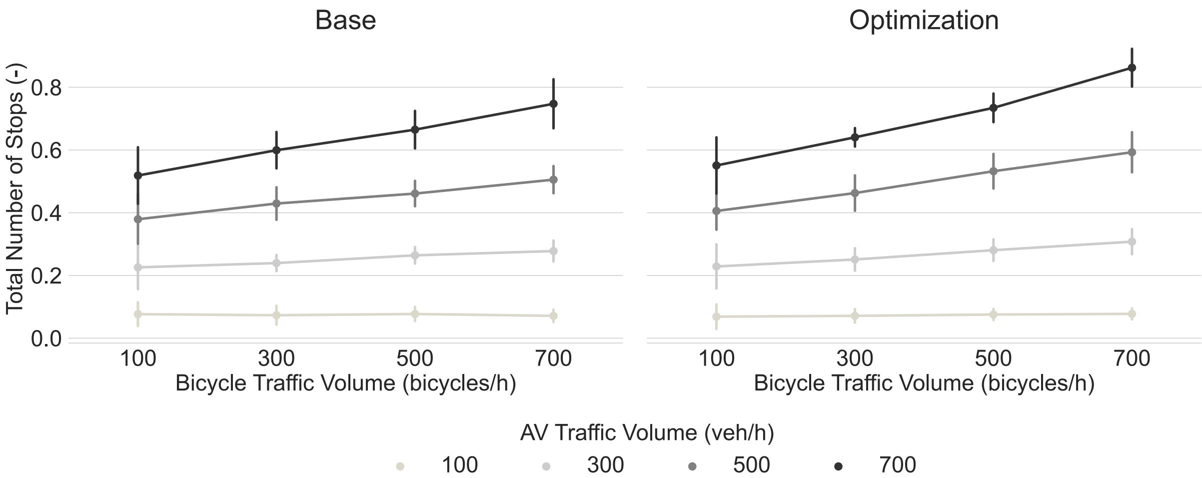


Figure 4.16: Simulation Scenario 1a: Bicycle traffic (minor stream) average stops.

Table 4.2: Simulation Scenario 1a: Bicycle traffic (minor stream) average stops. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)**			
	100	300	500	700
100	-10.492% 0.632	-2.529% 0.871	-2.255% 0.844	8.850% 0.441
300	1.278% 0.924	4.815% 0.397	6.214% 0.225	10.781% 0.072
500	6.961 0.386	7.759% 0.165	**15.452%** 0.002	**17.296%** 0.001
700	6.168% 0.414	6.851% 0.117	**10.461%** 0.006	**15.382%** 0.001

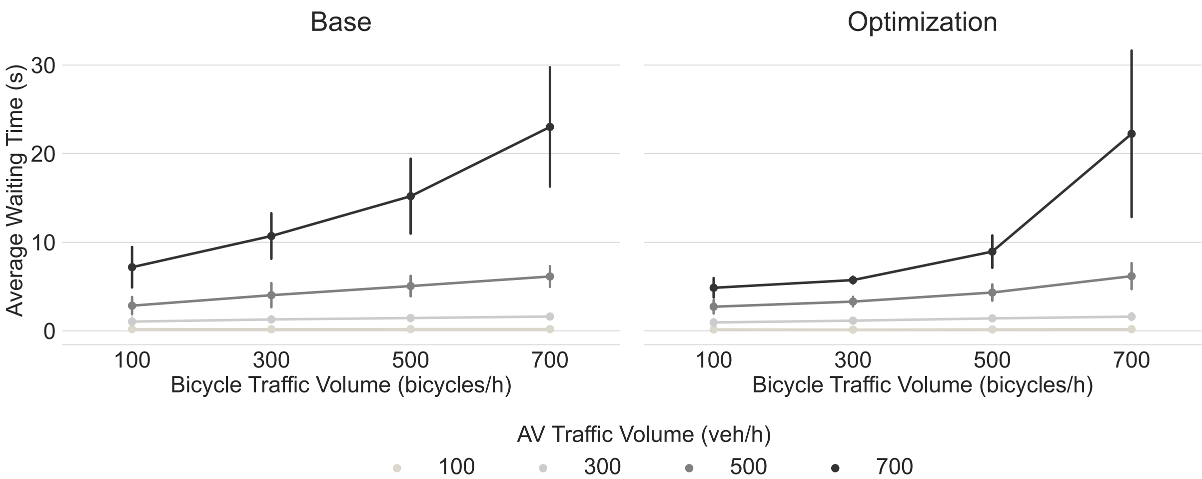


Figure 4.17: Simulation Scenario 1a: Bicycle traffic (minor stream) average waiting time.

Table 4.3: Simulation Scenario 1a: Bicycle traffic (minor stream) average waiting time. Statistical test results.

AV (veh/h)	Bicycles (bikes/h) 100	300	500	700
100	-18.084% 0.609	-26.007% 0.442	-15.719% 0.509	-1.0001% 0.968
300	-9.042% 0.596	-10.645% 0.298	-2.719% 0.740	-0.846% 0.927
500	-4.178 0.754	-18.035% 0.114	-14.433% 0.115	0.613% 0.947
700	**-32.352%** 0.006	**-46.458%** 0.000	**-41.135%** 0.000	-3.358% 0.827

Overall, results for bicycle traffic suggest that the optimization method significantly improves traffic performance for high traffic volumes (700 veh/h) and for low to high bicycle traffic demand (100 – 500 bicycles/h). The remaining traffic performance differences for all other traffic compositions are found not to be statistically significant. Only the average number of stops per bicyclist is significantly increased for certain traffic compositions, while in contrast the average waiting time is significantly decreased.

4.3.1.1.2 AV Traffic (Superordinate Traffic Stream) Figures 4.18 and 4.19 present the traffic performance indicator results for the average delay and average number of stops. As AV traffic travels on the superordinate traffic stream, the traffic performance indicators in the "Base" scenario have no incurred delays, stops or waiting times, as all vehicles travel prioritized with their desired speed. Respectively, the AV traffic performance is negatively affected within the "Optimization" scenario, as the AVs need to provide priority to subordinate bicyclists. Incurred delays remain low, still corresponding to a LOS A according to the HBS [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015] for all traffic compositions.

With respect to the number of stops seldom incidents of AVs coming to full stops at the intersection approach as a result of the continuous flow of prioritized bicycle traffic are identified (Figure 4.19). This proves that the proposed method manages to maintain a steady uninterrupted flow of vehicles on the superordinate traffic stream. Overall, the negative effects of the proposed method on AV traffic are minor, while a stable and acceptable trade-off with the bicyclist traffic performance is established.

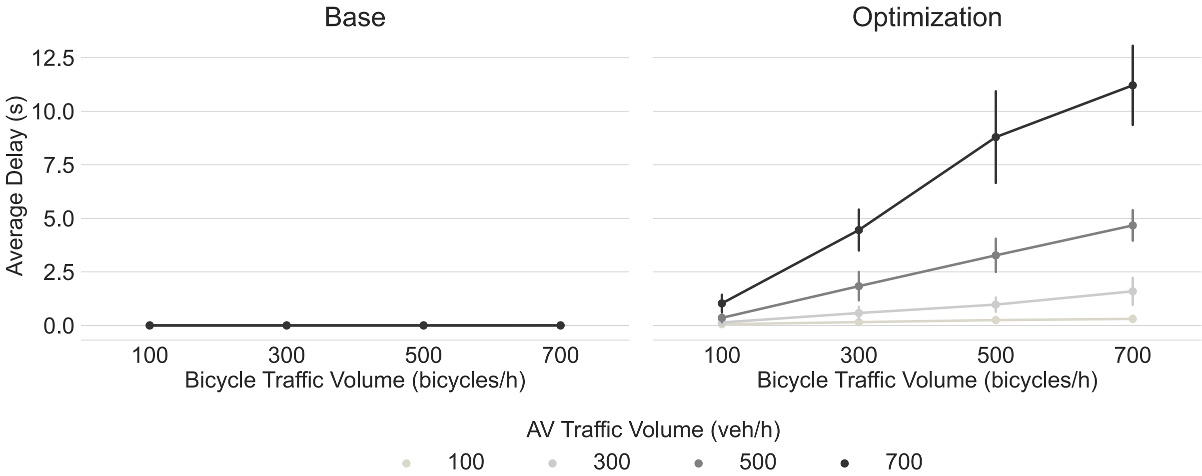


Figure 4.18: Simulation Scenario 1a: AV traffic (major stream) average delay.

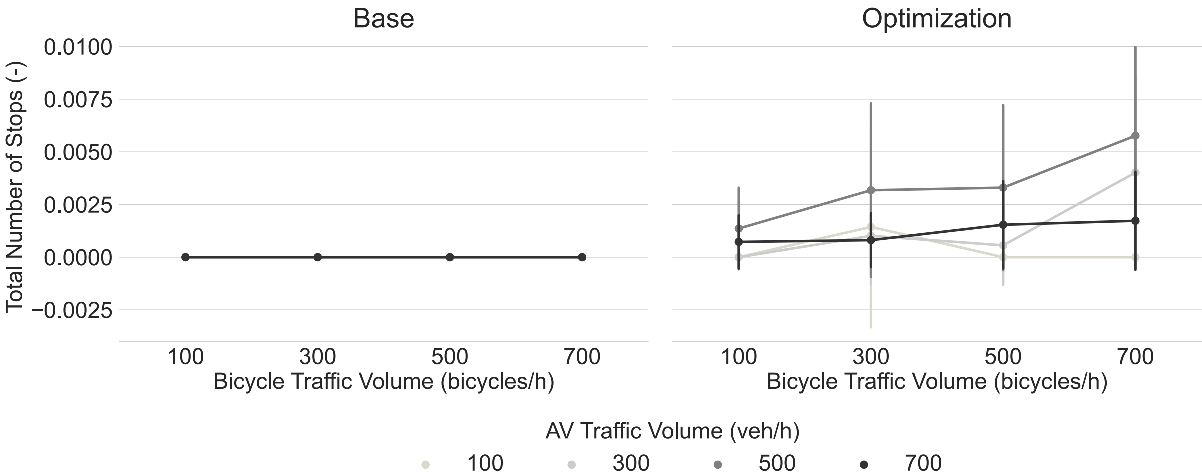


Figure 4.19: Simulation Scenario 1a: AV traffic (major stream) average stops.

4.3.1.2 Simulation Scenario 2a: Prioritization of a crossing bicycle stream from the minor road without concurrent bicycle traffic on the main road

4.3.1.2.1 Bicycle traffic (Subordinate Traffic Stream) Figures 4.20, 4.21 and 4.22 present the traffic performance indicator results for the average delay, average number of stops and average waiting time. The respective results of the statistical analysis are presented in Tables 4.4, 4.5 and 4.6. in this scenario, bicyclists have to cross the major road over two superordinate AV traffic streams. The respective AV traffic volume is defined for each traffic stream. Therefore, AV traffic volume is two times greater than the traffic volume in Scenario 1. Additionally, bicyclists have to cross two intersection points instead of one in Scenario 1. This is a far more demanding task for bicyclists as during higher traffic demand situations on the superordinate traffic stream simultaneous acceptable time gaps have to be found, while prioritization activation has to be enabled in parallel for two AV traffic streams. Thus, the scenario variations consider significantly greater traffic demand than in scenario 1. Also, in terms of traffic performance evaluation, the experienced bicyclist delays and waiting times with an AV traffic demand of 500 veh/h correspond to a severe congestion situation according to the LOS evaluation using the HBS for both the "Base" and the "Optimization" cases.

With respect to bicycle traffic delays, results suggest a consistent reduction through the proposed method. The majority of the identified differences to the "Base" scenario are also found to be statistically significant. It is important to mention that the experienced bicyclist delays for the scenario variation with AV traffic volume of 500 veh/h per traffic stream basically correspond to extreme congestion situations, where bicyclists cannot find acceptable time gaps to pass through the prioritized AV traffic without assistance. In these scenario variations, most of the highest reductions in average experienced delays are found, which shows that the proposed method can successfully assist bicyclist crossing maneuvers in congestion situations or with dense AV platoons.

In contrast to scenario 1a, where the average number of stops increased, in scenario 2 the proposed method succeeds in minor improvements compared to the "Base" scenario. However only, in a single scenario variation (AV: 500 veh/h, Bicycles: 300 veh/h) is the improvement statistically significant. Respectively an even greater reduction in average waiting times is observed in comparison to scenario 1, with the majority of differences being classified as statistically significant. The parallel comparison of the results of scenario 1 with scenario 2 reveals that the most significant improvements with the proposed method are found in the most demanding and complex traffic scenarios. Results, for low demand traffic compositions are mixed in comparison to the "Base" scenario, while any improvements are not statistically significant. However, with increased traffic demand and complexity, the proposed method exhibits increasingly improved performance in comparison to both the "Base" and the low traffic demand variations for bicycle traffic.

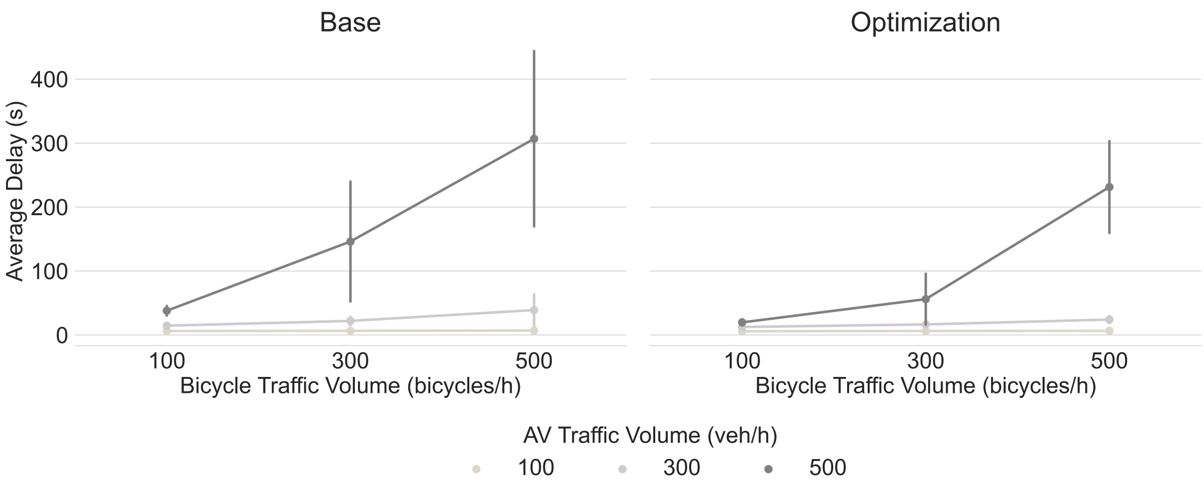


Figure 4.20: Simulation Scenario 2a: Bicycle traffic (minor stream) average delay.

Table 4.4: Simulation Scenario 2a: Bicycle traffic (minor stream) average delay. Statistical test results.

AV (veh/h)	Bicycles (bikes/h)		
	100	300	500
100	-5.050% 0.273	-4.724% 0.263	**-7.410%** 0.038
300	**-14.143%** 0.042	**-24.714%** 0.033	-38.021% 0.064
500	**-47.999** 0.000	**-61.621%** 0.010	-24.592% 0.125

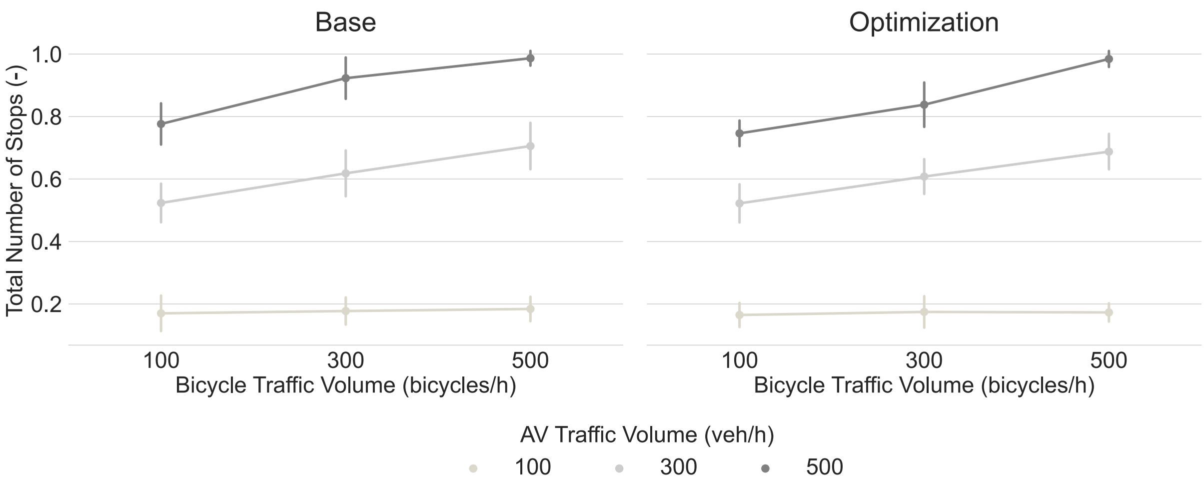


Figure 4.21: Simulation Scenario 2a: Bicycle traffic (minor stream) average stops.

Table 4.5: Simulation Scenario 2a: Bicycle traffic (minor stream) average stops per bicyclist. Statistical test results.

AV (veh/h)	Bicycles (bikes/h)		
	100	300	500
100	-3.084% 0.803	-1.610% 0.888	-6.027% 0.460
300	-0.247% 0.961	-1.680% 0.712	-2.542% 0.532
500	-3.866 0.214	**-9.205%** 0.008	-0.231% 0.831

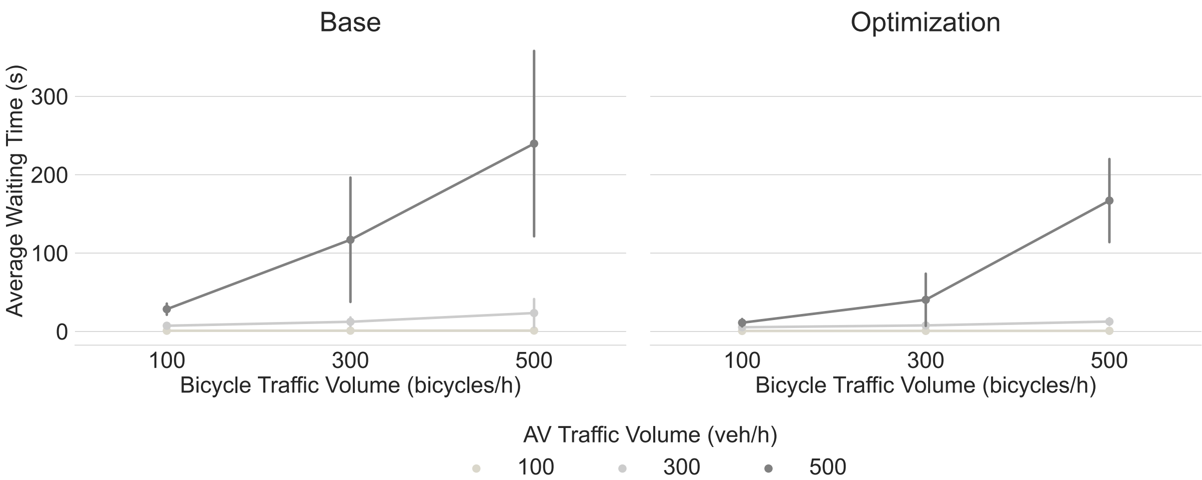


Figure 4.22: Simulation Scenario 2a: Bicycle traffic (minor stream) average waiting time.

Table 4.6: Simulation Scenario 2a: Bicycle traffic (minor stream) average waiting time. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)**		
	100	300	500
100	-27.563% 0.144	-26.917% 0.081	**-29.537%** 0.027
300	**-26.579%** 0.029	**-37.354%** 0.026	-46.269% 0.063
500	**-60.656** 0.000	**-65.449%** 0.010	-30.335% 0.082

4.3.1.2.2 AV Traffic (Superordinate Traffic Stream) Figures 4.23 and 4.24 present the traffic performance indicator results for the average delay and average number of stops. In comparison to Scenario 1, AV traffic streams accumulate greater average delays in Scenario 2 for the same traffic volume compositions. This is expected as more traffic streams and therefore on average more vehicles are involved in the prioritization processes. However, the average delays per vehicle are minor in comparison to the average bicyclist delays and the respective reduction through the proposed method. Incurred delays still correspond to a LOS A according to the HBS [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015] for all traffic compositions. Again, as in Scenario 1, the average number of stops per vehicle and the respective average waiting times remain minimal, indicating that only on rare occasions will the AVs on the priority stream come to a full stop. Finally, in this more complex prioritization scenario, where the prioritization has to be activated simultaneously for two intersection points, while at the same time bicyclists have a longer distance to cross in the intersection, the proposed method manages to preserve a steady and continuous flow on the superordinate traffic stream.

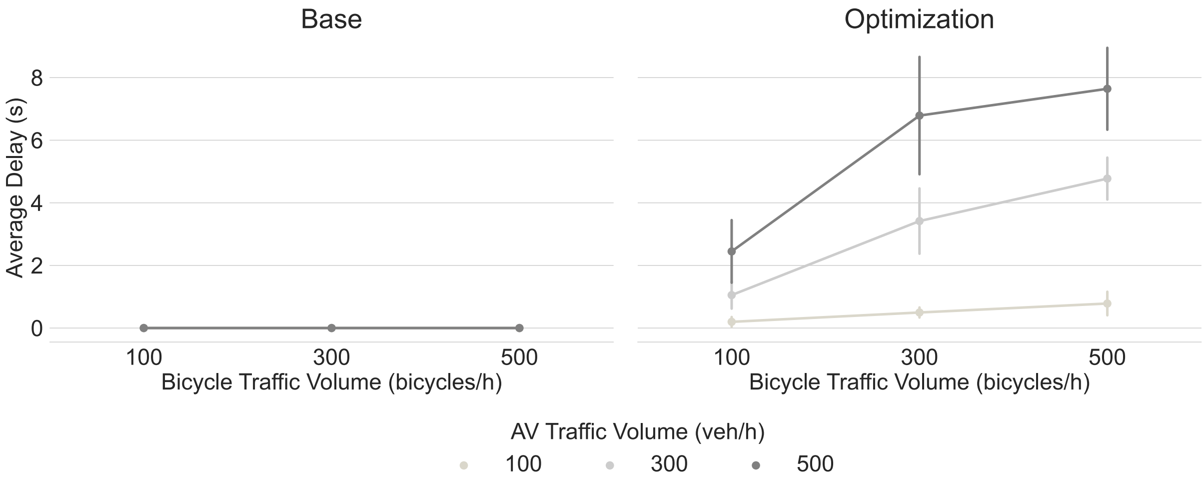


Figure 4.23: Simulation Scenario 2a: AV traffic (major stream) average delay.

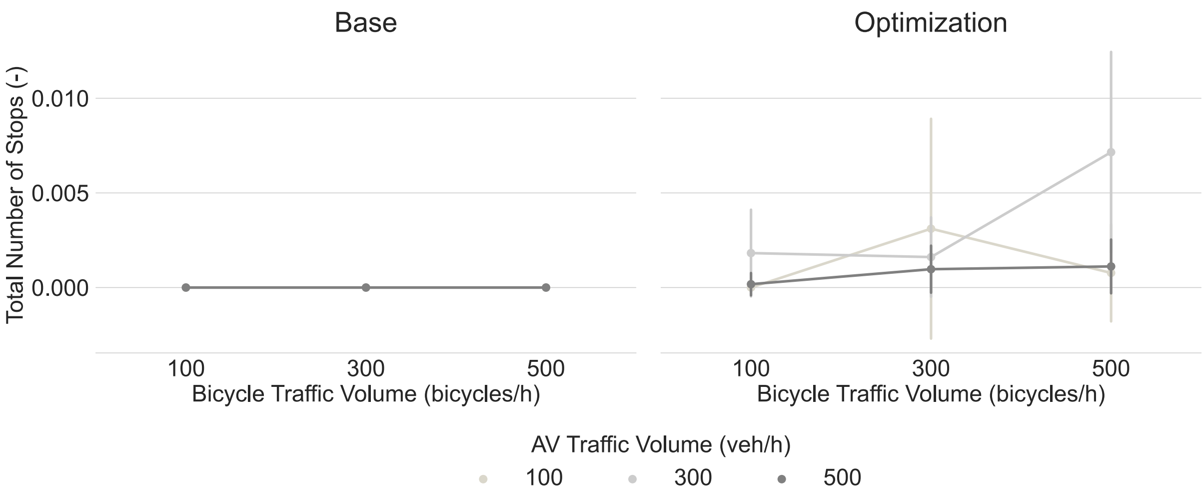


Figure 4.24: Simulation Scenario 2a: AV traffic (major stream) average stops.

4.3.1.3 Simulation Scenario 1b: Prioritization of left turning bicycle stream on main road with concurrent bicycle traffic on the main road

This simulation scenario investigates the effects of concurrent bicycle traffic demand on the superordinate traffic stream. It expands the analysis of simulation scenario 1a, by assessing the effect of the defined constraints that restrict the prioritization activation in the case of intersecting superordinate bicycle traffic flow. The respective results of the statistical analysis are presented in Tables 4.7, 4.8 and 4.9.

It is found that due to the obstruction of the superordinate bicycle traffic stream results for the average delay are mixed for all traffic compositions. This is an expected outcome as the prioritization is not activated in cases where bicycle traffic is detected in the superordinate traffic stream. Yet most of the differences for the average delays are not assessed as statistically significant. Regarding the average number of stops, results show that they significantly increase for subordinate bicyclists in most traffic composition cases examined. However, the average waiting time results are also mixed with the exception of the two border scenarios of low and high AV traffic (100 veh/h and 700 veh/h). For these two cases, waiting times consistently increase and decrease respectively for the low and high demand variations, with some of the differences being even classified as statistically significant. This once more indicates, that the proposed method manages to bring traffic performance improvements only for high traffic conditions, whereas in low traffic conditions, traffic performance is better by following the established traffic priority rules. It is safe to conclude that the intercepting superodinate bicycle traffic disrupts and limits the performance of the optimization method compared also to the performance in Scenario 1a. Finally, results for AV traffic in Scenario 1b remain comparable and mostly unchanged, compared to Scenario 1a. The AV traffic performance still corresponds to to a LOS A according to the HBS [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015] despite the increase in bicycle traffic flow and the not optimal operation of the prioritization method. Results are included as part of Appendices 3 and 3.

Table 4.7: Simulation Scenario 1b: Bicycle traffic (minor stream) average delay. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)**			
	100	300	500	700
100	5.624% 0.076	2.683% 0.306	2.514% 0.257	2.360% 0.275
300	-3.020% 0.636	-1.232% 0.776	**14.994%** 0.011	7.079% 0.311
500	-8.631 0.188	-1.639% 0.808	4.450% 0.522	10.449% 0.251
700	**-26.412%** 0.001	-14.668% 0.054	-0.353% 0.980	2.763% 0.870

Table 4.8: Simulation Scenario 1b: Bicycle traffic (minor stream) average number of stops per bicyclist. Statistical test results.

AV (veh/h)	Bicycles (bikes/h)			
	100	300	500	700
100	28.707% 0.050	12.293% 0.348	10.278% 0.378	9.161% 0.294
300	6.673% 0.575	3.129% 0.686	**26.211%** 0.002	12.256% 0.133
500	2.445 0.759	**14.087%** 0.011	**15.807%** 0.004	**18.504%** 0.000
700	-2.749% 0.687	**12.063%** 0.002	**13.870%** 0.000	**7.820%** 0.016

Table 4.9: Simulation Scenario 1b: Bicycle traffic (minor stream) average waiting time. Statistical test results.

AV (veh/h)	Bicycles (bikes/h)			
	100	300	500	700
100	**42.782%** 0.033	22.168% 0.277	18.654% 0.267	12.675% 0.293
300	-17.847% 0.302	-7.823% 0.512	25.004% 0.121	9.380% 0.579
500	-24.492 0.073	-8.497% 0.483	2.438% 0.833	9.481% 0.490
700	**-44.538%** 0.000	**-24.511%** 0.029	-4.934% 0.772	-0.657% 0.972

4.3.1.4 Simulation Scenario 2b: Prioritization of a crossing bicycle stream from the minor road with concurrent bicycle traffic on the main road

This simulation scenario investigates the effects of concurrent bicycle traffic demand on the superordinate traffic stream. It expands the analysis of simulation scenario 2a, by assessing the effect of the defined constraints that restrict the prioritization activation in the case of intersecting superordinate bicycle traffic flow on both superordinate traffic streams. In terms of traffic volumes, this is the most complex and demanding scenario examined during the evaluation. In this scenario, subordinate bicyclists have to cross a combined superordinate intersecting bicyclist demand of 100 bicycles/h. The results of the statistical analysis are presented in Tables 4.10 and 4.11. In terms of traffic performance evaluation, the experienced bicyclist delays and waiting times with an AV traffic demand of 500 veh/h correspond to a severe congestion situation according to the LOS evaluation using the HBS for both the "Base" and the "Optimization" cases.

The subordinate bicyclist average delays and average waiting times improve consistently with some differences between means being classified as statistically significant according to Tables 4.10 and 4.11. The average number of stops slightly improves fro most examined varations, however none of the changes is classified as statistically significant (see: 3 in Appendix 4). In comparison to Scenario 2b, without concurrent intercepting superordinate traffic, traffic performance improvements are limited, as the optimization activation is limited by the predefined operation constraints. Thus, the proposed method still manages to efficiently assist the subordinate bicyclists crossing the superordinate traffic stream

Finally, results for AV traffic in Scenario 2b remain comparable and mostly unchanged, compared to Scenario 2a. The AV traffic performance still corresponds to to a LOS A according to the HBS [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015] despite the increase in bicycle traffic flow and the not optimal operation of the prioritization method. These results are presented as part of Appendices 3 and 4.

Table 4.10: Simulation Scenario 2b: Bicycle traffic (minor stream) average delay. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)**		
	100	300	500
100	-8.278% 0.063	-3.142% 0.493	-4.041% 0.317
300	-11.925% 0.301	-9.185% 0.667	**-37.002%** 0.023
500	-16.198 0.335	-39.475% 0.054	**-24.630%** 0.005

Table 4.11: Simulation Scenario 2b: Bicycle traffic (minor stream) average waiting time. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)** 100	300	500
100	**-31.480%** 0.027	-12.033% 0.289	-14.534% 0.149
300	-18.822% 0.253	-13.359% 0.612	**-39.613%** 0.018
500	-20.475 0.296	**-41.852%** 0.044	**-25.104%** 0.008

4.3.1.5 Simulation Scenario 1c: Prioritization of left turning bicycle stream on main road. Sensitivity analysis of bicyclist maneuver prediction confidence.

This simulation scenario investigates the sensitivity of the proposed method utilizing the quantification of the bicyclist maneuver prediction uncertainty that has been introduced as a weight factor for the road user based traffic state estimation. As the uniform distribution used to model uncertainty quantification is shifted below the threshold for differentiating between certain and uncertain predictions, bicyclists are either not considered in the objective functions, or, the ones that have a higher certainty than the threshold value are considered but on average with a lower weight factor value than the Scenario 1a. As part of this analysis results are compared for the optimization method between the case of high average prediction confidence and low average prediction confidence.

For bicycle traffic, the comparison of the performance indicators reveals no statistically significant differences with only slight improvements for the average delay and waiting time, and slight deterioration for the average number of stops. This suggests that for the evaluated scenario bicycle traffic does not significantly benefit from the inclusion of the prediction confidence and any improvements are limited. This is however still in agreement, with the previous analysis results, as one would compare the reduced maneuver prediction confidence with the "Base" scenario, where bicyclists are not being actively prioritized. Similarly, the low confidence bicyclists are less considered in the objective functions and AVs remains prioritized. These results are presented as part of the Appendices 3 and 4.

With respect to AV traffic, the average delay increases significantly for the higher traffic demand variations as presented in Figure 4.25 and Table 4.12. This is an expected outcome as with increased bicycle traffic, the probability that the prioritization is activated also increases and thus delays incur. In both cases, the AV traffic performance still corresponds to to a LOS A according to the HBS [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015]. The assessment of the number of stops and waiting times for AV traffic also does not reveal any statistically significant differences. These results are presented as part of the Appendices 3 and 4.

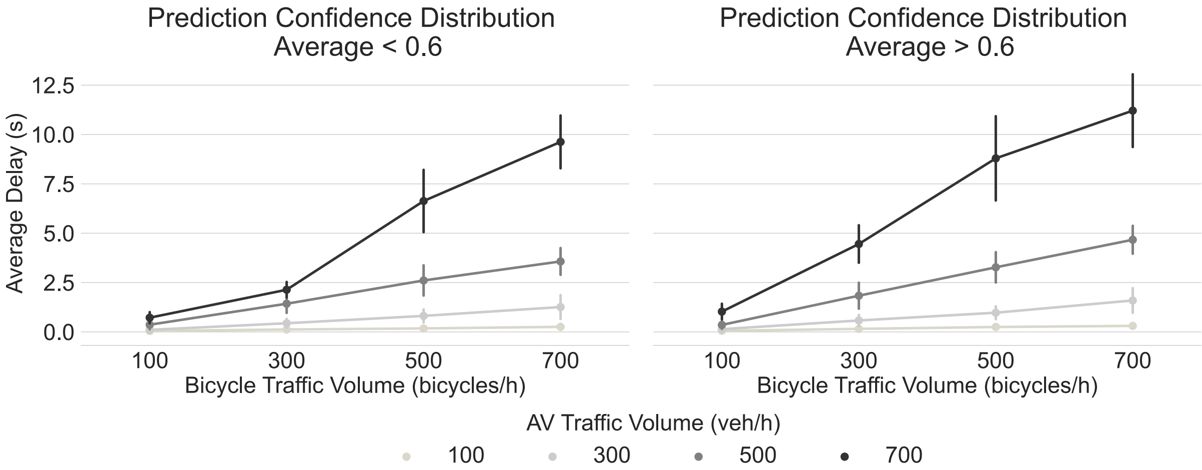


Figure 4.25: Simulation Scenario 1c: AV traffic (major stream) average delay. Sensitivity analysis of bicyclist maneuver prediction confidence.

Table 4.12: Simulation Scenario 1c: AV traffic (superordinate traffic stream) average delay. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)** 100	300	500	700
100	16.159% 0.804	25.222% 0.522	41.468% 0.189	18.714% 0.476
300	33.217% 0.476	32.084% 0.214	19.816% 0.263	26.426% 0.219
500	-2.746 0.914	28.446% 0.110	25.524% 0.055	**30.766%** 0.001
700	**42.710%** 0.050	**108.498%** 0.000	**32.601%** 0.013	**16.456%** 0.031

4.3.1.6 Simulation Scenario 2c: Prioritization of a crossing bicycle stream from the minor road. Comparison of low and high bicyclist maneuver prediction confidence.

This simulation scenario investigates the sensitivity of the proposed method utilizing the quantification of the bicyclist maneuver prediction uncertainty that has been introduced in proposed method as a weight factor for the road user based traffic state estimation. In contrast to Scenario 1c, bicyclists here face a more demanding and complex traffic situation as they have to cross two intersection points with the superordinate traffic flow.

4.3.1.6.1 Bicycle traffic (Subordinate Traffic Stream) The results of the statistical analysis for the traffic performance indicators, average delay, average number of stops and average waiting time are presented as part of the Appendices 3 and 4. Contrary to the results of Scenario 1c, the increased prediction confidence consistently improves the bicyclist average delays and waiting times for the medium to high traffic demand compositions. The average number of stops per bicyclist also improves for most traffic demand variations, however for the majority of examined compositions, differences are not classified as statistically significant. As the situation is more complex, arriving bicyclists on the minor stream with low confidence prediction values are less considered in objective functions. However, as they accumulate increasing delays over time eventually, they are assigned the prioritization activation. At that point also other incoming bicyclists, or bicyclists that have arrived, but due to the low confidence and thus small weight factor value, have not yet accumulated significant delays, still benefit from the prioritization activation. Eventually, the weight factor leads to a slower or faster reaction of the optimization algorithm depending on the traffic situation. This additionally explains, why the significant differences are only identified for the higher traffic demand compositions. In these cases both the AV traffic flow is higher on the major stream and thus, greater delays incur on the minor bicycle traffic, and additionally bicycle traffic demand is also higher, therefore it has to be faster considered by the optimization function. Thus, in complex and high traffic demand situations the maneuver prediction confidence factor has a significant influence on the performance of the optimization.

4.3.1.6.2 AV Traffic (Superordinate Traffic Stream) Figure 4.26 and Table 4.13 present the AV traffic performance indicator results for the average delay. In contrast to Scenario 1c, where the average AV delay increases with increased maneuver prediction confidence as a result of the more often prioritization activation, here the AVs profit significantly from the increased prediction confidence compared to the low confidence case. This is explained in combination with the results for bicycle traffic, as by the time a significant amount of bicycle delay is accumulated more bicyclists need to pass through the intersection. In contrast to Scenario 1, bicyclists need to cross a longer distance with two intersecting AVs traffic streams. Thus, the long dissolving bicycle queue occupies the intersection area for a longer period of time and therefore longer delays for AVs occur. This effect is statistically significant for the high demand traffic compositions as more AVs arrive at the intersection a upstream AVs also accumulate increased delays as a result of the AVs downstream waiting for the longer bicycle queues to dissolve. Contrary, when the prediction confidence is higher, the optimization method reacts faster to increasing bicycle delays and manages to prioritize bicyclists faster. Thus, the probability of a long bicycle queue is lower and bicyclists occupy the intersection points for smaller time periods. This, leads also to a faster termination of the prioritization as bicycle demand is no longer detected. The assessment of the number of stops and waiting times for AV traffic also does not reveal any important differences. These results are presented as part of the Appendices 3 and 4.

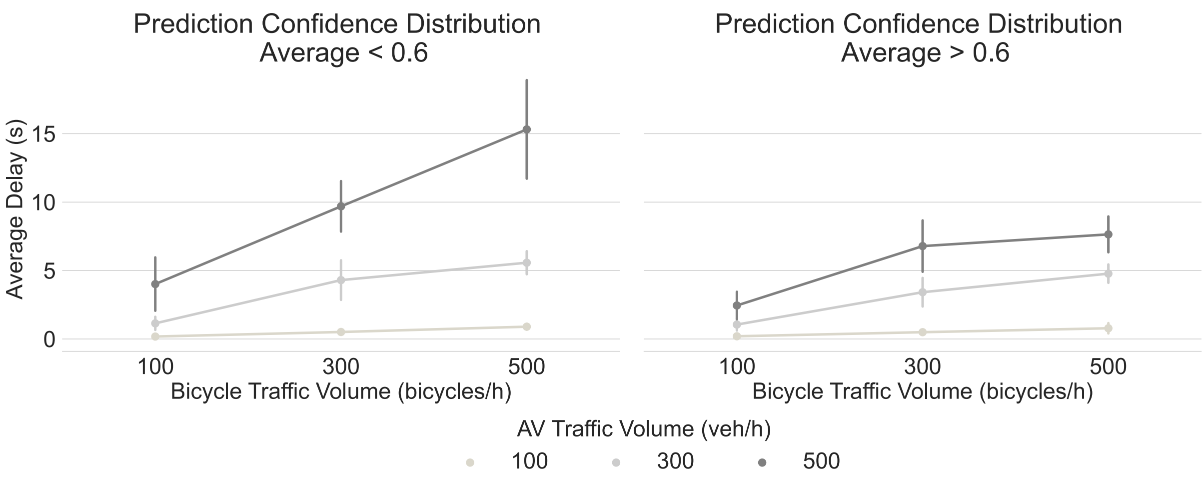


Figure 4.26: Simulation Scenario 2c: AV traffic (major stream) average delay. Sensitivity analysis of bicyclist maneuver prediction confidence.

Table 4.13: Simulation Scenario 2c: AV traffic (superordinate traffic stream) average delay. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)**		
	100	300	500
100	11.343% 0.722	-2.749% 0.838	-12.695% 0.395
300	-7.770% 0.653	-20.579% 0.114	**-14.322%** 0.022
500	**-38.991** 0.030	**-29.968%** 0.001	**-50.089%** 0.000

4.4 Discussion

Following the development of the deep learning model coupled with an uncertainty quantification mechanism that predicts the bicyclist intended maneuver type before an intersection approach with a level of confidence, a MILP optimization method is proposed that utilizes the prediction information in order to prioritize bicyclists over superordinate AV traffic streams at an unsignalized intersection. The proposed method is defined by two hierarchical objective functions, which based on the expected delays, expected stops and the maneuver prediction confidence for each road user try to minimize incurred delays for all road users and the number of stops for bicyclists for the entire intersection. The optimization method is further limited by a set of constraints and functions that are introduced to ensure safe traffic interactions among all road users and the uninterrupted AV flow on the major traffic streams. The performance of the proposed method is assessed in two main evaluation scenarios with a range traffic compositions from low to high traffic demand. Results, show that:

- **The proposed method consistently reduces delays and waiting times for bicyclists for moderate to high traffic demand compositions and outperforms the "Base" Scenario with common priority rules.**
- **The higher the complexity of the intended bicyclist maneuver at the intersection, the greater the bicycle traffic performance gains** and the greater the significance and influence of the maneuver prediction confidence.
- **The proposed method does not perform better in comparison to the "Base" Scenario for cases with low traffic demand.** In these cases bicyclists can easily find acceptable time gaps between prioritized AVs and do not normally require the assistance of the prioritization method to pass through. In general, active control measures do not outperform simple priority rules at intersections without signal control according to the HBS [Forschungsgesellschaft für Strassen- und Verkehrswesen (FGSV), 2015] as well as findings from previous research Y. Wu and F. Zhu [2021]. From a certain aspect, the proposed method can be regarded as a form of a traffic control measure, that regulates priority at the intersection in an effort to improve traffic performance.
- **The average number of bicyclist stops increased in some cases or no significant improvements were found.** This is a result of two factors: First, the delay is the primary optimization objective, as it a decisive variable for both bicyclist and AV traffic. Therefore, it is only considered by the optimization, when no significant deterioration of the first objective is identified. Further, one limitation of the proposed deep learning model is that it needs to accumulate bicyclist behavior data for 20m before entering the intersection area to be able to provide a sufficiently secure prediction for all bicyclist maneuver classes. This, limits the reaction time for the optimization method, as the AV does not have sufficient time to create acceptable gaps, unless the AV is in a specific position upstream of the intersection that allows it to decelerate conveniently in time. Also, in cases with increased traffic demand multiple AVs are already driving on the major traffic stream and thus, their presence weighs the optimization to their favor. The AV expected delays are also considered more in the objective functions through the maneuver certainty quantification factor as their maneuver is always known with a higher certainty than the bicyclist maneuver.
- **With respect to AV traffic, incurred delays are minimal.**
- **AV traffic flow was interrupted only on rare occasions** possibly due to a dissolving long bicycle queue. This is particularly important as the proposed method aims to improve traffic efficiency equally for all road users by leveraging on the competences of AV technologies and capabilities. As the introduction and inclusion of AVs in urban

traffic becomes an increasingly important topic, primarily due to traffic safety concerns, the development of novel methods for resolving traffic interactions with HRUs has the potential to accelerate the AV adoption and social acceptance of AVs in urban traffic. Social acceptance will not only consider safe interactions but it will also require that AVs provide equivalent or improved traffic efficiency compared to human driven motor vehicles. In this context, the proposed method assists bicyclists intercepting major AV traffic streams to complete their intended maneuver, while ensuring safe and efficient interactions both between the respective road users and for the entire traffic system as a whole.

- **The proposed method is found to be especially efficient in high traffic demand situations.** In unsignalized intersections, these situations are often characterized by highly complex and safety critical interactions. As AVs are integrated in the urban transportation systems both their role and the expected challenges in resolving these situations will increase. VRU behavior is highly uncertain and is characterized by increased flexibility. Eventually, the proposed method manages to reduce the time spend inside the intersection for bicyclists, which in turn reduces the AV effort to resolve such situations at the intersection area and the probability that deadlock situations for AVs will occur.

Chapter 5

Conclusions

This dissertation contributes scientific methods that allow AVs to understand and predict the bicyclist maneuver at an unsignalized intersection and adapt their driving behavior in order to optimize traffic performance for both bicyclists and AVs in the intersection areas. Section 5.1 presents a summary of the main contributions and conclusions of this dissertation. Section 5.2 discusses the main limitations in the progress of this research, while section 5.3 presents the most relevant and important areas fo future research based on the main contributions, conclusions and limitations of this dissertation.

5.1 Summary and Conclusions

This dissertation proposes scientific methods for assisting AVs and resolving their interactions with bicyclists in the use case of an urban unsignalized intersection with no bicycle infrastructure. Taking inspiration from the literature review and by identifying the research gaps in the fields of bicyclist behavior prediction, human-machine cooperation, communication and AIM research, this work proposes, in a first step, a deep learning model for predicting the bicyclist maneuver intention at an unsignalized intersection approach.

The deep learning model is based on B-LSTMs and considers dynamic and communication behavior features. The communication features include both implicit and explicit communication behavior features, that are pre-classified into gesture archetypes. The proposed model outperformed all versions where only dynamic, or only communication bicyclist behavior features have been used. This highlights the importance of the inclusion of communication behavior features in models for the bicyclist behavior prediction.

The deep learning model is further expanded with a method that allows the model to self-evaluate its prediction confidence. The evaluation can be performed using a variety of available confidence quantification metrics. This is an important addition, as most equivalent models in AV research developed to predict VRU behavior do not consider uncertainty. The quantification and assessment of the prediction confidence, especially for long-term prediction problem formulations is of high importance in improving and optimizing the driving behavior of AVs in traffic.

The proposed model is able to predict the bicyclist intended maneuver at an unsignalized intersection (Research Question 1, section 1.2) with a certain level of confidence (Research Question 2, section 1.2). This dissertation proceeds a step further and proposes the integration of the proposed method in a MILP optimization framework that aims to improve traffic performance for both bicyclists and AVs at an unsignalized intersection. In future urban traffic, the acceptance and integration of AVs in the urban transport system has to consider and adhere to HRUs requirements. Additionally, most research in the field of human-machine cooperation and communication investigates the necessity, means, acceptance, safety and comprehensiveness of frameworks for enabling and facilitating human-machine interaction in specific one-to-one interaction scenarios. The macroscopic and systemic effects and limitations of such solutions have not been researched. Especially, for AVs this is very important as their actions in such interactions can potentially have traffic safety and traffic efficiency implications for the entire traffic system.

In this context, the MILP optimization framework integrates the inherent bicyclist behavior uncertainty in the control actions taken to optimize traffic performance. It additionally considers the bicyclist individual behavioral characteristics by respectively adjusting the AV driving behavior and balances the requirements of the AV passengers. The proposed concept for the bicyclist prioritization is integrated seamlessly in the existing common traffic priority rules that regulate traffic at unsignalized intersections through the adaptation of the AV approach speed and the generation of acceptable time gaps for bicyclists of minor traffic streams to exploit. This ensures that the bicyclists still adhere to the common traffic rules, which define the intersection default control state. The acceptance of the AV prioritization actions relies on the bicyclists and is not enforced. Eventually, restrictions arising from the common traffic rules and the recognition that bicyclist behavior is not controllable, form the constraints and limitations for the safe and efficient operation of the optimization method. Additionally, no special equipment or devices are required by the bicyclists as both the detection and the communication of the prioritization status lies in th responsibility of the AVs. Communication, information exchange and cooperative decision making is assumed for all approaching AVs and is a strict requirement for the proper operation of the proposed prioritization method (Research Questions 3 and 4, section 1.2).

The proposed MILP optimization framework is evaluated in typical traffic scenarios, using SUMO, with subordinate and superordinate bicycle and AV traffic streams, in order to assess the overall performance of the proposed method and identify restrictions and limitations. Results, show that the proposed method consistently reduces delays and waiting times for bicyclists for moderate to high traffic demand compositions and outperforms the "Base" Scenario with common priority rules. The resulting delays for the superordinate AV traffic streams are minor and effectively not comparable to the significant gains for bicycle traffic. Furthermore results showcase that when considering prioritization measures for AVs and HRU one should consider traffic efficiency evaluations and define for which situations such measures would be necessary. Perhaps for special VRU groups, the evaluation of a concept for an AV–VRU collaboration should additionally consider the aggregated effects on traffic performance.

This dissertation combines the development and evaluation of a prediction model for supporting seamless and uninterrupted AV driving in the presence of bicyclists at unsignalized intersections with the development of a optimization method for resolving AV and bicyclist interactions while improving traffic performance. Ultimately, the main restriction and limitation that had to be addressed was the handling and consideration of bicyclist behavior uncertainty. The uncertainty quantification has not been integrated so far to human action prediction models in the context of AV research, while for the proposed optimization framework, the uncertainty quantification proved to be a significant factor for adjusting the AV driving behavior.

This proves the importance and added value arising from the combined approach for the two initially unrelated problem formulations, that in current scientific research are usually addressed independently. Especially for AV research and the development of AV driving functions, the experience gained from this work shows, that the consideration of traffic performance related aspects and applications in the development or expansion of existing models and driving functions, carries a hidden potential in further improving their solution performance and quality. Current AV research focuses mostly exclusively on the traffic safety related aspects of AV driving.

The possibilities arising from the consideration of traffic performance related factors are not being consistently addressed or explored, despite having the potential to further increase traffic safety. Using as an example the results from this dissertation, the prioritization of bicyclists at the intersection contributes to the reduction of time spent inside the intersection area for bicyclists. It assists bicyclists with the generation of safe and comfortable time gaps to cross the superordinate traffic streams and thus reduces the probability of safety critical bicyclist behavior due to impatience or misjudgment of the traffic situation. This proactively alleviates the automated driving task requirements for the interacting AVs. Additionally, during high traffic demand situations, the reduction of the number of bicyclists through their prioritization at the intersection reduces the complexity of the arising traffic situation at the intersection area as the number of interacting humans (bicyclists) is eliminated or remains low. This in turn, simplifies the path planning problem for incoming AVs. It reduces the situation uncertainty, where the number of road users with highly uncertain behavior (bicyclists) is kept low, leaving mainly road users with highly controllable and predictable behavior (AVs) to resolve the situation efficiently. Thus, the potential of a deadlock situation arising, where either the AV passenger or a remote control operator has to assume the AV control is reduced, which further increases traffic safety and ensures continuous uninterrupted autonomy.

With the continuous development and future expansion of AVs, ultimately the traffic safety aspects of their operation will be mostly fully addressed. At the same time, city authorities, stakeholders and HRUs will move their attention into other areas and aspects of the AV operation. Efficient driving, continuous autonomy, acceptable driving behavior and their integration with the traffic management will start to play an increasingly important role and will be the key differentiating features and the new area of competition among the different providers fleet operators for the successful integration and acceptance of AV fleets in the mobility system.

5.2 Limitations

In the context of this dissertation certain limitations are identified for the developed methods. With respect to the deep learning model for the bicyclist maneuver prediction, it is important to mention that the model was trained and validated using data coming from bicycle simulator experiments. Despite the positive evaluation of the bicycle simulator setup by the test subjects and the high quality of the behavior data gathered during the experiments, still the real-world implementation of the model would require the retraining of the model with additional real traffic data as variations in the bicyclist behavior in real traffic may be found.

Additionally, the real-world implementation would require extensive testing through the use of a greater data sample of bicyclist behavior, to account both for the great variety of bicyclist behavior and for the sensor and detector capabilities of AVs. Also, the consideration of different bicycle types (e-bikes, cargo bikes etc.) is highly recommended as these bicyclists may exhibit different dynamic, operational tactical and communication behavior that has not been studied in this work. Regarding bicyclist behavior, test subjects did not exhibit riding behavior that was contradicting common traffic rules. They never executed explicit hand gestures that were different from their intended driving maneuver (e.g. raising their left hand before turning right, raising their left or right arm before heading straight) or violated any traffic rules. In real traffic it is safe to assume that bicyclists may incline to such contradicting behavior for certain reasons. For example, a bicyclist might perform a hand gesture close to an intersection approach, not to indicate the intended maneuver at the intersection, but rather perform an overtaking maneuver or for any other reason that might be justified for interacting HRUs but not for AVs. The context in which the communication behavior was performed in this research has not been thoroughly analyzed and studied during the experiments and the respective information has not been introduced as part of the deep learning model. In this context, special studies with test subjects need to be performed, in simulators, test tracks or through data augmentation that are targeted in this kind of behavior analysis, in order to assess its effects on the prediction performance of the proposed model and on the proposed method for quantifying the prediction uncertainty. Eventually, it is possible that the prediction uncertainty method would be able to identify this kind of behavior, however this assumption is theoretical as it was not tested as part of this research.

For the proposed optimization framework, one important limitation remains the fact that the framework has only been evaluated using microscopic traffic simulation software. The compliance and acceptance study from the perspective of the bicyclists has not been part of this dissertation. As part of this dissertation, only theoretical recommendations for facilitating the communication to bicyclists are made, however their efficiency and acceptance has not been evaluated through real or simulator based experiments. As part of a coupled AV-bicycle simulator study conducted in parallel during the writing of this dissertation [Lindner, Georgios Grigoropoulos, et al., 2022], we evaluated a similar bicyclist prioritization concept for unsignalized intersections using a mobile application for facilitating the communication between a bicyclist and an AV. The solution was evaluated positively by both bicyclists and the AV passengers, however the proposed solution in this dissertation suggests a different approach for handling the interactions among AVs and bicyclists on the basis of eHMI without mobile application devices for the bicyclists. As the communication concept is different results are also not necessarily transferable. Thus, additional studies for the evaluation of the proposed communication concept need to be performed, that may ultimate limit or also improve the expected performance.

Finally, both the deep learning model and the proposed optimization framework are developed for the use case of a four-arm unsignalized intersection with one lane per travel direction. Therefore results might vary and applicability might be limited, when transferring the proposed methods in intersection with significantly different dimensions and layout characteristics. This may include for example entries, roundabouts, intersection with more than one traffic lanes per travel direction, significantly different traffic lane width, additional types of pedestrian or bicyclist infrastructure (crossings, bicycle boxes, bicycle lanes etc.).

5.3 Outlook

This dissertation proposes solutions for resolving AV and bicyclist interactions at unsignalized intersections. While considering the identified limitations that already indicate significant areas for possible improvement and further research, certain suggestions and directions for future research can also be provided.

The proposed deep learning model for the bicyclist maneuver prediction can be further expanded with the consideration of features that describe contextual information of the bicyclist surroundings. These may include the behavioral characteristics of other road users that are interacting or are in the vicinity of the bicyclist or information on the related infrastructure such as the relevant position of the bicyclist infrastructure. Additional behavior characteristics, such as considering whether the bicyclist belongs to a specific bicyclist group have the potential to further contribute to improved prediction accuracy. These features can be integrated with the existing model or a new model architecture can be proposed that utilizes on the one side the proposed model and on the other side a new model that processes the new features and correlates them with a specific intended maneuver. Both models can be then integrated in a single architecture through the use of an attention mechanism. Further, the proposed deep learning model can be modified and expanded with functions that predict the path of the bicyclist, where the long-term prediction limits the solution area for the bicyclist path prediction.

Regarding, the proposed optimization framework, one potential improvement may be the expansion or substitution of the optimization framework with a reinforcement learning based approach for adjusting the AV driving behavior and regulating prioritization. Training and fine tuning can be based on simulation and on real-world data. The main advantage of such an approach would be that in a potential future real world application, intersection specific features will be integrated into the decision making during the model training process without requiring their explicit definition in the optimization algorithm. During training, the effects of special intersection related characteristics such as the layout, the lane width size etc. will be considered in the model through their effects on the related traffic performance parameters.

Future research may also be directed towards evaluating the proposed optimization method performance not for a single intersection but for the wider transportation network. in this context, the potential for network wide traffic management strategies that incorporate the proposed solution arises. The possibility of using the AVs as supersensors that eventually may track other road users, match, and pinpoint their location across the entire network finds a possible area for the development of innovative traffic management solutions.

As part of this dissertation only unsignalized intersections with only bicyclists have been examined, however the proposed prioritization concept might find space for application in signalized intersections. Possible areas of research include the integration of the proposed AV functions in signalized intersections for conditionally compatible minor traffic streams through the generation of acceptable time gaps. Here, also the implications on other applied traffic management solutions such as bicycle signal coordination or public transport prioritization may be considered. With respect to the considered road users, pedestrians and human driven vehicles can be additionally considered in the context of an expanded prioritization and co-operation concept. With respect to the proposed deep learning model, its application is not limited to automated driving but it can also be expanded to local traffic management applications. The method can potentially be integrated with cameras at signalized intersections typically used to detect traffic for traffic management applications. Hence, the prediction of the intended bicyclist maneuver can be integrated with novel traffic control strategies for bicycle traffic prioritization and increase bicyclist traffic efficiency and traffic safety at signalized intersections.

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List of Terms and Abbreviations

ACC	Adaptive Cruise Control 42, 154
ADAS	Advanced Driver Assistance Systems 43, 154
AIM	Autonomous Intersection Management 47–50, 141, 154
ANN	Artificial Neural Network 23, 24, 154
API	Application Programming Interface 58, 66, 109–111, 154
AV	Automated Vehicle iii, iv, vi, vii, 1–7, 9, 11–15, 17, 20, 21, 23, 25, 29, 35–45, 47–49, 51–55, 63, 70, 80, 81, 83–92, 94, 96–118, 120–128, 130–132, 134–145, 149, 151, 152, 154, 181–184, 189–191, 193–195, 197, 198, 200
B-GRU	Bidirectional Gated Recurrent Unit 72, 154
B-LSTM	Bidirectional Long Short Term Memory Network iii, v, 9, 24, 65, 69, 72, 74, 80, 141, 154
B-RNN	Bidirectional Recurrent Neural Network 72, 154
CACC	Cooperative Adaptive Cruise Control 44, 49, 154
CAV	Connected and Automated Vehicle 47–51, 154
CNN	Convolutional Neural Network 23–25, 42, 154
CS	Critical Section 4, 154
dHMI	Dynamic Human Machine Interface 40, 53, 100, 154
eHMI	External Human Machine Interface 38–40, 53, 100, 144, 154
ETA	Estimated Time of Arrival 50, 51, 88, 92, 93, 95, 97, 154
FCFS	First Come First Serve 48–50, 154

GRU Gated Recurrent Unit 65, 66, 72, 154

HBS German Highway Capacity Manual 46, 90, 118, 125, 127, 130, 132, 134, 135, 139, 154

HCM American Highway Capacity Manual 46, 47, 90, 118, 154

HMI Human Machine Interfaces 2, 35, 38, 154

HRU Human Road User iii, 3, 12, 13, 23, 35–40, 47–49, 51, 53, 83, 86, 140, 142–144, 154

HUD Heads-Up Display 38, 154

IDM Intelligent Driver Model 42, 44, 154

iHMI Internal Human Machine Interface 29, 100, 154

KL Divergence Kullback-Leibler Divergence 71, 154

LNC Law of Non-Contradiction 79, 154

LOS Level of Service 46, 47, 87, 90, 118, 125, 127, 130, 132, 134, 135, 154

LSTM Long Short Term Memory Network 23–25, 52, 63–66, 69, 72, 150, 154

MADDPG Multiagent Deep Deterministic Policy Gradient 50, 154

MC Dropout Monte Carlo Dropout 71, 72, 75, 76, 150, 154

MILP Mixed Integer Linear Programming iv, vi, 44, 51, 54, 84, 88, 100, 138, 141, 142, 154

MPC Model Predictive Control 13, 154

NLP Natural Language Processing 70, 154

P2V Pedestrian-to-Vehicle 14, 154

ResNet	Residual Neural Network 24, 154
RNN	Recurrent Neural Network 23, 63, 65, 66, 72, 154
SAE	Society of Automotive Engineers 12, 86, 154
SGD	Stochastic Gradient Descent 154
StVO	German Traffic Regulations (Straßenverkehrs-Ordnung) 15, 16, 87, 154
SUMO	Simulation of Urban Mobility iv, vi, 27, 28, 32, 41–44, 56, 57, 61, 62, 70, 85, 108–111, 113, 114, 118, 120, 142, 151, 154, 181, 182
TDC Benchmark	Tsinghua-Daimler Cyclist Benchmark 24, 154
TraCI	Traffic Control Interface 27, 41–44, 58, 109, 110, 113, 118, 154
TTC	Time-to-Collision 39, 154
U-LSTM	Unidirectional Long Short Term Memory Network 65, 154
V2I	Vehicle-to-Infratructure 47, 154
V2V	Vehicle-to-Vehicle 14, 42, 47, 154
V2X	Vehicle-to-Everything 4, 6, 42, 154
VIL	Vehicle-In-the-Loop 41, 154
VRU	Vulnerable Road User iii, v, 3, 5, 9, 11, 13, 14, 16, 23, 35, 36, 49, 52–54, 83, 84, 100, 140–142, 154

Prepublications

Content of the following own peer reviewed conference papers is partially described in this dissertation, as part of Chapter 3 and Sections 2.2, 2.3 and 2.4.

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Appendix

The appendix includes additional information on the calibration of bicyclist and AV behavior, as well as simulation results from subsection 4.3.1 part of Chapter 4 that were excluded from the main text of this dissertation.

1 Calibration of Bicyclist Behavior

Table 1 presents the adjusted parameter values for calibrating the bicyclist behavior [Georgios Grigoropoulos, Lücken, et al., 2019; Georgios Grigoropoulos, Hosseini, et al., 2021; Georgios Grigoropoulos, Leonhardt, et al., 2022]. Specific bicyclist behavior model parameters are further adjusted for supporting the functions of the prioritization method. The *jmIngoreFoeProb* parameter is set to 1, in conjunction with the parameter *jmIgnoreFoeSpeed* which is fixed to the speed used by AVs in prioritization state (2.8 m/s or 10 km/h). This allows bicyclists to impede the respective AVs that travel with a speed equal or less than *jmIgnoreFoeSpeed*. Additionally, the parameter *jmIgnoreJunctionFoeProb* is set to 0, to restrict this type of behavior inside the intersection area, as it may lead to collisions and unrealistic driving behavior. The default SUMO values are set for the remaining of the behavior parameters.

Table 1: Bicycle behavior parameters [Georgios Grigoropoulos, Lücken, et al., 2019; Georgios Grigoropoulos, Hosseini, et al., 2021; Georgios Grigoropoulos, Leonhardt, et al., 2022].

Bicycle Behavior Parameters	**Value**
carFollowing	Krauss
laneChangeModel	SL2015
maxSpeed	Random selection with equal probabilities: 3,4,5,6 or 7 m/s
speedFactor	1
speedDev	0.6
sigma	0.5
tau	1.22
accel	0.78 m/s^2
decel	0.98 m/s^2
minGap	1
minGapLat	0.5m
latAlignment	compact
impatience	0.1
jmIngoreFoeProb	1 (applies only to vehicles driving below the *jmIgnoreFoeSpeed*)
jmIgnoreFoeSpeed	2.8 m/s (priority activation speed)
jmIgnoreJunctionFoeProb	0

2 Calibration of AV Behavior

Table 2 presents the adjusted parameter values for calibrating the AV driving behavior according to [Olstam et al., 2020]. In their work, behavior parameter values are provided for calibrating the AV driving behavior by adjusting the respective parameter of the Wiedemann 99 model. Based on their suggestions, the Wiedemann 99 is adjusted for the advanced AV class with the normal driving logic for the urban street environment as it considers the case of unsignalized at-grade intersections. The *Normal* driving logic assumes full compliance with the traffic rules, no stochasticity of the driving behavior, perfect deterministic automated driving, shorter reaction times and partial knowledge of the environment due to occlusion. Additionally, the parameter *jmSigmaMinor* $= 0$ as deterministic driving behavior is assumed. The default SUMO values are set for the remaining of the behavior parameters.

Table 2: AV behavior parameters. The Wiedemann 99 (W99) parameters are adjusted according to Olstam et al. [2020] for the normal driving behavior logic.

AV Behavior Parameters	Value
minGap	1.5
W99 – CC1	0.9
W99 – CC2	0
W99 – CC3	-8
W99 – CC4	-0.1
W99 – CC5	0.1
W99 – CC6	0
W99 – CC7	0.1
W99 – CC8	3.5
W99 – CC9	1.5
jmSigmaMinor	0

3 Simulation Results Optimization Method: Figures

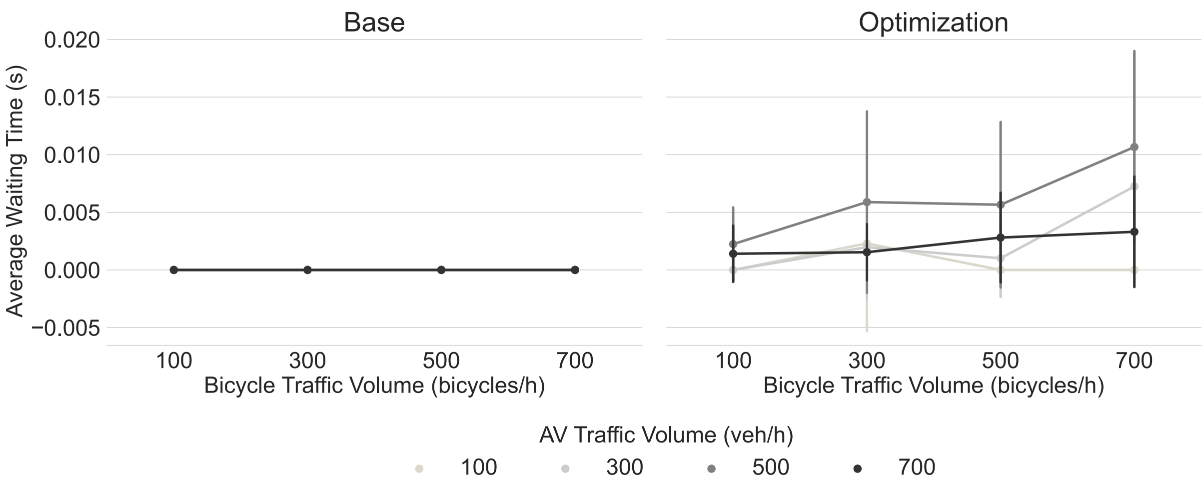

Figure 1: Simulation Scenario 1a: AV traffic (major stream) average waiting time.

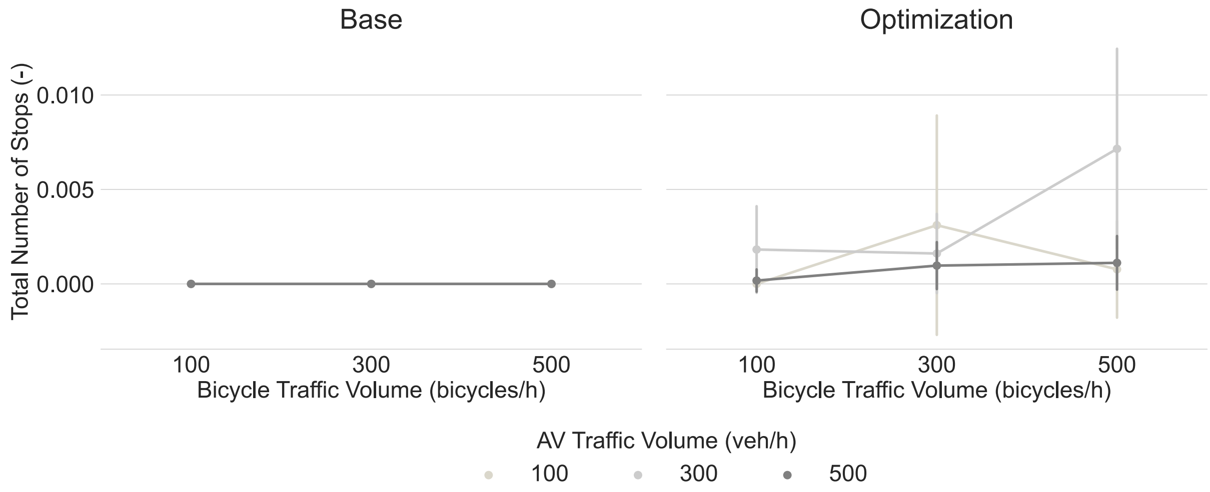

Figure 2: Simulation Scenario 2a: AV traffic (major stream) waiting time.

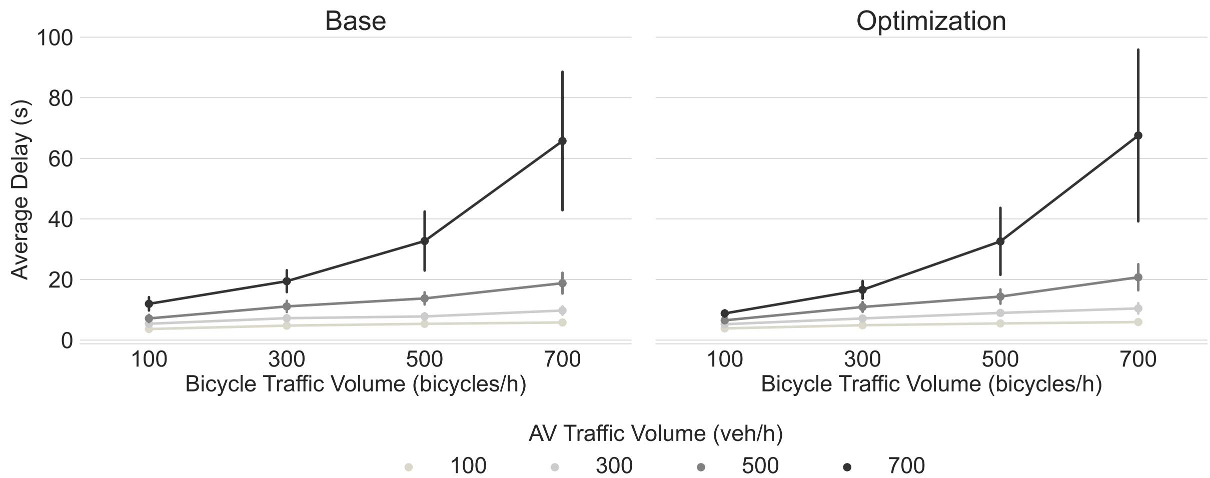

Figure 3: Simulation Scenario 1b: Bicycle traffic (minor stream) average delay with concurrent intercepting bicycle flow on the major road.

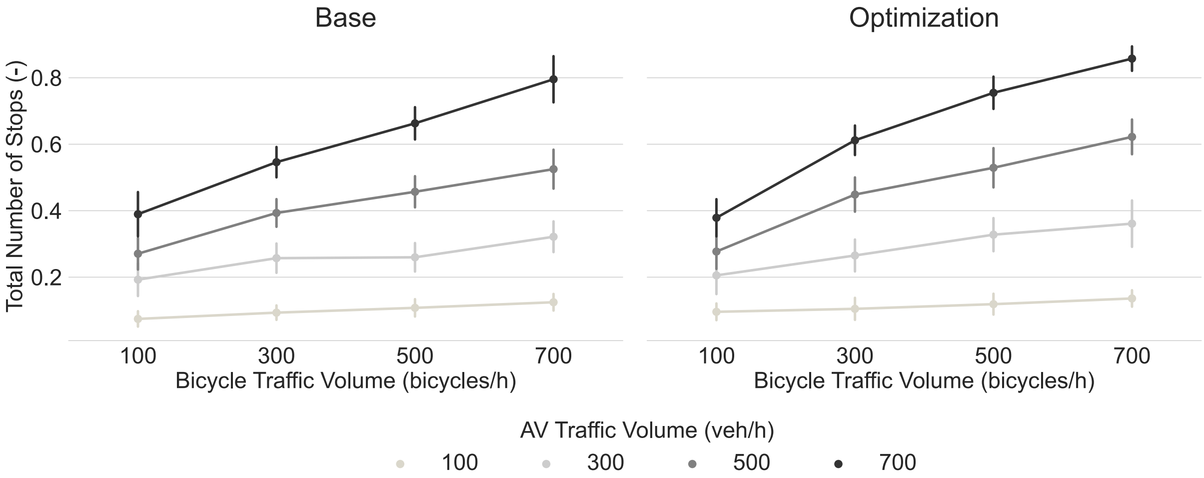

Figure 4: Simulation Scenario 1b: Bicycle traffic (minor stream) average stops with concurrent intercepting bicycle flow on the major road.

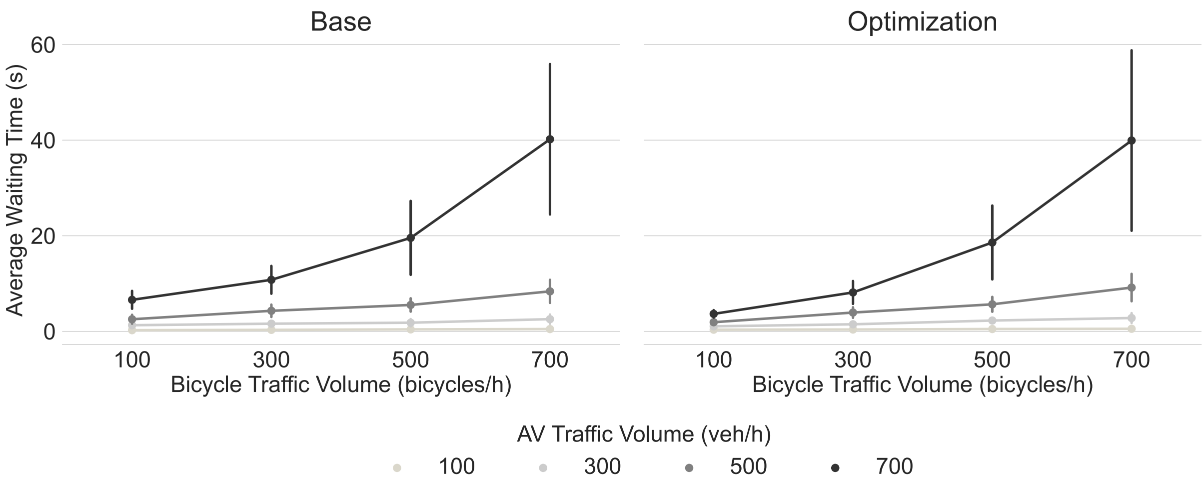

Figure 5: Simulation Scenario 1b: Bicycle traffic (minor stream) average waiting time with concurrent intercepting bicycle flow on the major road.

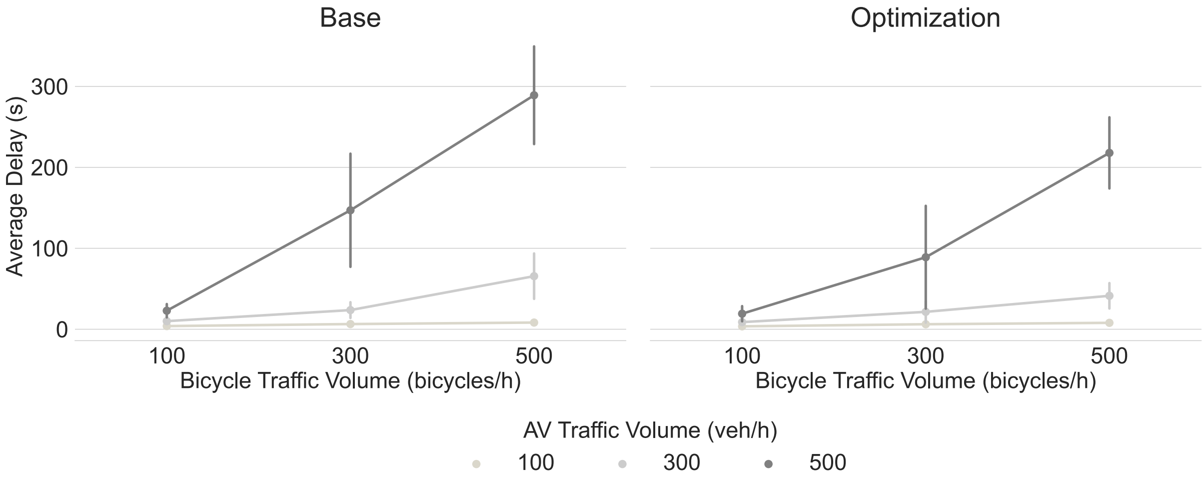

Figure 6: Simulation Scenario 2b: Bicycle traffic (minor stream) average delay with concurrent intercepting bicycle flow on the major road.

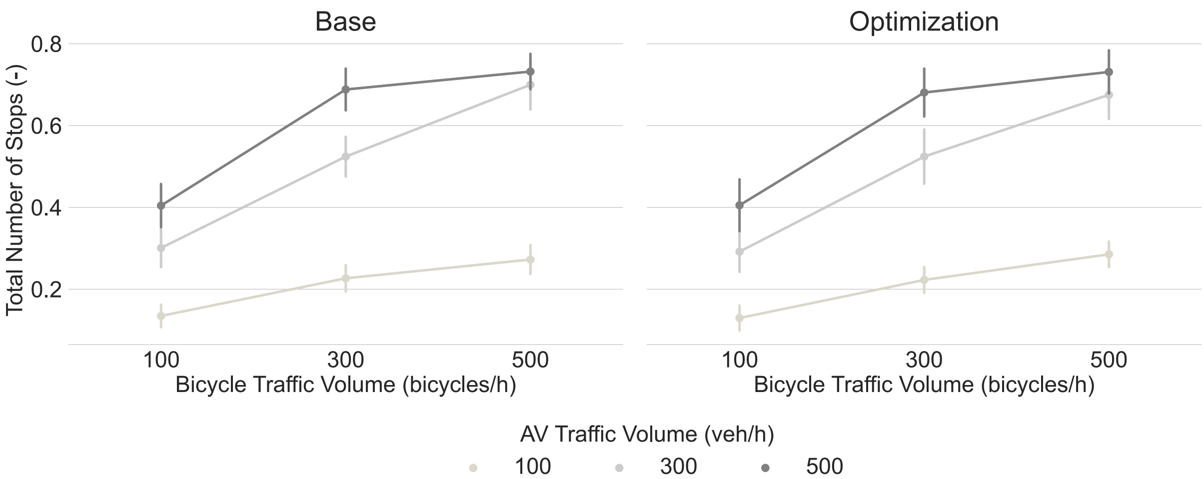

Figure 7: Simulation Scenario 2b: Bicycle traffic (minor stream) average stops with concurrent intercepting bicycle flow on the major road.

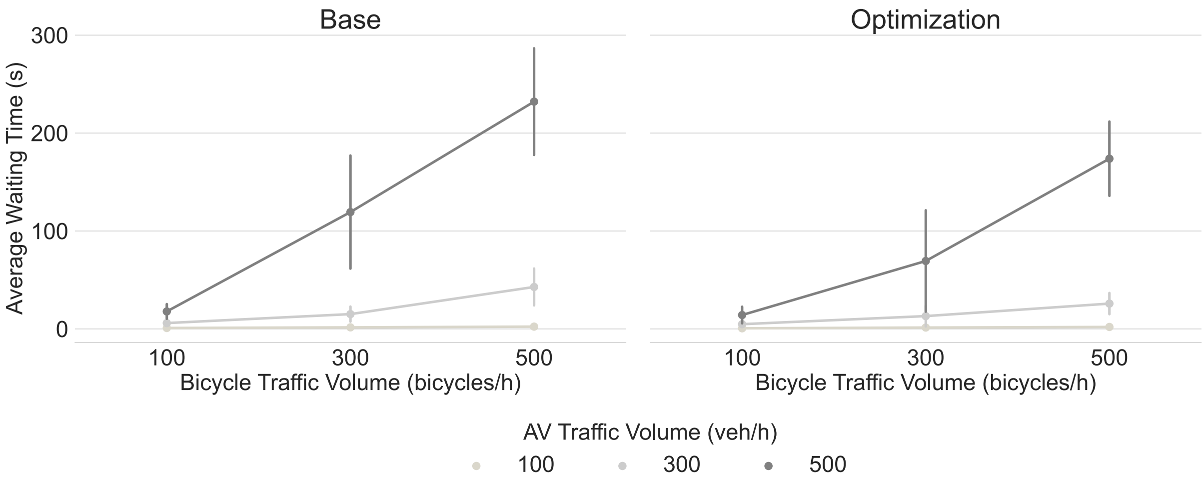

Figure 8: Simulation Scenario 2b: Bicycle traffic (minor stream) average waiting time with concurrent intercepting bicycle flow on the major road.

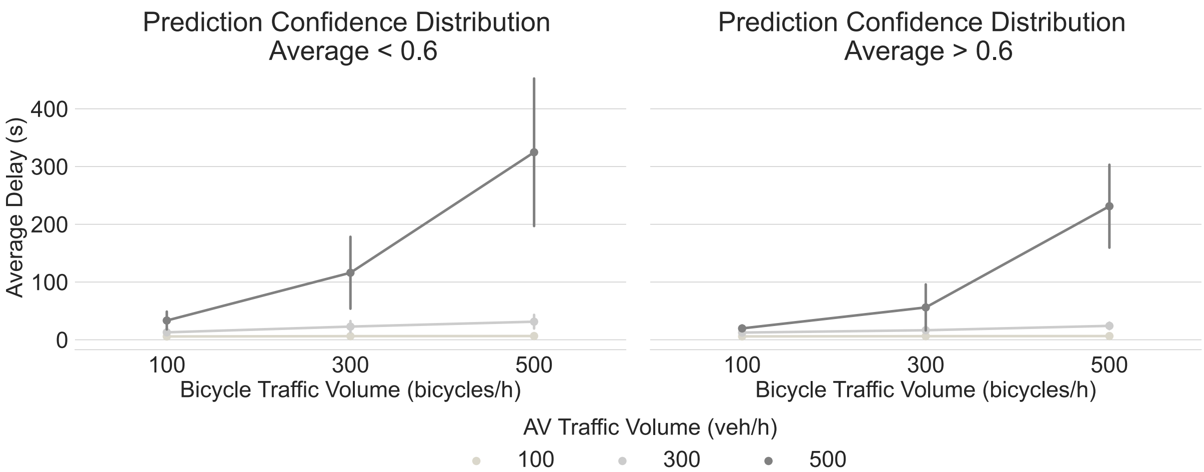

Figure 9: Simulation Scenario 2c: Bicycle traffic (minor stream) average delay. Sensitivity analysis of bicyclist maneuver prediction confidence.

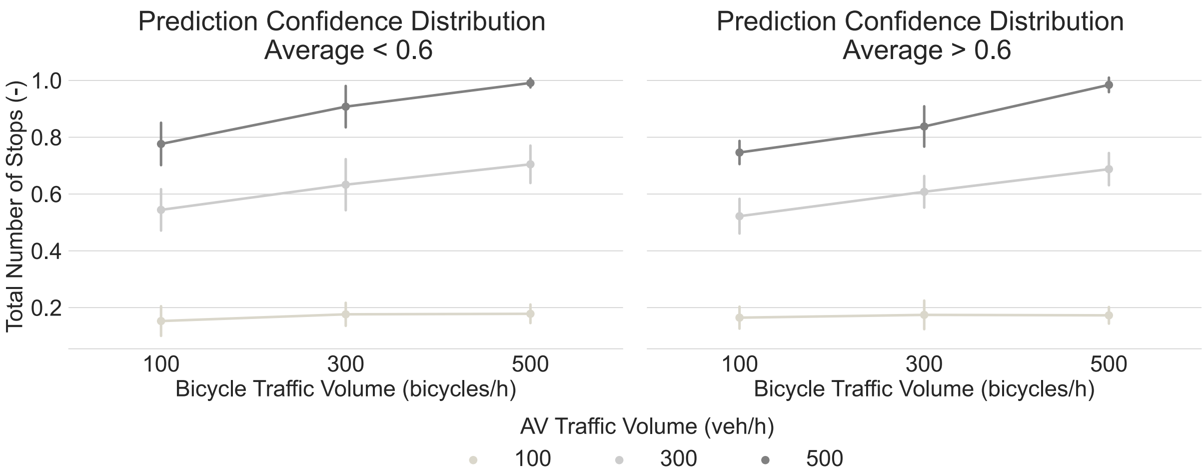

Figure 10: Simulation Scenario 2c: Bicycle traffic (minor stream) average stops. Sensitivity analysis of bicyclist maneuver prediction confidence.

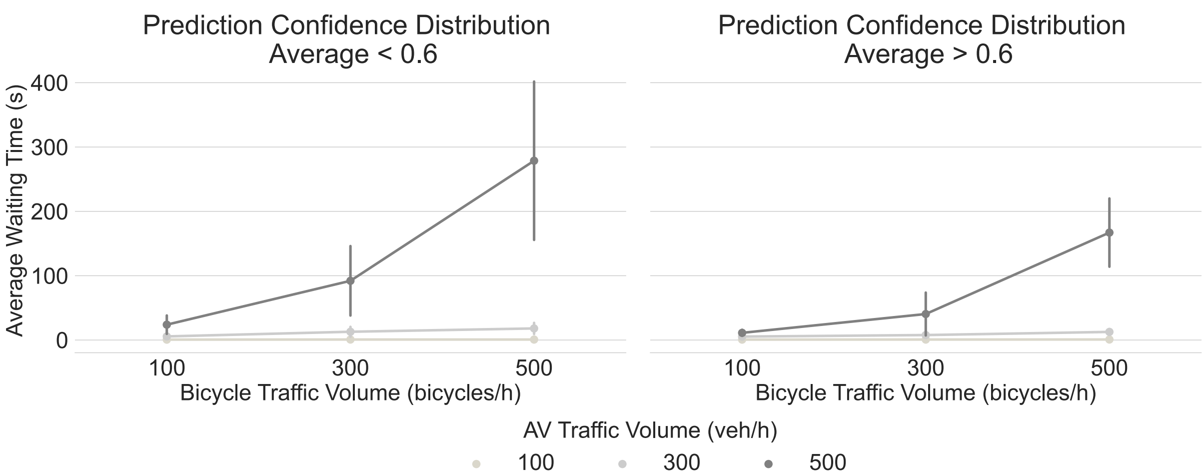

Figure 11: Simulation Scenario 2c: Bicycle traffic (minor stream) average waiting time. Sensitivity analysis of bicyclist maneuver prediction confidence.

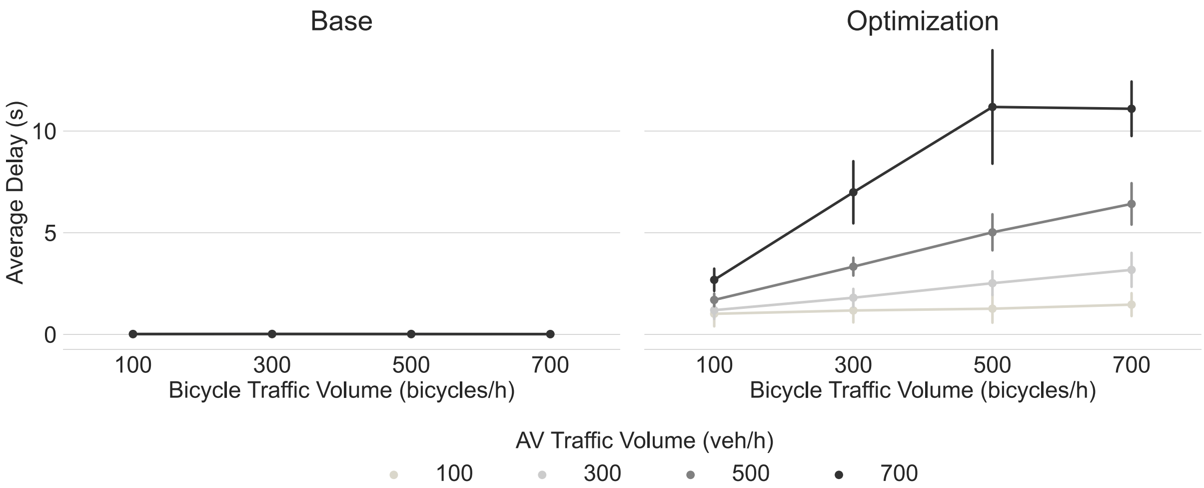

Figure 12: Simulation Scenario 1b: AV traffic (major stream) average delay with concurrent intercepting bicycle flow on the major road.

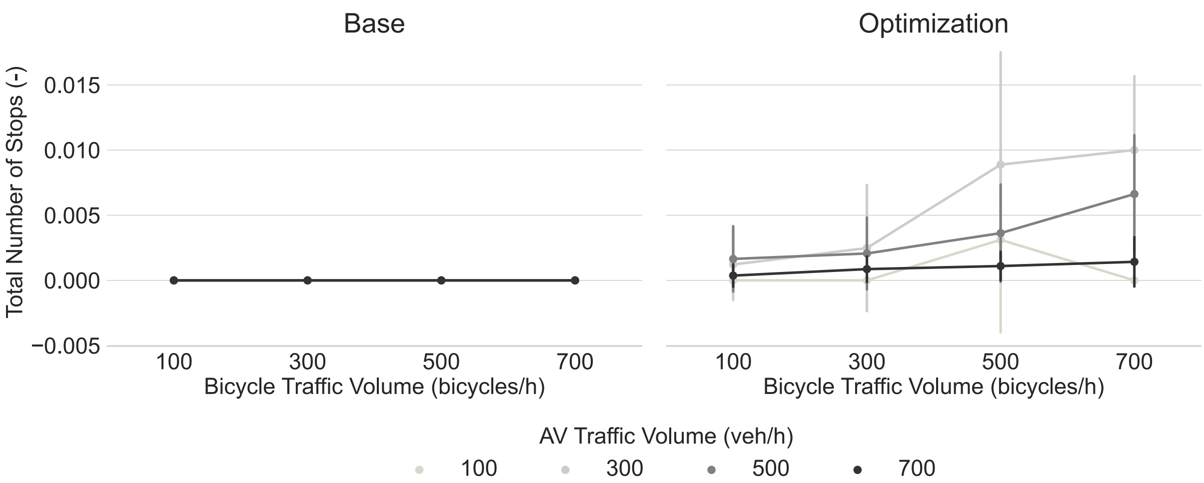

Figure 13: Simulation Scenario 1b: AV traffic (major stream) average stops with concurrent intercepting bicycle flow on the major road.

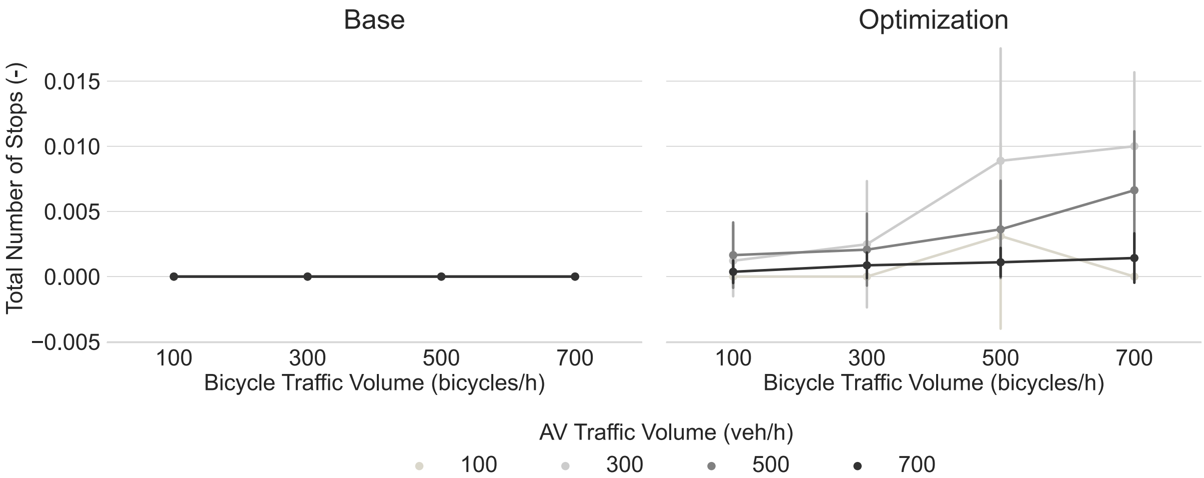

Figure 14: Simulation Scenario 1b: AV traffic (major stream) average waiting time.

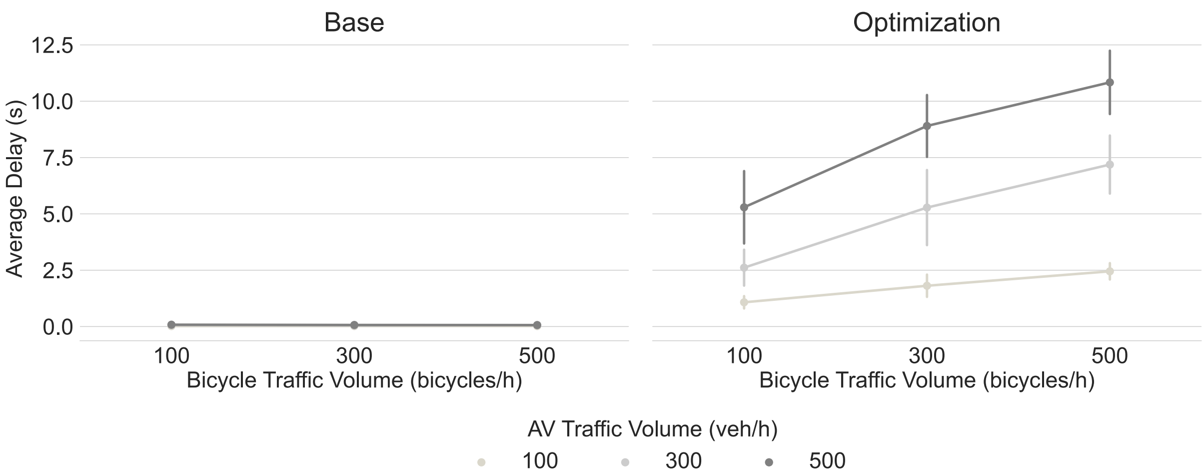

Figure 15: Simulation Scenario 2b: AV traffic (major stream) average delay with concurrent intercepting bicycle flow on the major road.

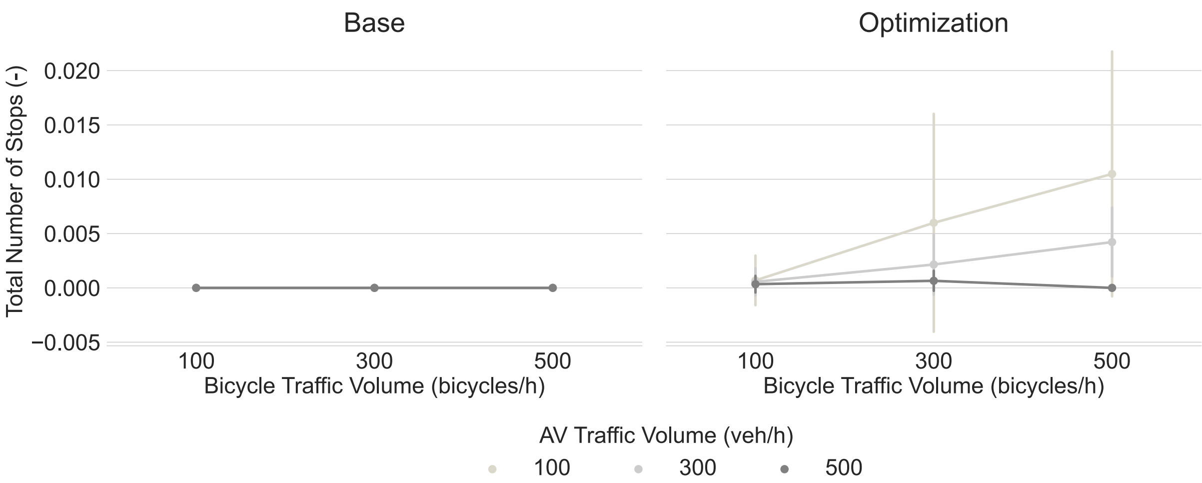

Figure 16: Simulation Scenario 2b: AV traffic (major stream) average stops with concurrent intercepting bicycle flow on the major road.

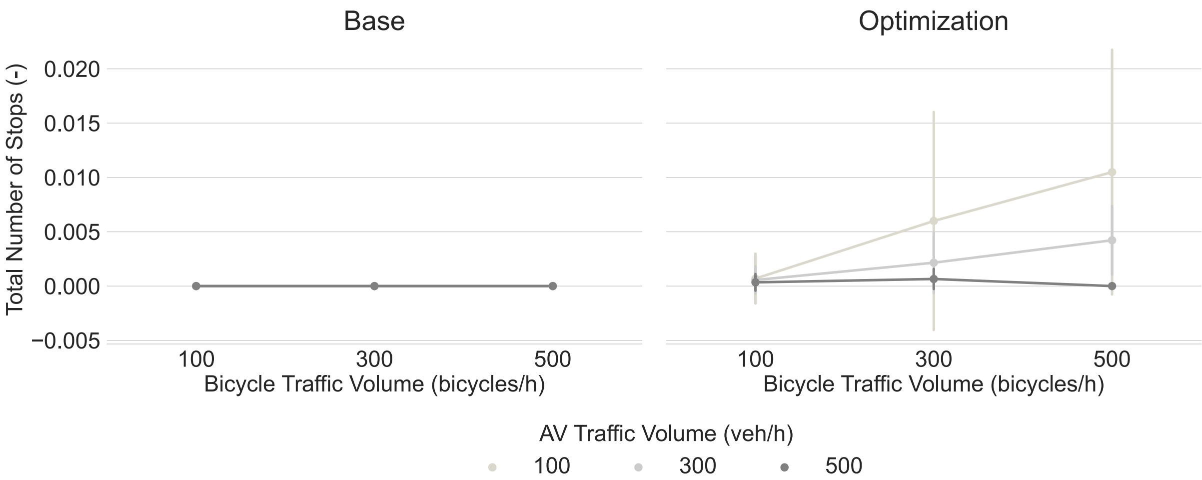

Figure 17: Simulation Scenario 2b: AV traffic (major stream) waiting time.

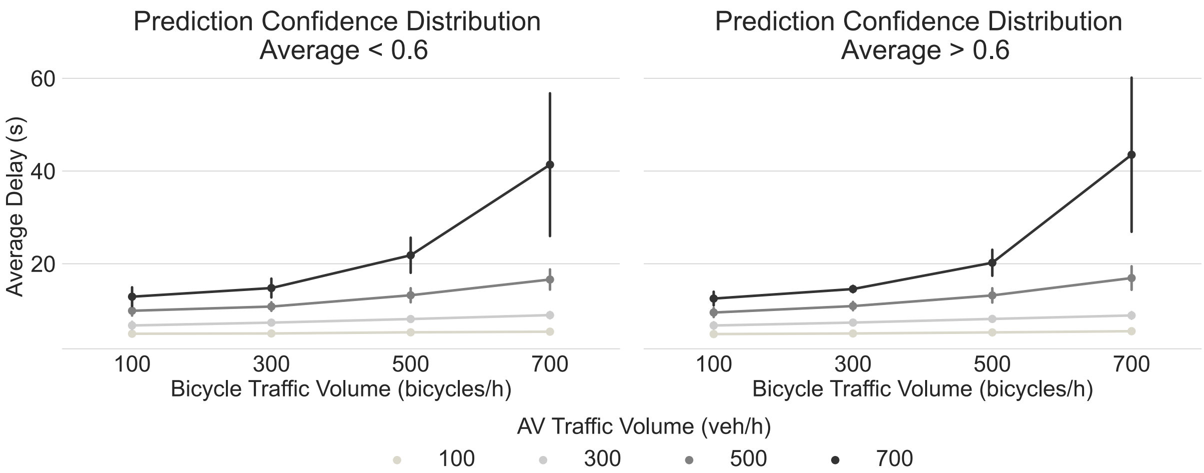

Figure 18: Simulation Scenario 1c: Bicycle traffic (minor stream) average delay. Sensitivity analysis of bicyclist maneuver prediction confidence.

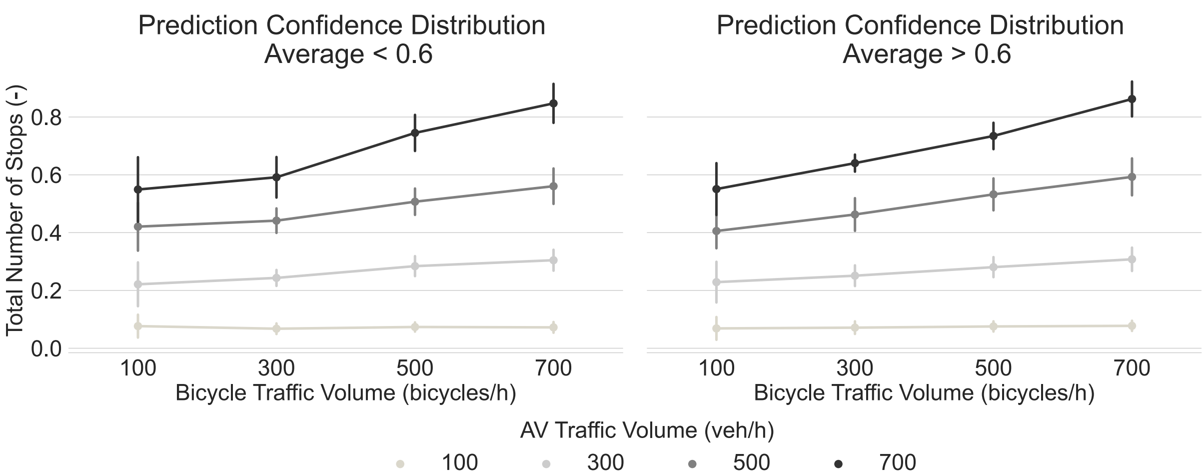

Figure 19: Simulation Scenario 1c: Bicycle traffic (minor stream) average stops. Sensitivity analysis of bicyclist maneuver prediction confidence.

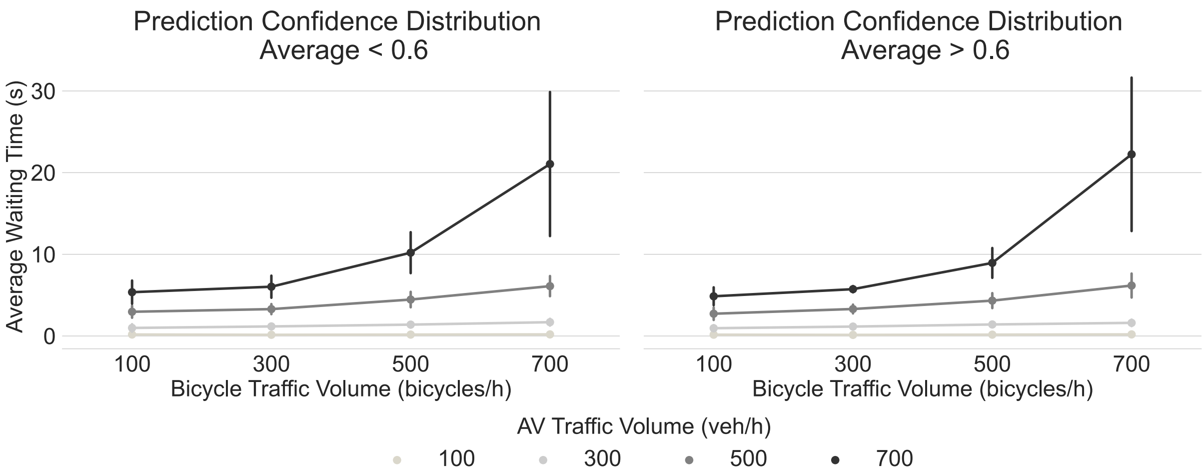

Figure 20: Simulation Scenario 1c: Bicycle traffic (minor stream) average waiting time. Sensitivity analysis of bicyclist maneuver prediction confidence.

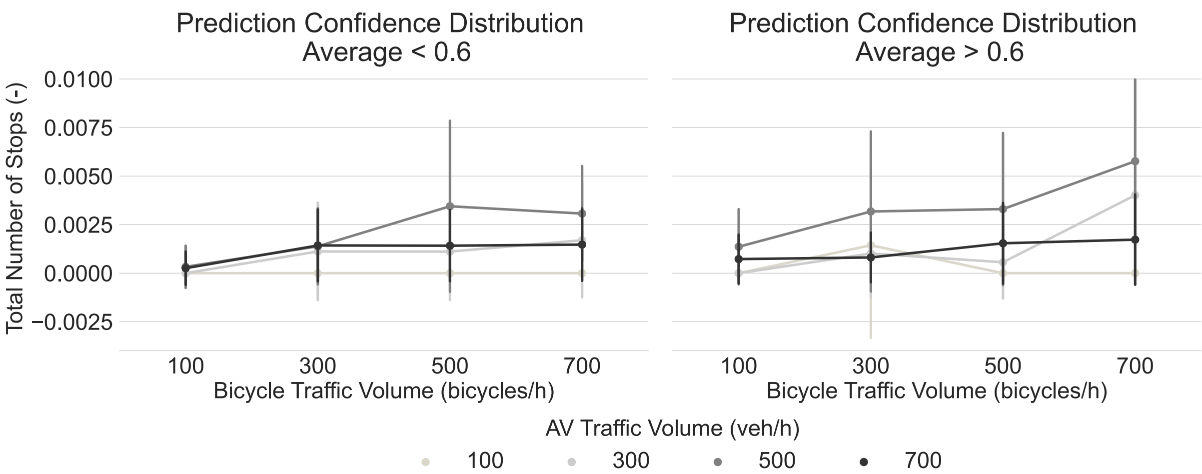

Figure 21: Simulation Scenario 1c: AV traffic (major stream) average stops. Sensitivity analysis of bicyclist maneuver prediction confidence.

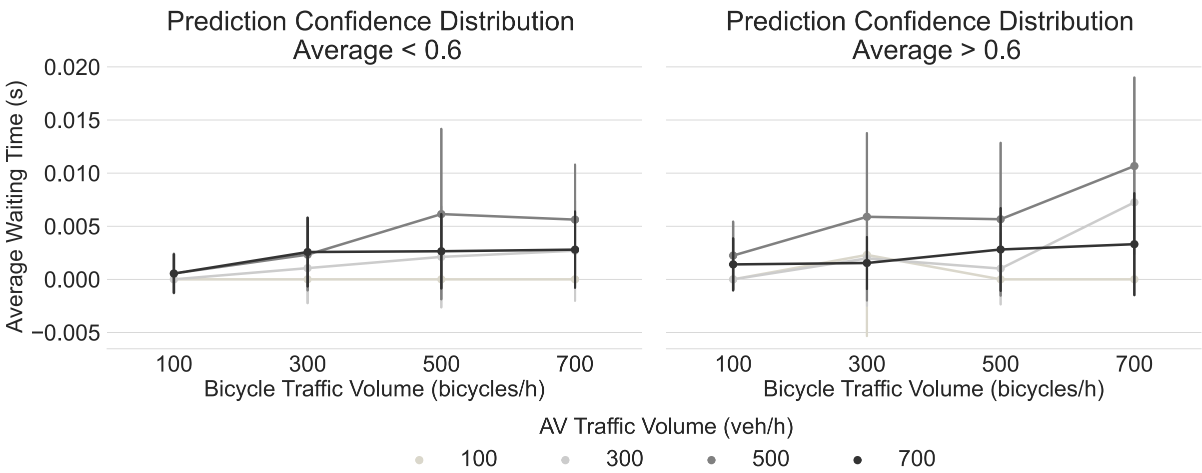

Figure 22: Simulation Scenario 1c: AV traffic (major stream) average waiting time. Sensitivity analysis of bicyclist maneuver prediction confidence.

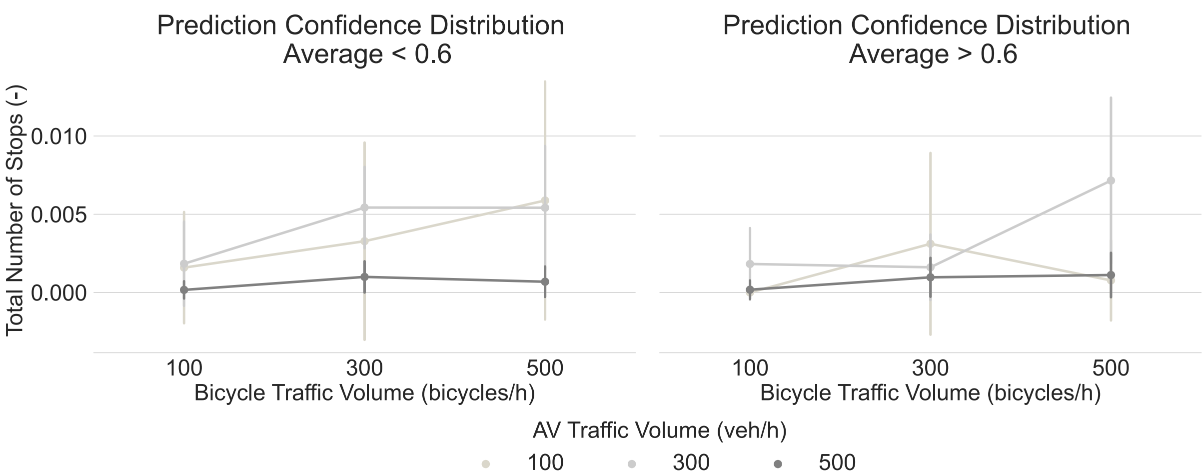

Figure 23: Simulation Scenario 2c: AV traffic (major stream) average stops. Sensitivity analysis of bicyclist maneuver prediction confidence.

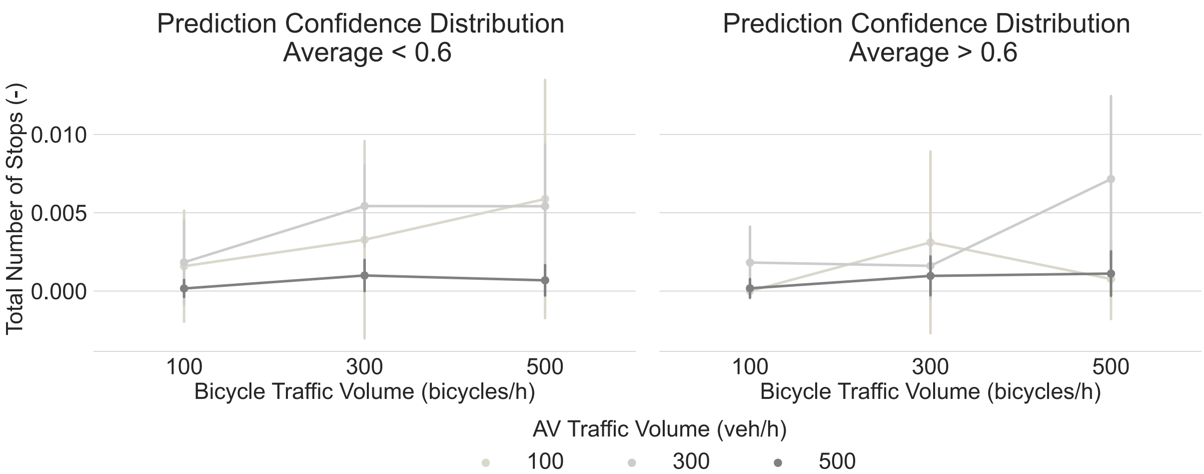

Figure 24: Simulation Scenario 2c: AV traffic (major stream) waiting time. Sensitivity analysis of bicyclist maneuver prediction confidence.

4 Simulation Results Optimization Method: Statistical Analysis

Table 3: Simulation Scenario 2b: Bicycle traffic (minor stream) average number of stops per bicyclist. Statistical test results.

AV	**Bicycles (bikes/h)**		
(veh/h)	100	300	500
100	-3.795% 0.684	-1.771% 0.772	4.666% 0.383
300	-3.028% 0.662	0.023% 0.996	-3.500% 0.348
500	0.201 0.974	-1.078% 0.755	-0.134% 0.962

Table 4: Simulation Scenario 1c: Bicycle traffic (minor stream) average waiting time. Statistical test results.

AV	**Bicycles (bikes/h)**			
(veh/h)	100	300	500	700
100	-1.457% 0.669	-0.056% 0.980	-0.378% 0.846	1.929% 0.388
300	-0.122% 0.980	0.134% 0.957	0.287% 0.923	-0.754% 0.826
500	-3.834 0.392	0.969% 0.792	-0.270% 0.957	1.932% 0.754
700	-3.129% 0.599	-1.443% 0.757	-7.417% 0.267	5.194% 0.756

Table 5: Simulation Scenario 1c: Bicycle traffic (minor stream) average number of stops per bicyclist. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)**			
	100	300	500	700
100	-10.394% 0.642	5.519% 0.669	2.567% 0.796	7.371% 0.498
300	3.409% 0.811	3.127% 0.583	-1.217% 0.817	1.044% 0.848
500	-3.581 0.631	4.814% 0.330	5.000% 0.253	5.752% 0.240
700	0.262% 0.974	8.281% 0.061	-1.413% 0.657	1.783% 0.586

Table 6: Simulation Scenario 1c: AV traffic (superordinate traffic stream) average stops per vehicle. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)**			
	100	300	500	700
100	0% 0	∞ 0.328	0% 0	0% 0
300	0% 0	-9.465% 0.918	-49.365% 0.565	136.477% 0.168
500	314.838 0.137	129.704% 0.206	-4.202% 0.936	87.825% 0.083
700	181.484% 0.319	-43.333% 0.470	8.742% 0.883	17.341% 0.779

Table 7: Simulation Scenario 1c: AV traffic (superordinate traffic stream) average waiting time. Statistical test results.

AV (veh/h)	Bicycles (bikes/h)			
	100	300	500	700
100	0% 0	∞ 0.328	0% 0	0% 0
300	0% 0	86.888% 0.588	-52.030% 0.537	168.867% 0.111
500	301.689 0.144	153.278% 0.181	-7.904% 0.882	89.712% 0.104
700	159.438% 0.355	-40.180% 0.498	6.207% 0.918	18.344% 0.779

Table 8: Simulation Scenario 2c: Bicycle traffic (minor stream) average delay. Statistical test results.

AV (veh/h)	Bicycles (bikes/h)		
	100	300	500
100	1.899% 0.586	-0.864% 0.828	-0.644% 0.811
300	-3.076% 0.644	-27.560% 0.059	-22.975% 0.084
500	**-40.877** 0.015	**-51.711%** 0.013	**-28.757%** 0.046

Table 9: Simulation Scenario 2c: Bicycle traffic (minor stream) average number of stops per bicyclist. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)**		
	100	300	500
100	7.790% 0.550	-1.128% 0.920	-3.018% 0.688
300	-4.078% 0.448	-3.963% 0.442	-2.415% 0.523
500	-3.879 0.254	**-7.688%** 0.033	-0.689% 0.461

Table 10: Simulation Scenario 2c: Bicycle traffic (minor stream) average waiting time. Statistical test results.

AV (veh/h)	**Bicycles (bikes/h)**		
	100	300	500
100	7.926% 0.643	-4.263% 0.802	7.112% 0.595
300	-4.469% 0.741	-39.847% 0.054	-29.925% 0.079
500	**-53.135** 0.015	**-56.085%** 0.013	**-40.077%** 0.011

Table 11: Simulation Scenario 2c: AV traffic (superordinate traffic stream) average stops per vehicle. Statistical test results.

AV (veh/h)	Bicycles (bikes/h)		
	100	300	500
100	-100% 0.152	-5.130% 0.949	-86.873% 0.054
300	-0.878% 0.988	**-70.334%** 0.001	32.058% 0.393
500	7.249 0.961	-2.637% 0.957	62.414% 0.417

Table 12: Simulation Scenario 2c: AV traffic (superordinate traffic stream) average waiting time. Statistical test results.

AV (veh/h)	Bicycles (bikes/h)		
	100	300	500
100	-100% 0.152	-42.893% 0.540	-76.126% 0.108
300	57.214% 0.479	**-70.472%** 0.004	339.380% 0.390
500	37.041 0.829	53.143% 0.475	34.831% 0.641