Carl von Ossietzky Universität Oldenburg
Fakultät II – Informatik, Wirtschafts- und Rechtswissenschaften
Department für Informatik

Simulations for Cooperative Driving

Methodology for Verification and Validation of Cooperative Driving Functions with Intelligent Co-Simulation Framework

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Kurzfassung

Die kooperative Manöverkoordinierung stellt eine der richtungsweisenden Technologien auf dem Weg zum automatisierten und vernetzten Fahren der Zukunft dar. Diese Technologie ermöglicht sowohl autonomen als auch manuell gesteuerten Fahrzeugen mit der Unterstützung von Kommunikation über kooperative Fahrmanöver zu verhandeln und diese auszuführen, um somit die Verkehrssicherheit und -effizienz auf den Straßen zu erhöhen. Heutzutage wird das kooperative Fahren als ein hochrelevantes Thema für zahlreiche Forschungsaktivitäten eingeschätzt.

Die Entwicklung von kooperativen Fahrfunktionen, welche die Manöverkoordinierung in Form von anspruchsvollen Hardware- und Softwaresysteme realisieren sollen, bedarf eines umfassenden Testens aufgrund einer großen Anzahl zu berücksichtigender Aspekte. Deshalb stellt die Verifizierung und die Validierung von solchen Systemen auch unter der Nutzung von modernen virtuellen Fahrversuchstechniken eine herausfordernde Aufgabe dar.

Die vorliegende Dissertation schlägt eine neuartige Methodik zur Verifizierung und Validierung von kooperativen Fahrfunktionen durch ein Intelligent Co-Simulation Framework vor. Die dazugehörigen Ansätze zur Bewertung des kooperativen Fahrens, wie etwa – die Vorbereitung von Szenarien durch maschinelles Lernen, die gekoppelte Simulation von Fahrzeug und Verkehr, die Anwendung von ausgewählten Metriken der Verkehrsqualität – werden dabei erarbeitet.

Als Ergebnis wird eine Demonstration der Methodik in Form von einer simulationsbasierten Remote-Adaptable Prototype-in-the-Loop Methode durchgeführt, bei der reale und virtuelle Fahrzeuge eine Manöverkoordinierung vollziehen, was im Sinne eines weiteren Schritts hin zur Lösung für schnelles und aufwandseffizientes Testen von kooperativen Fahrfunktionen beiträgt.

Abstract

The cooperative maneuver coordination represents one of the pioneering technologies on the way to the automated and connected driving of the future. It allows for autonomous, as well as manually driven vehicles to negotiate and to execute cooperative driving maneuvers with a support of the communication, in order to increase the traffic safety and efficiency on the roads. Nowadays, the cooperative driving provides a highly relevant topic for numerous research activities.

The development of the cooperative driving functions, which ought to realize the maneuver coordination as sophisticated hardware and software systems, requires a comprehensive testing, due to a large number of aspects needed to be considered. Therefore, the verification and the validation of such systems even by means of modern virtual test driving techniques poses a challenging task.

The dissertation at hand introduces a novel methodology for the verification and validation of the cooperative driving functions with an intelligent co-simulation framework. The associated approaches for an assessment of the cooperative driving, such as – a preparation of scenarios through machine learning, a coupled simulation of vehicle and traffic, an application of selected traffic quality metrics – will be hereby elaborated.

As a result, a demonstration of the methodology will be performed in form of a simulation-based Remote-Adaptable Prototype-in-the-Loop method, where real and virtual vehicles engage in the maneuver coordination, thus, delivering one further step towards the solution for a fast and effort-efficient testing of the cooperative driving functions.

Acknowledgment

The research and development activities leading to this dissertation were accomplished over the course of my employment at Opel Automobile GmbH (Stellantis NV) in the scope of my assignment to the consortium project IMAGinE, thankfully funded by the Federal Ministry for Economic Affairs and Climate Action of Germany. Therefore, I would like to acknowledge everyone, including all the project partners, who supported this scientific initiative, for the productive and amicable cooperation.

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Apart from that, I am utterly grateful to my family members, most of all to my mother Galina, father Grigorij and brother Andreas Lizenberg, as well as to my friends for their moral backup. And finally, I would like to cordially thank my fiancée Priscillia Ernewein – I could not have undertaken this journey without her.

Thank you all for your support!

Contents

Nomenclature

Abbreviations

	Definition
ADAS	Advanced Driver Assistance System
ASG	Automatic Scenario Generation
BMWK	Federal Ministry for Economic Affairs and Climate Action (in German)
CAM	Cooperative Awareness Message
CAN	Controller Area Network
CAV	Connected and Automated Vehicle
CE	Concurrent Evaluation
CPM	Collective Perception Message
CPU	Central Processing Unit
ETSI	European Telecommunications Standards Institute
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GPU	Graphics Processing Unit
GUI	Graphical User Interface
HiL	Hardware-in-the-Loop
HMI	Human-Machine Interface
IEC	International Electrotechnical Commission
ISD	Intelligent Scene Detection
ISO	International Organization for Standardization
LoD	Level of Detail
MC	Maneuver Coordination
MCM	Maneuver Coordination Message
MDR	Message Delivery Ratio
MiL	Model-in-the-Loop
ML	Machine Learning
NoA	Number of Agents
ITS	Intelligent Transportation System
OEM	Original Equipment Manufacturer
PiL	Prototype-in-the-Loop

	Definition
RAM	Random-Access Memory
RA-PiL	Remote-Adaptable Prototype-in-the-Loop
RoI	Region of Interest
ROS	Robot Operating System
RQ	Research Question
RTV	Real Test Vehicle
SAE	Society of Automotive Engineers
SC	Successful Cooperation
SiL	Software-in-the-Loop
SPA	Sense-Plan-Act
SuT	System-under-Test
TCP/IP	Transmission Control Protocol / Internet Protocol
TETTC	Time-Exposed Time-to-Collision
TraCI	Traffic Control Interface
TTC	Time-to-Collision
UTM	Universal Transverse Mercator
ViL	Vehicle-in-the-Loop
V2X	Vehicle-to-Everything
XiL	Anything-in-the-Loop

Symbols

	Definition	Unit
CV_i	Coefficient of variation	—
k	Traffic density	veh/km
L	Label	—
n_Γ	Number of vehicles per group	veh
n_K	Number of vehicles per combination	veh
n_RoI	Number of vehicles in RoI	veh
O	Observation	—
p_i	Vehicle position	m
Δp_{ij}	Relative vehicle position (distance)	m
q	Traffic flow	veh/h

	Definition	Unit
r_i	Distance to centroid	m
TTC_{ij}	TTC metrics	s
$TETTC_i$	TETTC metrics	s
t	Simulation time	s
T	Total simulation time	s
${}_{\mathrm{in}}T_i$	Simulation time of vehicle entry	s
${}_{\mathrm{out}}T_i$	Simulation time of vehicle exit	s
v	Traffic velocity	km/h
$\overline{v}$	Mean traffic velocity	km/h
v_i	Vehicle velocity	m/s
$\overline{v}_i$	Mean vehicle velocity	m/s
Δv_{ij}	Relative vehicle velocity (speed difference)	m/s
x	Horizontal coordinate	m
y	Vertical coordinate	m
σ_{v}	Standard deviation of traffic velocity	km/h
$\sigma_{\mathrm{v}i}$	Standard deviation of vehicle velocity	m/s
τ	Simulation time step	s
φ_i	Angle to centroid	rad
i	Index – of vehicle i	—
ij	Index – between vehicles i and j	—

1 Introduction

In a general sense, the cooperation stands for a goal-oriented relation or interaction between partners or system components [1]. In the context of automotive industry, the domain of cooperative driving is crucial for paving the way to the Intelligent Transportation Systems (ITS) of the future [2] [3]. The focus of this technology lies in the increase of traffic safety and efficiency, by enabling a controlled cooperative behavior between multiple Connected and Automated Vehicles (CAV) as cooperation partners [4].

Figure 1.1: Vision of interconnected traffic participants in the future (from [1])

Online:
[1] 5gaa.org/news/europes

Typically, modern vehicles affiliated with ITS are designed to exchange considerable portions of the required information via electromagnetic wireless communication, often commonly referred to as the Vehicle-to-Everything (V2X) communication, which involves infrastructure, pedestrians and other traffic participants [5] [6]. Figure 1.1 illustrates a vision of an interconnected multimodal transport in the urban environment, aimed to be achieved with a broad usage of the V2X communication in prospect. Here, for example, various traffic participants, potentially also including CAVs, inform each other via wireless networking about traffic jams, vulnerable road users and emergency vehicles between the city blocks.

Nowadays, the development of systems that ought to realize the cooperative driving for CAVs in different traffic situations represents a topic of wide research interest. This constitutes vibrant activities of numerous research projects, notably one of them being the German public funded consortium project IMAGinE [1] that was engaged in the design, implementation and evaluation of several prototypical driving functions based on the cooperative Maneuver Coordination (MC), led by Opel Automobile GmbH. Moreover, the goals of the project included advances in the cooperative environment model, communication mechanisms, human-machine interaction and simulation environment.

This dissertation was established as a part of the Opel research activities for IMAGinE, thus, it will substantially deal with the subjects elaborated in this project. Apart from that, most of the important aspects of the cooperative driving will be covered within the framework of this thesis for a better comprehension of the corresponding scientific discussion, regarding both various already existing technologies, as well as novel forthcoming technological approaches.

1.1 Motivation

Alongside with the high potential to improve traffic safety and efficiency, the technology of cooperative driving also bears a lot of challenges, such as a general lack of methodological testing and examination procedures during the research and development process of the corresponding driving functions, required for their further homologation. Therefore, these challenges have yet to be contemporarily addressed.

[1] imagine-online.de/en/home

First, in order to assess the cooperative MC, it is essential to define independent aspects that may have influence on it, such as (according to [AAET]):

- traffic quantity
- driving function
- vehicle and driver
- infrastructure
- environment

The traffic quantity is determined by the type and number of vehicles, as well as their positioning on the road, thus, it is a crucial condition for a correct behavior of CAVs during a cooperative maneuver. Hereby, the driving function, which is responsible for the technical fulfillment of the MC, in addition to the vehicle and driver, has an important impact on the course and outcome of the cooperation. Apart from that, the infrastructure (incl. road topology and geometry) and the environment (incl. weather) also significantly contribute to this process.

Second, it is necessary to define dependent aspects that are expressed by the cooperative MC as a result, such as (according to [AAET]):

- traffic quality
- driving performance
- comfort
- robustness
- system complexity

The traffic quality is determined as a measurable state of traffic flow on the road, mainly concerning the safety (e.g., intermediate distances) and efficiency (e.g., travel time and energy waste) of the vehicles, which can indicate a positive or negative impact of the cooperative interaction between traffic participants. At the same time, during a maneuver carried out by CAVs, an effective MC must provide high-grade driving performance, comfort and robustness, based on the usability and reliability of the driving function, in order to achieve a successful cooperation. Moreover, it is beneficial to keep the complexity (incl. costs) of systems behind the MC as low as possible.

This way, the independent and dependent aspects act as input and output for the yet unknown effects of the cooperative driving with MC. This simple causality link is shown in Figure 1.2. Evidently, a variation of the independent aspects results in a variation of the dependent aspects, thus, allowing to identify the characteristics and hidden properties of the cooperative driving.

Currently, the versatility of solutions that aim to facilitate the cooperative driving needs to be exceptionally high, due to the necessity to consider large numbers of combinations for the independent and dependent aspects. This prerequisite is justified by the high amount of possible interactions between multiple CAVs as separate systems with their autonomous, complementary to cooperative or non-cooperative, behavior. Therefore, a homologation of the cooperative driving functions, followed by their deployment and operation in vehicles, requires reliable verification and validation procedures, especially during pivotal development phases of the involved systems and sub-systems.

Figure 1.2: Link between independent and dependent aspects of the cooperative driving

1.2 Proposal

Different approaches to evaluate the efficiency and effectiveness of the cooperative MC between CAVs under various conditions pose a promising subject for the scientific research. Hereby, it is important to clearly specify the dependent and independent aspects, as well as to in-depth analyze their interrelation. Also, in order to verify and to validate the cooperative driving functions in vehicles, eventually, an appropriate methodology is required. Meanwhile, it is problematic to fulfill this task entirely by real-world road (incl. proving grounds) driving tests. This is where virtual methods, such as the simulation, offer an opportunity for a faster and more effort-efficient testing.

Research Questions

Derived from the motivation and this problem statement, the following Research Questions (RQ) are to be answered in the course of this dissertation:

I) How to detect the MC relevant conditions of traffic quantity?
II) How to comprehensively test the MC in the cooperative driving functions?
III) How to evaluate the MC effects on traffic quality?

Hereby, the RQs I and III cover the traffic quantity as an independent aspect and the traffic quality as a dependent aspect, respectively. Their choice holds merely an exemplary character, since the resulting methodology must be transferable to other aspects as well. In order to deal with these questions, suitable sets of scenarios and metrics are needed. Then, the RQ II brings the RQs I and III together, defining the overall simulation-based methodology. The corresponding basic idea of the methodology is depicted in Figure 1.3.

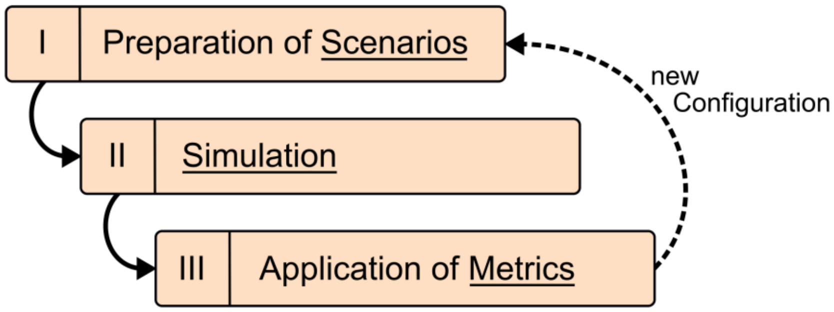


Figure 1.3: Idea of the methodology (from [AAET] with adaptations)

This idea contains three steps I, II, III that are conducted sequentially. The steps can be repeated with a new configuration, when a sequence is completed. By doing so, a potent test automation can be achieved, in order to enable a comprehensive verification and validation of the cooperative driving functions. The precise substance of these steps will be later defined within the scope of the work at hand by the answers to the corresponding RQs I, II, III.

1.3 Outline

This dissertation is organized as follows. After the introduction in Chapter 1, the background information regarding the current research activities (incl. IMAGinE project), the cooperative driving functions and the virtual test driving will be provided in

Chapter 2. Then, Chapter 3 will describe the actual methodology with the associated system-under-test and the intelligent co-simulation framework. Afterwards, Chapter 4 will deal with the design and the implementation of the methodology, including related work, architecture, workflow and utilization. Subsequently, Chapter 5 will show the evaluation results with the selected metrics and scenarios. In Chapter 6, the experimental realization of the methodology will be presented as a novel Remote-Adaptable Prototype-in-the-Loop method. Finally, the dissertation will be concluded with Chapter 7. The resulting documentation structure is outlined in Figure 1.4.

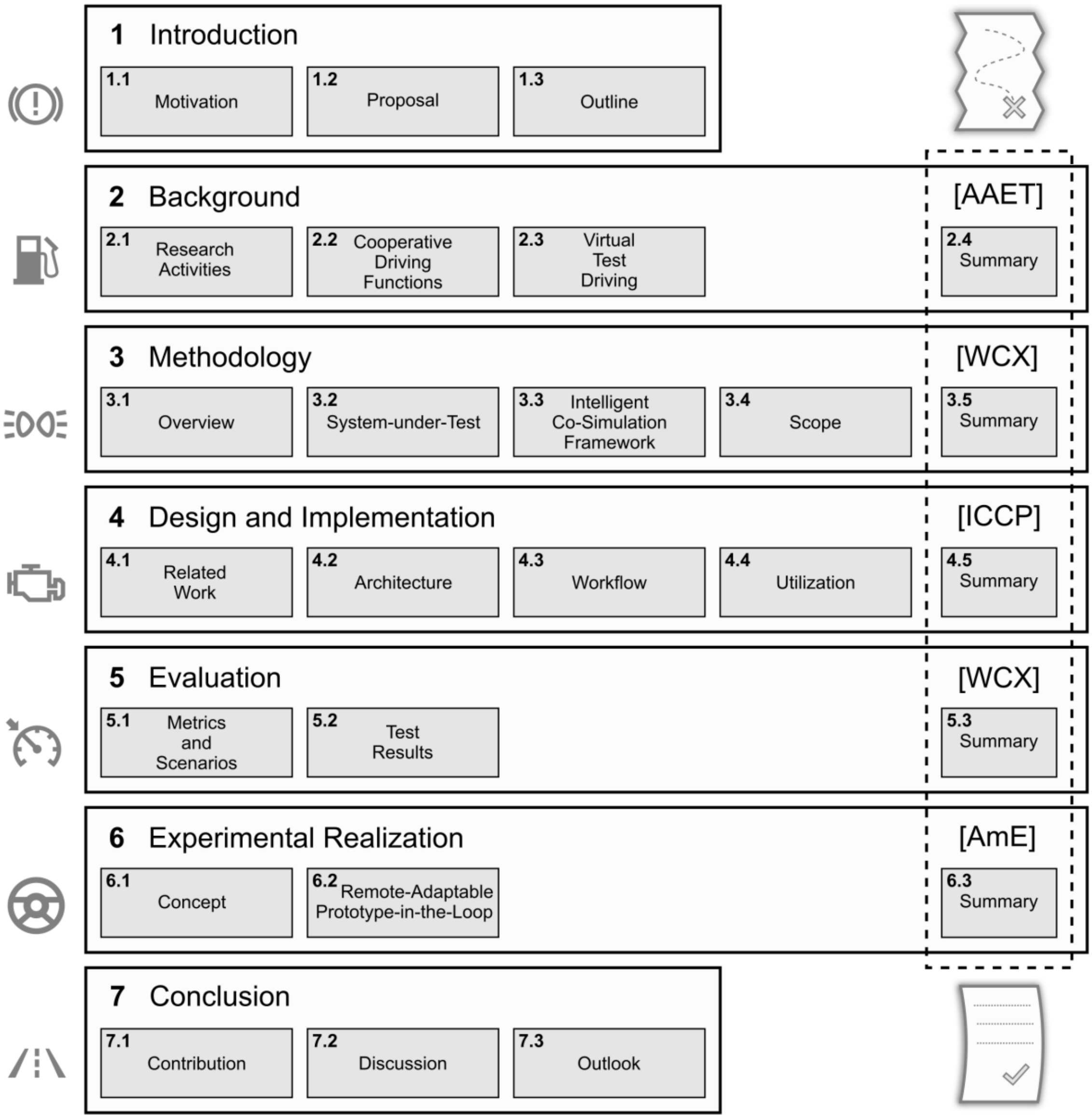


Figure 1.4: Structure of the dissertation

To be noted that every Chapter between 2 and 6 builds upon the elements that have already been partially published in the author's peer-reviewed scientific works [AAET] [AmE] [WCX] [ICCP] (see Authored Publications in Bibliography for citations). Additionally, these Chapters will be complemented with the associated summary sections, in order to gather the most important findings and to gradually consolidate the maturity of the methodology, progressing from a basic idea to a fully developed technical specification, by delivering answers to the RQs.

2 Background

Before introducing the methodology, in order to handle the substantial topics of the dissertation, it is vital to gain an insight into the background needed for their general understanding. Consequently, the following content will provide an underlying information regarding the related recent und current research activities, as well as the perspectives on the cooperative driving functions and the virtual test driving.

This section is based inter alia on the author's publication [AAET].

2.1 Research Activities

Nowadays, a sustainable progress of the ITS technologies from the recent years continues to inspire scientists towards further innovations in the autonomous and cooperative driving worldwide, among others in the European Union and particularly in Germany. Serving as a widespread foundation for numerous research activities, the levels of the on-road motor vehicle automation were defined in the taxonomy standard J3016 [7] by the international Society of Automotive Engineers (SAE), which was later extended with the standard J3216 [8] for the cooperative automation. Based on this groundwork, the academia and the automotive industry pursue the goal to gradually advance from the lower to higher levels of automation and cooperation, through an ongoing rollout of the more and more ingenious technological approaches.

In the research and development process of the associated driving functions, alongside with the actual engineering, a successive safeguarding also plays a very important role, striving to provide a reliable and secure functionality of the elaborated hardware and software solutions in the vehicles, by means of profound verification and validation. In this context, a short thematic overview of the public funded consortium research projects in Germany [9] [10] [11], which are related to the work at hand, will be given in the following.

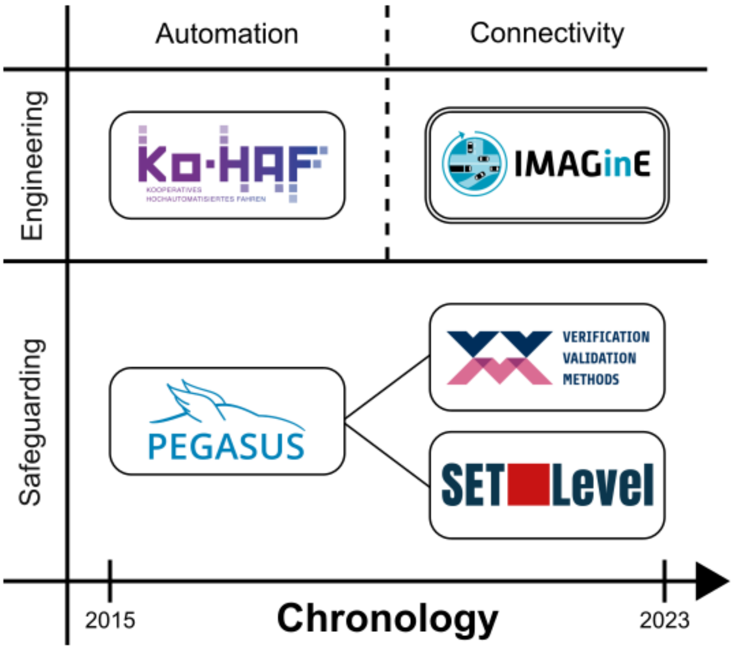


Figure 2.1: Thematic overview of the related research projects

Recently, a prototypical engineering of the autonomous and cooperative driving functions for CAVs was addressed in the projects Ko-HAF [1] and IMAGinE [2] with partially differing priorities on the automation and the connectivity, respectively. On the one hand, Ko-HAF was responsible for the realization of highly automated driving solutions, including environment perception and representation with backend support-server, localization in static environment, vehicle guidance with controllable automation, functional concept for normal and emergency operation, as well as conclusive testing. On the other hand, IMAGinE was primarily involved into the specification, implementation and evaluation of the cooperative driving functions with a focus on the following five core innovations: cooperative MC, cooperative environment model, communication mechanisms, human-machine interaction and simulation environment.

[1] ko-haf.de
[2] imagine-online.de

At the same time, research projects from the PEGASUS Family (PEGASUS [1], VV Methods [2] and SET Level [3]) were engaged in the elaboration of safeguarding approaches for different representative use-cases of the autonomous driving. Hereby, PEGASUS initially provided general descriptions of the quality criteria, tools and methods for the identification of critical scenarios and situations. It was chronologically followed by VV Methods and SET Level, which were dealing with the verification and validation methods for highly automated vehicles in urban environments, as well as the simulation-based development and testing of highly automated driving functions, respectively.

A simple thematic overview of the previously mentioned projects in a chronological order is displayed in Figure 2.1. Since IMAGinE is especially relevant for this dissertation, due to the predominant subject of connectivity and cooperative driving, it will be covered with more details in the following section.

2.1.1 Project IMAGinE

IMAGinE “Intelligent Maneuver Automation – cooperative hazard avoidance in real-time” was a research project in the period from 2016 to 2022, which was assigned with the research and development of the state-of-the-art cooperative driving functions for CAVs within a consortium of several automotive Original Equipment Manufacturers (OEM), Tier-1 suppliers, technology companies and academic institutions. It was funded by the Federal Ministry for Economic Affairs and Climate Action (BMWK) of Germany with the project partners: BMW, Bosch, Continental, Die Autobahn, IPG, MAN, Mercedes-Benz, Nordsys, Opel, TU Munich, Volkswagen and WIVW. In total, IMAGinE developed six functions for cars and trucks, ranging from merging and longitudinal control on highways to overtaking and turning on rural roads, as displayed in Figure 2.2.

The goal of the project was to elaborate solutions for the cooperative MC using V2X communication, with a potential to increase safety and efficiency of the vehicles in various traffic scenarios. In the process, a proof-of-concept for these solutions, which were developed as sophisticated cooperation algorithms, was conducted on prototypical systems in simulation, as well as in real test vehicles (manually driven and automated).

[1] pegasusprojekt.de
[2] vvm-projekt.de
[3] setlevel.de

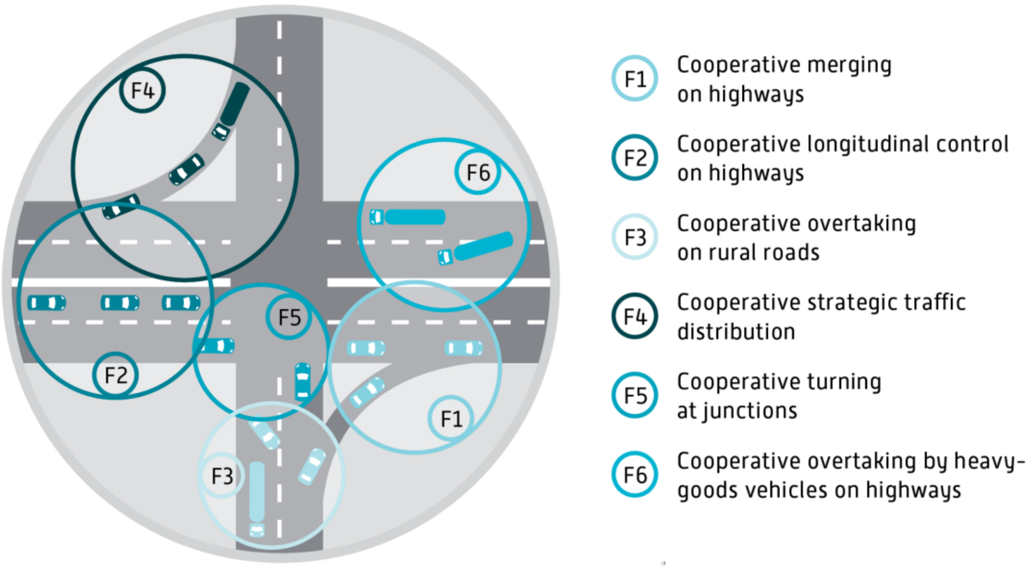


Figure 2.2: Cooperative driving functions in the IMAGinE project (from [1])

During the work on the project, several software frameworks and simulation tools were actively used and extended with new capabilities, needed to cover various aspects of the cooperative driving in the course of the respective verification and validation. The results of the project were documented in multiple scientific publications (e.g., [AAET] [AmE] [WCX] [ICCP]) and demonstrated on May 19, 2022 on a proving ground in Pferdsfeld, Germany. More detailed information about the IMAGinE cooperative driving functions, regarding their categorization, use-case analysis and requirements harmonization, can be found in the open project deliverables [12] [13] [14] [2].

2.2 Cooperative Driving Functions

According to the initiative of the IMAGinE project, the cooperative driving functions in CAVs have a potential to tangibly improve safety and efficiency of the vehicular maneuvering on the roads, due to a cooperative behavior. Thereby, cooperative behavior can be defined, according to sources [15] [16] [17], as an aggregation of the own and the other's utilities among the cooperation participants. A behavior can be regarded as cooperative, if the total collective utility of this behavior surpasses the utility of a

[1] imagine-online.de/en/cooperative-functions
[2] imagine-online.de/en/findings-publications

reference behavior. At the same time, if every individual utility of the cooperation surpasses the utility of a reference behavior, then this behavior is called 'rational-cooperative'. The latter stands for the most preferable way of cooperation, since in this case, all cooperation participants benefit from it. Also, higher utility means lower cost of a maneuver, for instance, which can be expressed in a lower travel time and energy waste of the vehicles. The corresponding coherency of the own and the other's utilities, as an example for two cooperation participants, is shown in Figure 2.3.

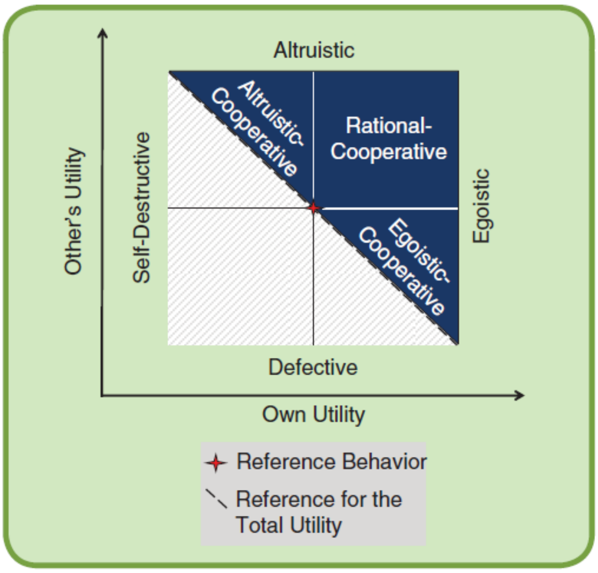


Figure 2.3: Cooperative behavior defined by utilities (from [16])

Based on this idea, the cooperative driving functions for on-road motor vehicles can be described as Advanced Driver Assistance Systems (ADAS) [18], which are able to interact with other vehicles and assert the cooperative behavior. In case of autonomous vehicles, the corresponding maneuver execution can be achieved by a fully automated motion control on part of the driving functions. However, if the vehicles are manually operated, then ADAS can support the involved human drivers via suitable Human-Machine Interfaces (HMI). Hereby, the drivers can be engaged to carry out the driving maneuvers cooperatively, if they agree to.

As a result, the cooperative driving functions technically act as ADAS that rely on the MC with cooperative vehicular maneuvering [19] and cooperative vehicular networking [20], which will be presented with more details further on.

2.2.1 Maneuvering

To begin with, the characteristic traits of the cooperative driving functions with MC for the cooperative vehicular maneuvering will be explained on a traffic scenario that is shown in Figure 2.4. It illustrates an exemplary merging maneuver on the highway, where the red vehicle plans to enter the gap between the blue and the green vehicles, which initially may not be large enough. This particular scenario corresponds to the primary use-case of the cooperative driving function F1 from the IMAGinE project (see Figure 2.2).

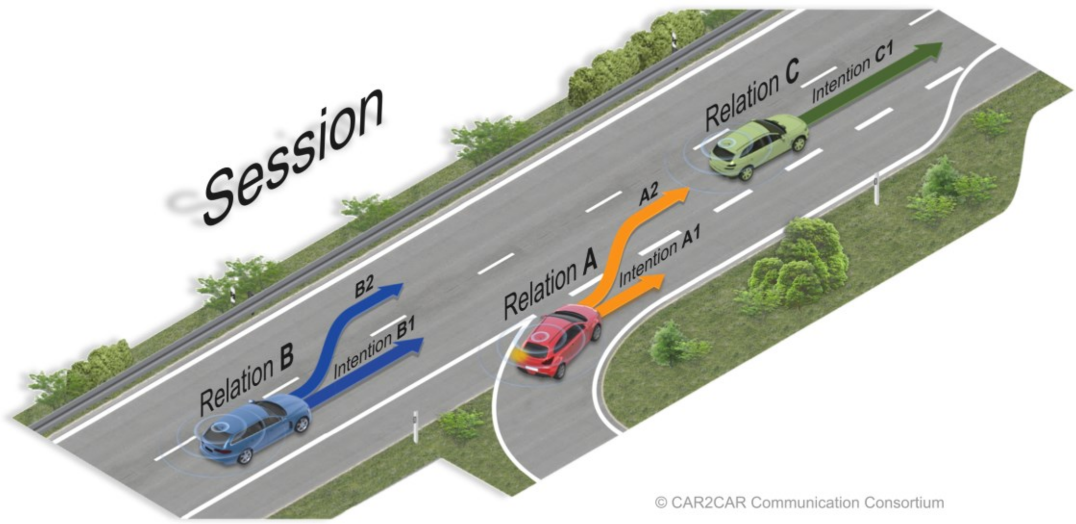


Figure 2.4: Exemplary merging maneuver on the highway (from [AAET] with adaptations)

In this scenario, the participating vehicles exchange various types of information via the inter-vehicular communication needed for the cooperation, which can be performed on different levels of abstraction, as described in [AAET]: session, relation and intention. On the lowest level, the red vehicle can broadcast its intentions **A1** (deceleration) and **A2** (acceleration with lane-change). As a reaction to that, the blue vehicle can offer intentions **B1** (deceleration) and **B2** (lane-change), in order to allow the red vehicle to enter the highway. Furthermore, the green vehicle can follow the intention **C1** (acceleration) to make the merging space bigger. Apart from the intentions, the vehicles can also interact based on their relations **A**, **B**, **C** that are reasoned by their roles in the scenario. In this case, **A** is requesting, as well as **B** and **C** are offering the cooperation. Another level of interaction can be expressed in an interactive session, where the vehicles act together according to a common protocol of this session. Possible compositions of intentions, relations and sessions that eventually enable the red vehicle to enter the highway, leading hereby to a higher utility of the maneuver, would consequently result in a cooperation.

2.2.2 Categorization Scheme

Elaborated by the IMAGinE project, the cooperative driving functions contain following main phases that can be cyclically repeated: communication, negotiation and execution. Basically, this corresponds to the Sense-Plan-Act (SPA) paradigm for the operation of CAVs, originally coming from the field of robotics [21]. Thereby, the communication and the negotiation act as the primal elements of the MC and, thus, are crucial for a successful execution of maneuvers. In the following, a categorization scheme, which was developed for the work at hand in compliance with the IMAGinE findings [22] [1], will be discussed to give a better insight into the principles behind the cooperative driving functions in general, as well as the MC in particular.

On the one side, the described scenario (from Figure 2.4) of the cooperative vehicular maneuvering represents a case of a direct negotiation, since the exchanged information between certain cooperation participants about their intentions, relations and sessions is distinctly targeted at the MC process to achieve a cooperative behavior. On the other side, a cooperative maneuver can also be accomplished by an indirect negotiation, when the partners mainly broadcast supportive information about their vehicles (e.g., positions, velocities, etc.) and their environment (e.g., other vehicles). In this case, the resulting behavior is determined by each participant independently, based on its interpretation of the situation. Apart from that, the negotiation can be explicit or implicit (depending on the liability of partners to ensure cooperation), centralized or decentralized (depending on the presence of a central controlling entity for cooperation), as well as event-triggered or continuous (depending on the temporal progression of cooperation), according to [22].

Initially, the negotiation phase obtains the required information for the MC from the communication phase, which can be achieved in ad-hoc or cellular form (i.e., heterogeneously [23]), in coherence to the extent of the infrastructural involvement within the overlying networking technology (e.g., without or with backend support). Eventually, the negotiation phase leads to the execution phase, which can be realized as automated or

[1] imagine-online.de/en/findings-publications

manual, expectedly resulting in a safe and efficient maneuvering, in dependence on the surrounding environmental conditions and the behavior of other vehicles.

Furthermore, the MC processes can be categorized by the levels of planning and decision-making. Hereby, the planning reflects a temporal forecast of the driver's or vehicle's plans: operational (split-seconds to seconds), tactical (seconds to minutes) and strategical (minutes to hours) [24]. Respectively, these so-called planning horizons are typical for the stabilization, guidance and navigation tasks in the autonomous vehicles [25]. In addition, the decision-making reflects a degree of the utility that is considered during a MC process: local (solely deciding vehicle), regional (vehicles in certain proximity) or global (all involved vehicles).

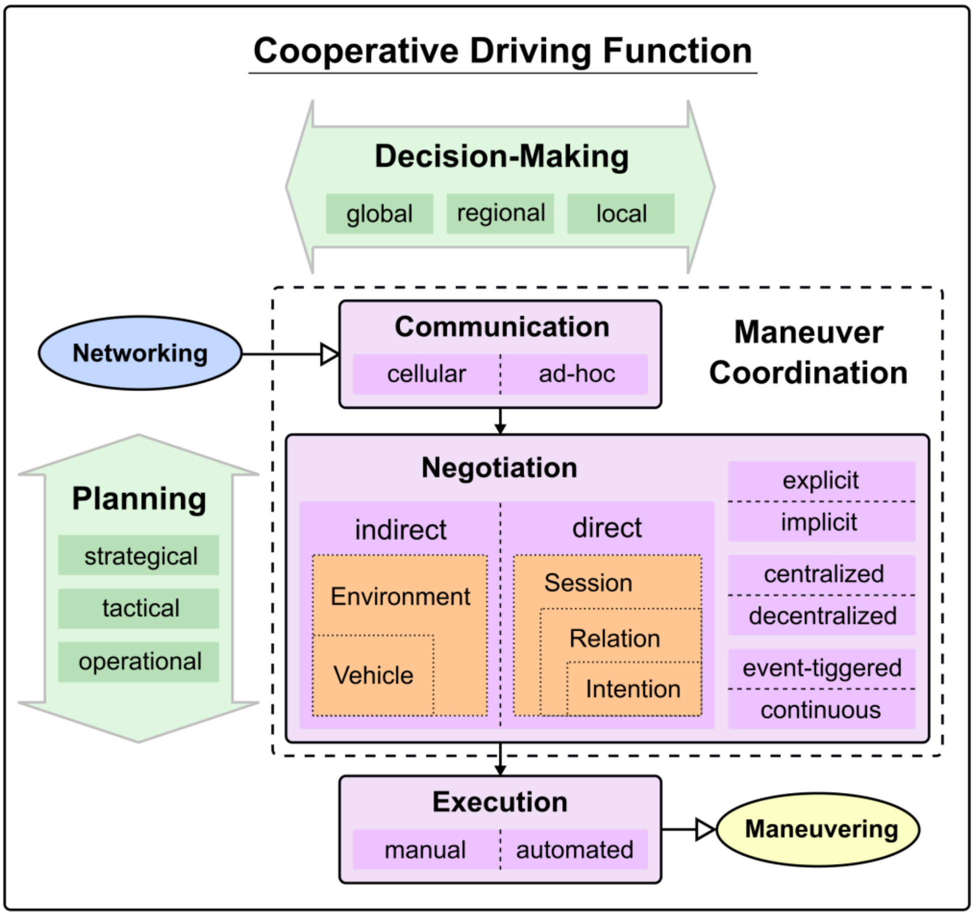


Figure 2.5: Categorization scheme of the cooperative driving functions (from [AAET] with adaptations)

In conclusion, all the characteristics, which were described above in the scope of the cooperative vehicular maneuvering and networking, are gathered in Figure 2.5. This scheme represents a guideline for an approximate (i.e., exceptions are possible) categorization of the cooperative driving functions with MC.

Table 2.1: Exemplary categorization of the IMAGinE functions

Function **Principle**	**Planning**	**Decision-Making**	**MC Negotiation**
F1 [16]	operational tactical	local regional	direct – Intention implicit decentralized continuous
F2 [26]	tactical strategical	local regional	direct – Relation explicit decentralized continuous
F3 [16]	operational tactical	local regional	direct – Intention implicit decentralized event-triggered
F4 *other*	tactical strategical	regional global	direct – Session implicit centralized continuous
F5 [16]	operational tactical	local regional	direct – Intention implicit decentralized continuous
F6 [26]	tactical strategical	local regional	direct – Relation explicit decentralized event-triggered

By applying this categorization scheme to the cooperative driving functions from the IMAGinE project (F1 to F6 in Figure 2.2), one can achieve an exemplary overview given in Table 2.1. All of the considered functions are conceptually able to act independently of the networking and maneuvering technologies, which is why they only distinct in the negotiation phase (with different levels of planning and decision-making), but not in the communication and execution phases.

These functions are specified to work with the direct negotiation, which is supported by the data about the vehicle and the environment from the indirect negotiation. Herein, the majority of solutions for the negotiation phase are built upon two different principles: [16] proposes to use trajectories (as intentions for MC), which provide information about the planned spatiotemporal movements of vehicles with a certain planning horizon, usually on operational-tactical level; whereas [26] proposes to use roles (as relations for MC), which are assigned to vehicles and managed by a distributed state machine, derived from the current cooperative session.

2.2.3 Networking

Throughout a MC process, the exchange of information needed for the cooperative maneuvering between vehicles is achieved with a cooperative networking. For this, the participating vehicles can be organized into cellular or ad-hoc networks via V2X communication on the current technological platforms [27] [28], such as 3GPP 4G LTE and 5G NR (i.e., broadband mobile networks) or IEEE 802.11P and 802.11BD (i.e., local area networks), respectively. Hereby, the wireless data transmission is realized via services with corresponding V2X message formats [29]. In this regard, relevant for the work at hand are three following messages:

- Cooperative Awareness Message (CAM)
- Collective Perception Message (CPM)
- Maneuver Coordination Message (MCM)

CAM and CPM are widely used in the research landscape and are already partially standardized with ETSI EN 302 637-2 [30] and TR 103 562 [31]. By specification, the CAM contains information about the vehicle itself from its internal sensors (incl. dimension, location and dynamic values), whereas the CPM about the other surrounding vehicles from its external sensors. This data can be utilized for the creation of a common environment model, which can be especially helpful for the MC with indirect negotiation.

Currently, the MCM represents one of the most crucial message formats needed for MC, which is still in the early development. However, numerous proposals for its work-in-progress specification already exist, such as [32] [33] [34] [35] [36]. All these specifications have in common that MCM is required to contain at least one trajectory (i.e., path that a moving vehicle follows through space and time), which can be used for the direct negotiation in MC, acting as an intention for the exchange with other vehicles.

2.3 Virtual Test Driving

Typical for ADAS, the development of the cooperative driving functions requires a continuous and profound testing. This represents a challenging task, since the corresponding test scenarios are hard to establish, to assess and eventually to reproduce, due to the high technical complexity of the involved systems (vehicles) and sub-systems (vehicle hardware), as well as a great number of independent and dependent aspects needed to be considered. Therefore, the verification and the validation of the cooperative driving functions purely with real test driving on the road would require too much time, money and effort. Hence, the modern virtual test driving Anything-in-the-Loop (XiL) methods, including Model (MiL), Software (SiL), Hardware (HiL), Vehicle (ViL) and others, offer a substantial help. Rationally, these methods can be put into practice as testing routines and arranged in a system engineering V-model [37] [38], as shown in Figure 2.6.

Utilization of XiL methods encourages frontloading (i.e., higher investment of resources in the beginning of a design process), leading to the virtual tests before real tests, where issues can be resolved faster and easier. This way, through a regular verification and validation of the intended functionality, a higher maturity of the cooperative driving functions as a product can be achieved in the earlier stages of development. Hereby, the verification serves to enable that the requirements from the given specification are being fulfilled; whereas the validation serves to ensure that the actual needs of the customer are being met, thus, providing a certain value to the product in total. In order to realize virtual test driving with the XiL methods, different simulation tools can be used in a combination of the virtual and real test environments, ultimately progressing through the whole V-model from the initial customer requirements to the final acceptance test.

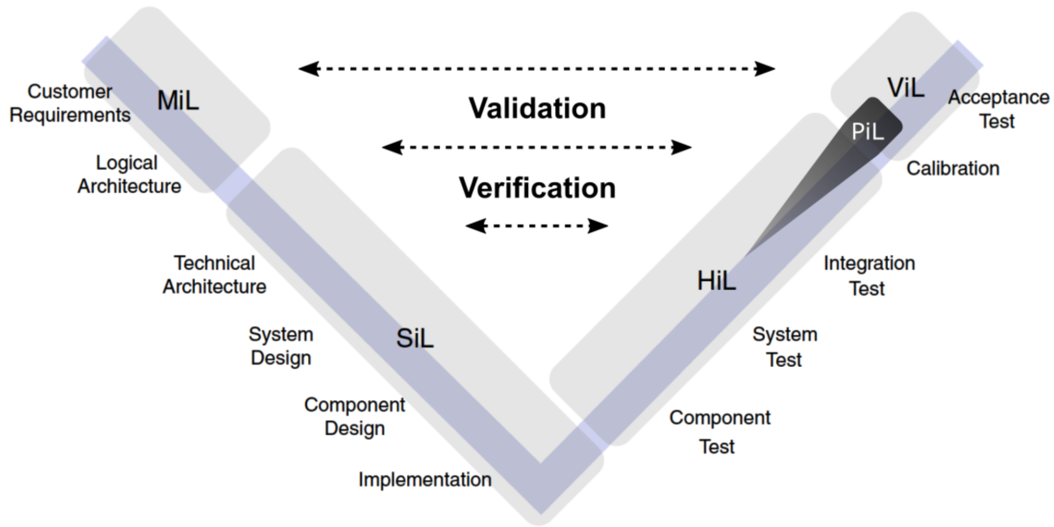


Figure 2.6: XiL methods in the V-model (from [38] with adaptations)

2.3.1 Simulation Tools

The simulation can be applied to imitate real-world aspects as models with simplified assets, in order to study certain effects of interest. However, currently available simulation tools naturally specialize on competences with a limited number of aspects, rendering them not sufficient for a profound evaluation of the cooperative driving, if regarded separately. In case of MC, since the versatility of the associated systems and processes requires a coverage of many various aspects at the same time (see Subchapter 1.1), it may be advantageous to adopt multiple simulation tools, moreover, to couple them together, forming a co-simulation [39] [40].

Ideally, the cooperative driving functions require a realistic simulation of the vehicle, traffic and network [AAET], in order to recreate an overall suitable environment with various conditions, needed for the testing of MC, as well as maneuvering and networking. A selection of the corresponding competences, which are important for the respective simulation tools, is presented in Figure 2.7.

Different tools can be incorporated into one co-simulation software framework, thus, providing a combined virtual environment for a specific simulation-based methodology. As a result, such an approach can be put into practice to simulate the effects of the cooperative driving, using appropriate scenarios and metrics. This way, a co-simulation framework may be able to realize the methodology idea of this dissertation that initially builds upon the three steps (see Subchapter 1.2): preparation of scenarios, simulation, application of metrics.

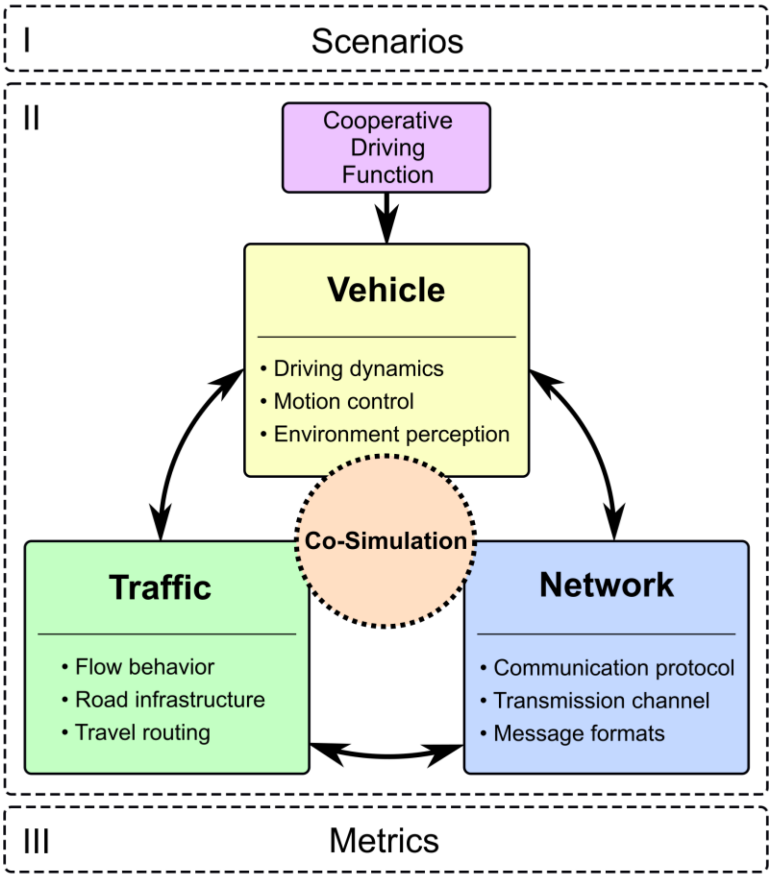


Figure 2.7: Competences of simulation tools for the cooperative driving (from [AAET] with adaptations)

In addition, Figure 2.7 determines a rudimentary color scheme for the parts of the framework (i.e., yellow for vehicle, green for traffic, blue for network), which was universally adopted on all graphic illustrations in the documentation at hand.

A wide range of ready-to-use simulator software for the vehicular applications already exists in the academia and industry landscapes. Available comprehensive surveys about popular simulators for the vehicle dynamics [41] [42] [43], the traffic flow [44] [45] [46] and the communication network [47] [48] [49] deliver in-depth descriptions and comparisons of their respective competences. A review of further proficient solutions for the co-simulation of vehicular maneuvering and networking can be found in [50].

For example, appropriate simulators for a potential utilization in the co-simulation, with a goal to study the cooperative driving, can be represented by: CARMAKER [1] for vehicle, SUMO [51] [2] for traffic and OMNET++ [52] [3] for network. CARMAKER stands for a widespread proprietary simulation software that offers realistic driving dynamics, motion control and environment perception; SUMO (open-source) delivers an extensive simulation of the traffic flow behavior with far-reaching road infrastructure and travel routing; OMNET++ (open-source) allows for an intensive simulation of the communication protocol with transmission channel and configurable message formats.

A conceptual illustration of the co-simulation with the vehicle, traffic and network simulators is shown in Figure 2.8, which demonstrates a use-case of the highway merging scenario. Hereby, a continuous traffic flow enters a certain Region of Interest (RoI), where a group of relevant vehicles can conduct a cooperative maneuver. In this arrangement, each simulator is responsible for covering of the required aspects with the corresponding competences. For instance, the V2X messages are exchanged in the network simulator, so that the vehicles can interact according to MC in the vehicle simulator, causing a positive or negative impact on the traffic flow in the traffic simulator.

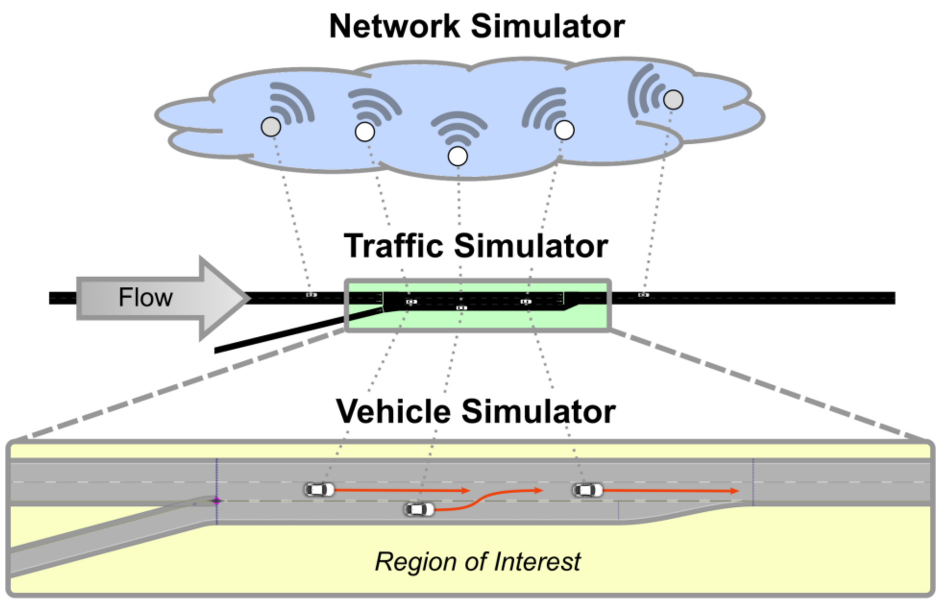


Figure 2.8: Co-simulation concept with multiple simulators (from [AAET] with adaptations)

[1] ipg-automotive.com/en/products-solutions/software/carmaker
[2] eclipse.dev/sumo
[3] omnetpp.org

Apart from the simulation tools, the development of the cooperative driving functions needs a software platform for the actual implementation of the associated cooperation algorithms, which eventually determine the behavior of the vehicles. Notable example of an expedient open-source middleware suite is Robot Operating System (ROS) [53] [1], which was also used in the IMAGinE project. It represents a modular framework with numerous packages for robotic applications, mainly based on the publish-subscribe mechanism, which offers a high practicability for operations with various sensors and actuators, thus, also making it suitable for the utilization in CAVs.

2.3.2 Mixed Reality

In order to realize the XiL methods during the development of ADAS in the form of V-model process, different combinations of virtual (simulated) and real test environments can be utilized, as outlined in [54]. Hereby, the transitioning phases between fully virtual and fully real environments are commonly referred to as the mixed reality [55], which eventually stands for a hybrid environment with variable proportions of virtual and real elements. Therefore, in case of verification and validation purposes for the cooperative driving functions, different aspects can be covered either virtually or really, depending on the goal of the tests according to the V-model.

In this regard, one important representative of the XiL method family is Prototype-in-the-Loop (PiL) [56] [57], which was developed during the research activities of the Ko-HAF and PEGASUS projects (see Subchapter 2.1). Hereby, a real CAV equipped with hardware and integrated software is put on a real test track with simulated traffic participants. As a result, system-under-test of the real vehicle is expected to appropriately interact with the virtual vehicles and vice-versa. As previously shown in Figure 2.6, PiL can be considered as a subpart of ViL, however, with a partial takeover of HiL tasks, since the main focus of this method lies on the behavior analysis of certain prototypical system-under-test components and less on the vehicle itself. Therefore, this approach may be useful for system and integration tests, as well as calibration of the driving functions.

In the scope of this dissertation, the PiL method will be used and enhanced with additional competences, such as an ability for remote V2X communication and an adaptable creation

[1] ros.org

of simulation scenarios, in order to realize the proposed methodology as a novel Remote-Adaptable Prototype-in-the-Loop approach (later in Subchapter 6.2).

Simple test drives in the context of mixed reality with the V2X communication have already been concluded in the author's publication [AmE]. An exemplary visualization of such a mixed reality test with two real vehicles and one virtual vehicle is shown in Figure 2.9. Hereby, the real and virtual vehicles were communicating via V2X and jointly processed in a mixed reality environment. Their visualization was achieved with ROS package RVIZ [1] and additional custom software, which is further described in [AmE].

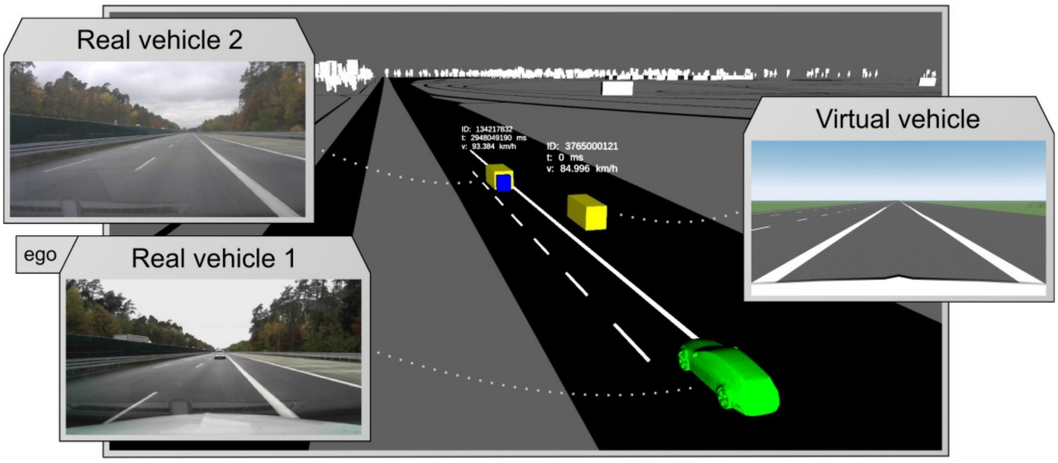


Figure 2.9: Exemplary visualization of a mixed reality test (from [AmE] with adaptations)

2.3.3 State of the Art

In this section, a selection of currently existing approaches that are comparable to the undertaking of this dissertation will be analyzed as a state of the art for the virtual test driving. Hereby, the matter of several thematically linked literature sources will be regarded as self-contained methodologies, provided that they offer sufficient information about the used scenarios and metrics, as well as the simulation solutions.

A comparison of the chosen methodologies, along with the anticipated methodology of the work at hand (denoted as this), is given in Table 2.2. Here, the associated sources are examined considering their approaches towards the preparation of scenarios, the

[1] wiki.ros.org/rviz

simulation (incl. tools and methods) and the application of metrics, in compliance with the proposal of this dissertation, as previously described in Subchapter 1.2. In this respect, all the involved comparison criteria will be explained hereinafter.

Table 2.2: Comparison of methodologies as state of the art

Sources	**Scenarios**	**Simulation: Tools**	**Simulation: Methods**	**Metrics**	**remote / adaptable**
Wen et al. [58] [59] [60]	authentic stochastic	custom	MiL	relevancy criticality	no / yes
Son et al. [61]	synthetic deterministic	CarMaker	ViL	criticality	no / no
Feng et al. [62] [63]	authentic stochastic	CARLA Vissim	ViL	criticality	yes / yes
Ramakrishna et al. [64] [65]	synthetic stochastic	CARLA	SiL	relevancy criticality	no / yes
Szalay et al. [66] [67] [68]	synthetic deterministic	SUMO	ViL	relevancy criticality	yes / no
Solmaz et al. [69] [70]	synthetic deterministic	CarMaker SUMO	ViL	relevancy	no / no
Nalic et al. [71] [72] [73]	authentic stochastic	CarMaker Vissim	SiL	relevancy criticality	no / yes
Waschl et al. [74] [75]	synthetic deterministic	CarMaker Vissim	HiL	relevancy criticality	no / no
Hallerbach et al. [56] [57]	synthetic deterministic	CarMaker SUMO	ViL (PiL)	criticality	no / no
this	synthetic stochastic	CarMaker SUMO	ViL (PiL)	relevancy	yes / yes

Regarding the scenarios: authentic scenarios are extracted from the real-world data, whereas synthetic scenarios are generated with purely virtual techniques; also, stochastic scenarios contain randomized elements and vary, whereas deterministic scenarios are scripted and highly repeatable, yet, both can deliver reproducible results.

Regarding the simulation: the utilized software tools are listed in a combination with methods that represent the furthest levels of the major XiL testing routines, which were achieved by the respective methodologies within the V-model of the vehicular development process (according to Figure 2.6).

Regarding the metrics: relevancy metrics assess the effects of the related driving actions in ordinary conditions (e.g., traffic efficiency), whereas criticality metrics aim to identify the events of an extraordinary importance (e.g., traffic safety).

Moreover, Table 2.2 includes an estimation whether the methodologies offer remote and adaptable competences. Hereby, remote means that the simulation and the system-under-test interact via a distant communication, whereas adaptable means that the simulation provides flexible configuration options with a capability to spontaneously adjust the scenarios during an already running simulation, in dependence on the behavior of the system-under-test.

The following analysis of the sources suggests a presence of two general tendencies in the research and development of the autonomous and cooperative driving functions, concerning usage of the scenarios and metrics for the respective verification and validation tasks:

- authentic and stochastic scenarios with relevancy metrics
- synthetic and deterministic scenarios with criticality metrics

In the former case, the authentic scenarios from real-world datasets are altered to numerous stochastic variations, which are then applied with the relevancy metrics on the earlier XiL methods, in order to extensively verify the driving functions during the design and implementation period. In the latter case, the synthetic scenarios are created with mainly deterministic traits, which are then applied with the criticality metrics on the later XiL methods, in order to intensively validate the driving functions during the evaluation period. However, for the sake of a better test coverage in total, often a combination of both relevancy and criticality metrics is utilized. Furthermore, it is remarkable that the adaptable capabilities of the methodologies usually rely on the stochastic scenarios.

An eventual state of the art comparison with the help of Table 2.2 reveals the approach [62] [63] being the closest to the idea of this dissertation, since it offers coexisting remote and adaptable competences that may be helpful for testing of the cooperative driving functions, realization of which will be addressed later. In this respect, the methodology [62] [63] proposes a usage of data-driven probabilistic models with artificial intelligence for a generation of scenarios with adversarial behavior of the traffic participants. Hereby, the simulation data is evaluated with metrics regarding the safety distances, velocities and accelerations of the vehicles. However, this solution focuses on a highly detailed simulation of only one CAV as a system-under-test, which may be not sufficient for testing of the cooperative driving functions, where the maneuvers normally involve multiple equivalent CAVs at a time. Apart from that, the scenarios and the metrics defined there are not directly transferable to the assessment of MC in the scope of the work at hand, with a goal set to examine traffic quantity and traffic quality, thus, requiring an elaboration of new more suitable approaches towards their preparation and application.

For the generation of stochastic scenarios, it may be advantageous to incorporate authentic traffic recordings from the real world into the simulation as an origin of data. However, an initial proof-of-concept for the novel methodologies can also be performed on exemplary synthetic scenarios, which can later be seamlessly extended with authentic scenarios for more plausible simulation results. Concerning noteworthy approaches towards a recording process of the real-world traffic data for an utilization in the research and development of the autonomous and cooperative driving functions, refer to [76] [77] and [78] [79], as well as towards a consecutive data-driven extraction of the authentic test scenarios for an integration into the simulation, refer to [80] [81] [82] [83]. Profound reviews of the already existing and publicly available datasets with numerous traffic recordings from various perspectives (e.g., stationary fixed or moving with vehicles) can be found in [84] [85] [86] [87].

2.4 Summary

This section provided background information regarding the current research activities (incl. IMAGinE project), the cooperative driving functions and the virtual test driving, which together form an essential foundation for the further elaboration of the methodology.

With respect to the RQ I, typical use-cases of the cooperative driving suggest that only specific conditions of the traffic quantity can be relevant for the MC, such as certain arrangements of vehicles in certain areas (e.g., merge-in maneuver on highway entrance). Concerning the RQ II, the cooperative driving functions can be tested through the utilization of various simulation tools in mixed reality environments, in order to comprehensively examine their functionality during different stages of the development process with XiL methods, based on the assessment of the causality link between the independent and dependent aspects. For this, a detailed analysis of the state of the art was conducted. Lastly, it was shown that the MC is composed by numerous characteristics, including the distinctions in the networking and maneuvering that can differently influence the traffic quality as an outcome of the cooperative driving, which requires a suitable approach for the evaluation in compliance to the RQ III.

3 Methodology

In order to extensively test the cooperative driving functions in the majority of relevant traffic situations, an exceptional variety of scenarios must be considered, which is reasoned by the numerous independent and dependent aspects, as well as a large parameter space involved. Since the software algorithms within the systems behind the cooperative driving functions are also very computationally intensive, it is necessary to distinguish relevant aspects from less relevant, resulting in a difficulty of finding an appropriate Number of Agents (NoA) and Level of Detail (LoD). Therefore, even virtual testing with the modern simulation technologies requires new methodical approaches, in order to overcome the challenge of a prolonged simulation procession and, thus, inefficient generation of results.

In this part of the work at hand, a simulation-based methodology for the testing of cooperative driving functions will be presented, addressing the issues mentioned before and delivering a way to evaluate the effects of MC on traffic quality under relevant traffic quantity. Hereby, the scope of the corresponding design and implementation tasks will be determined in relation to other adjoining research activities.

This section is based inter alia on the author's publication [WCX].

3.1 Overview

The goal of the methodology is to establish a generic simulation-based work sequence, which opens a possibility to assess different MC systems (incl. software algorithms) and eventually to compare them with each other in a computationally reasonable manner. The corresponding methodology is schematically shown in Figure 3.1, whereas its working steps will be explained in detail further on.

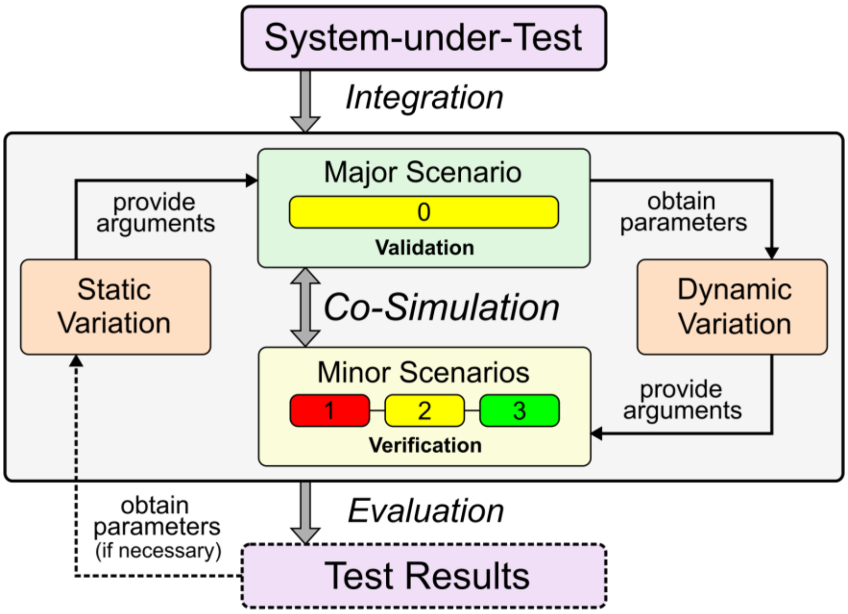


Figure 3.1: Overview of the proposed methodology (from [WCX] with adaptations)

System-under-Test (SuT), containing among others a MC algorithm that needs to be examined, must be integrated into the test environment and connected with the simulation in accordance to the consistent interfaces. Thus, the SuT can exert action on the simulation, as well as the simulation can exert reaction on the SuT (and vice-versa). Consequently, an ongoing interaction between the SuT and the simulation is achieved, creating a closed feedback loop. The SuT itself can exist in form of a model, software, hardware or vehicle. Therefore, the methodology is generically applicable to various steps of the XiL testing procedures. One representative baseline approach for the cooperative MC, which was specifically developed and used as a SuT for the proof-of-concept of this methodology, will be presented in Subchapter 3.2.

As demonstrated in [88], a rational co-simulation of several software tools with different NoA and LoD in the macroscopic, microscopic and mesoscopic scope can significantly improve the simulation performance. Since, on the one hand, computationally intensive MC algorithms are typically applied to a limited amount of cooperation participants on the small-scale in short-term, and, on the other hand, one is interested in the investigation of their effect (e.g., on traffic flow) in various traffic situations on the large-scale in long-term, this creates a conflict between the NoA, LoD and the performance of the simulation. Therefore, a solution to this was elaborated as a combination of two simulators, which are statically and dynamically coupled (see [56] [57]), running synchronously and, thus, resulting in one common co-simulation environment. In this particular case, a traffic flow simulator, which is responsible for the procession of a single major *large-scale long-term* scenario (with higher NoA and lower LoD), and a vehicle dynamics simulator, which is responsible for the procession of multiple minor *small-scale short-term* scenarios (with lower NoA and higher LoD), are utilized.

The major scenario (**0** in Figure 3.1) is created by the logic of static variation, mainly involving the road topology and geometry (e.g., shape of segments, number of lanes) and the demanded traffic flow. The minor scenarios (**1**, **2**, **3** in Figure 3.1) with their corresponding traffic quantities are situationally derived from the major scenario by the logic of dynamic variation, whereas the number and the constellation (incl. positions, velocities, etc.) of the participating vehicles define the initial states (i.e., scenes) of the resulting minor scenarios. The co-simulation environment, which is embedded into the intelligent framework, including the concept of static and dynamic variation, will be further described in Subchapter 3.3.

Moreover, the vehicle models of agents in both major and minor scenarios are alternately simulated as subject-vehicles (with high LoD) or object-vehicles (with low LoD). Hereby, a low number of subject-vehicle agents can actively participate on the cooperative maneuvering, whereas a high number of object-vehicle agents only passively, thus, making the co-simulation in general require less computational resources.

Once the co-simulation, including the integrated SuT, is running, both major and minor scenarios can be analyzed with appropriate macroscopic, microscopic, nanoscopic and individual metrics (see [56] [57]), depending on the use-case. For instance, in case of a major scenario, a MC algorithm can be evaluated regarding its safety and efficiency (e.g., intermediate distances, travel time, energy waste, etc.), as well as regarding an overall impact on the traffic quality (i.e., continuousness of traffic flow), which can be applied for the validation of the function. Additionally, in case of a minor scenario, evaluation of a MC algorithm can be suited towards its effectiveness (e.g., driving performance, comfort, robustness, etc.), which can be applied for the verification of the function.

After the complete co-simulation is finished, if necessary, the produced test results can be used to adapt the arguments in the parameters through the static variation and, thus, to prepare a new major scenario for the next simulation. The corresponding traffic quantity scenarios and traffic quality metrics, alongside with the studies conducted with this methodology, will be later explained in Chapter 5.

3.1.1 Requirements

Commitment to this methodology raises a number of functional requirements, concerning the preparation of scenarios, the simulation and the application of metrics (refer to proposal in Subchapter 1.2), which must be fulfilled, in order to obtain appropriate results. These requirements are gathered with their respective prioritization in Table 3.1.

Table 3.1: Functional requirements of the methodology

	Requirement	Priority
Scenarios	Variability	high
	Automatic generation	high
	Real-world origin	low
Simulation	Realistic vehicle dynamics	high
	Realistic traffic flow	high
	Multi-instance support	high
	Real-time procession	low
	Realistic communication network	low
Metrics	Transferability	high
	Visual presentability	high
	Model-based evaluation	low

At first, it is important for the scenarios to showcase a high stochastic, but still reproducible, variability of the traffic quantity, which can be accomplished through an automatic generation, in order to achieve a wide coverage of the associated tests. For a proof-of-concept, these scenarios can be of a synthetic manually created origin, which can later be extended with an authentic data from real-world recordings.

With regard to the simulation, the proposed methodology requires a realistic behavior of the vehicle dynamics and the traffic flow, in order to credibly imitate the cooperative driving with different NoA and LoD, as well as a multi-instance support, in order to ensure a full interaction of multiple equivalent and highly detailed agents (i.e., subject-vehicles) during the cooperative maneuvers. In this work, the computational real-time capability of the simulation procession is only needed for the experimental realization (later in Chapter 6), whereby, a soft real-time [89] must suffice for this task. Furthermore, the simulation of the communication can be simplified to a few most essential physical effects.

At last, the foreseen metrics must be generically transferable to many various traffic scenarios and provide a way for a visual representation of the traffic quality. For a proof-of-concept, the evaluation can be performed based on several fundamental criteria, whereby the usage of complex models is not necessary.

Apart from the functional requirements mentioned above, the methodology must be elaborated as a comprehensive software toolchain in compliance with multiple further non-functional requirements. In accordance to the system and software quality standard ISO/IEC 25010:2011 [90], these requirements commonly are: functional suitability, performance efficiency, compatibility, usability, reliability, security, maintainability and portability. Hereby, a special attention must be given to interoperability (part of compatibility) and modularity (part of maintainability) of the software for a benefit of exchangeable SuTs, with remote and adaptable competences for a potential application in different XiL methods.

> As a development platform, a regular commercial portable workstation (2.8-3.8 GHz 4/8 cores/threads CPU, 32 GB RAM, dedicated GPU) with UBUNTU Linux [1] will be utilized throughout the work at hand.

3.2 System-under-Test

In the scope of this dissertation and as a contribution to the project IMAGinE, a simplified cooperation algorithm (further denoted as Core approach) was developed and published in [WCX], which acts here as a baseline SuT for the methodology.

The introduced algorithm belongs to the group of MC with an implicit, decentralized, continuous and direct intention-aided negotiation on operational-tactical planning and local-regional decision-making levels (refer to Figure 2.5), comparable to the approaches

[1] ubuntu.com

[32] and [34]. This means that the participating vehicles can exchange their intentions in form of trajectories via ad-hoc or cellular V2X communication, in order to coordinate their maneuvers for the automated or manual execution. The functionality of this algorithm was originally described in the patent Mspa.3 with alternative variants in Mspa.1 and Mspa.2 (see Submitted Patent Applications in Miscellaneous).

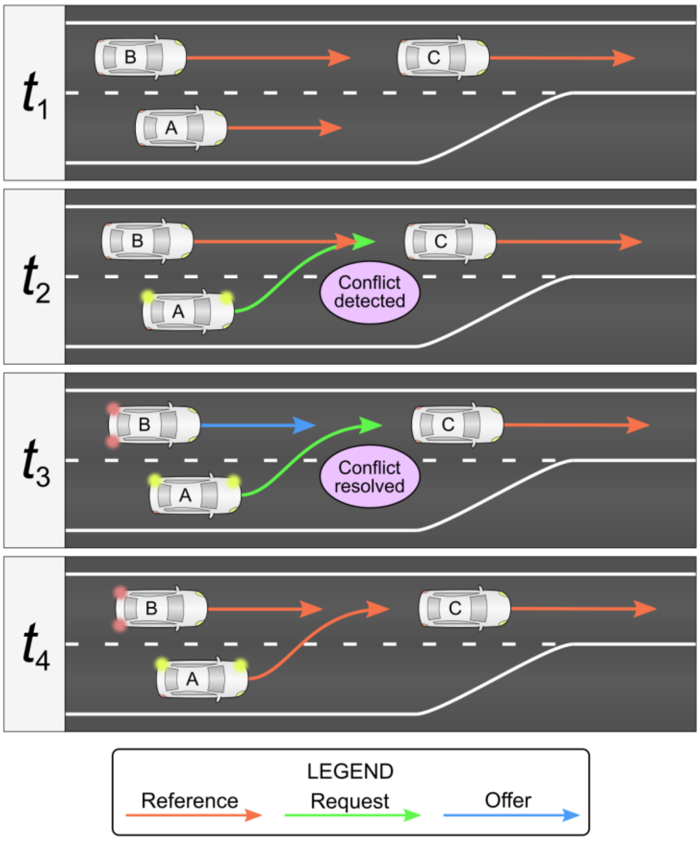


Figure 3.2: Highway merging with the Core MC approach (from [WCX] with adaptations)

The principle of the Core approach will be explained on the following traffic scenario, which is illustrated in Figure 3.2, where the trajectory-aided MC leads to a successful cooperative merging maneuver between 3 CAVs on a highway entrance. There, at the initial state t_1, all vehicles follow their original trajectories with no conflicts. At t_2, as soon as the vehicle **A** intends to perform a lane-change, it broadcasts a new trajectory that causes a conflict (i.e., intended collision) with a trajectory of the vehicle **B**. By waiving its right-of-way, the vehicle **B** may cooperate by decelerating, in order to expand the gap for merging of the vehicle **A**. At t_3, after the vehicle **B** cooperatively adapted and transmitted its new trajectory, the conflict is resolved. At t_4, the vehicle **A** can follow its trajectory to merge-in.

3.2.1 Characteristics

A vehicle equipped with the Core MC algorithm is required to broadcast only one trajectory at a time, in order to reduce the amount of data exchanged via V2X and, thus, to lower the channel load. This property also makes the algorithm suitable for the use in a mixed traffic (i.e., between automated and manually driven vehicles), since the cooperation here is based only on one driving trajectory per participant. In case of manual driving, a trajectory is derived from the observation of vehicle's motion and driver's behavior. Cooperative maneuvers with the Core MC include deceleration, acceleration and lane-changes, as well as support cascaded (i.e., multiple successive) negotiation processes. Hereby, a trajectory is described in Frenet coordinates [91] [92], denoting a planned movement of the vehicle in space and time relative to the road and lane it is driving on. Similar to the solution [34], a trajectory in this approach can belong to one of the three different types, depending on the intention it symbolizes, which are:

- reference – no active cooperation (default)
- request – asking for cooperation without right-of-way
- offer – responding to cooperation with right-of-way

In Figure 3.2, the reference trajectories are displayed in red, request in green and offer in blue colors. For the exchange via V2X communication, a trajectory with its type is transmitted and received as a MCM (refer to Subchapter 2.2).

The Core MC is independently performed in every subject-vehicle (i.e., MC capable vehicle simulated with high LoD), which is actively participating on the cooperation. This results in a decentralized planning and decision-making process, meaning that each subject-vehicle can autonomously, yet cooperatively or non-cooperatively, determine its course of action, based on its own maneuver planner and information from the V2X. If a non-communicating object-vehicle, which cannot transmit any trajectory, is present in a cooperative situation, then its most probable trajectory must be estimated (e.g., based on driving dynamics) by the subject-vehicles and used as a substitute for its reference trajectory.

3.2.2 Components

The algorithm of the Core MC approach consists of several components, whose execution is serially arranged and cyclically repeated. An overview of these components (incl. their inputs and outputs) is shown in Figure 3.3.

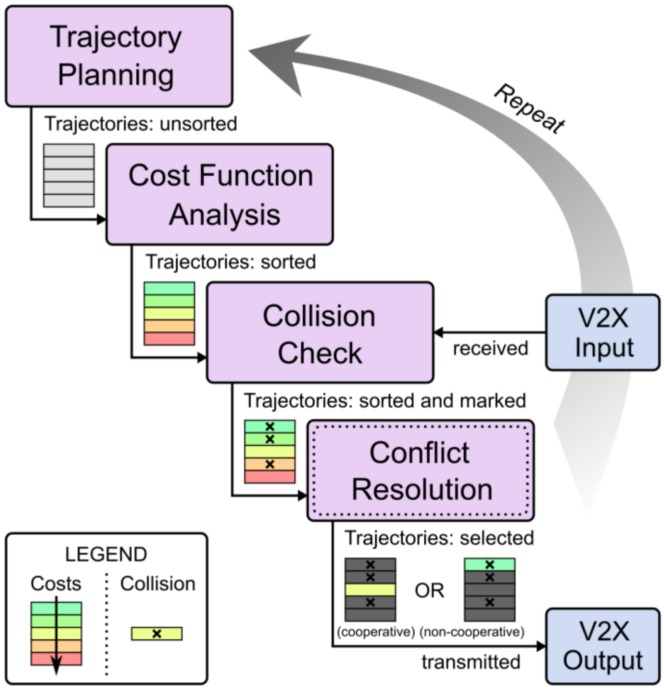


Figure 3.3: Components of the Core MC approach (from [WCX])

The task of the first component 'trajectory planning' is to generate an internal list with a wide variety of possible driving trajectories for the subject-vehicle. It is implemented as a custom simplified planner based on polynomial curves [93] [94], where the planning horizon (i.e., temporal range of trajectories) is a configurable parameter. The output of this component is an unsorted list of trajectories, which is then processed by the next component. In the 'cost function analysis', the trajectories in the list are assessed and ranked according to their cost values. These values result from the cost functions in respect to the driving behavior (e.g., deviation from desired velocity, distance to other vehicles, lane-changes) and the driving safety (e.g., violation of road boundaries and vehicle's limits) of the subject-vehicle. Further possible cost functions for the cooperative MC can be found in [17] and [95]. Consequently, the list of the trajectories becomes sorted and is then passed to the next component. In the 'collision check', the trajectories of the subject-vehicle are inspected for collisions with the trajectories that are received via V2X communication from other vehicles. The colliding trajectories are marked in the list and, afterwards, the list is handed over to the next component.

In the 'conflict resolution', which represents the most significant component of this MC approach, the algorithm makes a decision, depending on the right-of-way rule and the acceptability of the maneuver. The logic of this component is depicted in Figure 3.4.

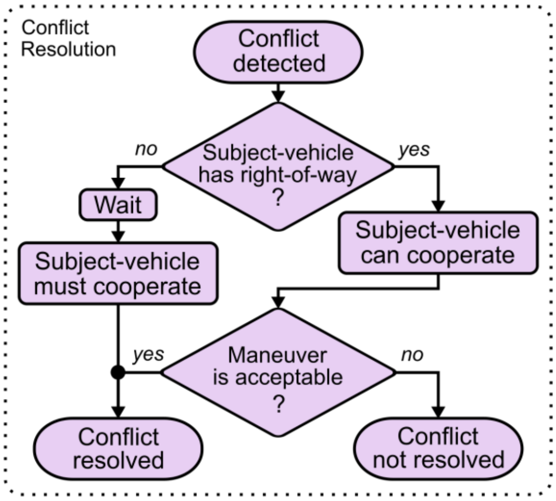


Figure 3.4: Component 'conflict resolution' in the Core MC approach (from [WCX])

First, the algorithm determines, whether the subject-vehicle possesses the right-of-way or not. If yes, the algorithm decides, whether the maneuver is acceptable for the subject-vehicle or not, based on a certain cost threshold, which is applied on its sorted list with marked trajectories. As a result, the subject-vehicle can choose either the best collision-free (i.e., cooperative) or the best collision-afflicted (i.e., non-cooperative) trajectory.

In contrast, if the subject-vehicle possesses no right-of-way, it has to wait for a certain amount of cycles, during which the conflict may be resolved. Thereafter, in any case, the algorithm chooses the best collision-free (i.e., cooperative) trajectory for a safe maneuvering. The final trajectory, which is selected by the 'conflict resolution' this way, is then transmitted to other vehicles via the V2X communication. After that, the algorithm repeats a new cycle, by beginning from the 'trajectory planning'.

3.2.3 Alternative Approach

Besides the Core MC, an alternative approach from the IMAGinE project (further denoted as Joint approach), which is based on the invention [96] [34], will be used in this dissertation for a comparative evaluation later in Chapter 5. The Joint MC builds on an implicit, decentralized, continuous and direct intention-aided negotiation, where the vehicles can exchange multiple trajectories (reference, request, offer) at a time, thus, allowing for a wider maneuvering options. Hereby, the costs of the exchanged trajectories are already included into the MCM with normalized values, ranging from -1 (i.e., most preferable maneuver) to $+1$ (i.e., least preferable maneuver). In the work at hand, the implementation of the Joint MC algorithm represents a more versatile and sophisticated SuT with a smoother trajectory planning for a more plausible driving behavior.

An illustrative comparison of both MC approaches for the scenario of highway merging is given in Figure 3.5. In case of the Joint MC, the numbers denote exemplary cost values of the respective trajectories. For more details about the Joint approach refer to [34].

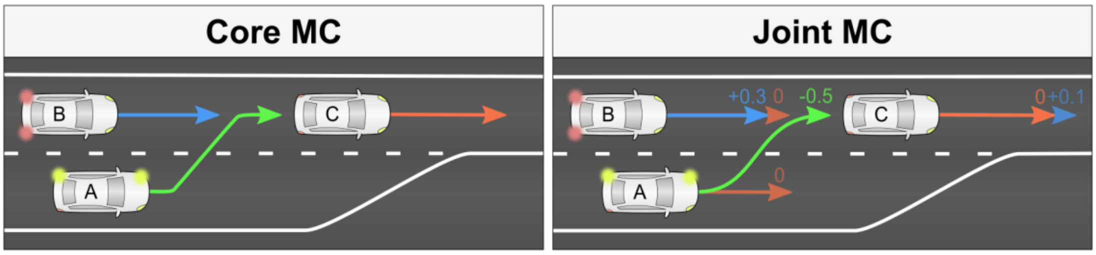


Figure 3.5: Illustrative comparison of the Core and Joint MC approaches

3.3 Intelligent Co-Simulation Framework

As a part of the evaluation methodology for the cooperative driving functions, a novel intelligent co-simulation framework was established in the scope of this dissertation. In contrast to the comparable solutions [97] [98] [99] [100] with predetermined NoA and LoD, this framework supports a simultaneous simulation of major *large-scale long-term* scenarios with higher NoA and lower LoD, as well as minor *small-scale short-term* scenarios with lower NoA and higher LoD. Hereby, the coupled simulation runs as a one uninterrupted process with varying properties, thus, offering a comprehensive opportunity to assess the impact of cooperation on the traffic quality.

According to the concept of layers for a structured description of traffic scenarios [101], a variation of arguments to different parameters within these scenarios serves for an accomplishment of different purposes. In this context, on the one hand, the static variation of major scenarios can be used to adapt: the road infrastructure (incl. traffic guidance entities), the roadside structures, as well as the associated temporary modifications. Whereas on the other hand, the dynamic variation of minor scenarios can be used to adapt: the movable subjects and objects (e.g., vehicles), the environmental conditions, as well as the digital information.

In the following, the focus will be put on the static variation of the road infrastructure with the dynamic variation of the movable subjects and objects, which are especially important for the testing of cooperative driving functions during the proof-of-concept. Noteworthy, the intelligent logic of the framework, which is responsible for the dynamic variation, is realized by machine learning elements. The corresponding design and implementation will be later discussed in Chapter 4.

3.3.1 Framework Structure

As illustrated in Figure 3.6, the intelligent co-simulation framework consists of a cooperative driving function (i.e., SuT), a vehicle dynamics simulator and a traffic flow simulator. Here, the cooperative driving function, represented by the Core MC algorithm that was implemented as a proof-of-concept software in ROS (in form of nodes [53]), is responsible for the control of the cooperative subject-vehicles in the co-simulation via trajectories. At the same time, the simulation of the subject-vehicles is carried out by CARMAKER with ROS interface extension [102], as well as the simulation of the object-vehicles (i.e., traffic) is carried out by SUMO, which exchanges the data with CARMAKER via so-called Traffic Control Interface (TraCI) [1].

CARMAKER and SUMO are statically and dynamically coupled, similar to the solutions [56] [57] and [103] [104] [105] (alternatively, see also VISSIM Interface add-on [2] for

[1] sumo.dlr.de/docs/TraCI.html
[2] ipg-automotive.com/en/products-solutions/software/add-ons

CARMAKER), meaning that they share the same road topology and geometry, as well as exchange the data about vehicles in a cyclically synchronous simulation process. Herewith, it is important to differentiate between the cooperative subject-vehicles (white), often also referred to as the 'ego vehicles', which are controlled by the MC through CARMAKER, as well as the non-cooperative object-vehicles (gray), which are controlled entirely by SUMO as a part of the traffic flow.

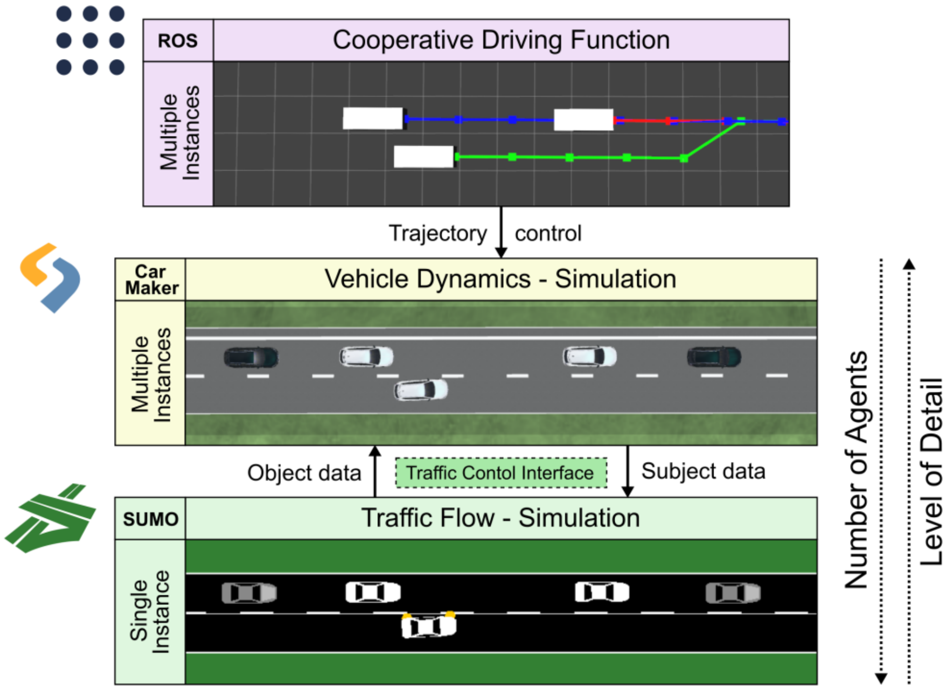


Figure 3.6: Structure of the intelligent co-simulation framework (from [WCX] with adaptations)

On the one side, SUMO is running as a single instance, which performs the simulation of the object-vehicles with a lower LoD in large-scale. On the other side, CARMAKER is running in multiple instances (one per each subject-vehicle) and simulates a realistic movement of the corresponding subject-vehicles, which are participating in the cooperative maneuvers with a higher LoD in small-scale. Hereby, the maneuver control of the subject-vehicles is carried out by the MC algorithm, which is also present in multiple instances (one per each subject-vehicle), by passing trajectories to CARMAKER for the execution. Transmitting and receiving of the trajectories between the cooperating subject-vehicles is achieved in this setup via an exchange of MCMs within ROS (in form of topics [53]).

The graphical visualization capability of each co-simulation component ROS, CarMaker and SUMO is also shown in Figure 3.6. In case of ROS, the visualization is accomplished by the software from [AmE], which was extended in the course of the IMAGinE project with an option to visualize the V2X trajectories (colors correspond to trajectory types).

3.3.2 Co-Simulation Logic

Apart from the coupled simulation environments of SUMO and CarMaker, the intelligent co-simulation framework contains two principal logic elements that allow for the adaptable interaction of these environments (as shown in Figure 3.1): static and dynamic variation.

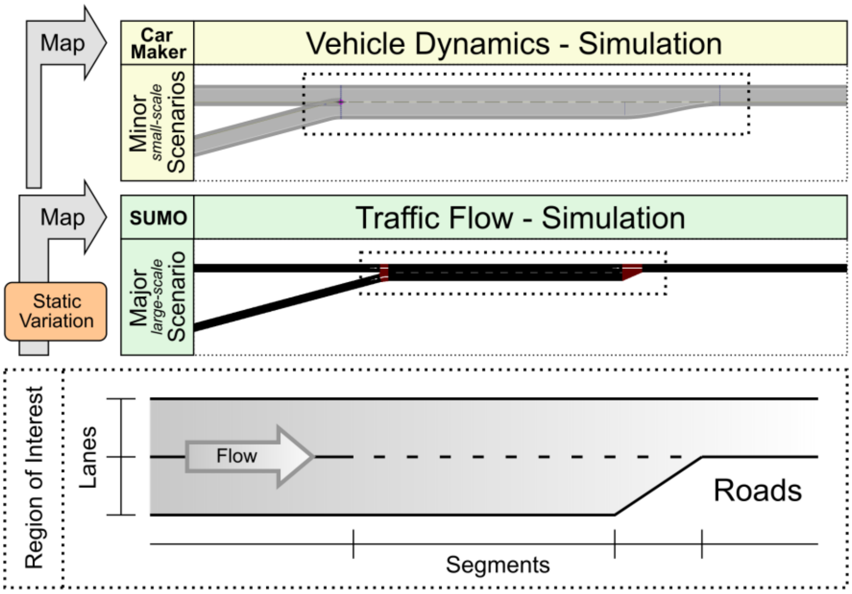


Figure 3.7: Logic of the static variation

The logic of the static variation is responsible for the preparation of a map with an information about the infrastructure (particularly, the road topology and geometry) and a roughly predefined traffic quantity, which is then used in both major and minor scenarios within the traffic and vehicle co-simulation for the static coupling. For the work at hand, as a one straightforward option, an easy-to-use software tool was developed to procedurally generate two maps for SUMO and for CarMaker with approximately identic location- and dimension-wise RoIs (refer to Subchapter 2.3), including configurable roads, lanes and segment sizes, what was achieved by a textual manipulation of predefined template map files. The corresponding logic of the static variation is illustrated in Figure 3.7.

Another possible option of the static variation is to manually create (using available graphical editors) one common map in a transitory format, such as OPENSTREETMAP [106] [1] or OPENDRIVE [107] [2], and then to automatically convert it to two further maps, which are individually compatible with SUMO and with CARMAKER. Alternatively, instead of a manual editing, an existing real-world map data could be utilized in prospect, provided that it is already present in one of the mentioned formats.

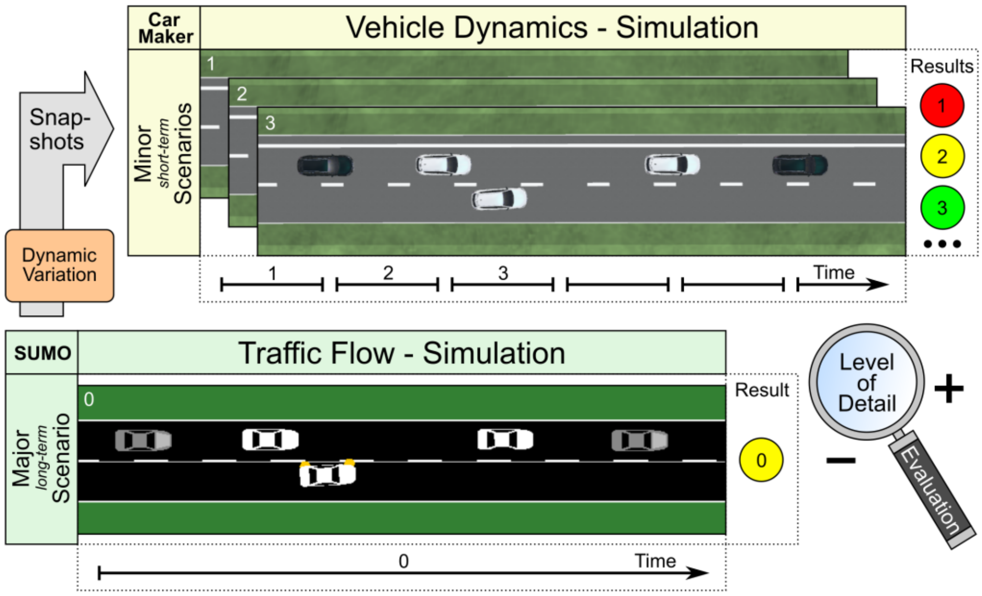


Figure 3.8: Logic of the dynamic variation (from [WCX] with adaptations)

The logic of the dynamic variation acts as an intermediate step in the SUMO-CARMAKER dynamic coupling and is illustrated in Figure 3.8. As long as no cooperative maneuver is running, only SUMO is simulating a major scenario with a full control of all vehicles in it. Once the dynamic variation detects a potential cooperative situation, it triggers the generation of a so-called snapshot, which is utilized as a scene (i.e., initial state) for a minor scenario. Herewith, a snapshot is defined as a captured constellation of vehicles

[1] openstreetmap.org
[2] asam.net/standards/detail/opendrive

(incl. their positions and velocities) at a given point in time. When creating a snapshot, a certain number of vehicles, which are expected by the dynamic variation to participate in a cooperative maneuver, are promoted to subject-vehicles (white), whereas the others remain object-vehicles (gray).

The captured snapshot from SUMO is then loaded in CARMAKER, which starts a co-simulation of the resulting minor scenario. During the execution of the minor scenario on top of the major scenario, multiple instances of CARMAKER with the MC algorithms in ROS are controlling the subject-vehicles, whereas SUMO continues to control the object-vehicles, which act as non-cooperative moving obstacles in the minor scenario. Once the co-simulation of the minor scenario is finished, SUMO retracts control of all vehicles, by demoting the subject-vehicles back to object-vehicles, and continues to simulate the major scenario alone, until a next cooperative situation is detected, triggering the generation of a new minor scenario by the dynamic variation. In case of a highway entrance (Figure 3.1), the trigger for a snapshot may be, for example, an appearance of a vehicle on the acceleration lane, which may potentially lead to a cooperative merging maneuver.

As a result, the dynamic variation undertakes here the task of an explorative generation of many new minor scenarios that are different from each other. Herewith, a major scenario allows for a simpler, but longer evaluation due to the lower LoD, whereas minor scenarios allow for more complex, but shorter evaluations due to the higher LoD. Since the goals of both simulators SUMO and CARMAKER are different, their output can be examined with different metrics.

3.4 Scope

In this section, the scope of the consecutive research and development tasks, which were needed to put the theory of the methodology into practice, with regard to the related tools and methods of the project IMAGinE, will be outlined. The corresponding overview can be found in Figure 3.9.

The simulation environment of CARMAKER and ROS for the testing of cooperative driving functions was elaborated within the IMAGinE project consortium and connected by the author with SUMO for the traffic co-simulation. Hereby, the associated scenarios and metrics were designed, as well as the intelligent logic of the static and dynamic variation was implemented for further evaluation. As an exemplary baseline SuT for the methodology, the Core MC algorithm was developed by the author in ROS. Apart from that, the Joint MC algorithm from the IMAGinE project was utilized as an alternative, more versatile and sophisticated SuT, in combination with the attached simplified V2X communication model.

For the experimental realization of the methodology as PiL method, a real test vehicle, as well as its digital twin (i.e., affiliated vehicle model with high LoD) for CARMAKER simulation, were provided by Opel as a contribution to the IMAGinE project. Hereby, a remote and adaptable interaction between the real test vehicle and the simulation environment was realized by the author (see Appendix for the vehicle build). Furthermore, for demonstration purposes of the PiL method functionality, a HMI-support software, which is responsible for the interaction with the driver during cooperative maneuvering, was designed, implemented and integrated into the real test vehicle.

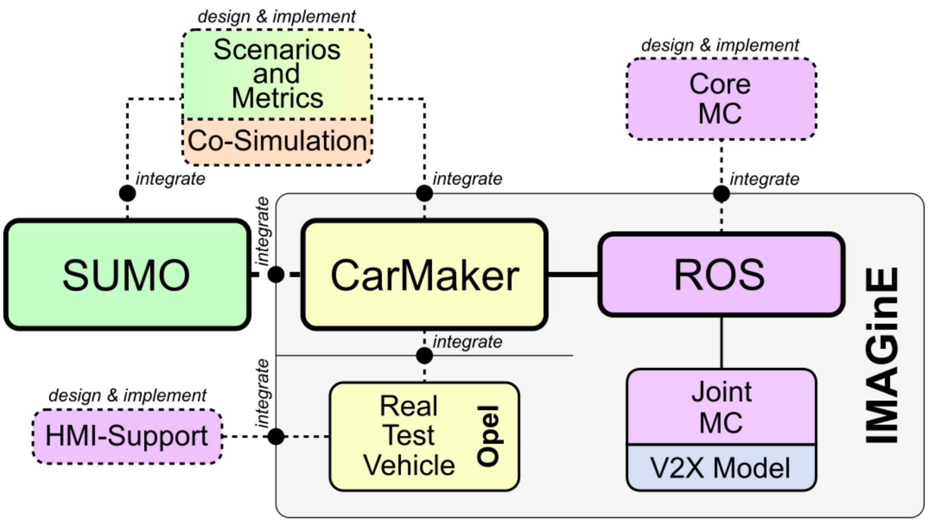


Figure 3.9: Scope of the tasks needed for the methodology

During the whole process, the author equally contributed to the IMAGinE initiative in a collaboration with other project partners, including the work on the simulation interfaces between CARMAKER and ROS, the specification and testing of the Joint MC algorithm, as well as the configuration of the real test vehicle. At the same time, the associated design and implementation tasks were partially supported by students via academic projects and theses Mssw.1 to Mssw.9 (see Supervised Student Works in Miscellaneous).

For a cumulative description of the activities within IMAGinE refer to the final project report [108] [1]. In addition, for more detailed findings by a concurrently conducted research on the cooperative driving, with a focus on the coupled simulation of traffic flow and communication network by means of SUMO and OMNeT++, refer to [109].

3.5 Summary

This section presented the actual methodology proposed by the dissertation, including the overview, the SuT, the intelligent co-simulation framework with a coupled vehicle and traffic simulation, as well as the scope of the consecutive research and development tasks. Herewith, the emphasis was put on the structure and logic of the static and dynamic variation with an introduction of the major *large-scale long-term* scenarios and minor *small-scale short-term* scenarios.

A solution on how the minor scenarios with relevant conditions of the traffic quantity can be deduced from the major scenarios, is yet to be addressed by the RQ I. Subsequently, the described methodology can be applied for testing and in-depth examination of the cooperative driving functions, as requested by the RQ II, since it allows for their comprehensive evaluation, due to the coverage of multiple aspects at the same time. Hereby, one can use the minor scenarios to verify and the major scenarios to validate the functionality of the MC – at the given moment of progression in this documentation, however, purely in a virtual environment. The evaluation approaches for the effects on traffic quality in the simulated scenarios will be thoroughly covered later in correspondence to the RQ III.

[1] imagine-online.de/ergebnisse-publikationen

4 Design and Implementation

The content of the following section will cover the design and implementation of the intelligent co-simulation framework, which is required for the consecutive realization of the methodology in practice. Hereby, the focus will be put on two representative use-cases of the cooperative driving functions from the IMAGinE project, which are illustrated in Figure 4.1: F1 (merging on highways) and F5 (turning at junctions). There, in case of the function F1, vehicle **A** can merge-in between vehicles **B** and **C**, if the latter two arrange a suitable gap; whereas in case of the function F5, vehicle **A** can perform a left-turn, if vehicles **B** and **C** decelerate and grant enough time for the former to do so.

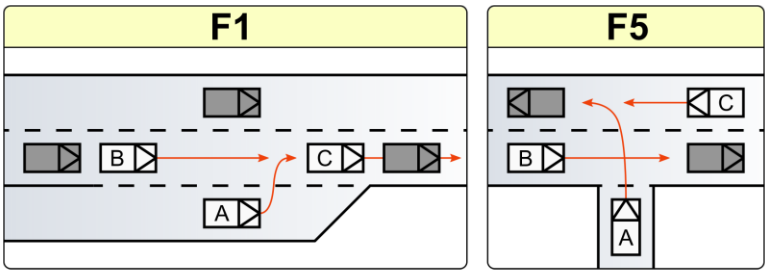


Figure 4.1: Use-cases of the cooperative driving functions F1 and F5 (from [ICCP])

In order to fulfill the co-simulation task among several simulation environments, especially for the logic of the dynamic variation, as previously described in Chapter 3, the intelligent co-simulation framework must detect scenes, generate scenarios and evaluate them throughout the simulation. In the work at hand, the definition of scenes and scenarios will be used according to [110]. That means, a scene reflects a momentary arrangement of relevant agents, which is utilized as an initial state for a scenario; whereas a scenario describes a temporally continuing evolution of a scene with determined events and actions.

This section is based inter alia on the author's publication [ICCP].

4.1 Related Work

For the logic of the dynamic variation, in order to generate the minor *small-scale short-term* scenarios for CarMaker, the corresponding scenes (as snapshots) must be detected in the major *large-scale long-term* scenario of SUMO. The issue of the computer-aided detection and eventually generation of scenes or scenarios for the testing of CAVs has already been extensively examined in the recent research activities worldwide. At this point, for the sake of providing an insight, a summary of the existing work related to this topic will be presented, including the methodologies with adaptable competences from the state of the art of virtual test driving (refer to Subchapter 2.3).

In [111], a method for the training of vehicular control algorithms with neural networks in a simulation environment, by means of a repeated variation of scenarios and relevant algorithm properties, is outlined.

In [112], the scenes for the scenarios are selected from a real-world traffic dataset, whereas a certain number of cooperative vehicles is periodically extracted and filtered from the continuous traffic flow within a recorded area.

In [113], the authors introduce a matrix-based semantic language for a pseudo-random generation of the synthetic roads and vehicles, which are constrained by a set of predefined parameters.

In [114], depending on various conditions that can be modified through a user interface, the corresponding test cases are systematically derived from a multi-source database.

In [115], the authors propose an ontology-based approach, where a natural language is used to express and to create scenes, represented by a concept of layers.

In [116], a factor graph is applied to characterize the distribution of scenes with a certain arrangement of vehicles, which is trained on a real-world data.

In [117], a Bayesian network is used for the generation of scenes, whereas the included vehicle positions are described in Frenet coordinates.

In [118], the authors train recurrent neural networks with simulated data, in order to compose synthetic accident scenarios for a further evaluation.

In [60], complete traffic events are recreated in a simulation environment, achieved through several deep learning techniques, by training on real-world video materials.

In [62], the authors perform adversarial adjustments to the naturalistic driving behavior of traffic agents, through an application of data-driven probabilistic models and artificial intelligence, in order to efficiently generate critical scenarios during a continuous simulation process.

In [64], another testing framework for vehicles with a scenario description language, which is used to generate test cases with adversarial operating conditions, such as bad weather, in order to provoke sensor and actuator faults, is introduced.

In [71], a technique for stress testing of the vehicle and traffic co-simulation with numerous scenario variants, which are created by combinatorial calculations, is presented.

In [83], the authors propose an approach for the extraction of multimodal test scenarios from a real-world urban traffic data with trajectory information, by means of an unsupervised machine learning pipeline, which includes spatiotemporal filtering, feature analysis and extraction, as well as clustering.

Conclusively, in [56] [57], a co-simulation toolchain, consisting of CarMaker and SUMO akin to this dissertation, is used to identify critical scenarios with the appropriate safety and efficiency metrics for a consecutive application in the PiL method.

Summarizing, the related work reveals a high variety of different approaches, dedicated to an effective detection of scenes and an efficient generation of scenarios, with a dominating tendency to the application of statistical methods and artificial intelligence.

However, the majority of these approaches focuses on the simulation of critical traffic situations, foremost with solely one high LoD subject-vehicle at a time, which is not practicable for a comprehensive evaluation of the cooperative driving. Nevertheless, the utilization of artificial intelligence in a suitable attempt, particularly in form of Machine Learning (ML) for the proof-of-concept, has a high potential to deliver promising results, wherefore it will be incorporated into the architecture of the co-simulation framework and assessed hereafter.

4.2 Architecture

According to the previous description in Chapter 3, the architecture of the intelligent co-simulation framework consists of the traffic flow simulator SUMO (version 1.7.0), vehicle dynamics simulator CarMaker (version 7.1.2) and ROS (Kinetic Kame release), as shown in Figure 4.2. Between the simulators, the objective of a so-called orchestrator (see [40]), which is responsible for the dynamic variation and the overall management of the co-simulation, is executed by a custom software OverWatch that was specifically designed and implemented for the realization of the methodology in the scope of this dissertation.

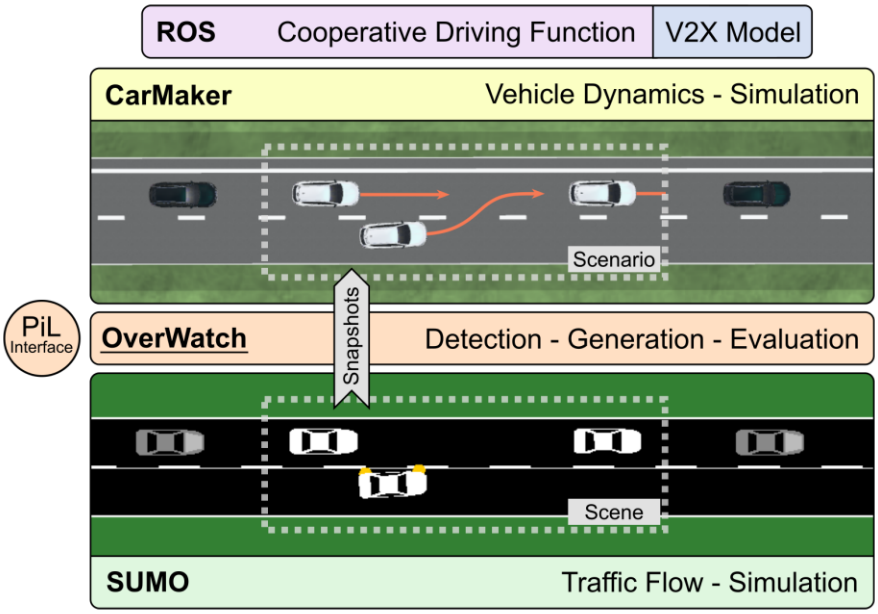


Figure 4.2: Intelligent co-simulation framework with OverWatch (from [ICCP] with adaptations)

Within this setup, OVERWATCH derives snapshots (i.e., functional representation of scenes) from the major scenario of SUMO and transfers them to CARMAKER for a simulation as minor scenarios with a lower NoA and a higher LoD. Herewith, a certain number of vehicles in a snapshot is promoted to the cooperative subject-vehicles (white), whereas the others remain considered as the non-cooperative object-vehicles (gray). The control of the subject-vehicles is performed in ROS by a cooperative driving function, which can be interchanged with different MC approaches. A phenomenological V2X model for the imitation of a communication channel with simplified physical effects (range, latency and message losses) is also situated in ROS.

In addition, this framework features a PiL interface that allows for manipulation of the desired vehicle agents within the co-simulation from an external signal source (e.g., V2X hardware). It will be closer discussed later in Chapter 6.

To be noted, all of the co-simulation elements possess their own standard Graphical User Interfaces (GUI), which will be presented in Subchapter 4.4. For a better maintainability, the co-simulation orchestrator OVERWATCH was designed and implemented as a modular software, which will be introduced in this section. The corresponding architecture in the context of the co-simulation framework is shown in Figure 4.3. The associated software development activities were carried out on a regular commercial portable workstation hardware (for specification refer to the requirements in Subchapter 3.1).

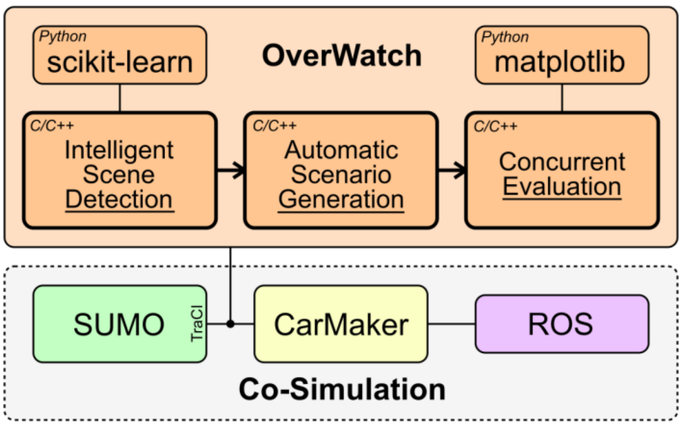


Figure 4.3: Software architecture of OVERWATCH (from [ICCP] with adaptations)

In total, OVERWATCH consists of three custom main modules: Intelligent Scene Detection (ISD), Automatic Scenario Generation (ASG) and Concurrent Evaluation (CE). As noted in the architecture diagram Figure 4.3, the main modules of OVERWATCH were implemented in C/C++, whereas the auxiliary modules (SCIKIT-LEARN and MATPLOTLIB) were integrated from Python as already existing software packages. Hence, the functionality of the ISD, ASG and CE modules will be explained further on in detail.

4.2.1 Intelligent Scene Detection

The task of ISD is to observe the traffic condition in the major scenario of SUMO via TraCI and, once a certain arrangement of vehicles indicating a high likelihood of cooperation is present there, to detect it and to create a scene. Based on the information from Subchapter 4.1, this functionality was achieved through the utilization of supervised ML. In this particular case, an open-source Python library SCIKIT-LEARN [119] [120] [1], which provides a broad selection of different ML approaches, was integrated into the C/C++ code of ISD. In addition, a generic workflow leading to the setup of ISD, which will be specified later in Subchapter 4.3, was established. After a scene is detected by ISD, it triggers a procession of the next module – ASG.

When detecting a scene, ISD determines the initial state of vehicles within the future minor scenario. Hereby, being trained on an annotated traffic data, the explorative character of ML allows for a recognition of further similar scene variants, which can exceed the data it originally learned.

4.2.2 Automatic Scenario Generation

ASG receives the scene from ISD and converts it as a snapshot into an intermediate format (so-called 'TestRun') that is interpretable by CARMAKER. Then, a parallel and synchronized co-simulation of the corresponding minor scenario on top of the major scenario is started, whereby CARMAKER controls the subject-vehicles with the cooperative driving functions from ROS, as well as SUMO controls the non-cooperative object-vehicles. In the process, the dynamic coupling of both simulators is realized as a Jacobi scheme (refer to [121] [122] [123] for in-depth theory of solver coupling), meaning that the vehicle data between them is synchronized simultaneously and

[1] scikit-learn.org

bidirectionally. Each time after a minor scenario in CarMaker is finished, SUMO retracts control of all vehicles.

In contrast to solutions [56] [57] and [103] [104] [105] that are based on MATLAB/Simulink programming, the SUMO-CarMaker coupling here was implemented in C/C++ for a better integrity with the rest of the framework and especially with ROS. For this, the CarMaker executable with SimNet add-on [1], which enables a distributed multi-instance simulation, was enhanced to cyclically communicate with SUMO via TraCI (using TCP/IP).

The concept of the dynamic coupling is illustrated in Figure 4.4. Due to how SimNet works, one randomly chosen subject-vehicle (i.e., primary) obtains the traffic data from SUMO, whereby the other subject-vehicles (i.e., secondary) obtain this data subordinately from the primary subject-vehicle. In the process, during the exchange of vehicle information (positions, velocities, etc.) between SUMO and CarMaker, an appropriate coordination transformation must be conducted, since the vehicle reference points in both simulation environments differ (front-middle in SUMO and rear-middle in CarMaker). Apart from that, for a better computational performance of the co-simulation, the object-vehicles from the traffic flow are synchronized with the subject-vehicles not in the whole RoI, but only in certain areas (e.g., circles with 100 m radius) around the subject-vehicles.

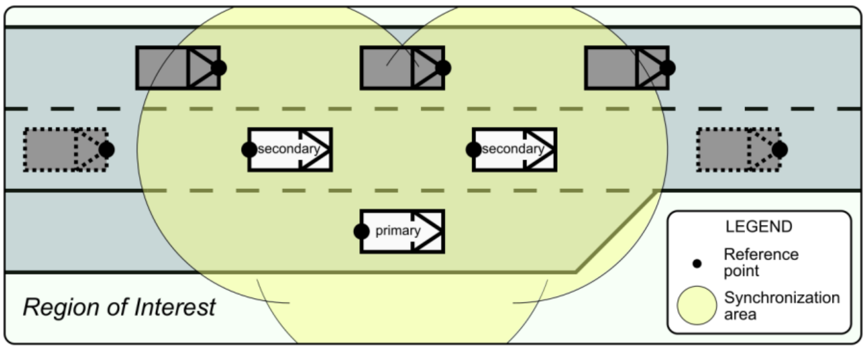


Figure 4.4: Dynamic coupling of the subject- and object-vehicles

Over the course of the co-simulation, the resulting motion data of the vehicles from SUMO (major scenarios), CarMaker (minor scenarios) and ROS is recorded in the

[1] ipg-automotive.com/en/products-solutions/software/add-ons

corresponding formats for further evaluations. Since this data can also be replayed at any time, it can be potentially used to supply external datasets with numerous various scenarios for the testing of autonomous and cooperative driving functions.

4.2.3 Concurrent Evaluation

During the whole runtime of the SUMO simulation, CE performs a simultaneous evaluation of the current state of the traffic flow, by acquiring data via TraCI. At the same time, the results of this evaluation are visualized with an open-source Python library MATPLOTLIB [124] [1], which is wrapped into C/C++ code of CE by means of MATPLOTLIB-CPP [2], being executed in a parallel thread.

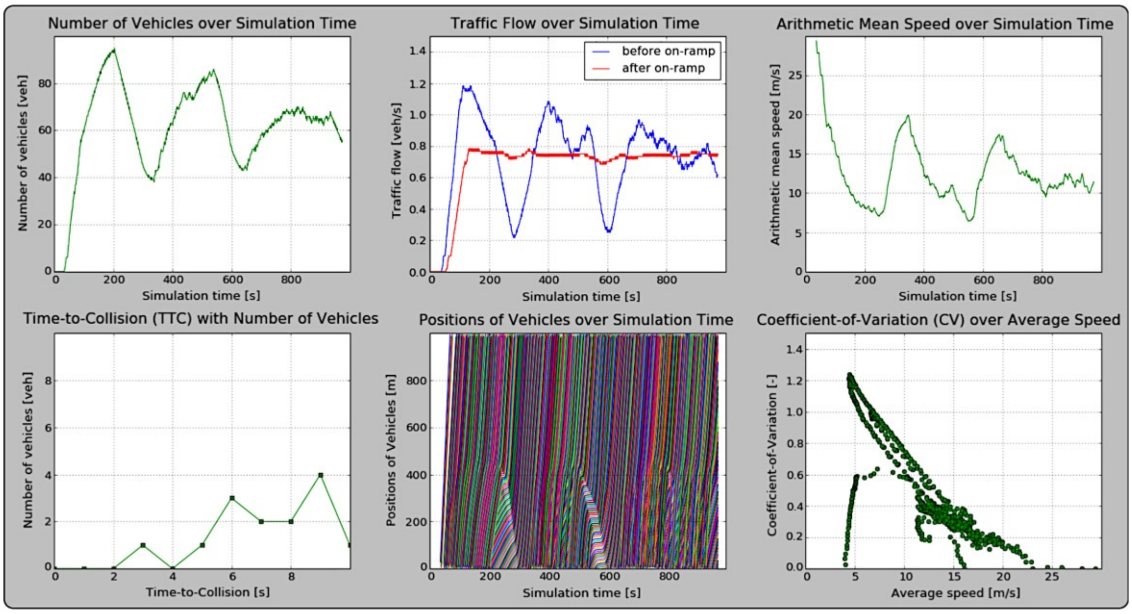


Figure 4.5: Exemplary visualization of the simulation results created with CE module (from [ICCP])

CE assesses the traffic quality with various metrics that will be closer described as a part of the methodology evaluation in Chapter 5. For now, an exemplary visualization achieved with it can be seen in Figure 4.5. Here, the metrics are used to indicate the traffic

[1] matplotlib.org
[2] matplotlib-cpp.readthedocs.io

density (top left), flow (top middle), velocity (top right), as well as the time-to-collision (bottom left), the spatiotemporal pattern (bottom middle) and the coefficient of variation (bottom right).

This way, the intelligent co-simulation framework delivers a vivid overview of the current state of the traffic flow in the running (i.e., not yet finished) simulation, which significantly simplifies the evaluation of the test results and helps for test automation, due to the prompt availability of the interim simulation results.

4.3 Workflow

For the sake of the dynamic variation, one is interested in the detection of scenes that only lead to the scenarios, which are relevant for the simulation of the cooperative driving functions. However, it would be very laborious to realize this detection in ISD as a comprehensive set of rules through manual programming. This is the reason, since one is able to simply determine the desired input (i.e., observations) and output (i.e., labels) from the simulation, why the use of supervised ML is favorable for this task, being trained to classify the scenes either as relevant or as irrelevant.

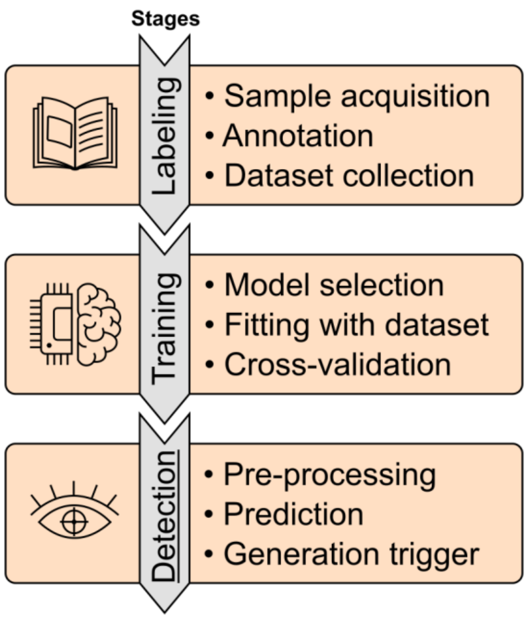


Figure 4.6: Workflow leading to the setup of operational ISD (from [ICCP] with adaptations)

In order to achieve the goal mentioned above and to set up an operational ISD, a generic workflow was specified, which is shown in Figure 4.6. This workflow contains following stages, which are typical for the utilization of ML: labeling, training and detection. These stages will be further discussed in this section.

4.3.1 Labeling Stage

In the labeling stage, the object-vehicle data (e.g., positions and orientations) is retrieved from the SUMO simulation and used to capture the constellations of vehicles as observations, as well as to label (i.e., manually annotate) them afterwards. This way, one basically applies the fundamental technique of shape recognition akin to the approach [125]. In this work, the focus will be put on 3 vehicles per scene, which corresponds to the minimal desired number of subject-vehicles for a cooperative scenario, as demonstrated in the use-cases from Figure 4.1.

One begins with an acquisition of samples, each containing an observation O and a corresponding label L. For an observation, a triangular pattern is utilized with a tuple of 6 features that are represented in Figure 4.7. These features are agnostic, thus, they must be equally valid for any vehicle constellation (from F1, F5 and other use-cases).

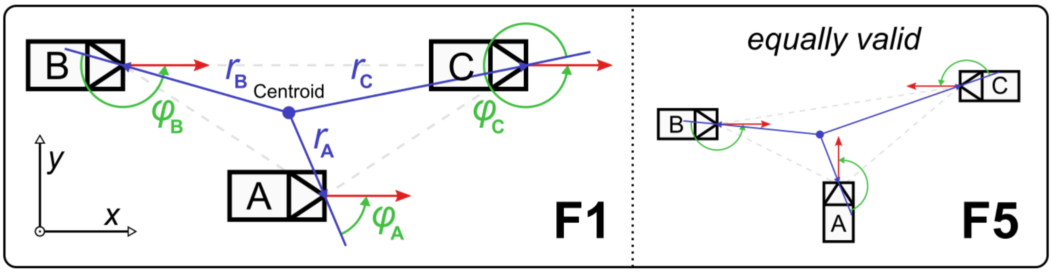


Figure 4.7: Features of an observation as a vehicle constellation (from [ICCP] with adaptations)

To acquire these features, first, one calculates a centroid (see [125]) among the 3 abstract vehicles **B**, **A**, **C** with vehicle references located in front-middle. Then, one calculates the distances $r_{\mathbf{B}}, r_{\mathbf{A}}, r_{\mathbf{C}}$ between the centroid and the vehicle positions. One also calculates the angles $\varphi_{\mathbf{B}}$, $\varphi_{\mathbf{A}}$, $\varphi_{\mathbf{C}}$ between the theoretical centroid-vehicle lines and the vehicle orientations. However, the resulting angle values are initially situated in the interval $[0,2\pi]$, which causes an undesired discontinuity at the interval boundaries. In order to avoid this problem, one uses complex numbers $\underline{\varphi}_{\mathbf{B}}$, $\underline{\varphi}_{\mathbf{A}}$, $\underline{\varphi}_{\mathbf{C}}$ with $|\underline{\varphi}_i| = 1$ as a representation for the angles. As a result, one obtains the following definition of an observation O for this kind of vehicle constellation:

$$O := \langle r_{\mathbf{B}}, \underline{\varphi}_{\mathbf{B}}, r_{\mathbf{A}}, \underline{\varphi}_{\mathbf{A}}, r_{\mathbf{C}}, \underline{\varphi}_{\mathbf{C}} \rangle \tag{4.1}$$

$$r_i \in [0, \infty[\qquad \underline{\varphi}_i := \left\langle \begin{matrix} \mathrm{Re}(\underline{\varphi}_i) \in [-1,1] \\ \mathrm{Im}(\underline{\varphi}_i) \in [-1,1] \end{matrix} \right\rangle = \left\langle \begin{matrix} \cos(\varphi_i) \\ \sin(\varphi_i) \end{matrix} \right\rangle \tag{4.2}$$

With this definition, one achieves a minimal quantitative representation needed to describe a constellation of 3 vehicles in a scene. Although the sequence of features in O is important, it is invariant towards a relocation in the fixed Cartesian coordinate system (x, y) of the simulation environment.

Next, for the annotation, one runs several stochastic simulations in SUMO and, at the same time, periodically captures random scene observations, as well as manually labels them. For this, the scenes with iteratively selected vehicle constellations are chromatically highlighted in the simulation environment, and one is asked by OVERWATCH to annotate these scenes through a simple question dialog, as depicted in Figure 4.8.

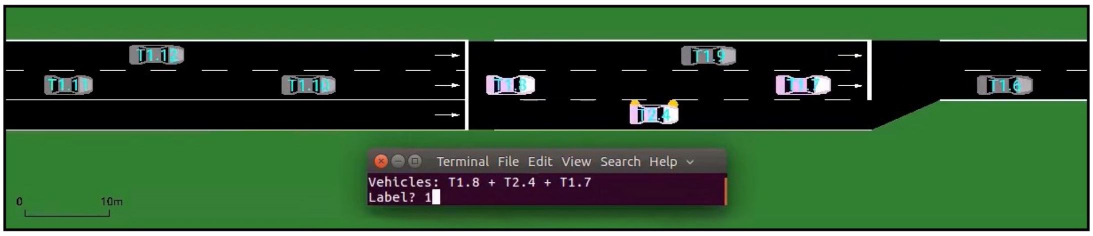


Figure 4.8: Labeling of observations on the example of function F1

In the process, three classes of scenes with the label L were defined:

- 'F1' – relevant for function F1
- '0' – irrelevant
- 'F5' – relevant for function F5

This way, in the scope of this dissertation, a dataset of 10 000 samples in total could be collected, whereas it took approximately 1 person-hour per 1 000 samples. Hereby, the distribution of observations and corresponding labels in the dataset is given as follows: 8 682 observations with label '0', 708 with 'F1' and 610 with 'F5'. In order to assess the collected dataset, it can be visualized as a selection of pair plots, as shown in Figure 4.9.

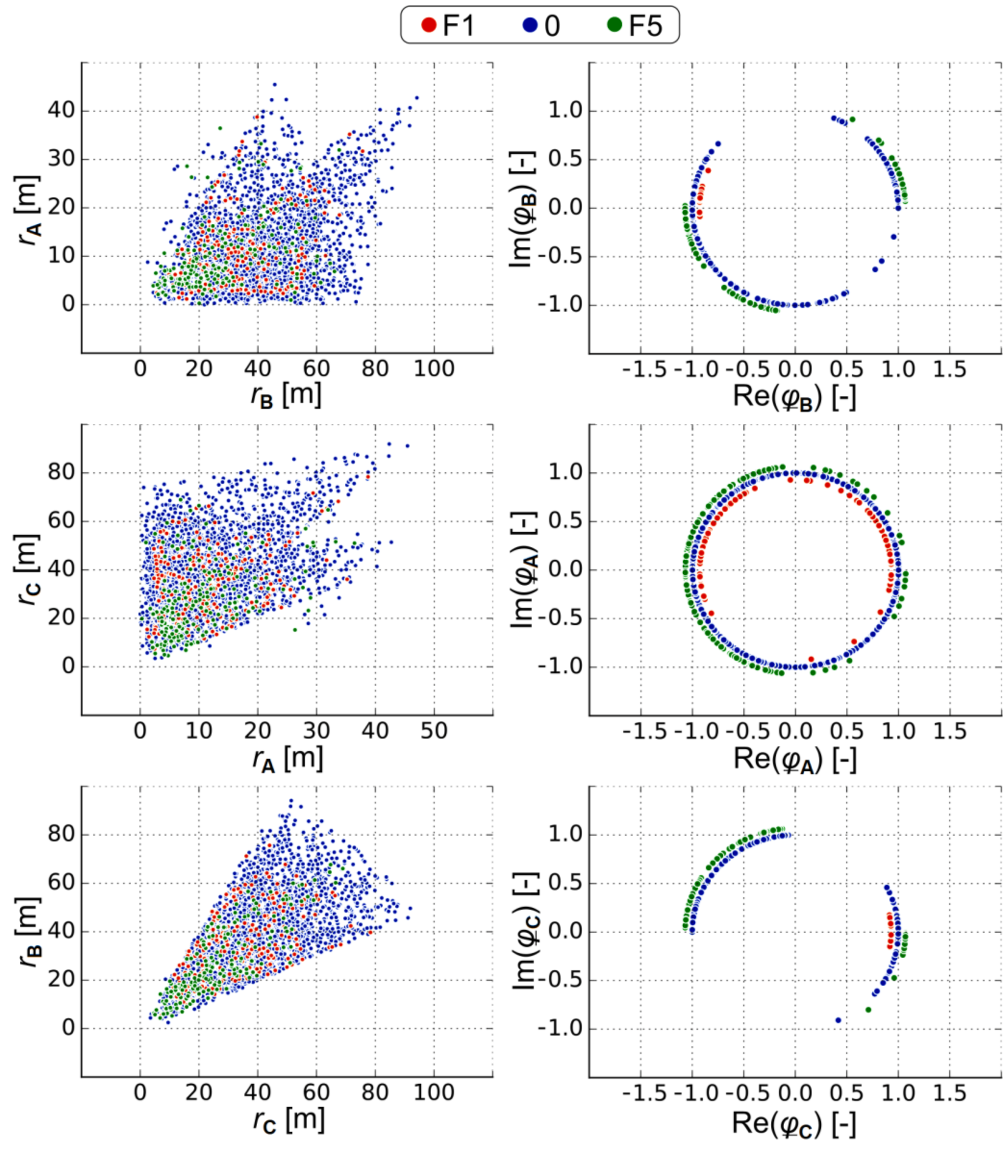


Figure 4.9: Visualization of the labeled dataset as selected pair plots (from [ICCP])

Here, the distribution of the labeled observations is displayed as crucial relations between the centroid-vehicle distances r_i among all vehicles (left column) and the centroid-vehicle angles $\underline{\varphi_i}$ for each vehicle (right column). In case of distances, on the one hand, the observations labeled as ‘0’ are strongly scattered, indicating that bigger distances between the vehicles in a scene tend to be classified as irrelevant for a potential cooperative driving scenario. On the other hand, the observations labeled as ‘F1’ and ‘F5’ are located more centrally, demonstrating a strong overlapping without clearly distinguishable clusters. Thus, the distances alone are not a sufficient indicator for the classification of a scene. At this point, however, the angles provide a substantial support. The observations of angles are arranged in circles, due to their complex number representation, and uncover more distinguishable clusters, particularly between the labels ‘F1’ and ‘F5’.

Conclusively, a correct classification of a scene can be achieved only through the consideration of all features in an observation. Nevertheless, the assessment of the dataset reveals that the required classification represents a challenging task, due to the strong scattering and overlapping of the data. Therefore, a well-founded choice and training of an appropriate classification model is important, which will be addressed next.

4.3.2 Training Stage

As a successive step in the workflow, here one needs to find the best performing classification approach for the detection of relevant scenes, through the selection of several appropriate models, fitting them with the dataset and completing a cross-validation. For this task, the focus will be put on classic supervised ML classification approaches [126], which are also available in the SCIKIT-LEARN library [119] [120].

Hereby, the following classifiers will be examined: ‘naive Bayes’ (model GaussianNB), ‘support vector machine’ (model SVC), ‘nearest neighbors’ (model KNeighborsClassifier), ‘neural network’ (model MLPClassifier) and ‘decision tree’ (model DecisionTreeClassifier) in their default parameter and attribute configurations, as they are offered by SCIKIT-LEARN. Furthermore, in order to balance the values in the samples of the dataset, one applies a ‘standard scaler’ (model StandardScaler), which is placed together with each classifier into a so-called pipeline. This standardizes the feature values by removing their mean and by scaling them to the unit variance.

For the evaluation of the chosen classifier models, one splits the dataset into 5 k-folds of training (80 %) and test (20 %) sets, used for the cross-validation. In the process, one fits the classifiers and rates their performance with the following metrics [127]: accuracy, macro-average precision, macro-average recall and macro-average f1-score. In this case, one uses macro-averages due to the uneven distribution of samples with a strong bias to the label ‘0’. Then, the calculated metrics for the test sets from every k-fold are averaged to produce the final scores.

The results of this comparative cross-validation for all k-fold test sets, by different supervised ML models that were fitted with the corresponding k-fold training sets, are presented in Figure 4.10. According to the applied metrics, the ‘decision tree’ classifier (with default parameters) has demonstrated the best classification performance with an average accuracy of 0.99. Even after an additional parameter tuning, these results could not be noticeably improved.

	Test Set # k-fold					
Naive Bayes	1	2	3	4	5	average
Accuracy	0.41	0.40	0.40	0.41	0.41	**0.40**
Macro precision	0.45	0.44	0.45	0.46	0.46	**0.45**
Macro recall	0.63	0.64	0.62	0.64	0.65	**0.63**
Macro f1-score	0.37	0.36	0.37	0.38	0.39	**0.37**
Support Vector Machine	1	2	3	4	5	average
Accuracy	0.90	0.93	0.91	0.91	0.90	**0.91**
Macro precision	0.57	0.62	0.62	0.62	0.60	**0.60**
Macro recall	0.56	0.63	0.58	0.56	0.56	**0.58**
Macro f1-score	0.56	0.62	0.59	0.58	0.58	**0.59**
Nearest Neighbors	1	2	3	4	5	average
Accuracy	0.96	0.97	0.97	0.96	0.96	**0.96**
Macro precision	0.87	0.89	0.91	0.90	0.91	**0.90**
Macro recall	0.93	0.95	0.90	0.90	0.89	**0.91**
Macro f1-score	0.90	0.92	0.90	0.90	0.90	**0.90**
Neural Network	1	2	3	4	5	average
Accuracy	0.97	0.98	0.97	0.98	0.97	**0.97**
Macro precision	0.93	0.94	0.94	0.95	0.95	**0.94**
Macro recall	0.91	0.95	0.91	0.92	0.88	**0.91**
Macro f1-score	0.92	0.94	0.92	0.94	0.91	**0.93**
Decision Tree	1	2	3	4	5	average
Accuracy	0.99	0.99	0.98	0.99	0.98	**0.99**
Macro precision	0.96	0.97	0.96	0.97	0.98	**0.97**
Macro recall	0.96	0.96	0.96	0.96	0.94	**0.95**
Macro f1-score	0.96	0.96	0.96	0.96	0.96	**0.96**

Acceptability of Results

Figure 4.10: Results of a comparative cross-validation (from [ICCP] with adaptations)

Furthermore, an exemplary confusion matrix of the 3rd k-fold training and test set, carried out by the 'decision tree', is shown in Figure 4.11. Here, one can observe an overall acceptability of results, although, a perfectly accurate classification is not achieved, due to the presence of particular marginal-inaccurately labeled scenes in the dataset.

During the cross-validation, this classification performance has demonstrated itself already as sufficient for the detection of the desired triangular patterns of vehicles (illustrated in Figure 4.7), which equate to relevant scenes for the cooperative driving functions (illustrated in Figure 4.1). Therefore, hereafter the 'decision tree' will be utilized as an appropriate ML model for the task of dynamic variation in the methodology.

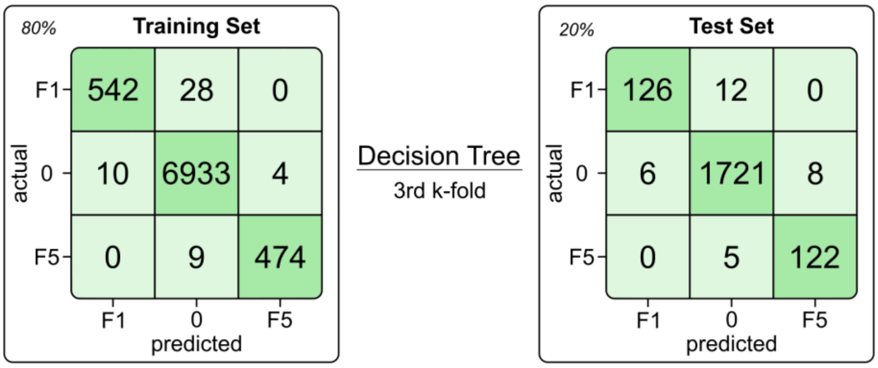


Figure 4.11: Exemplary confusion matrix of a training and test set (from [ICCP] with adaptations)

4.3.3 Detection Stage

After the selected ML model is trained on the labeled dataset, it is integrated into the ISD module of OVERWATCH, in order to intelligently detect the scenes in the running simulation of a major *large-scale long-term* scenario in SUMO. Each time a relevant scene is detected by ISD, it triggers ASG, leading to a parallel and synchronized co-simulation of an automatically generated minor *small-scale short-term* scenario in both SUMO and CARMAKER (with an active cooperative driving function in ROS). This way, the coupled simulation of traffic flow and vehicle dynamics is achieved, with a focus on different aspects, as well as NoA and LoD, which is important for a comprehensive evaluation of the cooperative driving functions. Hereby, the procession speed of the coupled simulation decreases approximately by factor 10 (from 1.0 to 0.1 real-time), which is not critical for purely virtual simulations, but can be a problem for the experimental realization as PiL method (later addressed in Subchapter 6.2).

An exemplary outcome of the OVERWATCH utilization, with an operational detection stage in the ISD module on a running traffic flow simulation, is demonstrated as a timeline in Figure 4.12. As shown there, only at the moments when vehicles form an arrangement according to the use-cases of the cooperative driving functions F1 and F5 (compare to Figure 4.1), a scene with the corresponding subject-vehicles is detected as relevant.

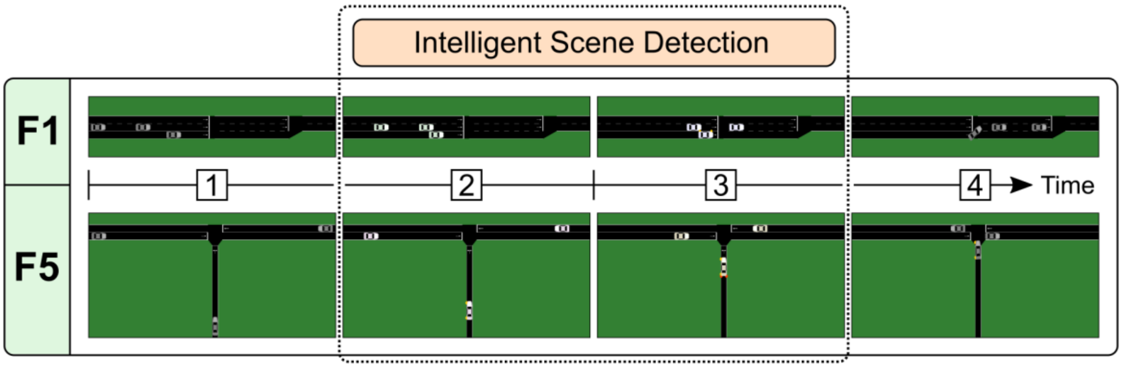


Figure 4.12: Timeline as a demonstration of operational ISD for the functions F1 and F5 (from [ICCP])

In this example, the scenes in snapshots **2** and **3** are correctly detected as relevant, whereas in **1** and **4** as irrelevant. Hereby, the ML classifier detects triangular patterns of vehicles, as it was trained to, by marking them white.

4.4 Utilization

A practical utilization of ISD, including further information about the implementation of its nested procedures, will be described in this section. To achieve an operational ISD module, its integrated ML model must be fed with object-vehicle data (e.g., positions, velocities, etc.) from the SUMO simulation.

In order to reduce the computational complexity of the detection, only vehicles in a specific RoI are considered. Hereby, the actual detection process of ISD consists of two fundamental procedures: pre-processing (‘project’, ‘sort’, ‘group’, ‘combine’) and prediction (‘scale’, ‘classify’), which are illustrated in Figure 4.13 and will be explained further on. The procedures described here are serially executed after every simulation step of SUMO.

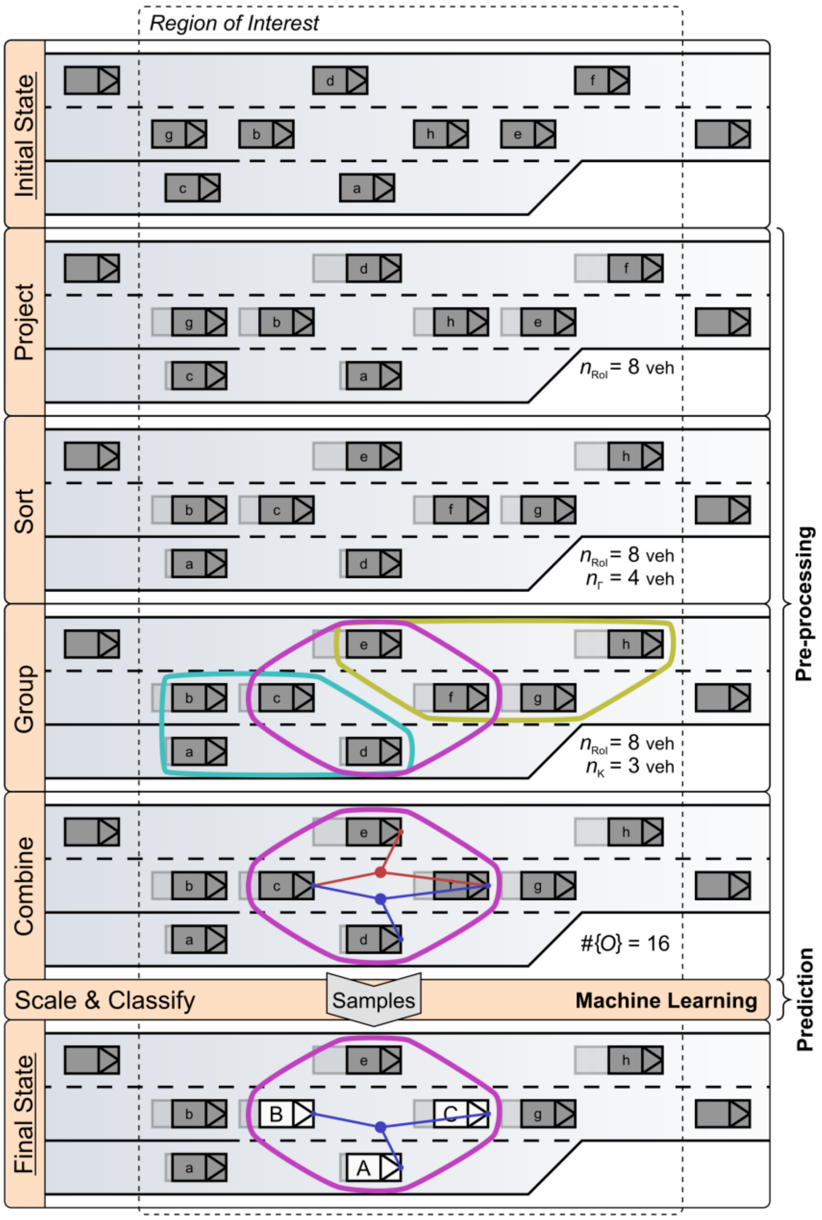


Figure 4.13: Animated representation of the procedures in ISD module (from [ICCP] with adaptations)

4.4.1 Pre-processing Procedure

At first, in the ‘project’ step, the positions of object-vehicles inside of the data retrieved from SUMO are projected into the future for a certain amount of simulation time through the extrapolation with a simple motion model, for example, such as the constant velocity model [128]. This way, the effect of a relative position change between vehicles, due to possible differences in their velocities, is taken into account. Then, in the ‘sort’ step, since the sequence of features in the observations is important, as described in Subchapter 4.3, all vehicles in the RoI of size n_{RoI} must be sorted along their longitudinal positions on the road. Thereafter, in the ‘group’ step, adjoining vehicles are put into groups of size n_{Γ}, according to their projected positions, what results in $(n_{\mathrm{RoI}} - n_{\Gamma} + 1)$ groups shifted by 1 vehicle, in order to reduce the number of possible combinations. Eventually, in the ‘combine’ step, every combination of size n_{K} (in this case 3 vehicles) is built with binomial coefficients, yielding ${n_{\Gamma}!}/{n_{\mathrm{K}}!\,(n_{\Gamma} - n_{\mathrm{K}})!}$ combinations without repetitions inside of every group. However, since the groups overlap by $(n_{\Gamma} - 1)$ vehicles, only unique combinations from all groups are considered as observations O in accordance with Equations 4.1, 4.2 and Figure 4.7.

To be noted, Figure 4.13 does not show all possible groups and combinations in the ‘group’ and ‘combine’ steps for visual clarity. In conclusion, after a construction and simplification of the corresponding formula, the total number # of records in a set of observations, which were obtained this way, can be calculated as follows:

$$\#\{O\} = (n_{\mathrm{RoI}} n_{\mathrm{K}} - n_{\Gamma} n_{\mathrm{K}} + n_{\Gamma}) \cdot \frac{(n_{\Gamma} - 1)!}{n_{\mathrm{K}}!\,(n_{\Gamma} - n_{\mathrm{K}})!} \tag{4.3}$$

4.4.2 Prediction Procedure

All observations from the pre-processing procedure are then handed over to the prediction procedure. Here, feature values in the observations are scaled with the ‘standard scaler’ first. Thereafter, the ML classifier, in this case the ‘decision tree’ model trained on the dataset, classifies each observation O through the prediction of a corresponding label L (‘0’, ‘F1’ or ‘F5’), which together are emitted as a sample. Samples labeled as ‘F1’ or ‘F5’, depending on the actual use-case, are considered as relevant and are used to create a snapshot of the scene.

To be noted, in one snapshot, several samples can be detected as relevant, meaning that a scene can contain more than 3 subject-vehicles at the same time, if multiple relevant vehicle constellations are present there. Afterwards, OVERWATCH is prompted to generate a scenario from the detected scene by starting the co-simulation. In the process, the involved subject-vehicles are highlighted through a color change (gray to white).

As an outcome, Figure 4.14 (at the end of this section) shows the co-simulation of an exemplary F1 scenario on a simplified map of a straight highway, with standard GUIs of the involved software tools: SUMO, CARMAKER and ROS (visualization package RVIZ). In all environments, one can notice 3 highlighted subject-vehicles, which were selected by OVERWATCH among the traffic flow. Moreover, SUMO displays every object-vehicle of the traffic, whereas CARMAKER only the ones being synchronized. In addition, ROS contains visualization of the trajectories needed for the MC. This way, all GUIs together contribute from their particular perspectives to the general view of the co-simulation.

4.5 Summary

This section described the design and implementation process of the intelligent co-simulation framework, including the related work, the architecture, the workflow and the utilization, which were applied on the cooperative driving functions F1 (merging on highways) and F5 (turning at junctions).

The content of this section is crucial for answering the RQ I, since it proposes a solution to detect the MC relevant conditions of traffic quantity as scenes in the major scenarios, which act as initial states of the minor scenarios for the co-simulation, by using popular supervised ML classification approaches. Consequently, these scenarios can be then utilized for the verification and validation of the cooperative driving functions in the scope of the RQ II. In order to achieve this, possible solutions for the evaluation of the co-simulation results, concerning the effects on traffic quality, are yet to be elaborated in compliance with the RQ III.

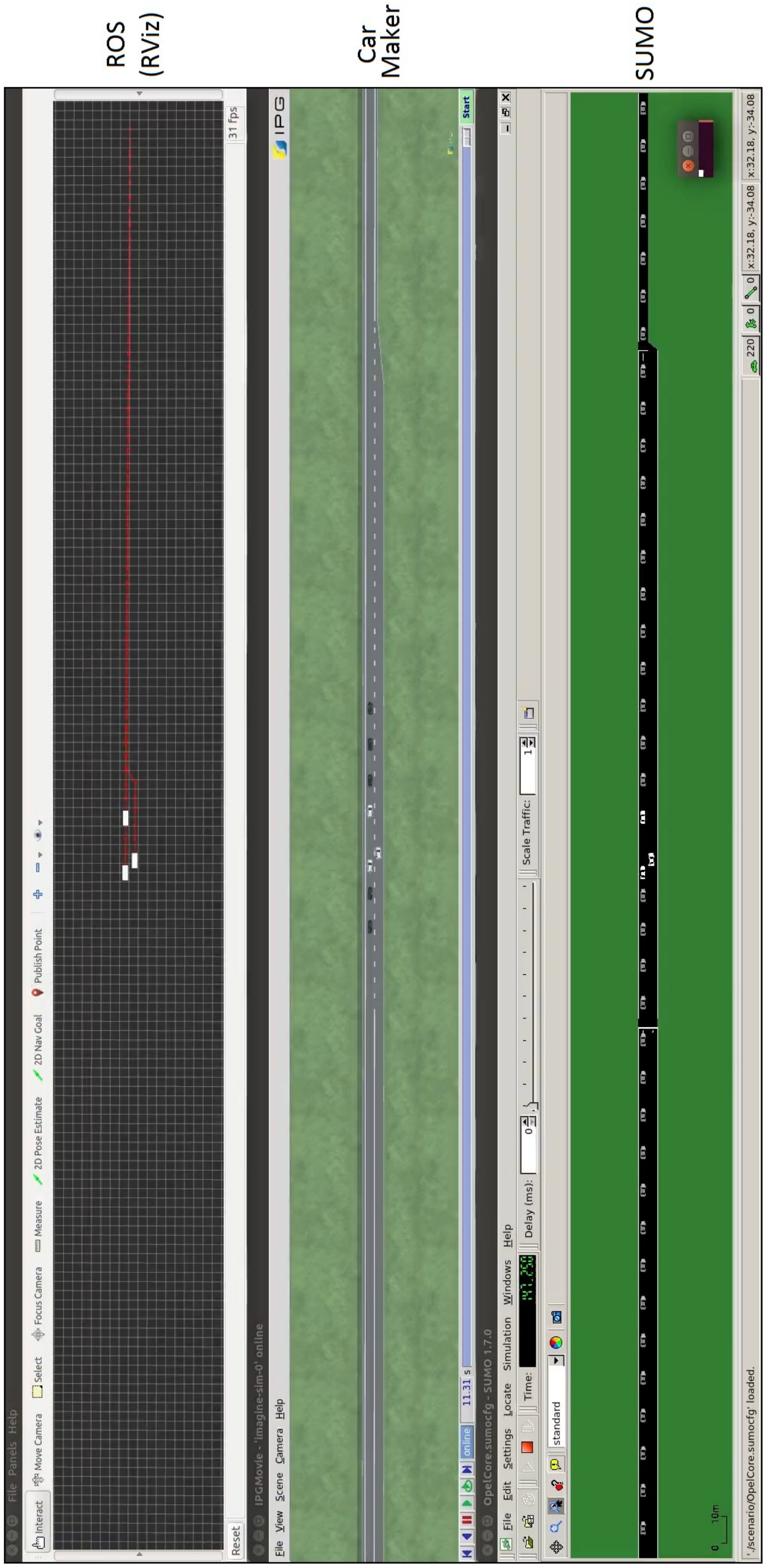


Figure 4.14: Simulation of F1 scenario with the intelligent co-simulation framework

5 Evaluation

After the methodology, including the associated intelligent co-simulation framework, was thoroughly discussed, this section will present the corresponding evaluation process and its successive results. Hereby, the evaluation will be performed by means of a MiL/SiL simulation with appropriate metrics on suitable scenarios for an exemplary use-case of the cooperative driving function F1, in the scope of two studies with different SuTs, in order to demonstrate the transferability of the methodology:

- 1st study – Effects on Traffic Quality
- 2nd study – Effects of Imperfect Communication

A common configuration of the co-simulation environment with essential parameters and arguments for both studies is listed in Table 5.1.

Table 5.1: Configuration of the co-simulation (from [WCX] with adaptations)

Parameters	Arguments
Time step of SUMO simulation	0.05 s
Time step of CARMAKER simulation	0.001 s
Average simulation speed of SUMO	1.0 real-time
Average simulation speed of SUMO & CARMAKER	0.1 real-time

This section is based inter alia on the author's publication [WCX].

5.1 Metrics and Scenarios

According to the previous simulation-based studies (e.g., [129] [130]), an ADAS supported merging of vehicles on highways can significantly improve the overall traffic flow. However, the associated evaluation requires a careful choice of metrics, which must be suitable for the accurate measurements of the effects on traffic quality due to the cooperative driving, as well as transferable enough for an application on different scenarios with variable traffic quantities, at the same time.

To begin with, the evaluation metrics and the corresponding major scenarios must be defined, in order to allow for a quantitative assessment of the MC impact on different aspects of the traffic quality. An overview of these metrics – traffic density-velocity-flow, coefficient of variation, time-exposed time-to-collision and spatiotemporal patterns – is illustrated in Figure 5.1 and will be further explained. These metrics are only applied to the subject-vehicles (white) and object-vehicles (gray) that are temporarily located in a stationary RoI, which includes a certain segment of the road, where frequent cooperative maneuvers are expected to occur (e.g., at highway entrance).

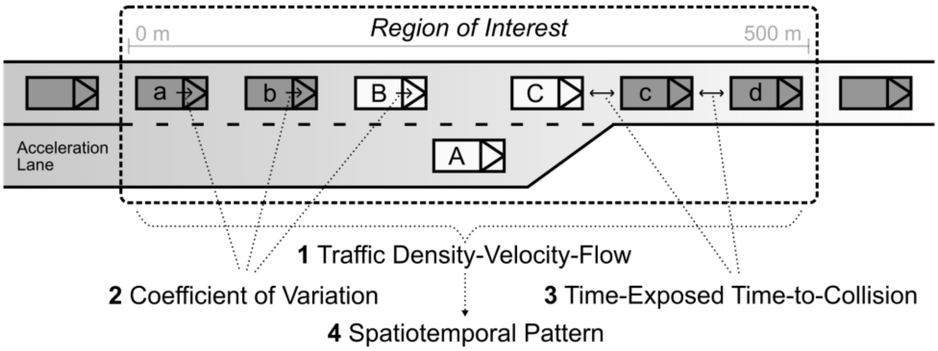


Figure 5.1: Overview of the traffic quality metrics (from [WCX] with adaptations)

During the simulation process with the intelligent co-simulation framework, every major *large-scale long-term* scenario is split into multiple minor *small-scale short-term* scenarios (as described in Subchapter 3.1). Hereby, each of the minor scenarios can have different outcomes, depending on the success of cooperation. Therefore, apart from the metrics, a definition of successful and non-successful cooperation is required, which is illustrated in Figure 5.2 for the case of 3 subject-vehicles.

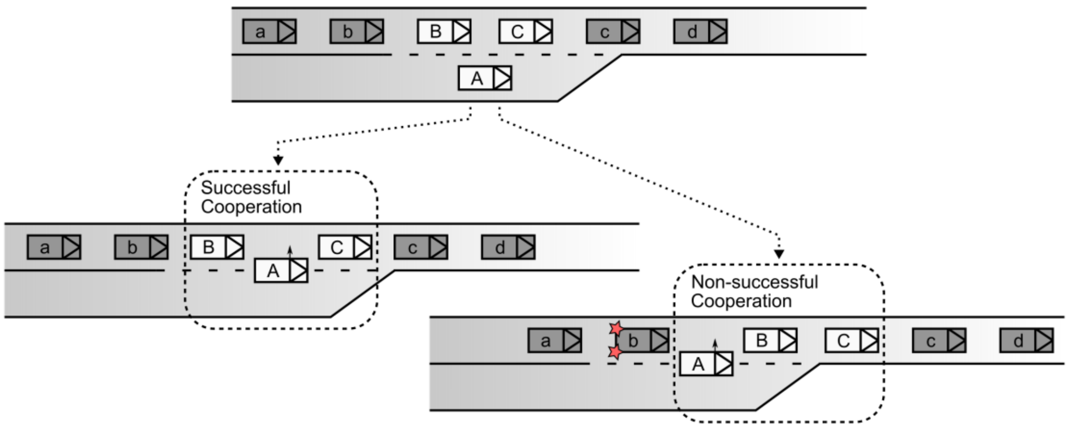


Figure 5.2: A minor scenario with two different outcomes

Here, on the one hand, subject-vehicles **A**, **B**, **C** are acting as CAVs simulated by the vehicle dynamics simulator with lower NoA and higher LoD, which are equipped with and controlled by the cooperative driving functions. On the other hand, object-vehicles **a**, **b**, **c**, **d** with higher NoA and lower LoD are not equipped with cooperative driving functions, therefore, they are completely simulated and controlled by the traffic flow simulator with a conventional car-following model (particularly, SUMO default Krauss model [131] [132]).

It is to assume that, in case of a successful cooperation, the vehicle **A** can uniformly merge-in between the vehicles **B** and **C**. In contrast, in case of a non-successful cooperation, the vehicle **A** must abruptly merge-in between the vehicles **b** and **B** (i.e., cooperation is forced), what causes a strong deceleration of the vehicle **b** and, to an extent, a distortion of the consecutive traffic flow.

5.1.1 Metrics

Before introducing the actual traffic quality metrics from Figure 5.1, some of their vital fundamentals will be defined here. To begin with, the traffic velocity v stands for an arithmetic mean of the vehicle velocities v_i among all n_{RoI} vehicles situated in RoI, including the object-vehicles (starting with index **a**) and the subject-vehicles (starting with index **A**). Thus, the traffic velocity is calculated as follows:

$$v = \frac{1}{n_{\mathrm{RoI}}} \sum_{i=\mathbf{aVA}}^{n_{\mathrm{RoI}}} v_i \tag{5.1}$$

Further, the mean traffic velocity $\overline{v}$ and the mean vehicle velocity $\overline{v}_i$ (of each vehicle i) with the respective standard deviations σ_{v} and $\sigma_{\mathrm{v}i}$ are defined in dependence on the discrete simulation time t. Hereby, $\overline{v}$ and σ_{v} are determined between 0 and T of the total simulation time; whereas $\overline{v}_i$ and $\sigma_{\mathrm{v}i}$ are determined between ${}_{\mathrm{in}}T_i$ and ${}_{\mathrm{out}}T_i$ of the time, when a vehicle i enters and exits the RoI. Conclusively, these quantities are calculated with the following formulas:

$$\overline{v} = \frac{1}{T}\sum_{t=0}^{T} v(t) \qquad \sigma_{\mathrm{v}} = \sqrt{\frac{1}{T}\sum_{t=0}^{T}\big(v(t) - \overline{v}\big)^2} \tag{5.2}$$

$$\overline{v}_i = \frac{1}{{}_{\mathrm{out}}T_i - {}_{\mathrm{in}}T_i} \sum_{t={}_{\mathrm{in}}T_i}^{{}_{\mathrm{out}}T_i} v_i\,(t) \qquad \sigma_{\mathrm{v}i} = \sqrt{\frac{1}{{}_{\mathrm{out}}T_i - {}_{\mathrm{in}}T_i} \sum_{t={}_{\mathrm{in}}T_i}^{{}_{\mathrm{out}}T_i} \big(v_i(t) - \overline{v}_i\big)^2} \tag{5.3}$$

Traffic Density-Velocity-Flow

The first evaluation metrics indicates the relation between the traffic density k, the space mean traffic velocity v and the traffic flow q [133] [134], which is defined as follows:

$$q = k \cdot v \tag{5.4}$$

Herewith, q describes the vehicle throughput of the road and is often used as an indicator of the traffic quality. In general, due to a limited traffic flow capacity and a mutual compensation of the traffic density and velocity, q should be achieved via lower k and higher v (not vice-versa). Lower k and higher v result in a free flow, whereas higher k and lower v result in a congested flow. This metrics is collectively applied to all vehicles in the RoI.

Coefficient of Variation

The second evaluation metrics is coefficient of variation [135], denoted here with symbol CV_i, which can be calculated as a quotient of the velocity standard deviation $\sigma_{\mathrm{v}i}$ and the arithmetic time mean velocity $\overline{v}_i$ of each vehicle i, thus, yielding the following formula:

$$CV_i = \frac{\sigma_{\mathrm{v}i}}{\overline{v}_i} \tag{5.5}$$

In general, higher CV_i values indicate a poorer traffic quality due to the higher $\sigma_{\mathrm{v}i}$, which means that the vehicles frequently have to adapt their velocities (by accelerating and decelerating), in order to stay synchronized with the overall traffic flow. Furthermore, due to a direct anti-proportionality, CV_i punishes lower and favors higher $\overline{v}_i$, since the higher vehicle velocities are more beneficial for the traffic quality. This metrics is individually applied to each vehicle in the RoI.

Time-Exposed Time-to-Collision

The next evaluation metrics can be derived from the Time-to-Collision (TTC) [136] [137], denoted as TTC_{ij}, which is defined as a quotient of the relative longitudinal position (i.e., distance, excl. vehicle lengths) Δp_{ij} and the relative longitudinal velocity (i.e., speed difference) Δv_{ij} between two vehicles i and j:

$$TTC_{ij} = \frac{\Delta p_{ij}}{\Delta v_{ij}} \tag{5.6}$$

In the scope of this evaluation, since the TTC_{ij} does not deliver an integral output value, an extended measure will be used, which is called Time-Exposed Time-to-Collision (TETTC) [136] [137], denoted as $TETTC_i$. Taking into account only positive TTC_{ij} of every vehicle i (i.e., TTC_i), as well as by specifying a minimal acceptable threshold TTC^*, the $TETTC_i$ of every vehicle i can be calculated as follows:

$$TETTC_i = \sum_{t={}_{\mathrm{in}}T_i}^{{}_{\mathrm{out}}T_i} \delta_i(t) \cdot \tau \tag{5.7}$$

$$\delta_i = \begin{cases} 1 & \forall \quad TTC_i(t) \leq TTC^* \\ 0 & \forall \quad TTC_i(t) > TTC^* \end{cases} \tag{5.8}$$

Herewith, the $TETTC_i$ is summed up for every time point t, with a time step τ, from ${}_{\mathrm{in}}T_i$ to ${}_{\mathrm{out}}T_i$ of the simulation time, when the corresponding TTC_i lies below the threshold TTC^*. Normally, TTC and TETTC are used as safety metrics, nevertheless they also suit for an assessment of the overall traffic quality, since both metrics indicate the continuousness of the traffic flow. Ideally, when all vehicles move with the same velocity without changing distances between them, this results in $TTC_{ij} \rightarrow \infty$ and $TETTC_i \rightarrow 0$, consequently. Both metrics are individually applied to each vehicle in the RoI.

Spatiotemporal Pattern

The last metrics, a so-called spatiotemporal pattern, which will be used here for the assessment of the traffic quality, does not contain any specific formula and serves mainly for a graphical evaluation (refer to [138] and [139]). A spatiotemporal pattern can be created by observing the movement of all vehicles in the RoI and recording their trajectories (positions p_i and velocities v_i over time t). Hence, the recorded p_i and v_i can be displayed as a spatiotemporal pattern in form of 2- or 3-dimensional diagrams. This way, an overview of the traffic quality can be achieved, allowing for an evaluation of the traffic flow with supplementary traffic theories. In addition, the traffic shockwaves, defined as an abrupt braking of several vehicles due to disturbances (e.g., merging vehicles), can be identified when examining the spatiotemporal patterns.

An example of a spatiotemporal pattern from a real-world traffic observation is shown in Figure 5.3, where each line in the diagram represents a movement of one single vehicle in space and time. Here, from a straightforward viewpoint, the traffic flow is divided into free and congested phases, which can be recognized on the higher and lower slopes of the lines, respectively. The congested phase is characterized by a shockwave, where the vehicles are forced to decelerate. Since the evaluation with a spatiotemporal pattern is typically applied to one lane of a road, the appearing and disappearing lines indicate lane-changes of the vehicles.

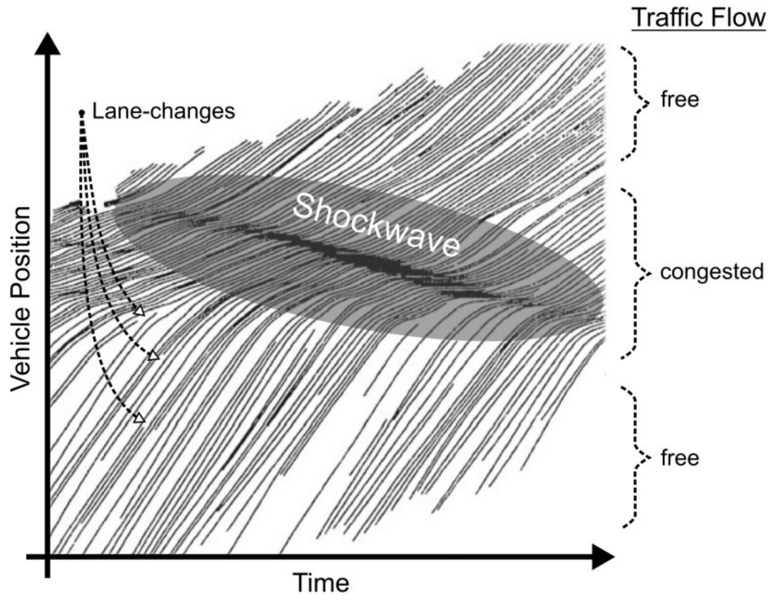


Figure 5.3: Example of a spatiotemporal pattern (from [139] [140] with adaptations)

5.1.2 Scenarios

For the task of traffic impact assessment due to the cooperative driving functions with the presented metrics, the evaluation of test results from the intelligent co-simulation framework will be performed only on major scenarios. The corresponding configuration of the co-simulation with essential parameters and arguments for all major scenarios of both studies is listed in Table 5.2.

In the scope of the 1st study – Effects on Traffic Quality – in order to demonstrate the plausibility of the chosen metrics, the focus will be on 3 concrete scenarios, which are derived from the logical scenario of a highway entrance. The corresponding major scenarios are synthetically generated with SUMO and denoted as follows, depending on the traffic conditions they aim to recreate:

- ‘Congested’
- ‘with MC’
- ‘Free’

In case of the ‘Congested’ and ‘Free’ major scenarios, the cooperative driving function with the MC algorithm as a SuT is deactivated, in order to produce edge cases for the later evaluations. In such an edge case, only SUMO simulation is executed, meaning that no minor scenarios for CarMaker are being generated. On the one hand, in the ‘Congested’ major scenario, the merging vehicles always drive until the end of the acceleration lane before they begin to non-cooperatively merge-in, thus, causing significant shockwaves each time (worst-case scenario). On the other hand, in the ‘Free’ major scenario, there are no merging vehicles at all, meaning that the traffic on the highway can flow undisturbedly (best-case scenario). For the major scenario ‘with MC’, the SuT and the whole toolchain of OverWatch are activated, resulting in multiple cooperative merging maneuvers as minor scenarios. This way, the outcome of the ‘with MC’ scenario is expected to lie in-between the outcome of the ‘Congested’ and ‘Free’ scenarios.

Table 5.2: Configuration of the scenarios (from [WCX] with adaptations)

Parameters	**Arguments**	
	1st study	**2nd study**
MC algorithm	Core	Core (baseline) Joint
Demand of traffic flow	7200 veh/h	1800 veh/h
MDR of communication model	100 %	0-100 % (variable)
Duration of a major scenario	90 s	90 s
Duration of a minor scenario	30 s (3 times)	30 s (3 times)
Number of subject-vehicles	3 veh	3 veh
Number of lanes on the highway	1	1
Speed limit on the highway	100 km/h	100 km/h
Length of the acceleration lane	250 m	250 m
Total RoI length	500 m	500 m

For this evaluation, the SuT with Core MC from Subchapter 3.2 is used. Hence, with an intent to achieve more apparent and distinctly interpretable results with the presented metrics, the traffic behavior in SUMO simulation is configured as ideal, concerning the car-following model and velocity keeping. Hereby, the deliberately exaggerated demand of the traffic flow is set to a relatively high value of 7200 veh/h. Furthermore, a perfect V2X communication is assumed (i.e., unlimited range with no latency and losses).

In the scope of the 2nd study – Effects of Imperfect Communication – another SuT with Joint MC is integrated into the intelligent co-simulation framework with an active OVERWATCH, in order to demonstrate the transferability of the methodology, as well as the ability for a comparison of different cooperation approaches with each other. Hereby, the Joint MC algorithm represents an implementation of the approach [34], which was realized by the IMAGinE project, with highly versatile dependent aspects of the cooperative driving (driving performance, comfort, robustness, etc.). In this regard, Core MC is acting as a baseline.

In order to assess the effects of imperfect communication, which can be caused by the respective independent aspects of the cooperative driving (infrastructure, environment, etc.), a variation of the communication quality is conducted. Thereby, in combination with the Joint MC, a phenomenological V2X model from the IMAGinE project is used for the simulation of a simplified communication channel. With this model, Message Delivery Ratio (MDR) of the MCMs, which contain trajectories for the cooperative MC, is altered in 10 % steps between 100 % (i.e., perfect communication) and 0 % (i.e., practically non-existent communication). In the process, the mean traffic velocity for a total duration of every major scenario with the corresponding number of Successful Cooperations (SC), according to Figure 5.2, is measured.

For this evaluation, the demand of traffic flow is set to a more realistic value of 1800 veh/h, which complies at 100 km/h driving speed to a time gap of 2 s between the vehicles, as a widely recommended safe trailing distance (two-second rule-of-thumb [141]).

5.2 Test Results

After having introduced the metrics and the scenarios, the evaluation for both studies will be presented and interpreted, using the simulation output data from SUMO, in this section. While doing so, the argumentation will be supported graphically.

5.2.1 Effects on Traffic Quality

This section covers the test results of the 1st study.

Traffic Density-Velocity-Flow

The evaluation results considering the traffic quality in time domain are shown as graphs in Figure 5.4. There, traffic density k, traffic velocity v (incl. one standard deviation) and traffic flow q are displayed, each in a separate diagram, over the simulation time t for all 3 long-term scenarios 'Congested', 'with MC' and 'Free'. Herewith, k and v are collectively determined from the simulated number and velocity of the vehicles in the RoI, whereas q is then calculated with Equation 5.4.

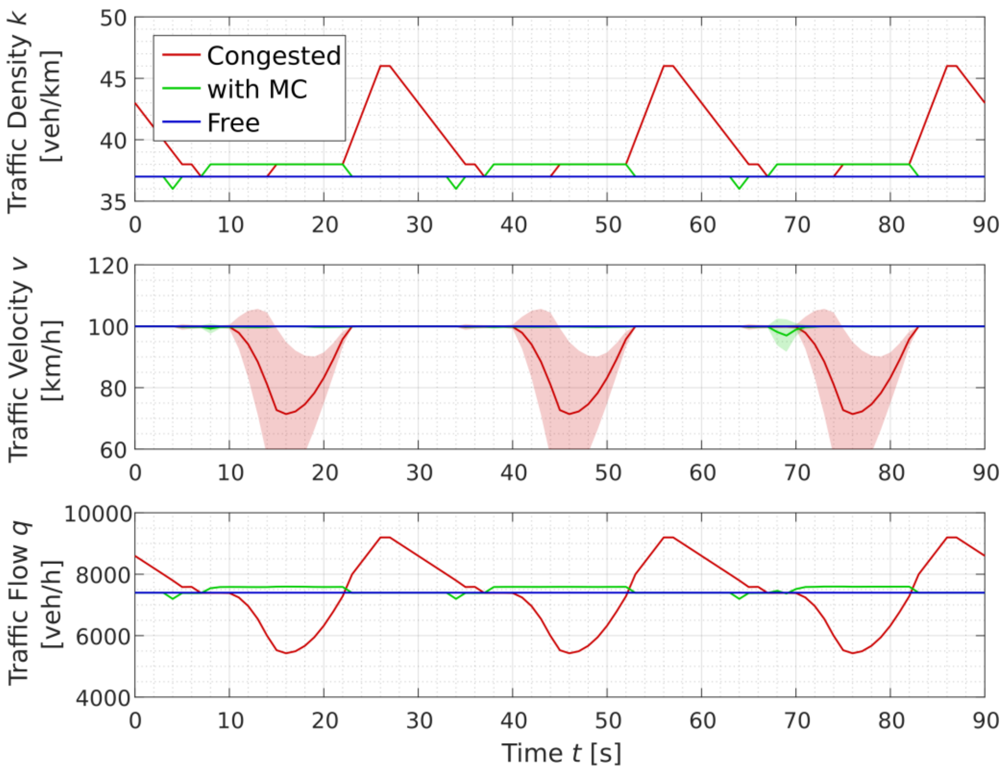
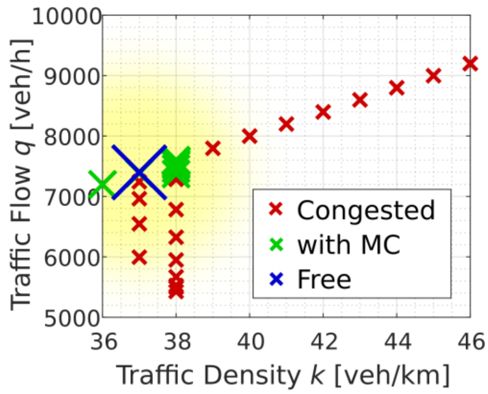


Figure 5.4: Results of the 1st study – traffic density-velocity-flow in time domain (from [WCX])

As one can see, in case of the ‘Congested’ scenario, 3 non-cooperative merging maneuvers cause a significant reduction of the traffic velocity (at 10-20 s, 40-50 s, 70-80 s), followed by an increase of the traffic density (at 25-35 s, 55-65 s), which therefore result in an oscillation of the traffic flow during the respective time periods. Contrarily, in case of the ‘Free’ scenario, the traffic density, velocity and flow remain always constant, due to a complete absence of the merging maneuvers there. At this moment, in case of ‘with MC’ scenario, where the course of k, v and q with small deviations resembles the results of the ‘Free’ scenario, the positive impact of MC on the traffic quality becomes apparent. This can be explained by the cooperation between vehicles, which allows for a much smoother highway merging, yielding almost constant (i.e., optimal) traffic density, velocity and flow.

Average …	Con-gested	with MC	Free
Traffic Density [veh/km]	39.6	37.5	37.0
Traffic Velocity [km/h]	93.3	99.8	100.0
Traffic Flow [veh/h]	7423	7479	7398



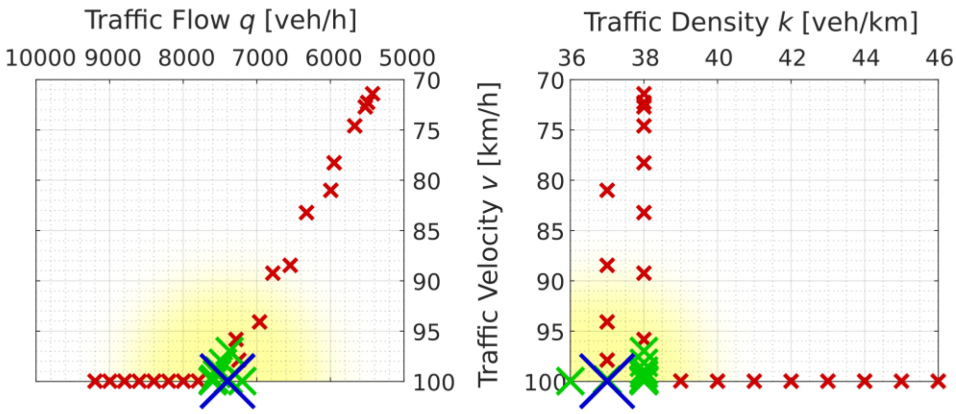


Figure 5.5: Results of the 1st study – traffic density-velocity-flow as fundamental diagram (from [WCX])

Identic simulation results can be displayed in a so-called fundamental diagram (refer to [133]), as shown in Figure 5.5. Herewith, the markings in the diagram represent pairwise relations between the traffic density k, velocity v and flow q at discrete points of time.

Basically, the closer the markings are located to the edge-case ‘Free’ (yellow zone), the better is the traffic quality. It can be seen that the markings of the ‘with MC’ scenario all lie in a proximity of the ‘Free’ scenario, whereas the markings of the ‘Congested’ scenario are more scattered, due to higher fluctuations in the traffic density, velocity and flow, as described before.

In a direct comparison between the ‘Congested’ and the ‘with MC’ scenarios, in average over the course of 90 s simulation time, the traffic density could be reduced by 5 % (from 39.6 veh/km to 37.5 veh/km) and the traffic velocity could be increased by 7 % (from 93.3 km/h tom 99.8 km/h), with a small improvement of the traffic flow (from 7423 veh/h to 7479 veh/h), as an effect of the cooperative driving. This way, the traffic density and velocity ‘with MC’ match better with the results of the ‘Free’ scenario (37.0 veh/km, 100.0 km/h), which shows, however, the lowest value of the traffic flow (7398 veh/h), due to the absence of the merging vehicles.

Coefficient of Variation

As a next step, the results of the evaluation considering the coefficient of variation of the vehicle velocities in the simulation will be presented. Herewith, the mean velocity $\overline{v}_i$ and the corresponding standard deviation $\sigma_{\mathrm{v}i}$ is determined for each vehicle, which is driving in the RoI during the runtime of a major scenario. Consequently, CV_i is calculated with Equation 5.5. Afterwards, every CV_i value is portrayed over $\overline{v}_i$ value in a scatter plot, as shown in Figure 5.6, where each point represents one vehicle.

In case of the ‘Free’ scenario, one can notice that all the corresponding points are located in one place, meaning that all vehicles in the simulation were ideally driving with 100 km/h without deviations. In case of the ‘Congested’ scenario, the points are scattered, indicating lower mean velocities with higher variations for many vehicles. In contrast to this, the ‘with MC’ scenario shows in-between values, meaning that the cooperation algorithm visibly improves CV_i, due to smoother merging maneuvers on the highway entrance. In general, for a better traffic quality, higher velocities and lower variations are preferable, which is represented by the yellow zone in the diagram. This results in a better travel time and a better energy efficiency (i.e., lesser fuel consumption and emissions) of the traffic.

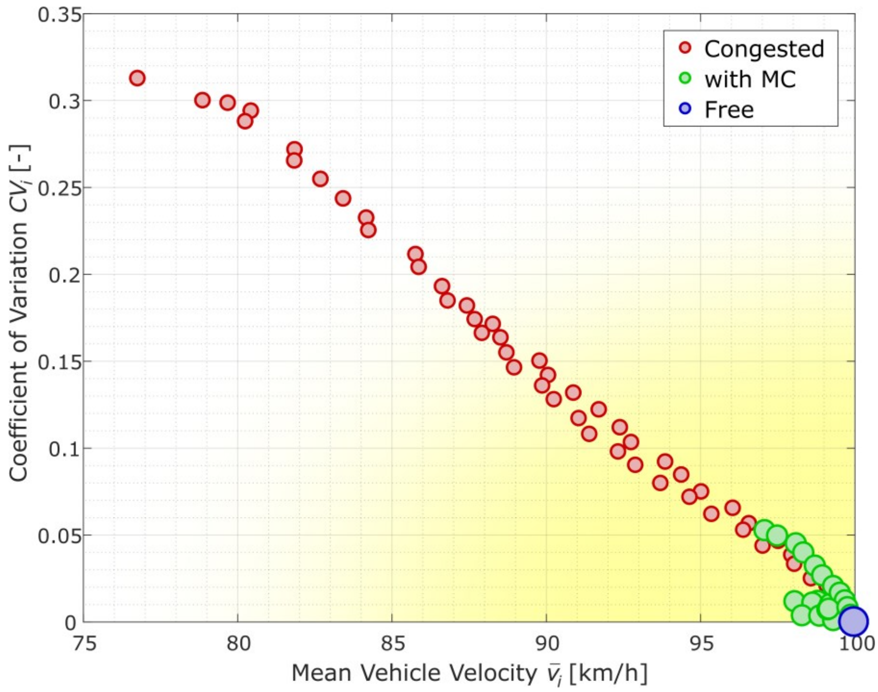


Figure 5.6: Results of the 1st study – coefficient of variation over mean vehicle velocity (from [WCX])

Time-Exposed Time-to-Collision

As a successive metrics for the traffic quality, the TETTC will be evaluated. The corresponding results are shown as a bar chart in Figure 5.7. In order to produce this diagram, one firstly calculates TTC_i for each vehicle at each time step of the simulation, which is then summed up to $TETTC_i$ according to Equations 5.7 and 5.8. Herewith, the TTC^* threshold is set to a relatively high value of 25 s, which is reasoned by the ideal driving behavior (car-following model) of the traffic in the simulation. Thereafter, one enumerates the numbers of the vehicles with equal $TETTC_i$ (rounded values), which are then displayed as bars. At the same time, one skips the vehicles with $TETTC_i = 0$.

In the resulting diagram, in case of the 'Congested' scenario, one can see that many vehicles demonstrate high $TETTC_i$, denoting that they had to reduce their distances to the preceding vehicles for longer periods of time (over several seconds), being obliged to do so due to the non-cooperative merging maneuvers. In contrast, in case of the 'Free' scenario, all vehicles have $TETTC_i = 0$. Eventually, in case of the 'with MC' scenario, the evaluation delivers in-between values, thus, indicating that the MC allows for more consistent longitudinal distances between the vehicles during merging.

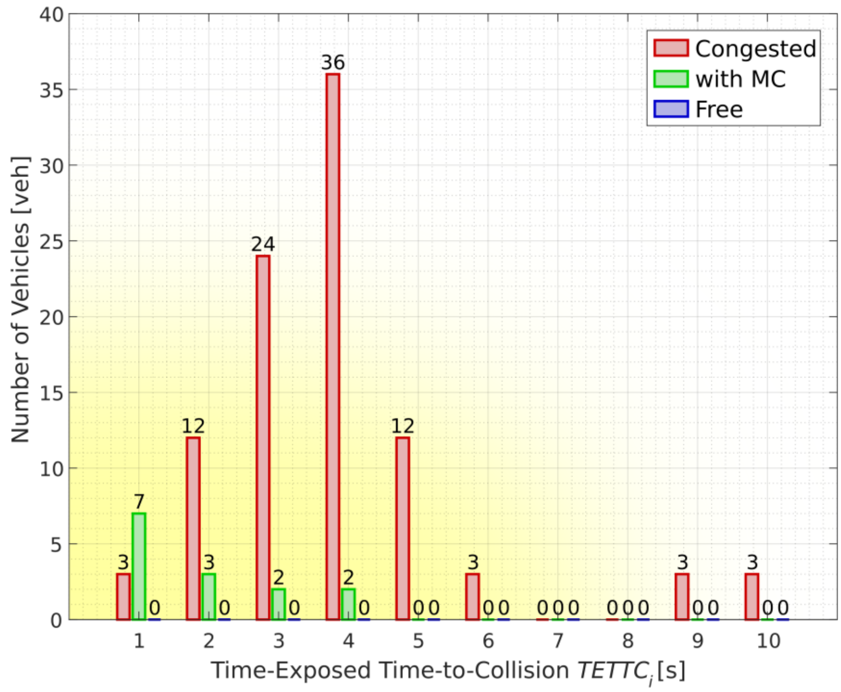


Figure 5.7: Results of the 1st study – number of vehicles with corresponding TETTC (from [WCX])

In general, fewer vehicles with less $TETTC_i$ characterize a better traffic quality, which is represented by the yellow zone in the diagram. In case of a more realistic traffic simulation (i.e., non-ideal driving behavior), which is also achievable with the co-simulation environment of the work at hand, the threshold TTC^* can be set lower, even into the range of safety relevant values. This way, the TETTC evaluation would be able to deliver information regarding the driving safety in addition to the traffic quality.

Spatiotemporal Pattern

As a final step of this evaluation, the spatiotemporal patterns will be presented, which are shown as separate diagrams for each scenario 'Congested', 'with MC' and 'Free' in Figure 5.8. Herewith, the individual positions of vehicles p_i in the RoI are displayed as their recorded trajectories over the simulation time t, as well as the velocities v_i are denoted with different colors. In all diagrams, 0 m corresponds to the beginning and 250 m corresponds to the ending of the acceleration lane, with a total RoI length of 500 m.

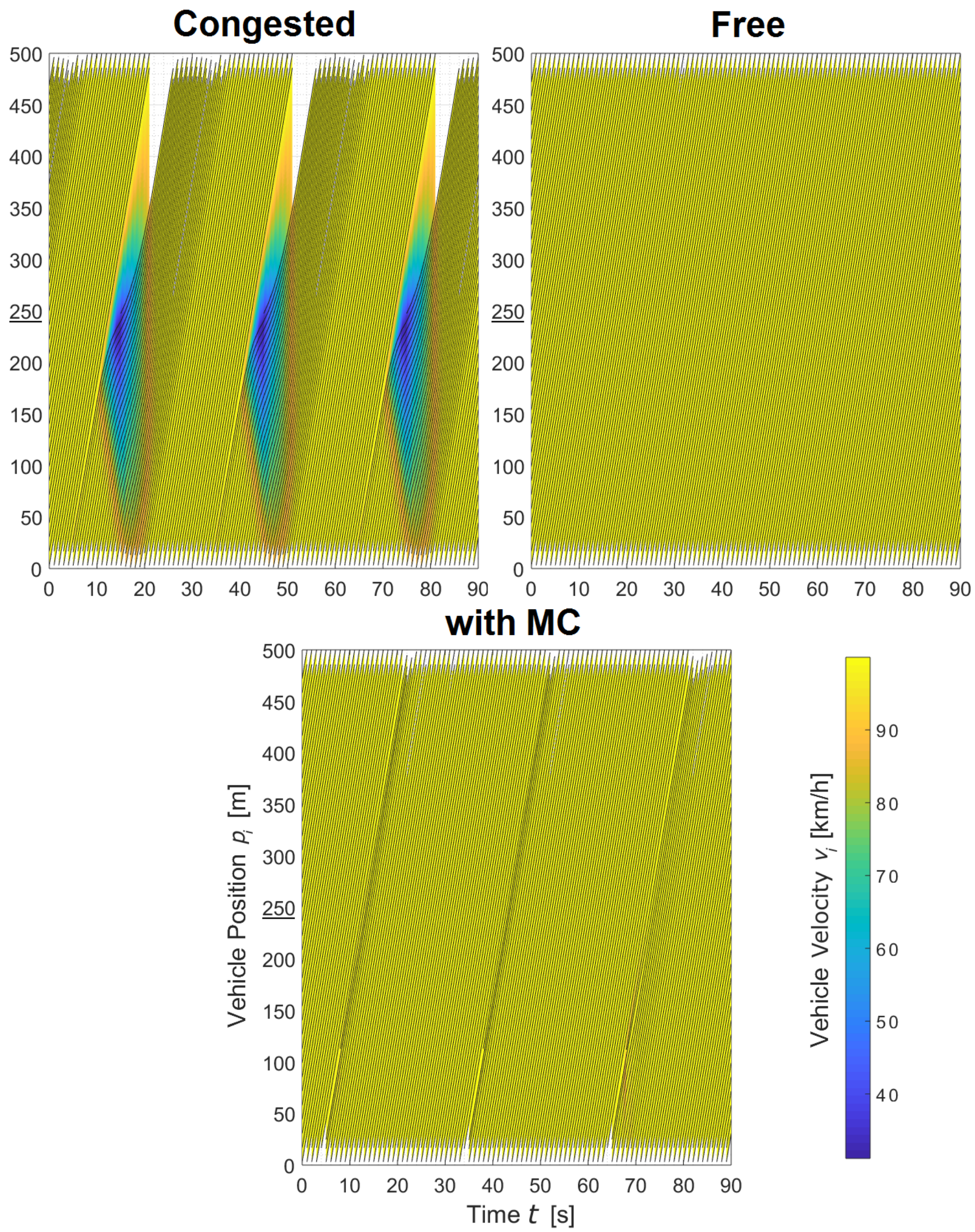


Figure 5.8: Results of the 1st study – spatiotemporal patterns (from [WCX] with adaptations)

In case of the ‘Free’ scenario, the spatiotemporal patterns demonstrate an ideal traffic quality, where all vehicles can always freely follow their ways. In case of the ‘Congested’ scenario, it is easy to recognize strong decreases in the velocity, which are caused by the 3 non-cooperative merging maneuvers in the simulation, occurring right in the end of the acceleration lane (approximately at 250 m). These velocity breakdowns result in intense shockwaves (compare with Figure 5.3), starting at the merging site and propagating upstream, implying that multiple vehicles on the main highway lane were forced to brake. After the actual merging maneuvers are fulfilled and the shockwaves dissolve there, the traffic recovers to the free flow conditions. In case of the 'with MC' scenario, the deviations in velocity are almost unnoticeable, since the merging vehicles are quickly synchronized with the overall traffic flow, whereas the merging itself occurs much earlier (between 100 m and 150 m), causing almost no perturbances for the traffic on the highway.

As a conclusive outcome of the 1st study, one can clearly distinguish the positive impact of the cooperative MC on the traffic quality, due to the reduced traffic density and the increased traffic velocity, including improvements in the traffic safety and efficiency. Furthermore, due to the prolific evaluation, the methodology and the intelligent co-simulation framework, as well as the chosen metrics and scenarios, could be proven as working, allowing to illustratively validate the functionality of the SuT with the Core MC approach on the use-case of highway merging.

5.2.2 Effects of Imperfect Communication

This section covers the test results of the 2nd study.

To begin with, some of the problematic effects on the cooperative vehicular networking and maneuvering, due to the imperfect communication, will be explained on an example of the highway merging use-case with the Core MC approach (as shown in Figure 3.2). There, in order to achieve cooperation, a 4-way handshake via the V2X communication is required, by a cyclic and asynchronous transmission of the trajectories contained in the MCMs. Hence, the communication quality can substantially affect the outcome of the cooperation, whether it becomes successful or non-successful (as shown in Figure 5.2). The underlying 4-way handshake process of the trajectory exchange between the vehicle **A** (requesting) and the vehicle **B** or **C** (offering), depending on who is mainly involved into the cooperation, is illustrated as a sequence in Figure 5.9.

If all trajectories are transmitted and received correctly, then a successful cooperation can be quickly executed. Otherwise, any of the steps from t_1 to t_4 in the 4-way handshake being disturbed can lead to a completely interrupted negotiation between the vehicles and, thus, to a non-successful cooperation. In case of communication problems, the negotiation can also take longer, since the messages must be re-sent over multiple cycles. Among various reasons, this can be caused by the losses of MCMs due to the imperfect MDR of the inter-vehicular communication.

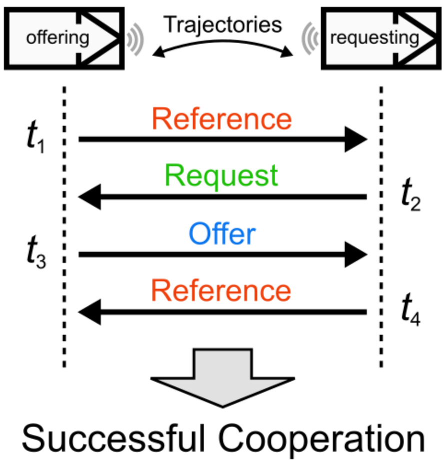


Figure 5.9: Sequence of cooperation process with the Core MC approach

In this evaluation, on the one hand, the Core algorithm stands for a simplified implementation of the associated MC approach with some idealized characteristics (e.g., plain trajectory planning with very short safety distances between vehicles) as a baseline SuT. On the other hand, the Joint algorithm, which allows for an exchange of multiple trajectories per vehicle at the same time, as previously introduced in Subchapter 3.2, represents an alternative, much more versatile and realistic implementation of the associated MC approach from the IMAGinE project (refer to [34] for details). Nevertheless, a cooperation with the Joint algorithm equivalently obeys to the principle of 4-way handshake, which is valid for the Core (baseline) algorithm, as described before.

However, the exact cooperation process also depends on further parameters and arguments, such as the planning horizon and the generation cycle frequency of the trajectories in MCMs, which will be fixed here at 10 s and 5 Hz for the Core, as well as 10 s and 3 Hz for the Joint approaches, respectively. Also, the inter-vehicular communication will be simulated as perfect, in case of the Core MC; whereas in case of the Joint MC, through the utilization of a V2X channel model from the IMAGinE project with a variable MDR.

Traffic Density-Velocity-Flow

Figure 5.10 visualizes the results of the 1 (MDR 100 %) and the 11 (MDR from 100 % to 0 % in 10 % steps) simulation runs of the major scenarios for the Core and the Joint MC SuTs, respectively. Hereby, the abscise denotes MDR and the ordinate denotes mean traffic velocity $\overline{v}$ with one standard deviation σ_{v} for the total duration of a scenario. In addition, this diagram shows the numbers of SCs that are chromatically highlighted.

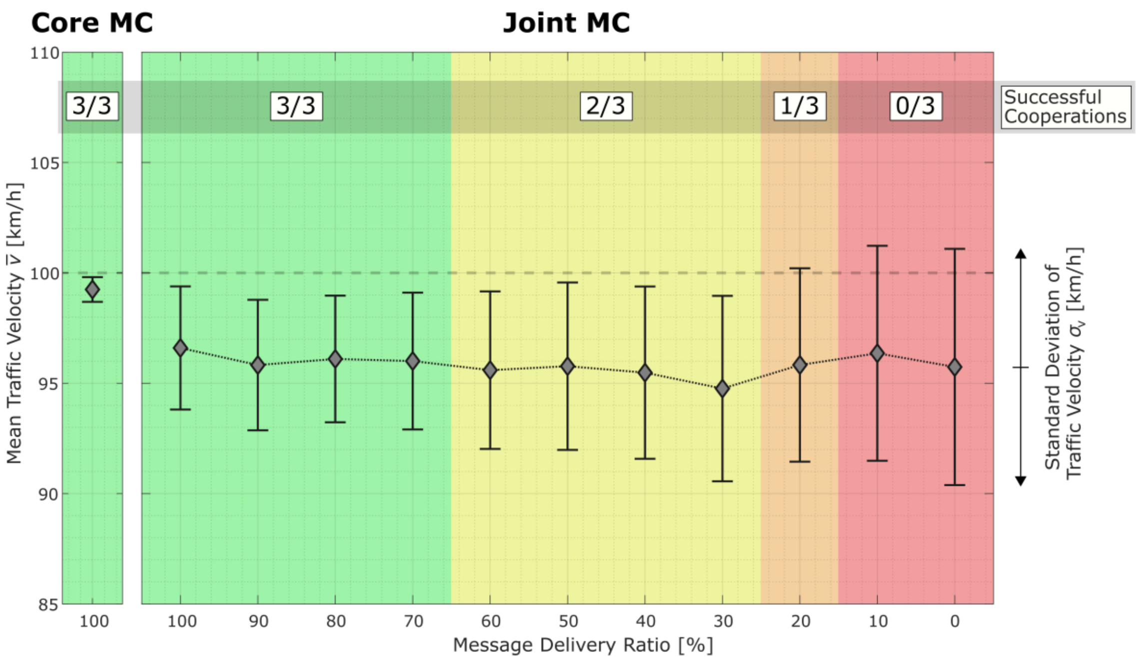


Figure 5.10: Results of the 2nd study – traffic velocity with SC over MDR

For this evaluation, the focus will be put on the observation of the traffic velocity, since it delivers straightforward and clearly interpretable results. Overall, one can recognize the following tendency here: with the lower MDR, the mean traffic velocity slightly decreases, which is reasoned by the longer lasting negotiation processes; as well as the standard deviation of traffic velocity considerably increases, which is reasoned by the corresponding lower number of SCs.

The lower MDR, the stronger retards the MC between the communicating vehicles, since the MCMs must be re-sent multiple times, in order to achieve a potential cooperation. Thereby, longer MC leads to the vehicle **A** (requesting) being obliged to wait on the acceleration lane by deceleration, so that after the merge-in, the vehicle **B** (offering) or rather the vehicle **b**, is forced to decelerate likewise. This causes a reduction of the mean traffic velocity $\overline{v}$. Moreover, the lower MDR, the fewer SCs occur consequently. In case of a non-successful cooperation, the merge-in of the vehicle **A** (requesting) leads to a higher standard deviation of the traffic velocity σ_{v}, since the vehicle **b**, as well as the successive object-vehicles must stronger decelerate and again accelerate to the initial speed, in contrast to the case of a successful cooperation with the vehicle **B** (offering).

As one can see in Figure 5.10, for the Joint SuT, in the 100-70 % MRD zone (3/3 SC), all cooperations are successful, so that the mean traffic velocity and its standard deviation demonstrate reasonable values that vary only marginally, what suggests a sufficient communication quality needed for the MC. In the 60-30 % MDR zone (2/3 SC), one can distinguish a significant decline of the mean traffic velocity, which can be explained by the longer lasting negotiation processes during the MC, even though most of them still result in successful cooperations. In the 20 % MDR zone (1/3 SC), the mean traffic velocity increases again, since the vehicles engage in cooperation less often, due to the insufficient communication quality, whereby they stop negotiating as soon as they make a decision for a quicker non-cooperative maneuver, however, on the cost of stronger fluctuations of the traffic velocity. This effect becomes even more obvious in the 10-0 % MDR zone (0/3 SC). Summarizing, in the direct comparison between 100 % (best-case) and 0 % (worst-case) MDR, $\overline{v}$ decreases from 96.6 km/h to 95.7 km/h, as well as σ_{v} increases from 2.8 km/h to 5.4 km/h, indicating a degradation of the traffic quality.

In contrast to the Joint, the Core SuT demonstrates unrealistically high $\overline{v}$ (99.2 km/h) and low σ_{v} (0.6 km/h) values of the traffic velocity, which is reasoned by the idealized implementation of the associated MC algorithm, acting as a baseline. Therefore, despite being technically correct, these simulation results represent an overly optimistic estimation of the impact on traffic quality.

Spatiotemporal Pattern

Figure 5.11 visualizes the identic data from all 1 and 11 simulation runs, for the Core (diagram in the upper left corner) and the Joint (all the other diagrams) MC SuTs as presented before. The resulting visualization is given here in the form of spatiotemporal patterns, including the related MDR and SC, with tuples of individual values for each merging maneuver specified in brackets. Hereby, 1 means a successful and 0 means a non-successful cooperation.

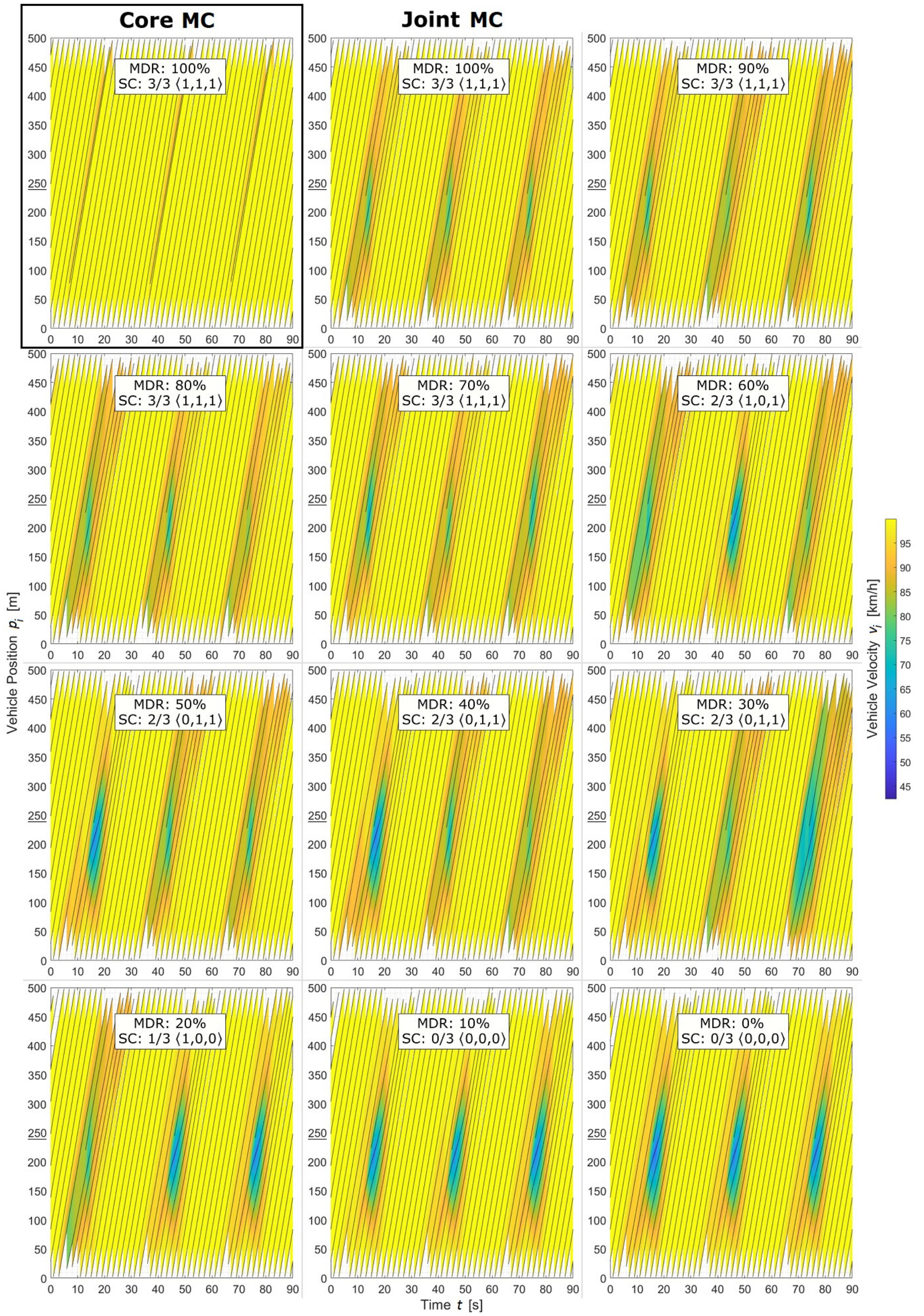


Figure 5.11: Results of the 2nd study – spatiotemporal patterns with MDR and SC

Basically, every highway merging causes a small shockwave in the traffic flow (compare with Figure 5.3), which differs in depth and size, depending on the success of a cooperative maneuver and its duration. Here, in case of successful cooperations, one can observe that the traffic velocity varies less, whereby the merging itself takes longer time than in case of non-successful cooperations. This supports the argumentation rendered by the previous metrics of the traffic density-velocity-flow. For instance, with 100 % MDR and 3/3 SC, the spatiotemporal pattern displays smooth shockwaves, due to a weaker deceleration of the vehicles for each maneuver, resulting in higher $\overline{v}$ and lower σ_{v}; whereas with 0 % MDR and 0/3 SC, the spatiotemporal pattern displays rough shockwaves, due to a stronger deceleration of the vehicles for each maneuver, resulting in lower $\overline{v}$ and higher σ_{v}.

The outcome of the 2nd study demonstrates that the cooperative MC can positively affect the traffic quality only under premise of a sufficient communication quality (i.e., with MDR of 100-70 %). If a high communication quality cannot be guaranteed in practice, an increase of the planning horizon and the generation cycle frequency for the trajectories, as well as an introduction of additional reliability mechanisms should potentially improve the robustness of the corresponding cooperative driving functions.

Apart from the test results, the performed evaluation could demonstrate the capability of the methodology with the intelligent co-simulation framework for a comparison of several cooperative MC approaches (Core and Joint) under variable conditions (i.e., imperfect V2X communication).

5.3 Summary

This section presented the evaluation of the co-simulation outcome in the scope of two studies – Effects on Traffic Quality and Effects of Imperfect Communication – applied on interchangeable SuTs for the cooperative driving function F1 (merging on highways), including the definition of metrics and scenarios, as well as the actual test results.

In the process, the static variation of the major scenarios was conducted through an adjustment of the relevant parameters and arguments, according to the evaluation goals; whereas the dynamic variation of the minor scenarios was achieved through their detection in the major scenarios by the intelligent co-simulation framework, as already addressed by the RQ I. The evaluation of the major scenarios, which is discussed in this section, can be primarily used for the validation of the cooperative driving functions, in order to test and to compare their functionality, as required by the RQ II, denoting the transferability of the proposed methodology on different scenarios with different SuTs. Finally, the findings of this section significantly contribute to the RQ III, since they offer solutions on how to evaluate the effects of MC on the traffic quality, with promising results (e.g., reduction of traffic density by 5 % and increase of traffic velocity by 7 %, according to the 1st study).

6 Experimental Realization

In this section, the experimental realization of the methodology for verification and validation of cooperative driving functions with intelligent co-simulation framework will be discussed. This includes the information about the concept in general and a newly developed method called Remote-Adaptable Prototype-in-the-Loop (RA-PiL) in particular, which was exemplarily put into practice on a Real Test Vehicle (RTV) during the work on this dissertation in the scope of the IMAGinE project.

This section is based inter alia on the author's publication [AmE], as well as the patent application Mspa.4. The approach described in [AmE] for vehicle testing in the mixed reality was further significantly enhanced, compared to the state of the art in the literature (see Subchapter 2.3), leading to the invention of RA-PiL method. After filing of RA-PiL as Mspa.4, the method was disclosed to the public at the IMAGinE final event [1] with the presentation Mip.1 (refer to Submitted Patent Applications and Invited Presentations in Miscellaneous).

6.1 Concept

First of all, this concept requires an additional symbolic convention regarding the vehicles that can be involved into the simulation of the cooperative driving. According to the idea of mixed reality (see Subchapter 2.3), the involved vehicles can exist in real and virtual (simulated) worlds, thus, differing in NoA and LoD. The corresponding convention is illustrated in Figure 6.1 with a real vehicle **A** (i.e., RTV), virtual subject-vehicles **B**, **C** and virtual object-vehicles **a**, **b**, **c** of the traffic flow. Hereby, the real vehicle and the

[1] imagine-online.de/en/news-events/final-event-agenda-1.html

virtual subject-vehicles are fully interactive, being equipped with the cooperative driving functions, whereas the virtual object-vehicles are only partially interactive and controlled by the simulation software.

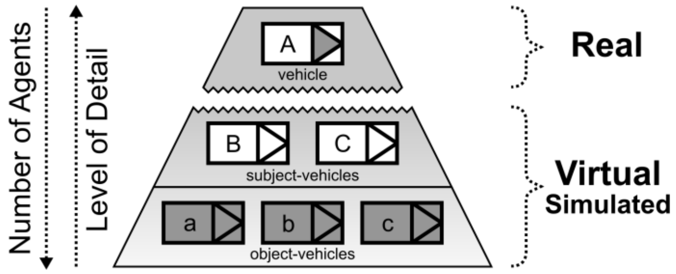


Figure 6.1: Symbolic convention for the experimental realization

In order to test the cooperative driving functions on the real road (for this experimental realization, a proving ground) in the context of mixed reality, a novel concept to couple the real and virtual worlds was elaborated. Originating on the purely virtual co-simulation approach of the vehicle dynamics with CarMaker and the traffic flow with SUMO, which was discussed in the previous sections of this dissertation, the idea here is to replace at least one virtual subject-vehicle by a suitable real vehicle counterpart. At the same time, this real vehicle will be mirrored into the simulation environment as a digital twin (i.e., a vehicle model placed into the virtual world with the same position and orientation as in the real world), therefore, making it able to interact and, eventually, to cooperate with the virtual subject-vehicles in a scenario.

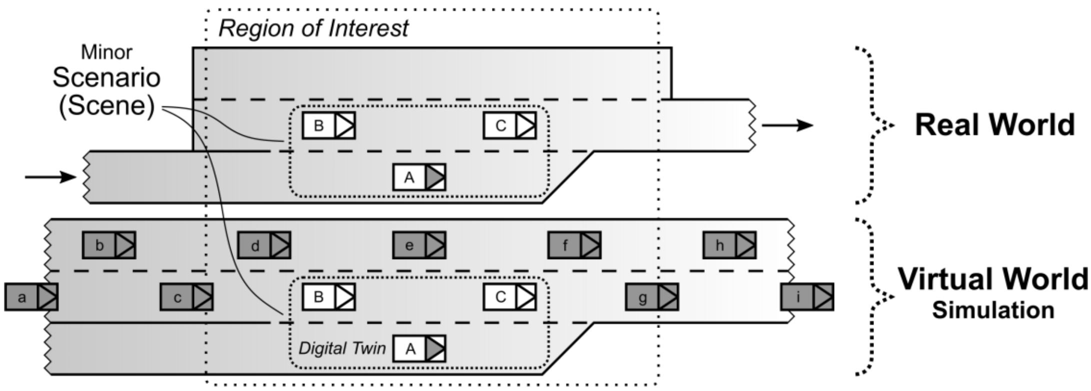


Figure 6.2: Coupling of real and virtual worlds for the experimental realization

The coupling concept of the real and virtual worlds, with the vehicle symbols as previously introduced in Figure 6.1, is depicted in Figure 6.2. An associated guideline with the activities, needed for the realization of this coupling with the intelligent co-simulation framework, will be explained next.

In this concept, the real vehicle **A** (i.e., RTV) is driving on the road of a confined test track in the real world. Simultaneously, numerous object-vehicles (low LoD) are simulated within a major scenario on the road of the virtual world (e.g., a full-scale highway model), which can be larger than the actual test track. Hereby, the simulation environment acquires the location of the real vehicle and places it into the virtual world as a digital twin. As soon as **A** enters a certain RoI (i.e., a highway entrance), OVERWATCH of the intelligent co-simulation framework detects a scene through the selection of potential cooperation partners **B** and **C** among the object-vehicles, which are then simulated as subject-vehicles (high LoD), equipped with the cooperative driving functions. Hereby, the virtual subject-vehicles become perceivable by the real vehicle (and vice-versa) in the real world, for instance via the V2X communication, allowing for a comprehensive interaction between them.

This way, a corresponding minor scenario is started, in which the vehicles **A**, **B**, **C** can communicate, negotiate and execute a cooperative maneuver. Eventually, after the maneuver is finished and the real vehicle leaves the RoI, the minor scenario ends, whereby the virtual subject-vehicles are converted back to object-vehicles. Within the major scenario, the simulation of the traffic flow continues uninterruptedly, thus, the real vehicle can return to its initial location and re-enter the RoI, repeating the procedure of the automatic minor scenario generation at any time.

Conclusively, for the realization of this concept, one must undertake following activities:

1) Define a map (incl. information about the traffic flow) congruent to the real-world test track, location- and dimension-wise in a certain RoI, which acts as a groundwork for the major scenario.
2) Specify rules for the creation of snapshots, which will be detected as relevant scenes and utilized to generate the minor scenarios of the cooperative driving, by training a ML classifier in OVERWATCH.
3) Activate the intelligent co-simulation framework, thus, starting a simulation of the traffic flow on the virtual road. Also, establish a connection with the RTV, in order to acquire its location for a placement of the digital twin.

4) Deploy the RTV on the proving ground and perform a test drive. Hereby, as long as the RTV traverses RoI, as well as once OVERWATCH likely detects a scene with its presence in the vicinity of the virtual object-vehicles, a co-simulation of the corresponding minor scenario will be running. At the same time, the involved virtual object-vehicles will be promoted to virtual subject-vehicles, able to interact with the RTV and engage in the cooperation. This activity can be serially repeated.
5) After a test drive is finished, assess the data that was collected in the process with appropriate metrics. As an outcome, this will determine the pass or fail result of the test.

The resulting guideline with the activities 1 to 5 is shown Figure 6.3, which complements the original methodology idea from Figure 1.3 of Chapter 1.2. Hereby, the exact substance of these activities arises from the answers to the RQs I, II, III. More precisely, these questions deliver the solutions on what scenarios to prepare, on how to simulate, as well as on what metrics to apply, respectively.

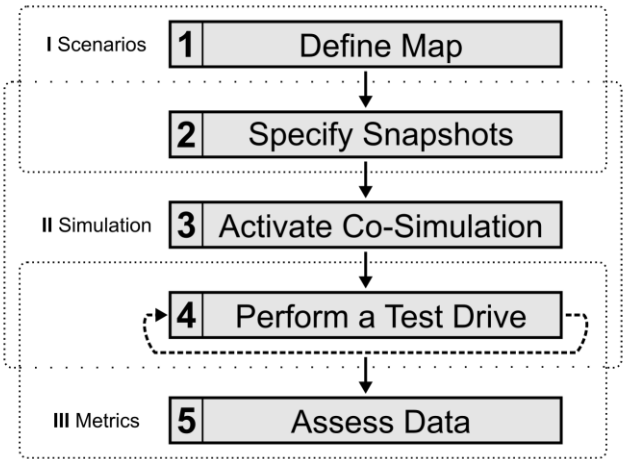


Figure 6.3: Guideline for the experimental realization

On the one hand, the results of each test drive in particular (i.e., minor *small-scale short-term* scenarios) can be used for the verification of a cooperative driving function, regarding its driving performance, comfort, robustness and other aspects. On the other hand, the results of all test drives in total (i.e., major *large-scale long-term* scenario) can be used for the validation of a cooperative driving function, regarding its impact on the traffic quality.

During the whole process, the co-simulation can run on a computer inside or outside of the RTV, depending on the provided wired or wireless communication, respectively. Hereby, the driver of the RTV can be involved into the simulated happening with the aid of a visual display.

In addition, Appendix of the work at hand contains supplementary materials for the concept described here. Figure A.1 shows a RTV build, Figure A.2 shows a conceptual animation and Figure A.3 shows a software activity diagram (implemented in the intelligent co-simulation framework) for the experimental realization of this approach, which will be demonstrated in the next section as RA-PiL.

6.2 Remote-Adaptable Prototype-in-the-Loop

This method acts as an extension for the already existing PiL method [56] [57], specifically developed and put into practice for testing purposes of the cooperative driving functions, in the scope of this dissertation during the work on the project IMAGinE. Hereby, Remote means that the interaction between the RTV and the simulation is realized via a physical V2X communication from Chapter 2, whereas Adaptable means that the control of the simulation (i.e., detection, generation, evaluation of the stochastic scenarios) is realized with the aid of a trainable artificial intelligence from Chapter 4.

Since the whole RTV is incorporated into the virtual environment here, the proposed method can be regarded as an early stage of ViL in the V-model (see Figure 2.6), with a certain shift in the evaluation task to a prevalence of the prototypical SuT in particular (incl. hardware and software) over the vehicle in general (incl. driving dynamics). For another noteworthy realization of the ViL method in the course of the IMAGinE project, with a focus on highly reproducible simulation of deterministic scenarios, which was achieved by means of a specialized ViL product solution for CarMaker [1], refer to [142] [143].

In the following, the experimental realization of the RA-PiL method will be demonstrated on one exemplary test drive, according to the typical use-case of the cooperative driving

[1] ipg-automotive.com/en/products-solutions/test-systems/vehicle-in-the-loop

function F1 (see Figure 4.1) – the cooperative merging on highways. The corresponding logical scenario with the involved vehicles **A**, **B**, **C** (one real, two virtual) on a proving ground is illustrated in Figure 6.4.

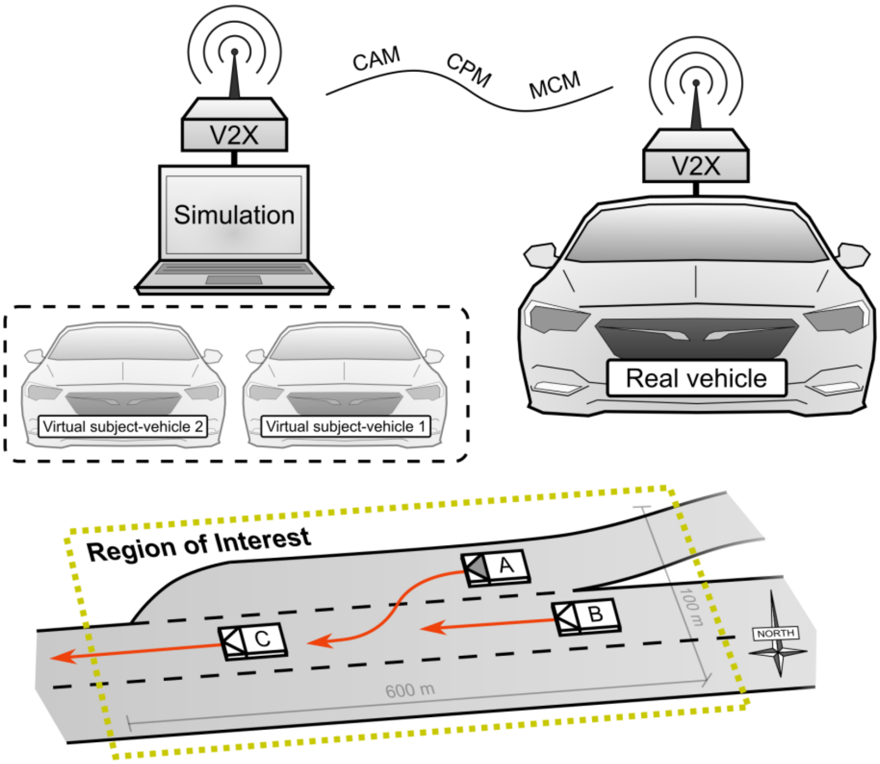


Figure 6.4: Logical scenario with involved vehicles for the RA-PiL method

In this test, the virtual subject-vehicles **1** and **2** are simulated by the intelligent co-simulation framework on a portable computer, which can be optionally placed inside of the RTV or elsewhere outside (for instance, in a remote simulation office). This computer is able to exchange messages (CAM, CPM, MCM) with the real vehicle through the utilization of an industrial V2X communication transceiver WAVEBEE [1]. Hereby, all involved vehicles (real and virtual) are equipped with complete SuTs from the IMAGinE project, featuring a prototypical implementation of the Joint MC algorithm [34].

As previously described by the concept in Subchapter 6.1, apart from the virtual subject-vehicles **1** and **2** with low NoA and high LoD, the computer with the intelligent co-

[1] keysight.com/us/en/products/wireless-network-emulators/wavebee-v2x-test-and-emulation

simulation framework is also responsible for the simulation of the surrounding virtual object-vehicles with high NoA and low LoD as a passive traffic. During a test drive, once the RTV enters the RoI, OVERWATCH generates a suitable scenario with the associated virtual subject-vehicles, which are expected to actively participate on the cooperation.

Conclusively, as shown in Figure 6.4, the vehicles in the scenario will be allocated for the upcoming demonstration as follows:

- **A** (requesting) – real vehicle (manually driven)
- **B** (offering) – virtual subject-vehicle **1** (automated)
- **C** (offering) – virtual subject-vehicle **2** (automated)

6.2.1 Hardware and Software Setup

The RA-PiL method requires a hardware and software setup that consists of two fundamental parts, each operated by one person: the simulation office with the intelligent co-simulation framework (incl. computer, transceiver, antenna) and the RTV, represented here by one of the Opel Insignia prototypes from the IMAGinE project. The test drive itself is performed on a highway emulation track of TRIWO [1] test center in Pferdsfeld, Germany. In order to ensure a sufficient remote connection between the simulation office and the RTV, a generic V2X repeater is installed on the proving ground.

Figure 6.5 showcases the described setup as photos, as well as the relevant extract of the OPENSTREETMAP with marked segments of the test track. These segments were used for testing of the cooperative driving functions F1 and F5, as they were established in the course of the IMAGinE project.

With this setup, the RTV can communicate with the simulation office, thus, forwarding its location and dynamic information to the simulation environment. This functionality is carried out by the PiL interface of the intelligent co-simulation framework, which extracts the CAM data received from the RTV via the V2X communication (with a frequency of 10 Hz) and transfers it to the traffic flow simulator SUMO (during the major scenario). Then, this data is used to replicate an associated digital twin of the RTV in the vehicle dynamics simulator CARMAKER (during the minor scenario).

[1] triwo-testcenter.de/en/tracks

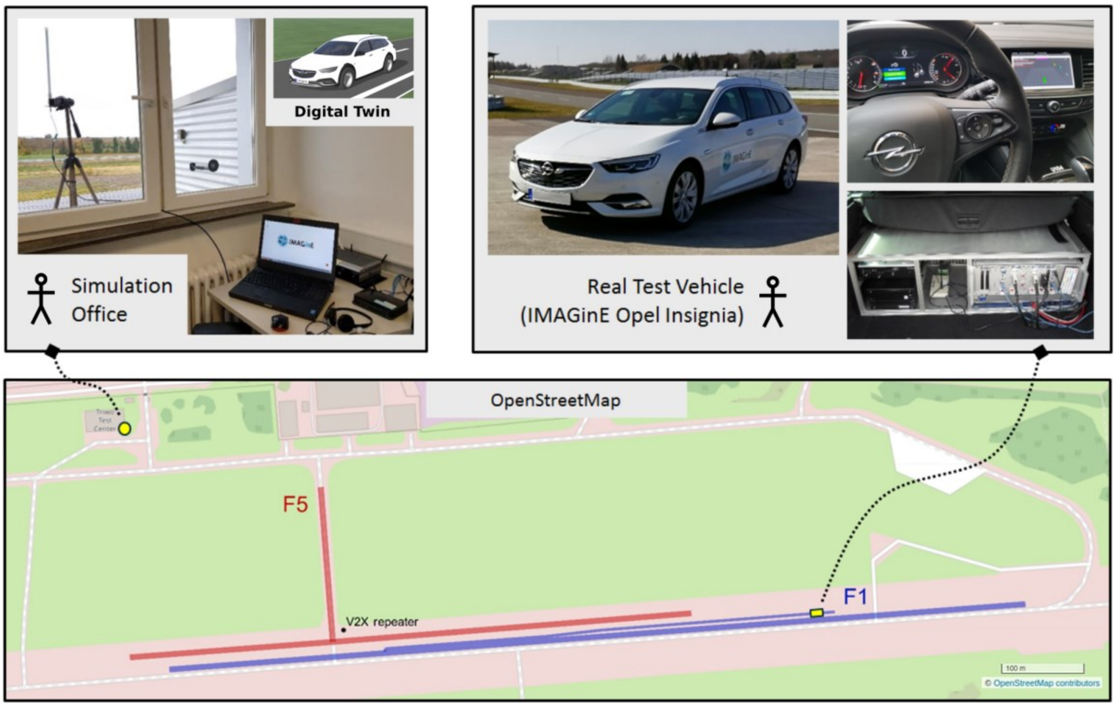


Figure 6.5: Setup on the proving ground for the RA-PiL method

The corresponding architecture of the RA-PiL method is displayed in Figure 6.6. On the left side, the simulation office reveals the intelligent co-simulation framework with the PiL interface, coupled simulation of SUMO and CarMaker (incl. OverWatch in-between), as well as ROS, which is exchanging data with the V2X hardware. On the right side, the RTV equally reveals the V2X hardware and ROS, which is further linked to the HMI, perception and localization applications within the vehicle. The tasks of these applications are achieved through an access to the vehicle's standard camera, radar and other sensors via the Controller Area Network (CAN) bus, as well as a supplementary high-precision Global Navigation Satellite System (GNSS) device, which is mainly using the differential Global Positioning System (GPS) information, supported by the inertia and odometry data of the vehicle.

On both sides, the V2X hardware (i.e., transceiver WaveBEE) allows for a bidirectional communication between the simulation office and the RTV, thus, forming a closed feedback loop of interaction between their cooperative driving functions within ROS. It also supports a multi-stack communication, enabling the transmission and reception of the V2X messages to and from multiple simulation instances in parallel.

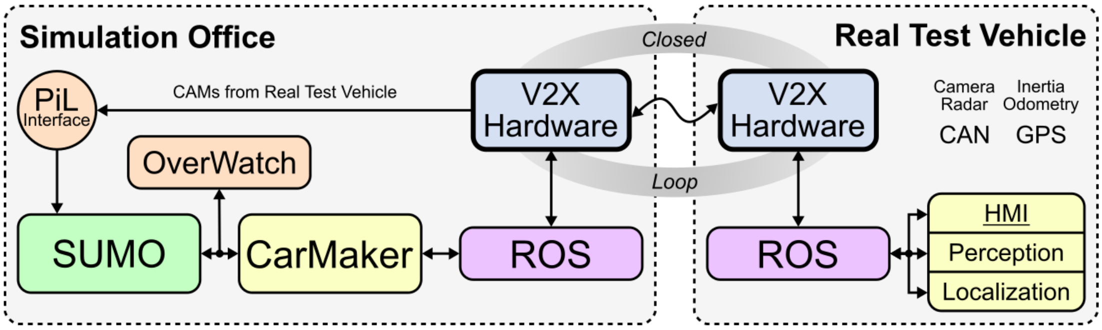


Figure 6.6: Architecture of the RA-PiL method

This way, the RTV is placed into the SUMO environment. As long as the real vehicle is situated in RoI, the trained OVERWATCH may detect in the stochastic traffic flow two virtual object-vehicles as potential cooperation partners, launching a coupled simulation with two additional instances of virtual subject-vehicles in CARMAKER, as well as the corresponding MC algorithms in ROS. In consequence, the SuT of the real vehicle on the proving ground will be able to remotely interact and to cooperate with the SuTs of the virtual subject-vehicles from the simulation.

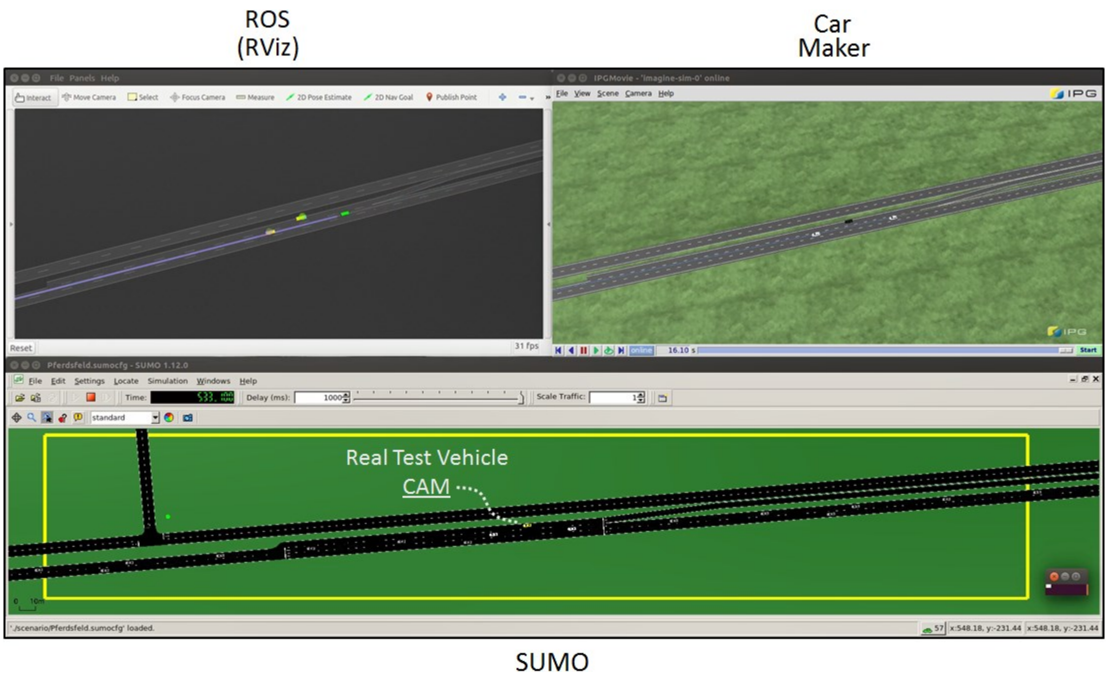


Figure 6.7: Intelligent co-simulation framework for the RA-PiL method

The resulting mixed reality environment of SUMO, CARMAKER and ROS within the intelligent co-simulation framework for the RA-PiL method, fed by the CAMs from the RTV, is exemplarily visualized with the respective GUIs in Figure 6.7. Here, 3 cooperative vehicles (real and virtual) are highlighted among the traffic flow of SUMO, which are then processed in CARMAKER and ROS with a high LoD and enabled MC algorithms. The associated RoI is displayed in SUMO as a yellow rectangular zone.

The synthetic map of the proving ground, utilized within the co-simulation as illustrated in Figure 6.7, was created by the IMAGinE project partners for CARMAKER and ROS, which was then converted (through OPENDRIVE as an intermediate map format) with the NETCONVERT [1] tool to SUMO for the application in RA-PiL method. During the co-simulation, all needed transformations between the real and virtual world coordinates are conducted by the GEOGRAPHICLIB [2].

The intelligent co-simulation framework can be operated in two modes: open-loop and closed-loop. At first, over the course of preparations for the experimental realization of RA-PiL, the simulation is supplied with a pre-recorded CAM data from previous test drives, meaning that the real vehicle shows no reaction to the virtual subject-vehicles (i.e., open-loop mode). In this step, if necessary, the scene detection accuracy of OVERWATCH can be adapted by an additional training. Later, when the RTV is deployed on the proving ground to perform new test drives, the simulation can directly communicate with it, enabling a full interaction between the real vehicle and the virtual subject-vehicles in real-time (i.e., closed-loop mode).

6.2.2 Computational Performance Optimization

In order to ensure a proper interaction between the real and virtual vehicles for the RA-PiL method, an important prerequisite is posed by the real-time capability of the intelligent co-simulation framework. This means, the simulated time in the virtual world must be able to proceed at least as fast as the time in the real world. However, since the co-simulation constitutes an interaction of several independent software tools, due to the overhead of data exchange between them, this approach inevitably leads to drawbacks in the computational performance (i.e., simulation speed). During the development of the intelligent co-simulation framework, as stated in Chapters 4 and 5, the average speed of

[1] sumo.dlr.de/docs/netconvert.html
[2] geographiclib.sourceforge.io

the coupled SUMO-CARMAKER simulation was originally only 0.1 real-time, running on a regular commercial portable workstation (see requirements in Subchapter 3.1 for the development platform specification).

In the process of the co-simulation, the computational performance is mainly biased by the number of object-vehicles and subject-vehicles that must be synchronized between the simulation environments, as well as by the corresponding synchronization frequency. For the sake of performance improvement, as already described in Subchapter 4.2, a limitation to synchronize the object-vehicles from the traffic flow only in certain proximity areas around the subject-vehicles was implemented. Furthermore, the software code responsible for the simulator coupling was thoroughly refactored.

In addition, an empirical technique for estimation of an optimal synchronization frequency was elaborated, in order to address the antagonism between the temporal delay of the co-simulation time step and the spatial mismatch among the co-simulated vehicle models. Hereby, the temporal delay stands for a span of real time needed to calculate one simulation step, whereas the spatial mismatch stands for a discrepancy of the vehicle model locations between the simulation environments of SUMO and CARMAKER during one synchronization cycle, which can contain from one to multiple simulation steps.

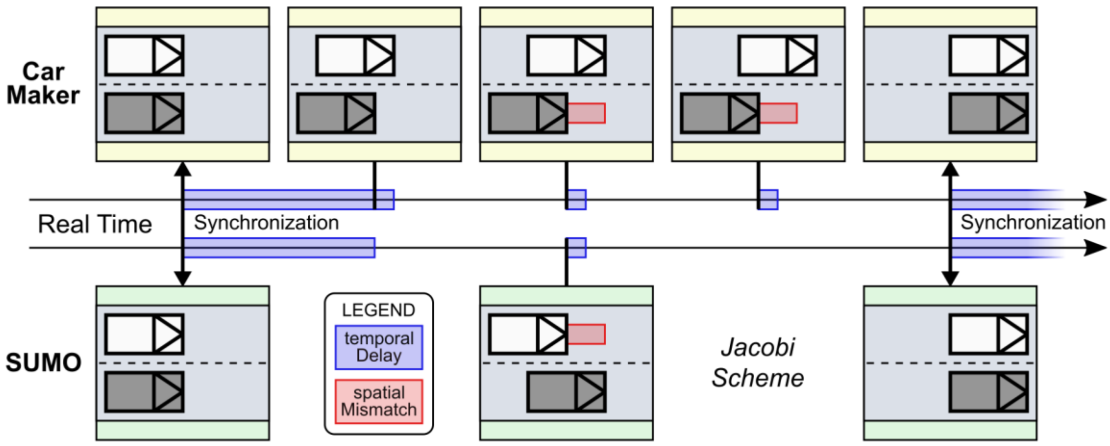


Figure 6.8: Co-simulation with temporal delay and spatial mismatch

The principle of how a temporal delay and a spatial mismatch emerge over the course of the co-simulation will be explained with the aid of Figure 6.8. In this illustration, CARMAKER, which is simulating the subject-vehicle (white), has a smaller step size than

SUMO, which is simulating the object-vehicle (gray). According to the Jacobi scheme (refer to [121] [122] [123]), in which the SUMO-CarMaker coupling is implemented here, both simulators are running in parallel, being synchronized simultaneously and bidirectionally with a certain cycle frequency. Thereby, during the synchronization, the temporal delay can be especially large, yet in average, it can be compensated by the successive ordinary simulation steps with smaller delays. Meanwhile, since SUMO and CarMaker are not exchanging data between the synchronization cycles, the locations of the affected vehicles begin to deviate between the simulation environments, causing a spatial mismatch.

Consequently, a higher synchronization frequency leads to a smaller spatial mismatch on the one hand, but a larger temporal delay on the other hand (and vice-versa). The spatial mismatch can also be potentially reduced through an implementation of other co-simulation schemes (e.g., Gauss-Seidel [121] [122] [123]) with auxiliary interpolation or extrapolation procedures, however, on further costs of the computational complexity, thus, eventually producing more temporal delay and diminishing the real-time capability.

To improve the computational performance with this setup, the following simple empiric technique can be applied. For this, one must define maximal tolerable values limits: for the temporal delay (e.g., 0.001 s), which is reasoned here by the recommended virtual time step size of CarMaker simulation that should not be exceeded to achieve real-time; as well as for the spatial mismatch (e.g., 1 m), which can be freely chosen with respect to the acceptable discrepancy of the vehicle model locations between the synchronization cycles. In addition, one must also define minimal value limits (e.g., 0 for both quantities). Then, the temporal delay and the spatial mismatch must be measured on several simulation runs of a desired RA-PiL scenario (as average values), in dependence on the variable synchronization frequency. The measurement should be done on the simulator with the smaller step size, in this case CarMaker (refer to Table 5.1 from Chapter 5), since its runtime is more critical for an upkeep of the real-time condition. Eventually, an intersection of the measured data can deliver an approximation for the optimal value of the synchronization frequency (e.g., 20 Hz).

The described technique is depicted as a diagram in Figure 6.9. Here, the measurement curves for the temporal delay and the spatial mismatch are denoted in blue and red colors, related to the right and left vertical axis, respectively. The corresponding synchronization frequency is related to the horizontal axis. With this groundwork, the defined maximal and minimal value limits for the temporal delay and the spatial mismatch must be aligned to the same vertical levels. This way, the intersection point of both measurement curves can deliver an approximate value for the optimal synchronization frequency, with the resulting in-between and, thus, tolerable values for the spatial mismatch and the temporal delay.

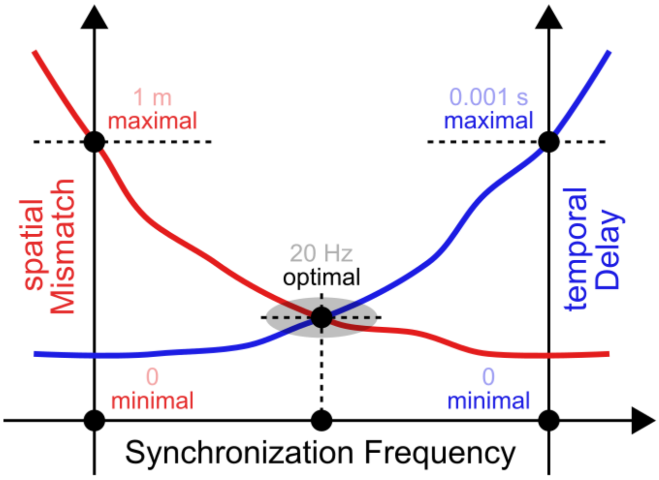


Figure 6.9: Empirical technique for finding of an optimal synchronization frequency

By virtue of all performance optimization activities mentioned before, the simulation speed of the intelligent co-simulation framework (originally 0.1 real-time) could hereafter steadily reach 1 real-time. To be noted, the experimental realization of the RA-PiL method is fulfilled with a soft real-time [89], meaning that the simulation is required to process just fast enough to provide the real-time capability, without additional synchronization mechanisms.

6.2.3 Human-Machine Interface

To demonstrate the benefit of the RA-PiL method on a viable application, the following description will focus on the HMI-support software (developed as a ROS node), which was designed and implemented in the scope of this dissertation. The objective of this software is to administer the information from an implicit cooperation process with the intention-based MC (refer to Subchapters 2.2 and 3.2 for details) of the Joint approach and, thus, to support the HMI with explicit notifications and instructions for the driver of the RTV, which are then displayed as graphical elements on the instrument panel cluster inside the vehicle. Hence, for instance, RA-PiL can be used to test the functionality of the HMI-support in the real vehicle, which should adequately react to the interaction with the virtual subject-vehicles.

A generic technique of how HMI-support recognizes a cooperation being granted (i.e., successful) or denied (i.e., non-successful) is shown in Figure 6.10 and will be explained on an example with two vehicles (requesting and offering) next.

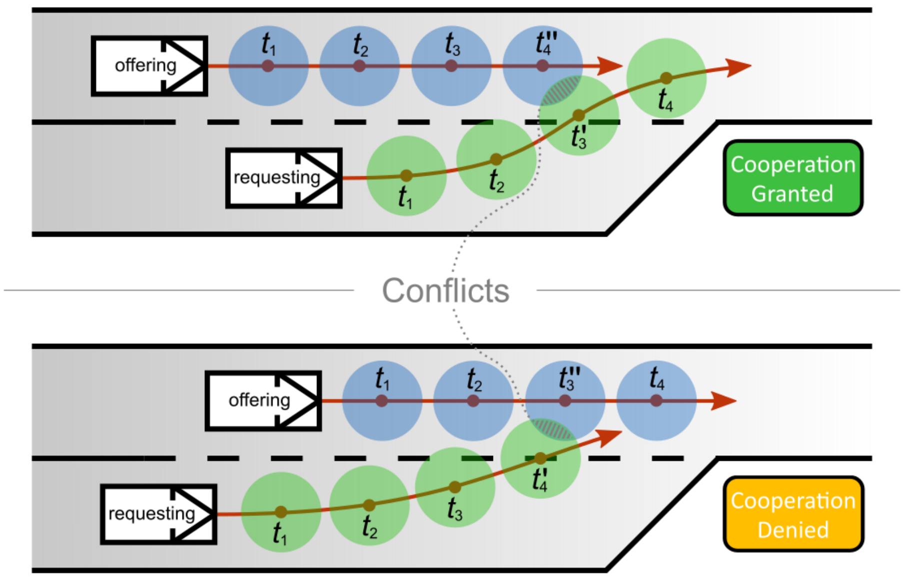


Figure 6.10: Recognition of a granted or denied cooperation with HMI-support

The HMI-support scans reference trajectories of both vehicles in temporally equidistant steps and searches for conflicts in a particular cooperation area (e.g., highway entrance) with a certain spatial margin. When a conflict is found, the corresponding time values of the trajectories are compared with each other. In the example of Figure 6.10, t' denotes the predicted conflict time for the requesting vehicle, as well as t'' for the offering vehicle. This information is then used by the HMI-support to release the corresponding triggers for driver notifications and instructions. Hereby, two essential cases can be distinguished, indicating different conditions of the cooperation:

- $t' < t''$ – ‘cooperation granted’
- $t' \geq t''$ – ‘cooperation denied’

This means, 'cooperation granted' entails a collision-free maneuver, where the requesting vehicle intends to pass through the cooperation area earlier than the offering vehicle, resulting in a granted cooperation. Contrary to this, 'cooperation denied' specifies that the requesting vehicle intends to pass through the cooperation area after the offering vehicle, what consequently results in a denied cooperation. Furthermore, a special case of 'cooperation denied' with $t' = t''$ implies a conflict with a potential collision that requires a prompt resolution by means of the MC algorithm (as depicted in Figure 3.2).

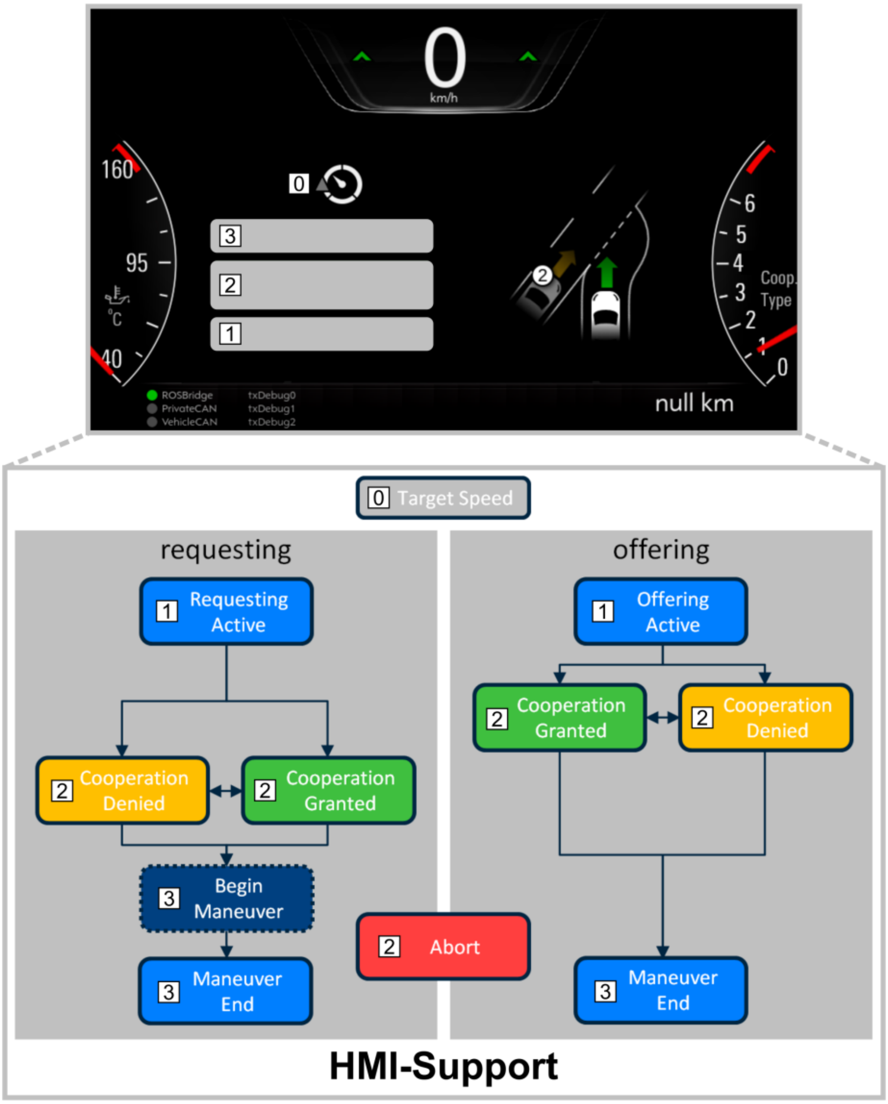


Figure 6.11: Graphical elements of the driver information with HMI-support triggers

This way, an implicit circumstance of the trajectory conflict is converted into an explicit statement about the granted or otherwise denied cooperation, which can be used as a driver notification. The described technique is universally applicable in various cooperative driving functions, specifically such as F1 and F5.

Apart from the recognition of cooperation, the HMI-support delivers a target speed, which is extracted from the trajectory data of the MC algorithm, as well as other instructions for the driver, which are triggered by several events, in dependence on the vehicle role in the scenario (i.e., requesting or offering). In total, the HMI-support is structured as a state machine that triggers the appearance of the associated graphical elements on the instrument panel cluster, which are presented in Figure 6.11 for the F1 function (links between triggers and graphical elements are denoted with framed digits).

For a better comprehension of the SuT status while driving, in addition to the notifications and instructions in the instrument panel cluster, the driver of the RTV is informed about the current situation in the virtual environment (incl. simulated vehicles), which is visualized as a mixed reality on the screen of the infotainment system (see example in Figure 2.9). A preliminary implementation of the corresponding visualization software is further described in [AmE].

6.2.4 Demonstration

For the demonstration of the RA-PiL method, a series of test drives (as multiple minor scenarios in a single major scenario) for the cooperative driving function F1 were performed, with vehicle **A** being the RTV, according to the arrangement from Figure 6.4. At the same time, the intelligent co-simulation framework was operated in a closed-loop mode, allowing for a full interaction between the real vehicle and the virtual subject-vehicles via the V2X communication. As an outcome, an assessment of the data generated by the SuT of the RTV from one exemplary test drive, which was recorded within ROS in a ROSBAG [1] format, will be presented in this section.

Figure 6.12 shows the corresponding data assessment results, targeted here on the examination of a correct HMI-support triggers occurrence. It displays positions of the vehicles **A**, **B**, **C** in the easting and northing Universal Transverse Mercator (UTM) coordinates as a horizontal diagram, as well as their respective velocity profiles over time

[1] wiki.ros.org/rosbag

as a vertical diagram. The associated HMI-support triggers, which were registered within the SuT of the real vehicle **A**, are indicated in the intermediate zone. The horizontal and vertical diagrams, as well as the HMI-support triggers, are connected with dotted lines, denoting a simultaneity of the related events. In the horizontal diagram, with the driving direction from north-east to south-west, the moving positions of the vehicles form a triangular pattern, which is typical for a highway merging (refer to Chapter 4). In the vertical diagram, the velocities of the vehicles are used to mark the cooperation process, when the gap for the merge-in is created.

The recorded scenario starts at 15 s and ends at 52 s. In all vehicles, the cooperative driving function F1 is activated and the driving set speed is configured to 13.9 m/s (50 km/h). Thereby, the real vehicle is manually controlled by a human driver in accordance to the notification and instructions on the HMI, as well as the virtual subject-vehicles are simulated as automated.

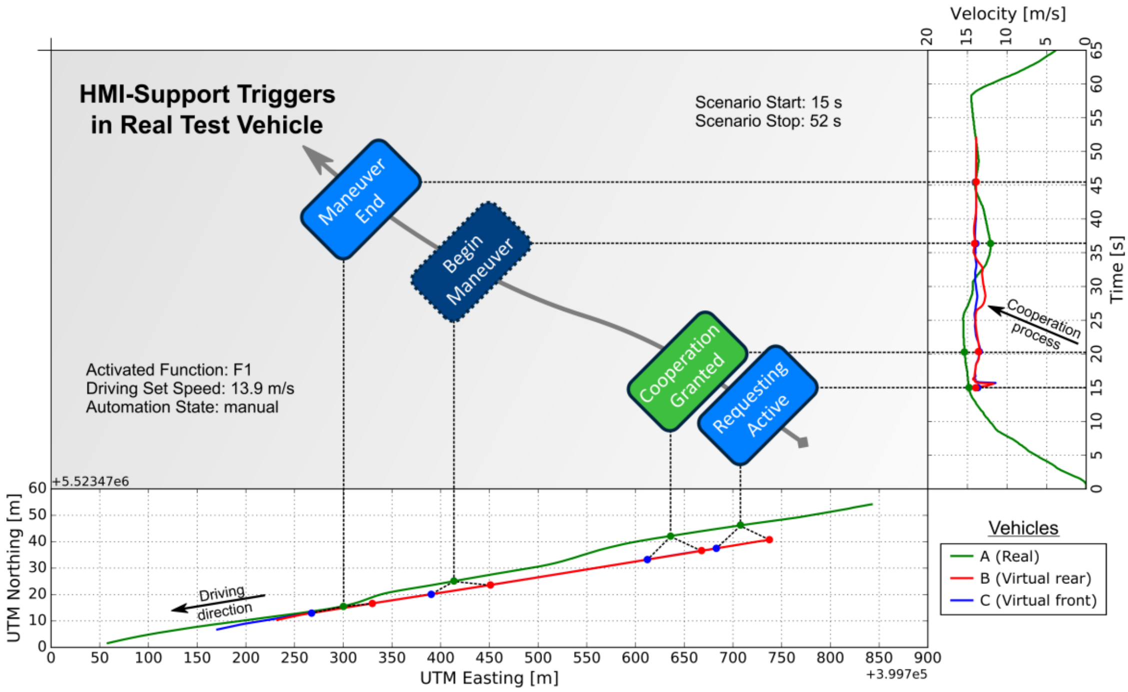


Figure 6.12: Assessment of the recorded data with HMI-support triggers

As one can observe here, at 15 s, both virtual subject-vehicles **B**, **C** that are detected in the RoI by OVERWATCH appear in the mixed reality, what results in a minor scenario start and a notification ‘requesting active’. At 20 s, as soon as all vehicles **A**, **B**, **C** approach the highway entrance, the trajectory analysis of the HMI-support delivers an information about a foreseeably successful cooperation, what results in a notification ‘cooperation granted’. Between 26 s and 34 s, the rear virtual subject-vehicle **B** distinctly decelerates (by approximately 2 m/s), in order to increase the gap for the merge-in of the real vehicle **A**. At 36 s, the trajectory analysis of HMI-support delivers an information that the real vehicle **A** can begin with the merge-in, what results in an instruction ‘begin maneuver’. At 45 s, the merge-in is initiated and quickly completed by the driver of the real vehicle **A**, what results in a notification ‘maneuver end’. At 52 s, the real vehicle **A** leaves the RoI, so that the minor scenario stops and the virtual subject-vehicles **B**, **C** disappear.

In conclusion, this test drive demonstrates a successful cooperation between the real and virtual vehicles by means of the MC in conformity with the RA-PiL method, whereby the RTV was controlled by a human driver. Also, it vividly verifies a correct functionality of the SuT, including the driver notifications and instructions being properly triggered by the HMI-support software.

In this context, Figure 6.13 (at the end of this section) reveals a momentary visualization of the recorded data as an environment model from the perspective of the RTV **A**. Besides images from the HMI (bottom left) and a dashboard camera (bottom right), this visualization portrays the road, the movable entities (i.e., real and virtual vehicles) and the trajectories that exist in the mixed reality environment of ROS. At this point, one can monitor the real vehicle **A** and the virtual subject-vehicles **B**, **C** that exchange information via the V2X communication about their locations through CAMs, as well as the trajectories through MCMs. To be noted, the virtual vehicles are only visible in the mixed reality and obviously not present in the raw camera image of the real world.

Furthermore, one virtual object-vehicle from the traffic flow (overtaking on the farthest left lane), which is not directly involved into the cooperation process, is perceived by **A** through CPMs of **B** and **C**. Originating from SUMO, this virtual object-vehicle is present in the coupled simulation environment of CarMaker, where the virtual subject-vehicles **B** and **C** can perceive it with their sensor models (refer to [144] [1] for details about the cooperative environment model in IMAGinE). This means that **A** can also perceive the virtual object-vehicles from the co-simulation via the V2X communication. Although the cooperative driving function of the RTV cannot interact with the virtual object-vehicles though the MC, however, it can observe and avoid them as moving obstacles on the road.

[1] imagine-online.de/en/findings-publications

This demonstration points out the ability of the RA-PiL method to act as a platform for testing of the cooperative driving functions in the context of mixed reality, given a limited number of RTV prototypes (in this case, one) on a limited territory of a proving ground, on the one hand, with virtually unlimited capabilities of the simulation, concerning the imitation of an artificial traffic flow on an artificial road, on the other hand. Hereby, the relevant scenarios are automatically generated by the intelligent co-simulation framework, considering the movement of RTV on the test track as a part of an adaptable workflow. Besides that, due to the utilization of a remote communication between the simulation and the SuT, the testing routines can be considerably streamlined. By means of the V2X communication, if necessary, additional RTVs can be incorporated into the same test drives at the same time. In prospect, this can be useful for testing of their interaction within the resulting common mixed reality, in the scope of even more complex scenarios of the cooperative driving.

6.3 Summary

This section highlighted the experimental realization of the methodology as a concept in general and as the RA-PiL method in particular, including several topics, such as the hardware and software setup, the performance optimization, the HMI, as well as the actual demonstration of the recorded data from an exemplary test drive. Hereby, a full interaction between the real and virtual vehicles in the context of mixed reality was achieved with the cooperative driving function F1 (merging on highways), which was verified through an assessment of the associated HMI-support triggers in one illustrative minor scenario.

The content of this section unites the previously elaborated answers to the RQs I and III, in respect to the detection, generation and evaluation of the scenarios with the intelligent co-simulation framework. It also introduces the RA-PiL method as an answer to the RQ II. Eventually, all the corresponding findings were brought together for the purpose to test the functionality of the cooperative MC, which was expressed in a guideline of activities (refer to Figure 6.3), leading to the experimental realization of the methodology proposed by this dissertation.

Figure 6.13: Visualization of an exemplary test drive with the RA-PiL method

7 Conclusion

After the experimental realization of the methodology, this dissertation will be concluded with a brief review of its content, followed by a contribution regarding the RQs, a discussion of the selected key solutions along with the overall rating, as well as an outlook with respect to the potential future work. Moreover, this section will include a final compilation of the methodology, providing a comprehensive overview of the associated findings, concerning their current benefits within the automotive industrial and academic landscape.

In the beginning of the documentation at hand, the motivation, the proposal and the outline were given by an introduction of three RQs, which were then gradually addressed. For this purpose, the background information about the current research activities (incl. IMAGinE project), the cooperative driving functions and the virtual test driving was provided. Based on this matter, the anticipated methodology for the verification and validation of the cooperative MC was specified, including the overview, the SuT, the intelligent co-simulation framework and the scope, with an objective to cover various aspects through the simulation of major *large-scale long-term* and minor *small-scale short-term* scenarios in statically and dynamically coupled environments of the traffic flow and the vehicle dynamics. Afterwards, the design and implementation of the methodology, concerning the related work, the architecture, the workflow and the utilization, with a focus on the OVERWATCH software and the associated ML approaches, were described. With the developed intelligent co-simulation framework, by means of the appropriate metrics and suitable scenarios, the test results for two exemplary studies – Effects on Traffic Quality and Effects of Imperfect Communication – were presented. Finally, the concept for the experimental realization of the methodology, which was put into practice as the RA-PiL method with an RTV in a mixed reality environment, was demonstrated on an exemplary test drive, with regard to the functionality of the HMI-support software, for the use-case of the cooperative driving function F1 (merging on highways).

7.1 Contribution

In this section, the findings made in the course of previously described activities will be assigned to the RQs I, II, III, in order to answer them, thus, composing the scientific contribution of this dissertation.

I) How to detect the MC relevant conditions of traffic quantity?

This can be accomplished through the utilization of a supervised ML that detects foreseen vehicle constellations in a certain RoI as scenes in major scenarios of the traffic flow simulation, which are then prepared and used as minor scenarios for the coupled vehicle dynamics simulation, as described in Chapter 4. Hereby, the ML needs to be trained depending on the desired use-cases of the cooperative driving functions. In the work at hand, an approach with the 'decision tree' classifier that was trained on 10 000 samples delivered a satisfactory output with 0.99 accuracy (see Figure 4.10).

II) How to comprehensively test the MC in the cooperative driving functions?

This can be realized through a statically and dynamically coupled simulation of the traffic flow and the vehicle dynamics, on the scenarios from the RQ I with the metrics from the RQ III, in order to cover multiple aspects with various NoA and LoD at the same time, optionally in form of the RA-PiL method in a mixed reality environment, as described in Chapter 6. The corresponding concept is framed into a guideline with 5 activities (see Figure 6.3). As a result, this approach delivers a fast and effort-efficient way for the verification and validation of the cooperative driving functions on minor and major scenarios, respectively, requiring only a small number of RTV prototypes and a confined proving ground. In the work at hand, for demonstrative purposes, the function F1 was tested by an examination of the HMI-support triggers (see Figure 6.12).

III) How to evaluate the MC effects on traffic quality?

This can be achieved with different metrics, such as the traffic density-velocity-flow, the coefficient of variation, the time-exposed time-to-collision, the spatiotemporal pattern (see Figure 5.1) and the count of successful cooperations (see Figure 5.2), applied primarily on major scenarios of the coupled traffic flow simulation, as described in Chapter 5. The corresponding test results can confirm that the successfully conducted communication, negotiation and execution on the part of the cooperative driving functions have a positive impact on the traffic under premise of a sufficient communication quality. In the work at hand, the Core and the Joint algorithms were comparatively evaluated as replaceable SuTs, denoting a transferability of the chosen approach.

7.1.1 Final Compilation

In the course of this dissertation, the answers to the RQs were thoroughly given and merged into the resulting methodology, which is summarized here in form of a final compilation, as illustrated in Figure 7.1.

As a central part of the methodology, the intelligent co-simulation framework allows for abundant in-depth and wide-ranging options for the verification and validation of the cooperative driving functions, regarding the effectiveness and efficiency of the underlying MC. For this, on the one side, the major scenarios for the traffic flow simulation and the minor scenarios for the vehicle dynamics simulation (detected in and generated from the major scenarios) are synthesized, providing an input for the co-simulation. Then, on the other side, an output of the co-simulation is analyzed with the appropriate metrics, for example, concerning effects on the traffic quality under an influence of the imperfect communication. In the work at hand, the focus was put on the traffic quantity and the traffic quality as independent and dependent aspects of the cooperative driving (refer to motivation in Subchapter 1.1), thus, determining the choice of the respective scenarios and metrics. However, since it is not a limitation of the methodology itself, this approach can be generically extended by a consideration of further aspects.

With this methodology, different cooperative driving functions can be extensively evaluated, offering a remarkable possibility for their immediate comparison. Furthermore, the intelligent co-simulation framework enables an intensive testing, with variable XiL methods of the V-model in general, including the novel RA-PiL method in particular. Hereby, due to the remote competence, the simulation can interact with the SuT over distance; as well as due to the adaptable competence, the simulation can constantly expose the SuT to various new scenarios. Moreover, RA-PiL can be applied on multiple SuTs (i.e., RTVs) on the road at the same time by means of the V2X communication.

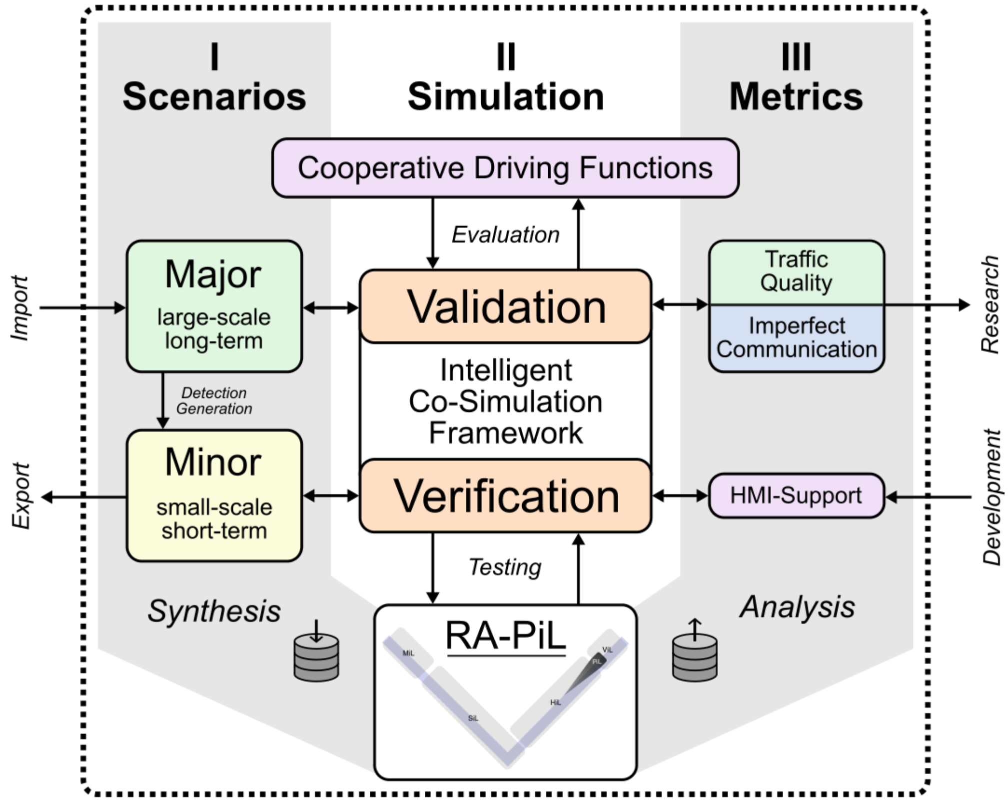


Figure 7.1: Final compilation of the methodology

In addition, the proposed methodology reveals a high potential for the utilization in a context beyond the use-cases addressed by this dissertation, making it even more valuable for the automotive industry and academia. For instance, the major scenarios can be imported and, most importantly, the thereof generated minor scenarios can be exported, contributing to the formation of external databases with MC relevant scenarios. Besides, the metrics can be used to support the development of further innovative driving functions and their components, such as the HMI-support in this case, as well as to discover other, possibly yet unknown, effects of the cooperative driving for the sake of scientific research.

7.2 Discussion

In this section, the key solutions and the ensuing overall rating of the methodology, which were established in compliance with the predefined functional and non-functional requirements (see Subchapter 3.1), will be discussed.

7.2.1 Key Solutions

During the work on this dissertation, several key solutions were made according to the functional requirements. These solutions determined the course of the corresponding design and implementation, evaluation, as well as the experimental realization activities, eventually leading to the contribution mentioned before. Hereby, depending on the priorities of the functional requirements (high or low), the attempt of the methodology was to fulfill these requirements completely or partially, accordingly. Hence, the key solutions, as presented in Table 7.1, will be discussed with their advantages and disadvantages next.

Table 7.1: Key solutions with their advantages and disadvantages

Solutions	Advantages	Disadvantages
Co-simulation of SUMO & CARMAKER	versatile proficient	slow-acting
V2X network simulation in ROS	simple	approximative
Synthetic major scenarios (maps)	reproducible comparable	idealized
3 subject-vehicles in minor scenarios (snapshots)	focused	specific
Features in Cartesian coordinates	agnostic	sensitive
Supervised ML classification	straightforward accurate	rigid
Synchronization with Jacobi scheme	quick	volatile
RA-PiL demonstration on F1 function	common available	—

A solution to use the co-simulation of SUMO and CarMaker offers a versatile and proficient way to investigate the cooperative driving, since both simulators are specialized on their own subjects, allowing to obtain realistic results from different perspectives with the associated NoA and LoD. However, a coupling of two independent software tools induces a relatively slow-acting simulation performance, therefore, a combination of both environments into one rigorously optimized tool could potentially diminish this problem in prospect.

A network simulation in ROS was chosen as a simple, but only approximative solution for a simulation of the V2X communication, which was sufficient for the needs of the conducted studies. Alternatively, a qualified network simulator, such as OMNeT++ (refer to Subchapter 2.3 for details), could be incorporated into co-simulation, however, causing further computational performance expenses, due to the complexity of an additional software in the toolchain.

In the course of the studies, synthetic major scenarios (maps) were utilized to initiate a reproducible and comparable simulation outcome, yet with idealized properties, in order to create apparent results by the selected metrics for the methodology proof-of-concept. This way, the transferability and the visual presentability of the metrics were uncovered.

Observations with 3 instances of subject-vehicles were implemented for the detection as least minor scenarios (snapshots), since they were focused on the wanted, but also relatively specific use-cases of the cooperative driving functions F1 and F5. Nevertheless, multiple relevant observations could seamlessly lead to more than 3 subject-vehicles in a minor scenario. A potential design with 2 subject-vehicles (i.e., absolute minimum needed for a cooperation) would probably provide a more universal solution, however, requiring a complementary definition of certain restrictive rules, in order to avoid the detections of unwanted observations (e.g., only vehicles **A** and **C** in the example of Figure 6.4).

Within the observations, the features were captured in Cartesian coordinates, thus, offering an agnostic solution, based on the relative distances and angles between the vehicles, independent of their absolute positioning. However, this approach revealed itself as sensitive against significant changes in the topology and geometry of the map, consequently, rendering OverWatch unable to produce snapshots without a new training. An alternative here can be suggested by an application of the Frenet coordinates (i.e., vehicle position relative to road and lane), making it possibly more robust against map changes.

Detection of scenes for the minor scenarios with a supervised ML classification, organized in a straightforward workflow, delivered very accurate results, enabling the automatic scenario generation with a relatively high scenario variability. However, this approach indicated a tendency to overfitting, which entailed a rigidity and a limited generalization capability. Other, more ambitious approaches of the artificial intelligence (e.g., deep learning) to flexibly create even more diversified, but still relevancy decent snapshots of the cooperative driving are yet to be researched in the future.

The synchronization of the coupled simulation environments of SUMO and CARMAKER was implemented with the Jacobi scheme as a quick process without additional interpolation or extrapolation operations, in order to achieve a real-time capability, due to a small temporal delay of the simulation steps in average. However, at the same time, this solution showcased a relatively volatile spatial mismatch of the synchronized vehicle locations. In prospect, this problem can be addressed through an assessment of the alternative synchronization mechanisms, based on further other co-simulation schemes, such as Gauss-Seidel.

A demonstration of the RA-PiL method was carried out in the real world by an illustrative examination of the HMI-support triggers for the function F1, which represents a common use-case of the cooperative driving from the daily life. Hereby, the SuT and the associated RTV were made available for this task on the part of the IMAGinE project.

7.2.2 Overall Rating

In the following, the methodology of the work at hand (more precisely, the intelligent co-simulation framework in tandem with the RA-PiL method) will be rated, by using the criteria defined in the system and software quality standard ISO/IEC 25010:2011 [90] as non-functional requirements. This includes the functional suitability, performance efficiency, compatibility, usability, reliability, maintainability, portability and excludes the security, which was not considered in this dissertation, due to a low relevance for the methodological proof-of-concept. Hereby, the chosen criteria will be assessed with respect to the effort and impact that often stand in a mutual opposition. Obviously, the most preferable and profitable solutions are usually characterized by a lower effort and a higher impact. Consequently, the resulting rating of the methodology is presented in Figure 7.2 as an effort-impact matrix.

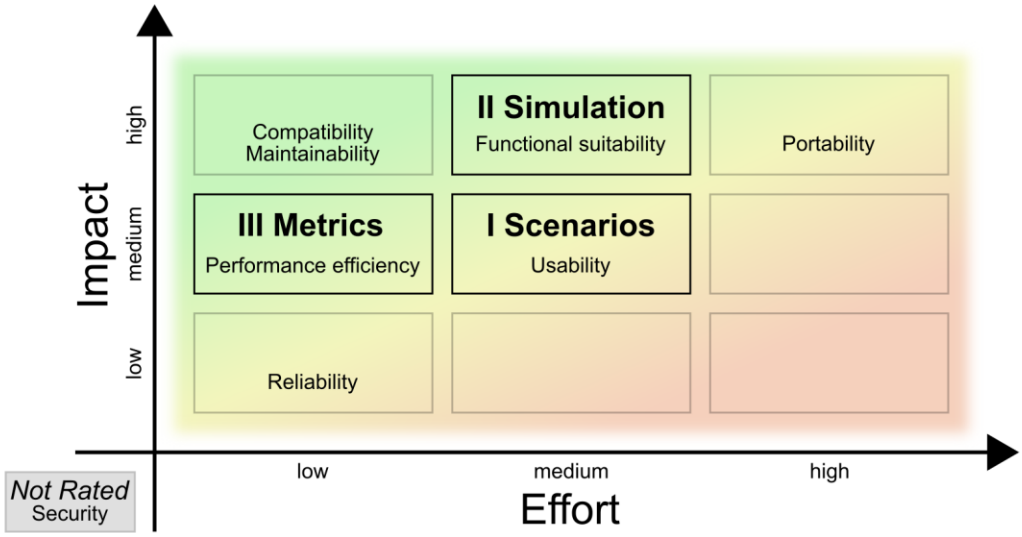


Figure 7.2: Overall rating of the methodology as an effort-impact matrix

To begin with, the intelligent co-simulation framework demonstrated valuable and, at the same time, simple compatibility and maintainability attributes, denoted by a high impact and a low effort. Both criteria were essential for the simulation of the cooperative driving functions, as a part of the respective research and development activities. For instance, the compatibility was provided by an interoperability of different MC algorithms as SuTs, as well as by a co-existence of multiple applicable evaluation metrics. At the same time, the maintainability was accomplished through a modularity of the implemented software (e.g., OVERWATCH with the ISD, ASG, CE modules), thus, allowing for additional modifiability, analyzability and testability.

Then, on the one hand, the functional suitability was put into practice with a high impact and a medium effort, since the related aspects of the cooperative driving could be precisely evaluated from different appropriate perspectives, such as the traffic flow, the vehicle dynamics and partially the communication network, realized with a transparent coupling of already existing software tools. On the other hand, influenced by computational drawbacks of the co-simulation, the performance efficiency was achieved with a medium impact and a low effort, thus, eventually allowing for a soft real-time procession through the utilization of rudimentary optimization techniques.

Apart from that, the portability of the co-simulation was accomplished with a high impact and a high effort, characterized by remarkable adaptability and installability attributes, which were necessary for the experimental realization of the RA-PiL method. Hereby, the interaction of the simulations office and the RTV delivered promising results within relevant scenarios of the cooperative driving, despite a relatively laborious hardware and software setup. Furthermore, the usability of the methodology was implemented equally with a medium impact and a medium effort, indicated by a moderate learnability, operability and accessibility, which were established with straightforward workflows and guidelines, however, often requiring a manual involvement into the toolchain (e.g., labeling and training of the ML). Lastly, the reliability of the co-simulation was determined by a low impact and a low effort, due to a raw maturity and a limited availability of such a complex software framework, which was primarily targeted at a proof-of-concept.

In total, when combining these criteria together with respect to the findings, motivated by the RQs of this dissertation, the following overall rating of the methodology can be stated:

- medium impact and medium effort for the preparation of scenarios (RQ I)
- high impact and medium effort for the simulation (RQ II)
- medium impact and low effort for the application of metrics (RQ III)

7.3 Outlook

Considering the future work, the methodology proposed by this dissertation can be applied on other aspects of the cooperative driving, apart from the already addressed traffic quantity and traffic quality, through the realization of more studies on different SuTs and associated MC algorithms (not only trajectory-aided). For this, the scenarios and the metrics can be extended with further specific accents (also safety relevant) and organized in test automation catalogues for the comprehensive testing routines of the cooperative driving functions.

The intelligent co-simulation framework of the methodology can be upgraded with solutions to import and export scenarios, in order to provide an interface for the data exchange with other adjoining research and development activities. Hereby, it would be beneficial to include options to support popular scenario formats (e.g., OPENSCENARIO [1]). Moreover, the synthetic traffic data for the co-simulation can be

[1] asam.net/standards/detail/openscenario

supplied by recordings from the real-life (with complexly shaped roads and noisy vehicle information), for the consecutive testing of CAVs based on authentic scenarios.

In the presented findings of the methodology, the minor scenarios could not temporally overlap within the major scenario (refer to the logic of the dynamic variation in Figure 3.8), due to the current implementation constraints of the coupled SUMO-CARMAKER simulation. A plausible resolution of this issue can be achieved through an enhancement of the co-simulation with an ability to dynamically add and remove the subject-vehicles in the already running minor scenarios. This would allow for a simulation of even more complex traffic situations with numerous alternating participants, however, requiring a scalability benchmark, regarding the consecutive impact on the computational efficiency of the co-simulation software. Ultimately, the limitations of the processing resources can be circumvented through the utilization of a distributed hardware in high-performance cloud computing environments.

In the process of the experimental realization of the RA-PiL method, the driver of the RTV was informed about the traffic situation in the mixed reality via a conventional visual display. In the outlook, the interaction with the driver can be improved through an incorporation of auxiliary technological solutions, such as the virtual or augmented reality glasses, which can then enable an evaluation of the driver experience and the associated CAV driving convenience.

During the test drives with RA-PiL, the simulation office and the RTV were exchanging messages based on the predominantly standardized V2X communication protocols, which can be potentially extended with new additional message types, specifically designed to further streamline the verification and validation routines for CAVs. Furthermore, provided that the proving grounds continue to develop their affiliated V2X infrastructures, the RA-PiL method can be easily deployed on multiple RTVs at the same time, for the purpose of testing along the ongoing progression towards more sophisticated use-cases of the cooperative driving in the future.

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Miscellaneous

Submitted Patent Applications

Mspa.1 H. Berninger & V. Lizenberg; "Verfahren und Vorrichtung zur Abstimmung von Fahrmanövern zwischen einem Fahrzeug und mindestens einem Alius-Fahrzeug", "Method and Device for Coordinating Driving Manoeuvres Between One Vehicle and at Least One Other Vehicle". *PSA Automobiles SA*; DE102018002609A1, EP3776515A1, WO2019185584A1; granted. 2019; Germany.

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Mspa.3 S. Knapp & V. Lizenberg; "Verfahren und Vorrichtung zum Abstimmen von Fahrmanövern". *PSA Automobiles SA;* DE102019208291A1; granted. 2020; Germany.

Mspa.4 V. Lizenberg & U. Eberle; "Validieren einer Fahrsteuerungsfunktion für den automatischen Betrieb eines Fahrzeugs", "Validation of a Driving Control Function for the Automatic Operation of a Vehicle". *PSA Automobiles SA*; DE102021209394A1, WO2023025613A1. 2023; Germany.

Invited Presentations

Mip.1 V. Lizenberg; "Continuous Cooperation Reduced", "Remote Adaptable Prototype-in-the-Loop". *IMAGinE Final Event*; Virtual Final Presentation. May 12, 2022.

Supervised Student Works

Mssw.1 V. Mestrum & A. Martin; “Aufbereiten von Fahrzeugdaten aus einem CAN-Bus und Austauschen dieser zwischen zwei Verkehrsteilnehmern”. *Project Report*. 2019; RheinMain University of Applied Sciences, Germany.

Mssw.2 M. Schwerzel; “Automatische Generierung von Szenarien zur Simulation von kooperativen Fahrfunktionen”. *Project Report*. 2019; RheinMain University of Applied Sciences, Germany.

Mssw.3 M. Schwerzel; “Erweiterung von Kommunikationsschnittstellen und dynamische Kopplung von Simulationsumgebungen”. *Project Report*. 2020; RheinMain University of Applied Sciences, Germany.

Mssw.4 J. Hermanns; “Automatische synchrone Auswertung von Ergebnissen der Verkehrssimulation”. *Project Report*. 2020; RheinMain University of Applied Sciences, Germany.

Mssw.5 B. Klement; “Generating Computational Efficient Trajectories to Support Large-Scale Simulation of Cooperative Maneuver Coordination”. *Master Thesis*. 2020; Technical University of Darmstadt, Germany.

Mssw.6 Y. Haridy; “Implementation and Simulative Evaluation of a Cooperative Maneuver Planning Algorithm Based on Vehicle-to-Vehicle Communication”. *Master Thesis*. 2020; Technical University of Darmstadt, Germany.

Mssw.7 M. Schwerzel; “Performanzbewertung und Optimierung der dynamischen Kopplung von Simulationsumgebungen für kooperative Fahrfunktionen”. *Bachelor Thesis*. 2020; RheinMain University of Applied Sciences, Germany.

Mssw.8 M.R. Alkrudi; “Simulation-Based Intelligent Recognition and Selection of Relevant Traffic Situations for the Cooperative Maneuver Planning”. *Master Thesis*. 2020; Darmstadt University of Applied Sciences, Germany.

Mssw.9 S. Schott; “Auswertung der Trajektorienplanung für manuell gesteuerte Fahrzeuge mit kooperativen Fahrfunktionen”. *Bachelor Thesis*. 2021; RheinMain University of Applied Sciences, Germany.

List of Figures

List of Tables

Appendix

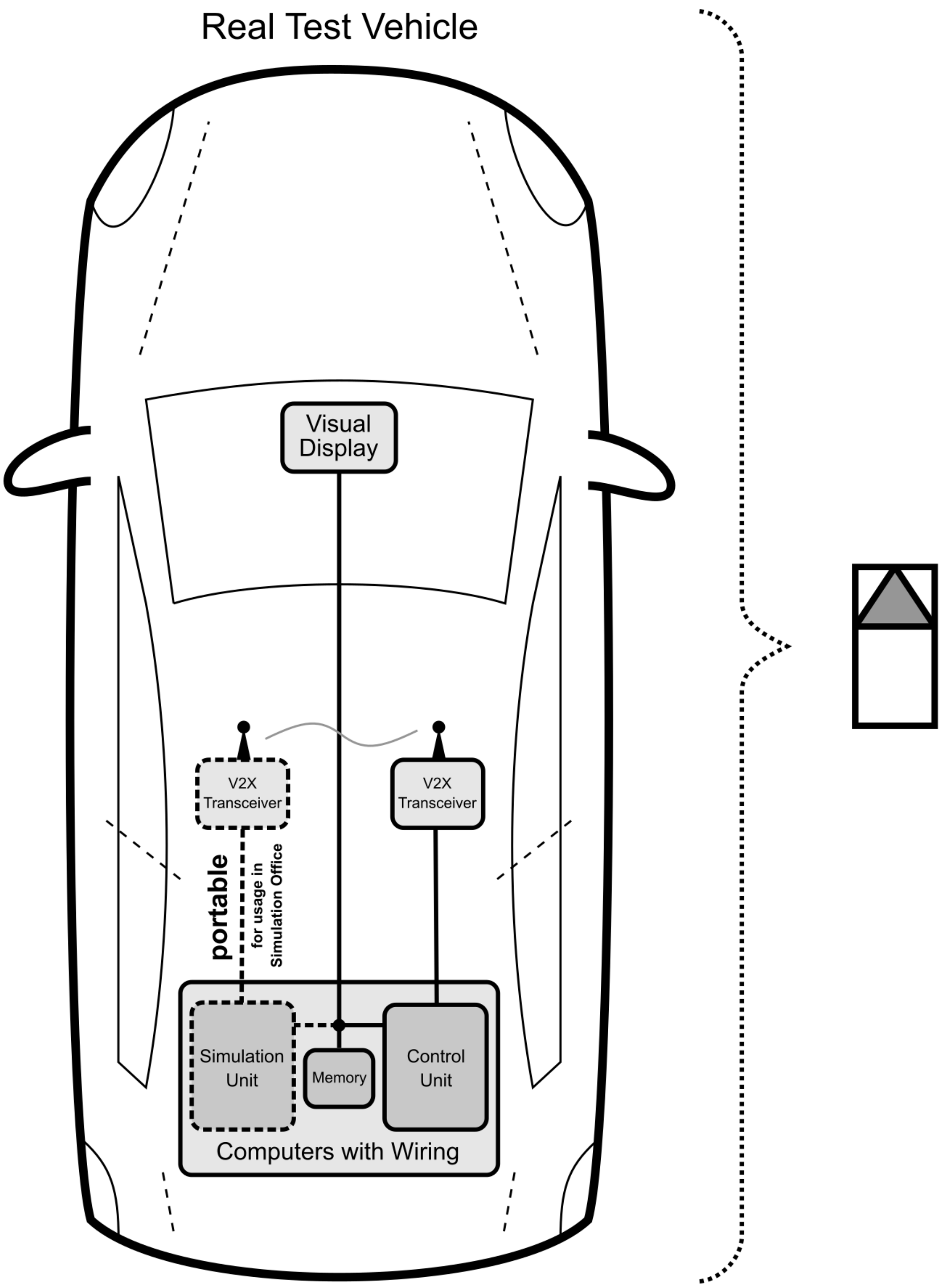

Figure A.1: RTV build for the experimental realization of RA-PiL

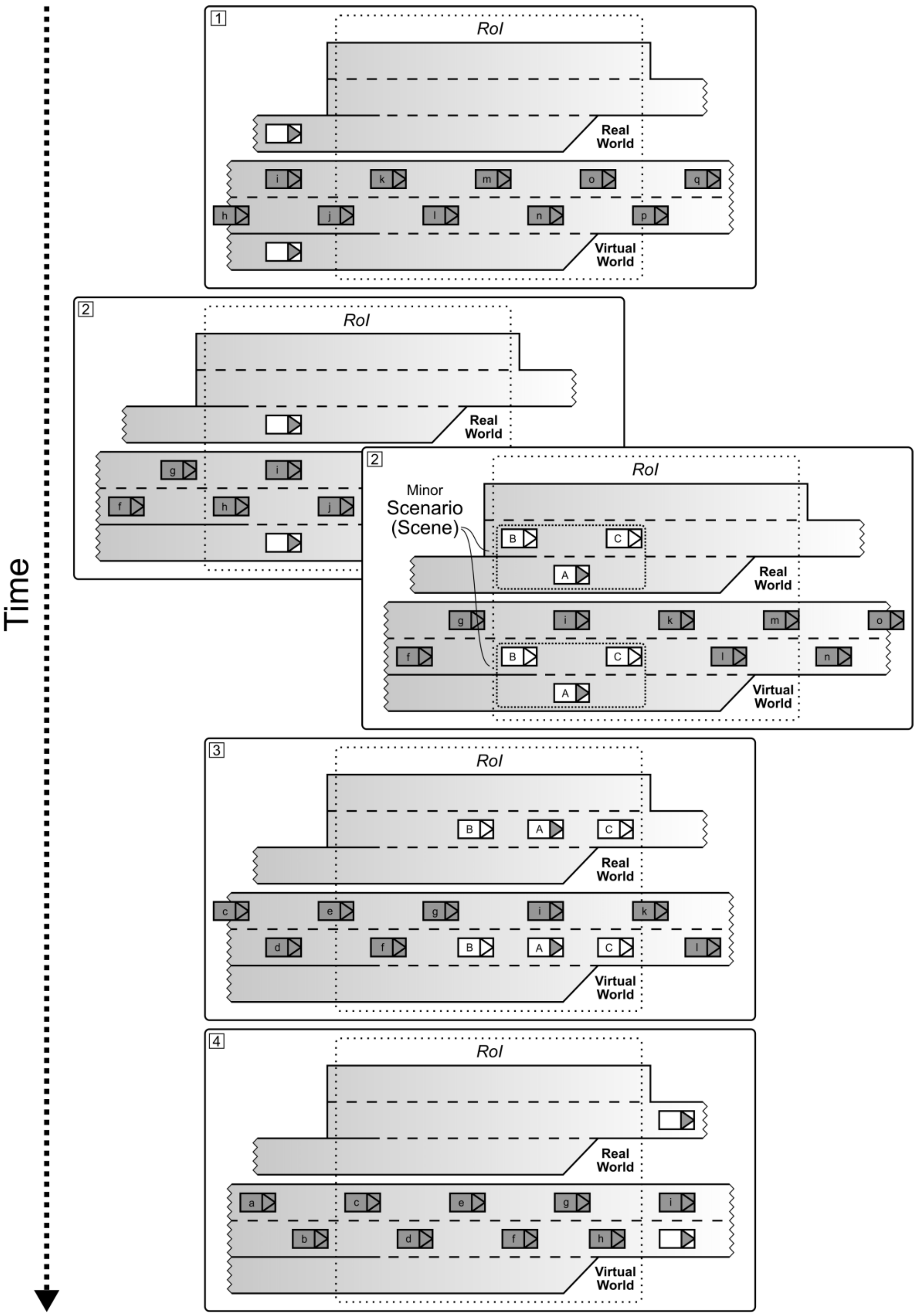

Figure A.2: Conceptual animation for the experimental realization of RA-PiL

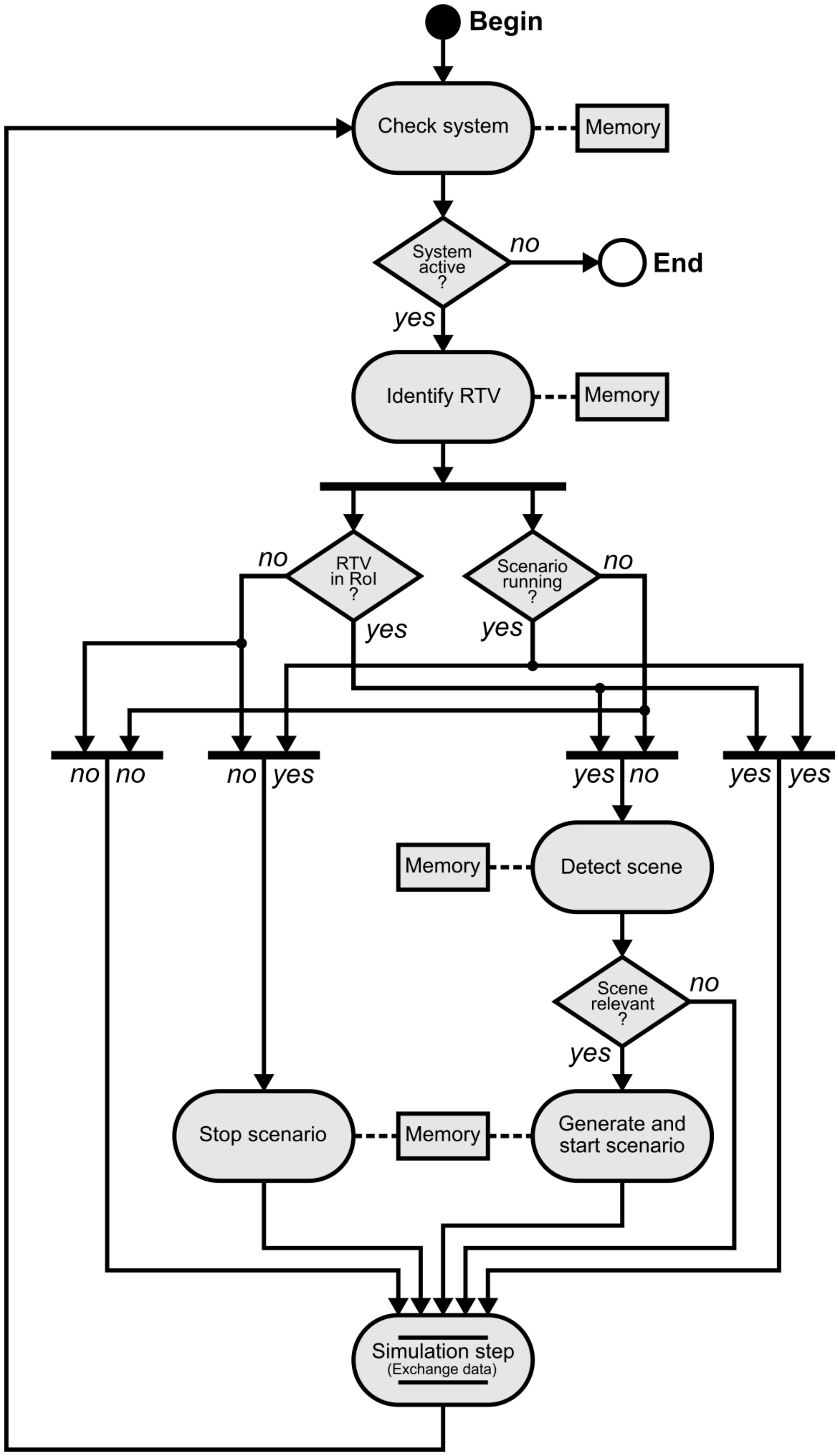

Figure A.3: Software activity diagram for the experimental realization of RA-PiL

Simulations for Cooperative Driving

Methodology for Verification and Validation of Cooperative Driving Functions with Intelligent Co-Simulation Framework