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SHARED CONTROL STRATEGIES FOR AUTOMATED VEHICLES

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Mauricio Alejandro Marcano Sandoval

Thesis Advisors:
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To Inés and Matías

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Grace is probably the most beautiful word that exists. It means *"to receive an undeserved favor"*. So first, I am grateful to the *God of my Salvation* for all the grace that has come to me during these years. Without it, I would never have made it this far. But grace is not an abstract concept, it often comes in the form of valuable people who surround you and without whom none of this would be possible. So I would like to thank them personally.

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SHARED CONTROL STRATEGIES FOR
AUTOMATED VEHICLES

Abstract

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The advent of Automated Vehicles (AVs) holds promise as an efficient and safer alternative to manual driving. In addition to reducing human-caused accidents, it is also a matter of driving more efficiently with regard to the energy consumption, traffic flow, and driver workload. However, these technologies are not yet mature enough for massive deployment in commercial vehicles, as assigning a passive role to humans in the driving task raises technical, social and legal issues. A technical limitation is that AVs cannot handle all driving situations, while a social problem is that humans like driving and have so far proven to be better drivers than machines. In this respect, the current approach in both the automotive industry and research community is not to replace the driver completely, but to let the driver and the automated vehicle cooperate within the traded control scheme (i.e., only one is charge of the driving task for a certain period). In this context, if the automation is responsible for the driving task, the driver is assigned the role of supervisor. Humans, however, have proven to be poor supervisors, as they tend to abuse automation, overtrust it, and are therefore unprepared to properly take back control when automation demands it. Furthermore, even attentive drivers are prone to lose situational awareness and may even become drowsy after a period of inactivity. As a result, any level of automated driving that partially or fully removes the human from the driver's role presents a complex challenge that is still being explored. Yet, accidents happen all the time, and new solutions are needed to improve road safety.

In this context, the shared-control approach offers the potential to improve driving safety and performance by keeping the driver involved in the control loop while taking advantage of recent advances in automated driving technology, such as perception systems, advanced control methods, and in-vehicle actuators. This control

scheme allows the driver and the automation system to become a well-coordinated team, continuously working together at the tactical and control levels of the driving task. Therefore, more advanced and cooperative driver assistance systems are being sought than those currently available in commercial vehicles. AVs would then be the supervisors that the driver needs, rather than the other way around.

Given these premises, the aim of this Ph.D. Thesis is to address both theoretical and practical aspects of shared-control in automated vehicles. First, a comprehensive review of the current state-of-the-art is performed to give an overview of the concepts and applications of shared-control that researchers have been working on over the last two decades. A practical approach is then taken by developing a steering shared-controller based on optimal control, which can assist the driver with different levels of haptic authority (intensity of torque) while maintaining performance and stability in all cases. This controller and its associated decision-system (Arbitration Module) will be integrated into the general framework of automated driving and validated in a driver-in-the-loop simulator platform. In a final stage, two real-world scenarios are used to demonstrate the effectiveness of the controller. One is used to support a distracted driver, and the other is used to implement a safety function that enables overtaking maneuvers on roads with oncoming traffic. Both systems were evaluated with real participants using objective and subjective assessment methods. The conclusion of this dissertation is that shared-control is a promising approach for future automated driving features that can improve road safety in the short term while allowing people to continue to enjoy driving.

RESUMEN

Los vehículos automatizados (AV, por sus siglas en inglés) han surgido como una solución tecnológica para compensar las deficiencias de la conducción manual. La motivación principal es reducir los accidentes causados por humanos y conducir de manera más eficiente en términos de consumo de energía, flujo de tráfico y carga de trabajo del conductor. Sin embargo, la tecnología aún no está lo suficientemente madura para su implementación masiva en vehículos comerciales, ya que asignar un papel pasivo a los humanos en la tarea de conducción plantea problemas técnicos, sociales y legales. Una limitación técnica es que los AVs no son capaces de manejar todas las situaciones de conducción, mientras que un problema social es que los humanos disfrutan conduciendo y hasta ahora han demostrado ser mejores conductores que las máquinas. En este sentido, el enfoque actual no es reemplazar al conductor por completo, sino dejar que el conductor y el vehículo automatizado cooperen dentro del esquema de control negociado (es decir, controlan el vehículo en diferentes momentos). En este contexto, al conductor se le asigna el rol de supervisor, mientras que el sistema de conducción automatizada se encarga de la tarea de conducción. Los conductores, sin embargo, han demostrado ser malos supervisores, ya que tienden a abusar de la automatización, confían demasiado en ella y, por lo tanto, no están preparados para tomar el control adecuadamente. Más aún, incluso los conductores atentos pierden rápidamente conciencia de la situación de conducción e incluso pueden sentirse somnolientos después de un período de inactividad. Por lo tanto, cualquier nivel de conducción automatizada que incapacite parcial o totalmente al conductor es un gran desafío. Sin embargo, los accidentes siguen ocurriendo y se necesitan nuevas soluciones para mejorar la seguridad vial.

En este contexto, el enfoque de control compartido, en el que el conductor permanece involucrado en el control del vehículo y, junto con el sistema automatizado, forma un equipo bien coordinado que colabora continuamente en los niveles táctico y de control de la tarea de conducción, es una solución prometedora para mejorar el desempeño de la conducción manual aprovechando los últimos avances en tecnología de conducción automatizada en términos de sistemas de percepción, métodos de control avanzados y actuadores de vehículos. Esta estrategia tiene como objetivo promover el desarrollo de sistemas de asistencia al conductor más avanzados y cooperativos en comparación con los disponibles en los vehículos comerciales. En

este sentido, los vehículos automatizados serán los supervisores que necesitan los conductores, y no al contrario.

Considerando lo anterior, la presente tesis trata en profundidad el tema del control compartido en vehículos automatizados, tanto desde un punto de vista teórico como práctico. En primer lugar, se presenta una descripción exhaustiva del de estado del arte, para brindar una descripción general de los conceptos y aplicaciones del control compartido en los que los investigadores han estado trabajando durante las últimas dos décadas. Luego, se adopta un enfoque práctico mediante el desarrollo de un controlador lateral basado en control compartido para ayudar al conductor. Este controlador y su sistema de toma de decisiones asociado (Módulo de Arbitraje) se integrarán en el marco general de conducción automatizada y se validarán en una plataforma de simulación de vehículos automatizados con capacidad para interactuar con el conductor. Finalmente, el controlador desarrollado se utiliza en dos escenarios del mundo real, uno en un sistema para assistir a un conductor distraído y el otro en la implementación de una función de seguridad para realizar maniobras de adelantamiento en carriles de doble sentido. Ambos sistemas fueron evaluados con participantes reales y se realizaron valoraciones objetivas y subjetivas. Como conclusión, el control compartido es un enfoque prometedor para futuros sistemas avanzados en vehículos automatizados, que pueden mejorar la seguridad vial a corto plazo y permitir que las personas sigan disfrutando de la conducción.

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[2] **Webpage**: Toyota Safety Sense → *https://www.toyota.com/safety-sense/*

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LIST OF ACRONYMS

ACC	Adaptive Cruise Control
AD	Automated Driving
ADAS	Advanced Driver Assistance System
ADF	Automated Driving Function
ADS	Automated Driving System
AI	Artificial Intelligence
ALC	Automated Lane Centering
AV	Automated Vehicle
CAN	Controller Area Network
CC	Cruise Control
CoG	Center of Gravity
DDT	Dynamic Driving Task
DiL	Driver in the Loop
DMS	Driver Monitoring System
ECU	Electronic Control Unit
FIS	Fuzzy Inference System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GPU	Graphic Processing Unit
HMC	Human-Machine Cooperation
HMI	Human-Machine Interface
IMU	Inertial Measurement Unit
IR	Infrared

LDW	Lane Departure Warning
LiDAR	Light Detection and Ranging
LKAS	Lane Keeping Assistance System
LMI	Linear Matrix Inequalities
LoA	Level of Automation
LoDA	Level of Driving Automation
LoHA	Level of Haptic Authority
LQR	Linear Quadratic Regulator
MIMO	Multiple Inputs Multiple Outputs
MIT	Massachusetts Institute of Technology
MPC	Model Predictive Control
NDRT	Non-Driving Related Tasks
NMPC	Non-Linear Model Predictive Control
ODD	Operational Design Domain
P	Proportional
PD	Proportional-Derivative
PID	Proportional-Integral-Derivative
RT	Real Time
SAE	Society of Automotive Engineers
SoA	State-of-the-Art
ST	Secondary Task
TLC	Time to Lane Crossing
TTC	Time to Collision
UC	Use Case
V2I	Vehicle to Infraestructure
V2V	Vehicle to Vehicle
V2X	Vehicle to Anything
VRU	Vulnerable Road User

LIST OF SYMBOLS

$\boldsymbol{\lambda}$	Level of Haptic Authority
$\boldsymbol{\lambda}_{-}$	Transition haptic authority
$\boldsymbol{\lambda}_{+}$	Added haptic authority
$\boldsymbol{\lambda_{mpc}}$	Nominal haptic authority of MPC controller
$\boldsymbol{\lambda_{sat}}$	Natural haptic authority of steering system
T_{mpc}	MPC torque
T_{sat}	Self-aligning torque
T_d	Driver torque
T_{λ}	Total haptic torque
T_{λ_+}	Added haptic torque
$\boldsymbol{X}$	Vehicle CoG X position
$\boldsymbol{Y}$	Vehicle CoG Yposition
$\boldsymbol{\Psi}$	Heading angle
$\boldsymbol{v_x}$	Longitudinal velocity
$\boldsymbol{v_y}$	Lateral velocity
$\boldsymbol{a_x}$	Longitudinal acceleration
$\boldsymbol{a_y}$	Lateral acceleration
$\boldsymbol{\psi}$	Yaw rate
$\boldsymbol{\theta}$	Steering wheel angle
$\boldsymbol{w}$	Steering wheel angular velocity
$\boldsymbol{\delta}$	Steering angle
$\boldsymbol{\beta}$	Side-slip angle
$\boldsymbol{C_{yf}}$	Cornering stiffness of the front axle

$\boldsymbol{C_{yr}}$	Cornering stiffness of the rear axle
$\boldsymbol{\alpha_{yf}}$	Sideslip angle of the front axle
$\boldsymbol{\alpha_{yr}}$	Sideslip angle of the rear axle
$\boldsymbol{F_{yf}}$	Lateral force on the front axle
$\boldsymbol{F_{yr}}$	Lateral force on the rear axle
$\boldsymbol{J}$	Inertia of the steering system
$\boldsymbol{b}$	Damping of the steering system
$\boldsymbol{k}$	Stiffness of the steering system
$\boldsymbol{\bar{\kappa}}$	Road curvature
$\boldsymbol{L}$	Vehicle length
$\boldsymbol{l_r}$	Distance CG to rear axle
$\boldsymbol{m}$	Vehicle mass
$\boldsymbol{I_z}$	Yaw inertia
$\boldsymbol{e_y}$	Lateral error
$\boldsymbol{e_\psi}$	Angular error
$\boldsymbol{\xi}$	Damping ratio
$\boldsymbol{s}$	States vector (MPC)
$\boldsymbol{u}$	Inputs vector (MPC)
$\boldsymbol{\Delta u}$	Inputs rate vector (MPC)
$\boldsymbol{z}$	Optimized states vector (MPC)
$\boldsymbol{l}$	External inputs vector (MPC)
$\boldsymbol{\tilde{z}}$	Constrained states vector (MPC)
$\boldsymbol{\tilde{u}}$	Constrained inputs vector (MPC)
$\boldsymbol{\tilde{\Delta} u}$	Constrained inputs rate vector (MPC)
$\boldsymbol{N_p}$	Prediction horizon (MPC)
$\boldsymbol{N_u}$	Control horizon (MPC)
$\boldsymbol{f}$	System model function (MPC)

Introduction

1

People have been driving cars for more than a century, gaining experience and knowledge about how to deal with the complex road traffic situations they encounter every day. However, humans still do not succeed in ensuring absolutely safe driving. Indeed, drivers have a limited ability to recognize, understand, and manage critical situations; they are also prone to misbehavior, drowsiness, and distraction. According to the National Highway Traffic Safety Administration (NHTSA), traffic accidents in the U.S. attributable to human error reach an alarming number of up to 94% [1]. Same trend was found for heavy truck accidents in Europe [2].

To improve road safety, Automated Vehicles (AVs) have emerged as a technological solution that can support, assist, or even replace humans in performing the driving task. In addition to safety, AVs also aim to improve the efficiency of the transportation system, increase driver comfort, reduce driver mental workload, permit Non-Driving Related Tasks (NDRT) to be performed, and promote social integration for people who are unable to drive a vehicle [3].

After an initial rush towards self-driving cars, the general approach of Automated Driving (AD) has been to gradually increase the Level of Automation (LoA) until the technology is ready for the deployment of reliable fully autonomous vehicles, while at the same time creating the regulatory framework and establishing acceptance of such systems in society. On the one hand, efforts over the past decade have resulted in Advanced Driver Assistance Systems (ADAS) that provide efficient but simple support to drivers (e.g., lane-departure systems and vehicle longitudinal control). On the other hand, automated functions that replace the driver are becoming more visible in prototypes and commercial vehicles. However, these have significant shortcomings related to the fact that the driver must still be ready to take control when needed. Humans, however, have been shown to be poor supervisors [4, 5].

The preceding points offer a panorama in which technological advances are great, but Automated Driving Systems (ADS) are still limited in functionality or, if too advanced, are fraught with safety concerns. This scenario raises the question: *How to take advantage of technological advances in automated driving while relying on safe driving?*. The answer is not trivial, but keeping the driver in the control loop seems like a reasonable answer. One approach is to develop strategies for Human-Machine Cooperation (HMC) so that the driver maintains situational awareness while taking a supervisory role. Another approach is to design the ADS as a driving partner that adapts to the driver's needs, i.e., instead of a system that completely replaces the driver, to have a complementary co-pilot that provides continuous and adaptive support during the driving task. Therefore, AVs could be the intelligent supervisor that humans need, rather than the other way around. This particular cooperative approach is known in the literature as *shared-control* [6–10].

Based on this premise, the objective of this Ph.D. Thesis is to investigate the development of functions based on shared-control for automated driving from a theoretical and application perspective. First, a comprehensive overview of the State-of-the-Art (SoA) is provided to analyze different strategies for to share driving tasks at the control level. Then, the integration of shared-control components into the AD framework is presented, followed by the development of a steering controller with a variable authority level. Finally, a comparative study between shared-control and other Automated Driving Functions (ADFs) is conducted.

This PhD thesis was developed within the *Automated Driving* research group of *Tecnalia Research & Innovation* in collaboration with the Department of Systems and Automation of the University of the Basque Country (UPV/EHU). Additionally, the work performed in this dissertation was partially supported by the following European and National Projects.

- **PRYSTINE** [11] (H2020 under grant agreement No. 783190). Stands for Programmable Systems for Intelligence in Automobiles and focus on fail-operational systems and advanced control functions for partial and conditional automation.
- **HADRIAN** [12] (H2020 under grant agreement No. 875597), stands for Holistic Approach for Driver Role Integration and Automation Allocation for European Mobility Needs, and explores a holistic approach between the vehicle, the infrastructure, and the driver for better vehicle-driver cooperation under the concept of *fluid* interfaces that creates the conditions for safe, comfortable, adaptive, and understandable communication and support that can be accepted by drivers under different roles when using automated vehicles.
- **AUTOEV@L** (Government of the Basque Country under grant agreement KK-2021/00123), stands for Technology Evolution for Multivehicular Automation and Evaluation of Highly Automated Driving Functions.
- **AUTOLIB** (Government of the Basque Country under grant agreement KK-2019), stands for Technology Preparation for Multivehicle Automation in the Industrial Sector.

1.1 Background

1.1.1 Human-Machine Cooperation

The field of Human-Machine Cooperation plays a key role in the development of automated driving technology. There are several modalities of human-robot interaction that can be applied to the cooperation between the driver and the automated vehicle. According to Yang *et al.* in their recent review of human-machine cooperation in robotics [10], there are three main strategies of cooperation based on the allocation of control authority. First: human-dominant and robot-auxiliary, where manual control is assisted by automation with additional information thanks to its perceptual capabilities. Second, robot-dominant and human-auxiliary control, in which the machine controls the task as the primary controller and the human issues higher-level commands or intervenes in special circumstances. Finally, the human-robot consensus, in which the different capabilities of the agents are combined in the execution of the task, either by splitting them into subtasks or by controlling them together. From these categories, five cooperation strategies are derived:

- **Guided control**: The driver has ultimate authority over the task, and the machine helps by influencing behavior through cues (e.g., visual, auditory, or haptic). An example would be a vehicle in manual mode and the automation positioning system provides visual cues for navigation, indicating the path to follow. The system does not solve the task, but it supports its correct execution.
- **Supervisory control**: The machine is in control and the human helps with the task. While in guided control the machine helps the human with indications, in supervisory control the human supports the machine mainly with tactical commands. An example is an automated vehicle where the driver has no direct control but monitors the system and the environment. The driver can even reprogram system functions, such as adjusting the speed of the vehicle, but does not perform the maneuver himself.
- **Traded control**: In this cooperation scheme, either the human or the machine has full control over the task (i.e., they work on the same task but at different time intervals). An example is an automated vehicle that performs the driving task itself, but only under controlled conditions. Therefore, at a given time, the system may request the driver to take full control of the vehicle.
- **Allocation control**: In this mode, the main task is divided into subtasks. The machine is in charge of one subset, while the human is responsible for the others. Automated vehicles such as those that perform automatic longitudinal control while the driver steers are examples of this.
- **Shared-control**: This mode of cooperation requires that the human and the machine perform the same subtask at the same time (i.e., they control the subtask together). An example of this, is a vehicle with a steering assistance system that helps the driver to follow lane center.

Figure 1.1 shows the different cooperation strategies in a graphical representation. It also shows the three hierarchical cognitive levels of cooperation [13], the strategic, tactical, and operational levels. The first relates to planning, the second to maneuver and decision-making, and the third to control actions. It is noticeable that most interaction types have a strong strategic and tactical component, but shared-control is the one with stronger cooperation at the control level (as shown in the blue box at the bottom right of Figure 1.1).

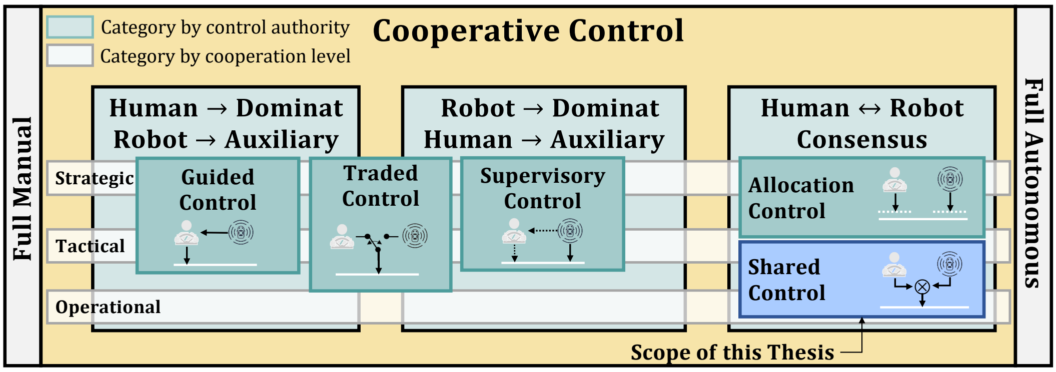
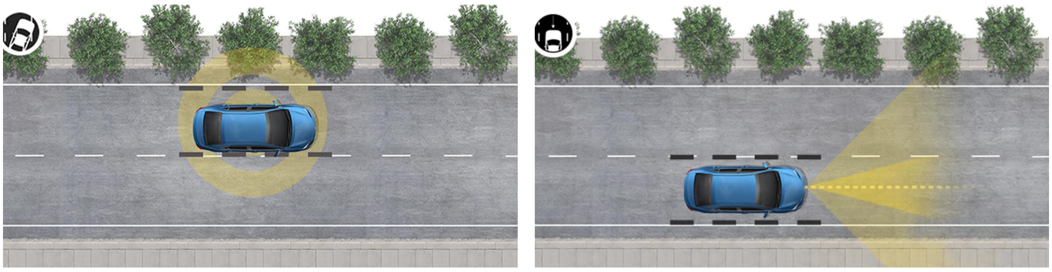


Fig. 1.1: Human-Machine Cooperation categories and strategies based the work of Yang *et al.* [10], combined with the hierachical levels of the driving task [13]

1.1.2 Automated Driving

According to the SAE J3016 standard, published in 2014 [14], and last updated in 2021 [15], six Levels of Driving Automation (LoDA) are recognized. Starting with no automation (or manual driving) at Level 0 (L0), each increase in LoDA removes one aspect of the driver's role in the Dynamic Driving Task (DDT): foot away (L1), hands away (L2), eyes away (L3), mind away (L4), and driver away (L5). A detailed description of these levels can be found below:

- ***L0*** - *No Driving Automation*: Vehicle without automated assistance functions, apart from indications to improve safety and driving behavior, such as the Lane-Departure Warning (LDW), which warns the driver by means of visual, acoustic or haptic cues when the vehicle is approaching the edge of the lane (see Figure 1.2a). There is a more advanced feature that provides torque correction (either through steering or differential braking) to prevent lane departure, commonly referred to as Lane Keeping Assist System (LKAS).
- ***L1*** - *Driver Assistance*: Automation controls the longitudinal *or* lateral movement of the vehicle, while the driver monitors the task performed by the automated system and controls the other. In practice, commercial vehicles with L1 functions use the Adaptive Cruise Control system (ACC) to maintain a safe distance from the vehicle ahead, while the driver is responsible for activation/deactivation and sends tactical commands (e.g., desired safe distance from the vehicle in front).



(a) Lane-Departure Warning/Assistance **(b)** Automated Lane Centering

Fig. 1.2: Lateral Advanced Driver Assistance Systems of Toyota Safety Sense System[1]

- **L2** - *Partial Automation*: Automation controls both longitudinal and lateral movement of the vehicle, while the driver supervise the system. At this level, the human is responsible for the Object and Event Detection and Response (OEDR) task, meaning that automation can fail at any time and the driver must be ready to intervene. The key feature is the Automated Lane Centering (ALC) system, which continuously centers the vehicle in the lane. It is usually confused with LKAS, but it is important to know that ALC provides continuous assistance, while LKAS provides only partial assistance when leaving the lane [16]. Also, ALC is usually only activated when ACC is also active. For this reason, it is rare to find L1 vehicles with ALC. Additional function of L2 vehicles includes Lane Change Assist (LCA), which performs the lateral maneuver of changing lanes after the driver commands the tactical decision by activating the turn signal. Commercial L2 vehicles are typically referred to as autopilots, and multiple automakers sells these features already with their vehicles. Names differ according to the company[2], examples are: Tesla (Autopilot), Cadillac (Super Cruise), Audi (Adaptive Drive Assist), BMW (Driving Assistance Pro), Ford (Co-Pilot 360), Kia/Hyundai (Highway Drive Assist), Volve (Pilot Assist), Mercedes (Driver Assistance Package Plus), Nissan (Pro-Pilot Assist), Toyota (Toyota Safety Sense) and Honda (Honda Sensing Suite). Some of these require the driver to steer the vehicle because they do not work perfectly in sharp turns. Others, such as Tesla's Autopilot (see Figure 1.3a) and Cadillac's Super Cruise (see Figure 1.3b), are a reference in the market with robust ALC systems. The former requires the driver to monitor by placing his hands on the steering wheel, while the latter requires the driver to keep his eyes on the road but allow hands to be off the wheel.

(a) Tesla Autopilot[3]

(b) Cadillac Super Cruise - Hands Free[4]

Fig. 1.3: L2 autopilots in commercial vehicles

- **L3** - *Conditional Automation*: Automation takes control of the entire driving task. The driver no longer needs to monitor the system, but must be prepared to act as a fallback mechanism (i.e., have sufficient situational awareness to regain control when the system demands it). In this mode, the driver is allowed to perform

[1] **Webpage**: Toyota Safety Sense → *https://www.toyota.com/safety-sense/*
[2] **Webpage**: L2 Autopilots Review → *https://www.autopilotreview.com/*
[3] **Webpage**: Tesla Autopilot → *https://www.tesla.com/autopilot*
[4] **Webpage**: Cadillac Super Cruise → *https://www.cadillac.com/super-cruise*

certain NDRTs. Commercial vehicles with L3 functions are generally limited to traffic jams at a maximum speed of approximately 60 km/h. Few automakers have taken the risk of selling an L3 functionality, as the legal responsibility in case of accident is on the company's side. Audi intitally offered an L3 functionality (Audi AI traffic jam pilot), but step back because of the regulatory hurdles. However Honda (Sensing Elite) and Mercedes (Drive Pilot) are bringing this system to the market in 2022 for traffic jam assistance, where drivers are able to engages in reading an article in the vehicle panel, watching a video, or playing a game. As a distinguishing feature, L3 vehicles can perform automatic lane changes without human intervention.

(a) Honda Sensing Elite[5]

(b) Mercedes Drive Pilot[6]

Fig. 1.4: L3 autopilots in commercial vehicles

- **L4** - *High Automation*: Automation controls all driving tasks and, while not capable of operating in all Operational Design Domains (ODDs), it is capable of performing the fallback maneuver without driver intervention and bringing the vehicle to a safe state. The maturity and quality of the technology for such automation is very high, although some experts believe it is worth working toward L4 vehicles and eliminating the problems created by having the driver act as a fallback mechanism in L3 mode. Common applications of L4 vehicles tend to focus on mobility services rather than private vehicles [17].
- **L5** - *Full Automation*: Automation follows the same scheme as for L4 vehicles, but works under all ODDs. This stage is the utopia of automated driving development. These vehicles could even drive without steering wheel and pedals.

Figure 1.5 shows a summary of the LoDA, each of which is associated with one of the forms of HMC described earlier. From this perspective, it is clear that the approach to increasing the LoDA is to remove more and more responsibility from the driver in relation to the DDT, but at the cost of creating new implementation challenges. This is especially true for L2/L3 vehicles, where the driver is placed in a supervisory/fallback role. With this kind of automation, the human mind begins to wander and turn away from the monitoring task. This is known as the out-of-the-loop problems [18], which also include increased cognitive workload during the takeover

[5] **Video**: Honda Sensing Elite → *https://www.youtube.com/honda-demo*
[6] **Video**: Mercedes Drive Pilot → *https://www.youtube.com/mercedes-demo*

request due to loss of situational awareness [4] and induction of drowsiness when the driver is not assigned a secondary task [5]. In addition, there are other issues such as mode confusion [19] and behavioral adaptation [20] that need urgent reconsideration to ensure AVs safe driving [21].

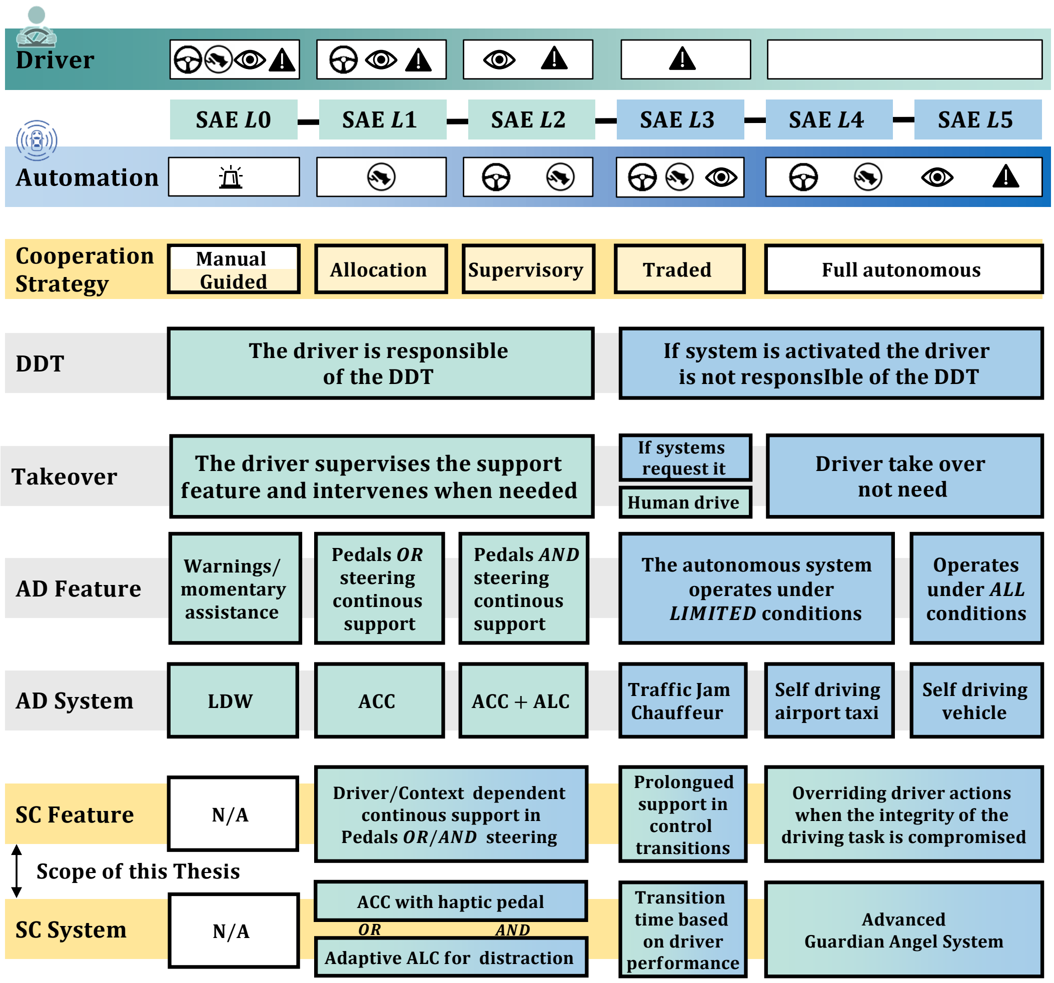


Fig. 1.5: Levels of Driving Automation defined by the SAEJ3016 standard, and linked to cooperative strategies and shared-control functionalities

To ensure a safe supervisory task, many efforts are being made to improve the quality of cooperation between highly automated vehicles and drivers. To this end, new bidirectional interaction strategies using Human-Machine Interfaces (HMIs) are being explored. On the one hand, pertinent information is communicated to the driver to maintain situational awareness and inform of the current state of automation and the associated role of the driver. On the other hand, the driver should be able to cooperate with the automation by sending commands at a tactical level to ensure his regular participation in the DDT. Another strategy, which has more to do with decision-making and control, is to adapt the behavior of the automation to the driver's state. In [22], Friedman presented seven principles for the concept of shared autonomy applied in a real-world demonstration using the Human-Centered Vehicle from the Massachusetts Institute of Technology's (MIT), shown in Figure 1.6a. It includes a dedicated Driver Monitoring System (DMS) used by the automation (which communicates with the driver by voice) to suggest control transitions, also based on the risk assessment of the scenario. Another approach [23], taken by the Spanish research institution CSIC (Consejo Superior de Investigaciones Científicas) as part of the Prystine project, is to develop a traded control system that dynamically changes the LoDA (and the role of the driver) depending on the assessment of the complexity of the scenario and the driver's state (see Figure 1.6b). Autoliv, a Swedish-American company, has also proposed an intelligent steering wheel system (zForce Steering, as shown in Figure 1.6c) that makes a dynamic transition of authority between the driver and the automated vehicle based on the position of the hands, as the system is able to activate the automated driving function when the hands are not on the steering wheel. In this system, the steering wheel is used not only as an interface for vehicle control, but also as a light-based HMI that provides the driver with information about automation operating mode.

(a) MIT Human-Centered Vehicle[7]

(b) CSIC Traded-Control Vehicle[8]

(c) Autoliv zForce Steering[9]

(d) Toyota Guardian Active Safety System[10]

Fig. 1.6: Real vehicles with enhanced Human-Machine Cooperation strategies

In previous systems, the general approach was to improve cooperation between driver and AV in the mode of traded control. However, there is another way, which is to use recent technological advances for automated driving in terms of perception, decision-making and control methods to improve manual driving with continuous support from automation, that is, the cooperation mode of shared-control. In this context, Toyota Research Institute (TRI) is working with the vision of using Artificial Intelligence (AI) to improve safety, mobility and human capabilities in automated driving. They have demonstrated a mature prototype called *Guardian* (see Figure

[7]**Video**: MIT Human-Centered Vehicle → *https://www.youtube.com/mit-demo*
[8]**Video:** CSIC Traded Control Vehicle → *https://www.youtube.com/csic-demo*
[9]**Video**: Autoliv zForce Steering → *https://www.youtube.com/autoliv-demo*
[10]**Video**: Toyota Guardian Vehicle → *https://www.youtube.com/toyota-demo*

1.6d) that operates on the concept of amplifying human control rather than removing it (i.e., shared-control [24]). This functionality is explained by Toyota as follows: "...the driver is meant to be in control of the car at all times, except in those cases where Toyota Guardian anticipates or identifies a pending incident and employs a corrective response in coordination with driver input"[11]. Features include activating automatic mode when the driver falls asleep or providing continuous support to the driver through the envelop control approach[12].

Given the current panorama of automated driving, further study of shared-control systems is needed. It is important to keep in mind that shared-control is not a new level of automation. It is a form of cooperation aimed at improving existing Active Safety Systems and ADAS that help drivers in terms of safety, performance and comfort. Thus, it is not limited to a specific LoDA, but extends across all. This means that shared-control functions can be available to vehicles with different LoDAs, resulting in functions with different levels of support, as shown at the bottom of Figure 1.5. Common applications of shared-control are often used in L1/L2 vehicles with continuous and adaptive haptic support in both the steering wheel and pedals. While conventional automated lane centering systems can only be enabled or disabled, shared-control functionality adds dynamic control intensity assignment depending on, for example, driver state [25]. For L3 vehicles, a transition of control with adaptive support over a longer period of time may offer advantages in a system-initiated takeover request compared to the binary on-off strategy [26]. On the other hand, L4/5 vehicles could have advanced safety features if humans voluntarily choose to drive. For example, TRI uses the same vehicle platform for the *Chauffeur* mode to operate in *Guardian* mode (based on a shared-control system). Due to the high level of automation, the system in this case could be given sufficient authority to override the driver's commands.

1.1.3 EU-Projects

Vehicle design and technology is one of the action areas of the "Vision Zero" movement, which aims to reduce traffic fatalities and serious injuries through a systemic approach to road safety. As part of the initiatives to achieve this goal, the European Commission and National Research Agencies have funded several projects over the past decade to achieve this goal. Many of them are concerned with improving human-machine cooperation between drivers and automated vehicles. Some of these projects are **Deserve** (future ADAS functions) [27, 28], **Haveit** (human-computer interfaces for highly automated vehicles) [29], **InteractiVe** (user-centered active safety systems) [30], **AdaptiVe** (dynamic change of the level of automation) [31], **ABV** (human-machine interaction in automated vehicles, with focus on shared-control) [32] and **AutoMate** (automation as a teammate of the driver) [33]. The most recent projects dealing with cooperative integration of drivers and automated

[11] **Webpage**: Toyota Guardian Concept → *https://www.tri.global/our-work/automated-driving*
[12] **Webpage**: Envelop Control Approach → *https://medium.com/toyotaresearch*

vehicles are **Prystine** [11] and **Hadrian** [11]. Part of this Ph.D. Thesis supported the development on shared-control for these projects.

PRYSTINE aims to realize fail-operational urban surround perceptION (FUSION) based on robust radar and LiDAR sensor fusion and control capabilities to enable safe automated driving in urban and rural environments. It covers multiple aspects of automated driving, such as sensors, perception, communication, and AI decision making. As part of the output enablers aimed at presenting relevant demonstrators for automated driving, one of them is specifically dedicated to human-centered vehicles and includes three main demonstrators covering a wide range of driver-automation collaboration (shared-control, traded control, and AI-based autonomous control [11]). Relevant applications were developed with the integration of decision systems, advanced control methods, driver monitoring systems, and visual human-machine interfaces in a multi-component integration for shared-control systems.

HADRIAN, on the other hand, explores a holistic approach between the vehicle, the infrastructure, and the driver for better vehicle-driver cooperation under the concept of *fluid* interfaces, which creates the conditions for communication and assistance to occur in a safe, comfortable, adaptive, and understandable manner that can be accepted by the driver. This framework considers the development of a "Guardian Angel" system for elderly drivers based on shared-control. This strategy will be supported by complementary HMIs (acoustic signals, ambient light indicators, tutoring system and others) that act as *fluid* interfaces. This means that the entire HMI system depends heavily on the state of the driver. A robust driver monitoring system is also part of the developments in this project, with the goal of obtaining a fit-to-drive score that serves as input to the HMI decision system.

(a) PRYSTINE[13] - Programmable Systems for Intelligence in Automobiles based on Fail-operational Urban Surround Perception

(b) HADRIAN[14] - Hollistic Approach for Driver Role Integration and Automation Allocation for European Mobility Needs

Fig. 1.7: Two recent EU-funded projects working with driver-automation cooperation

Recent projects appear to be further expanding human-machine collaboration by incorporating more interfaces, expanding experimental studies, and considering new cooperation strategies, with shared control envisioned as a solution for safe, efficient, and comfortable human-machine integration in automated vehicles.

[13] **Webpage**: Prystine Project → *https://prystine.eu/*
[14] **Webpage**: Hadrian Project → *https://hadrianproject.eu/*

1.1.4 Motivations

Based on the preceding premises, this dissertation explores shared-control in automated vehicles from the following perspectives and motivations:

- It has the potential to improve road safety.
- There is no need for humans to take on a new role, as they are retained as the primary driver, avoiding the familiar out-of-the-loop problems.
- It can take advantage of the latest advances in automated driving technologies in the areas of perception, decision-making, control algorithms, and HMIs while reducing requirements in these areas.
- Driving enthusiasts can continue to do what they enjoy but in a safer and less demanding manner.
- It is a solution that can be implemented in the short term compared to the uncertain schedule of highly automated vehicles.

1.2 Objectives

The main objective of this Ph.D. thesis is to explore, design, develop, validate, and evaluate shared-control strategies for automated driving. Alongside, the following sub-objectives are part of this work:

- To explore the state-of-the-art of shared-control in automated driving, examining both the concepts and the control algorithms available in the literature.
- To integrate the shared-control components into a general framework of automated driving, in both the software and hardware architecture of a driver-in-the-loop vehicle simulator platform.
- To design, develop, and validate a lateral vehicle control system based on steering shared-control with variable level of haptic authority.
- To design, develop, and validate an arbitration system that decides the level of haptic authority given to the steering controller for a variety of driving scenarios in which the driver and automation interact at tactical and control levels.
- To conduct experimental studies to evaluate ADAS based on shared-control in a driver-in-the-loop simulator using objective and subjective evaluation methods.
- To provide with the current state of shared-control systems in automated driving with recommendations, perspectives and future work for the coming years.

1.3 Structure

The organization of the manuscript of this Ph.D. Thesis is as follows:

- **Chapter 2. State-of-the-Art**: This chapter presents a systematic and comprehensive review of the works published over the past two decades on the topic of shared-control in automated driving. The review of the SoA includes an analysis from two directions. First, a discussion from a theoretical perspective in terms of definitions, metaphors, levels of cooperation, control frameworks, and its relationship to the arbitration module. Second, vehicle applications based on shared-control are examined, with emphasis on control techniques. This chapter provides an overall view of the current state of this technology and future trends.

- **Chapter 3. Shared-Control Framework for Automated Driving**: This chapter presents the components of shared-control within a known framework for automated driving and provides a modular comparison between the challenges of implementing shared-control and traditional approach to automated driving. The requirements for the decision and control modules are presented and a rationale for selecting the appropriate algorithm for each module is provided. In this sense, an introduction to the theoretical foundations of Fuzzy Inference Systems (FIS) and Model Predictive Control (MPC) is also given. It concludes with a description of the driver-in-the-loop vehicle simulator platform used for the development and validation of the algorithms, as well as the performance of experimental studies.
- **Chapter 4. Steering Shared-Controller**: This chapter presents the design, development, and validation of a steering shared-controller based on Nonlinear Model Predictive Control (NMPC). A stability criterion for different levels of haptic authority is also considered as part of the controller design. The development of the controller is presented in four iterations and validated together with an arbitration system based on a Fuzzy Inference System (FIS) for specific driving scenarios.
- **Chapter 5. Experimental Studies**: This chapter describes two experimets conducted in the driver-in-the-loop simulator platform. The first study dealt with assistance for a distracted driver, and the second with the evaluation of an active safety system for overtaking maneuvers on a road with oncoming traffic. In both scenarios, the shared-control approach was tested and compared with some baselines, such as manual driving, commercial ADAS, and automated driving functions. An objective and subjective evaluation is provided for each experiment.
- **Chapter 6. Conclusions**: This chapter concludes the dissertation and provides insight into the knowledge gained from the literature review, the development of the shared-control system, and the simulator studies conducted, as well as a detailed outlook for future work in this area.

1.4 Contributions

The main contributions of this Ph.D. thesis are summarized below:

- **Contribution 1**: A systematic review of shared-control in automated driving with a compilation of the most relevant contributions of the last decades.

- **Contribution 2**: The integration of the shared-control components by hierachical cooperation levels into the AD general framework and their implementation in a DiL hardware/software AD simulator. The final framework allows the reuse of the designed shared-scontroller at the operational level without any changes, while the arbitration system is adapted to each individual scenario.
- **Contribution 3**: A novel NMPC steering shared-controller, with the ability to increase and decrease the nominal haptic authority of the controller without the need to retune any of the NMPC parameters, providing stability in all cases.
- **Contribution 4**: A flexible Multiple-Input Multiple-Output (MIMO) FIS-based arbitration system that calculates the optimal level of haptic authority for the steering shared-controller, depending on the driver's need for assistance. It is able to adapt to different scenarios where the conditions of the driver, automation and environment play an important role in decision-making.
- **Contribution 5**: An ADAS based on lateral shared-control for distracted drivers, capable of keeping the driver in lane during short distraction events. Includes design, development, and experimental validation.
- **Contribution 6**: An ADAS based on shared-control to maintain safety and driving performance during overtaking maneuvers on roads with oncoming traffic. Includes design, development, and experimental validation.

1.5 Dissemination

1.5.1 Scientific Journals

- **J1**: *Marcano, M.*, Díaz, S., Pérez, J., & Irigoyen, E. (2020). A review of shared control for automated vehicles: Theory and applications. IEEE Transactions on Human-Machine Systems, 50(6), 475-491.
- **J2**: *Marcano, M.*, Tango, F., Sarabia, J., Castellano, A., Pérez, J., Irigoyen, E., & Díaz, S. (2021). From the Concept of Being "the Boss" to the Idea of Being "a Team": The Adaptive Co-Pilot as the Enabler for a New Cooperative Framework. Applied Sciences, 11(15), 6950.
- **J3**: *Marcano, M.*, Matute, J. A., Lattarulo, R., Martí, E., & Pérez, J. (2018). Low speed longitudinal control algorithms for automated vehicles in simulation and real platforms. Complexity, 2018.
- **J4**: *Marcano, M.*, Castellano, A., Díaz, S., Pérez, J., Tango, F., Landini, E., & Burgio, P. (2021). Shared and traded control for human-automation interaction: a haptic steering controller and a visual interface. Human-Intelligent Systems Integration, 3(1), 25-35.
- **J5**: Matute-Peaspan, J. A., *Marcano, M.*, Diaz, S., Zubizarreta, A., & Perez, J. (2020). Lateral-Acceleration-Based Vehicle-Models-Blending for Automated Driving Controllers. Electronics, 9(10), 1674.

- **J6**: Lattarulo, R., González, L., Martí, E., Matute, J., *Marcano, M.*, & Pérez, J. (2018). Urban motion planning framework based on n-bézier curves considering comfort and safety. Journal of Advanced Transportation, 2018.
- **J7**: Hidalgo, C., *Marcano, M.*, Fernández, G., & Pérez, J. M. (2020). Maniobras cooperativas aplicadas a vehículos automatizados en entornos virtuales y reales. Revista Iberoamericana de Automática e Informática industrial, 17(1), 56-65.

1.5.2 Conference Proceedings

- **C1**: *Marcano, M.*, Díaz, S., Matute, J. A., Irigoyen, E., & Pérez, J. (2020). A cascade steering shared controller with dual-level dynamic authority. IFAC-PapersOnLine, 53(2), 15353-15359.
- **C2**: *Marcano, M.*, Díaz, S., Pérez, J., Castellano, A., Landini, E., Tango, F., & Burgio, P. (2020, February). Human-automation interaction through shared and traded control applications. In International Conference on Intelligent Human Systems Integration (pp. 653-659). Springer, Cham.
- **C3**: *Marcano, M.*, Diaz, S., Vaca, M., Pérez, J., & Irigoyen, E. (2020, September). Shared control framework and application for european research projects. In International Workshop on Soft Computing Models in Industrial and Environmental Applications (pp. 657-666). Springer, Cham.
- **C4**: Vaca-Recalde, M. E., *Marcano, M.*, Sarabia, J., González, L., Pérez, J., & Díaz, S. (2020, July). A Fluid-HMI Approach for Haptic Steering Shared Control for the HADRIAN Project. In International Conference on Human-Computer Interaction (pp. 417-428). Springer, Cham.
- **C5**: Matute, J. A., Marcano, M., Diaz, S., & Perez, J. (2019). Experimental validation of a kinematic bicycle model predictive control with lateral acceleration consideration. IFAC-PapersOnLine, 52(8), 289-294.
- **C6**: Matute, J. A., *Marcano, M.*, Zubizarreta, A., & Perez, J. (2018, April). Longitudinal model predictive control with comfortable speed planner. In 2018 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC) (pp. 60-64). IEEE.
- **C7**: Mirnig, A. G., *Marcano, M.*, Trösterer, S., Sarabia, J., Diaz, S., Dönmez Özkan, Y., ... & Madigan, R. (2021, September). Workshop on Exploring Interfaces for Enhanced Automation Assistance for Improving Manual Driving Abilities. In 13th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (pp. 178-181).
- **C8**: Sarabia, J., *Marcano, M.*, Pérez Rastelli, J., Díaz Briceño, S., & Zubizarreta, A. (2021). Estudio preliminar de los métodos de evaluación del control compartido. In XLII Jornadas de Automática (pp. 325-332). Universidade da Coruña, Servizo de Publicacións.

- **C9**: Lattarulo, R., *Marcano, M.*, & Pérez, J. (2017, February). Overtaking maneuver for automated driving using virtual environments. In International Conference on Computer Aided Systems Theory (pp. 446-453). Springer, Cham.
- **C10**: Lattarulo, R., Martí, E., *Marcano, M.*, Matute, J., & Pérez, J. (2018, May). A speed planner approach based on Bézier curves using vehicle dynamic constrains and passengers comfort. In 2018 IEEE International Symposium on Circuits and Systems (ISCAS) (pp. 1-5). IEEE.

State-of-the-Art

2

This chapter provides a systematic review of shared-control in automated vehicles with the aim of summarizing the work done in the research community over the past decades. There are two main directions for research in this area. The first is to advance the theoretical understanding of shared-control [9, 34]. Second, there are a growing number of system applications that are currently emerging [35–37]. Nevertheless, there has been no comprehensive analysis of this technology to assess its current status or to lay the foundation for its future development. The author of a recent review article, Huang [38], examined shared-control in the automotive domain, but without evaluating the associated systems in detail. In addition, Petermeijer *et al.* [39] evaluated several haptic guidance systems reported by 2014 to support a variety of driving tasks, but only considered model-free control strategies. Wang *et al.* [6] also presented a recent extensive review covering theoretical and practical aspects, but did not include specific and detailed analysis of individual control algorithms. To cover the whole area of shared-control in automated vehicles, this section provides a comprehensive overview of this area with the following objectives:

- Summarize the contributions to the definition of shared-control in automated driving and distinguish it from other cooperation strategies.
- Group applications of shared steering control using appropriate categories.
- Review steering shared-control algorithms, including their design, implementation, evaluation, and results.
- Evaluate the status of the technology and suggest future work related to shared-control in automated driving systems.

It begins with an explanation of the methodology for the systematic review, including the selection of articles and the categories in which the review is organized. This is followed by a discussion of the theory, concepts, and definitions of shared-control, with an emphasis on applications to automated driving. There are two sections in the practical analysis, one for coupled and one for uncoupled shared-control. Both are related to the description of algorithms for steering control. The chapter concludes with a summary of the review, as well as a discussion and outlook on concepts, control methods and algorithms, related variables in shared-control, the current state of the technology and future works.

2.1 Methodology

The scientific literature for the systematic review was searched in a number of databases, including Web of Science, Google Scholar, IEEE Xplore, and ScienceDirect. A set of keywords was used to find papers related to shared-control in automated driving, the main terms being: shared-control, shared steering control, shared vehicle control, haptic guidance systems [39], haptic steering feedback [40], parallel autonomy

[41], semi-autonomous vehicle control [42], intelligent copilot [43], cooperative steering assistance system [44], torque steering assistance [34], and adaptive authority [45]. The first round of literature collection lasted from June 2017 to November 2018 and yielded 100 papers on this topic. A final round of additional data collection was conducted from December 2018 to August 2019. The selection criteria for the papers are as follows:

- Must be published in a scientific journal or conference proceedings.
- For theory-related papers, the search field is human-machine cooperation.
- For systems applications papers, search field is narrowed to automated driving.
- Valid application-oriented works are those which follows the definition of shared-control given by Abbink [8], and have been tested in simulation or real vehicles.
- Works that do not use conventional vehicle control mechanisms (i.e., steering, accelerator pedal, or brake) are excluded. For example, applications where the vehicle is controlled with a joystick.

After a first reading of the literature, the following preliminary conclusions can be drawn. First, experts in the field are working to propose the best definition for shared-control and to distinguish it from other similar concepts (e.g., the establishment of the Shared Control Committee [46] and a new topology for shared-control applications in various domains, including the automotive industry [8]). Second, the number of works addressing shared-control in automated driving has increased over the years and continues to grow. Finally, an increasing number of works presenting assistance systems based on shared-control use the steering wheel as the control interface, while only a few works consider longitudinal actuators (gas pedal or brake) [41, 47–54] (see [39] for more details on these systems).

Based on these premises, the state-of-the-art is divided into two overarching subsections: Theory and Applications. The theoretical section includes topics related to shared-control that can facilitate understanding of the concept in the context of automated vehicles. These are described below:

- **Definitions**: Understand how shared-control is described and defined in the literature and examine other terms that are often confused.
- **Metaphors**: Envision the concept of shared-control in real-life examples of interaction and collaboration to improve the understanding of the term.
- **Arbitration**: The high-level decision system that tells the shared-controller how much authority should assign to the driver and automation.
- **Levels**: Evaluates shared-control from the different driving task levels (operational, tactical, and strategical).
- **Use-cases**: Explores the application of shared-control in real scenarios related to automated driving systems.

- **Control frameworks**: Describes shared-control from the point of view of two different control schemes based on the steering actuation mechanism.

The subsection on applications, on the other hand, is divided according to the actuation mechanism, the method of control, and the specific algorithms of steering shared-control.

- **Control mechanisms**: Systems can be either mechanically *coupled* or *uncoupled*. In the first case, the driver interacts with the automated system via haptic feedback and has ultimate control as long as sufficient torque is applied. In the second case (e.g., steer-by-wire), the controller can supplement the driver's input and provides a new control paradigm in which the automation has final authority. Controllers for these two mechanisms differ in concept, design, and results.
- **Control methods**: Shared-control algorithms can be either *model-free* or *model-based*. This subdivision emphasizes the cooperation achieved by the interaction between the driver and the automation, rather than the controller itself (e.g., a model-predictive controller could be assigned to the model-free category if the cooperative/shared component is not modeled within the problem).
- **Control algorithms**: The steering controls and arbitration algorithms used to share lateral control of the vehicle.

Figure 2.1 shows the methodological framework described above along with the structure of the state-of-the-art, with shared-control considered from the outset as a particular form of the wide-ranging domain of Human-Machine Cooperation.

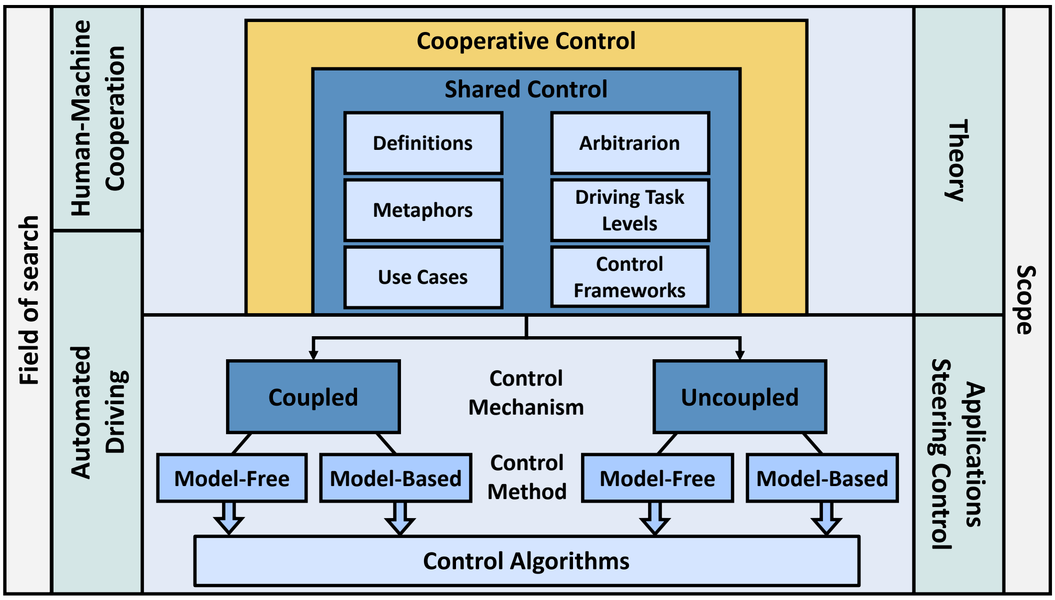


Fig. 2.1: Shared-control for automated driving state-of-the-art methodological framework

2.2 Theory

This section provides an overview of the concept of shared-control, based on an analysis of the major studies of the last twenty years dealing with human-machine cooperation and automated driving [8, 9, 34, 39, 55–72]. The aim of this section is to clarify the concept of shared-control, to find consensus in the research community, and to avoid misuse of the term, especially in the automotive industry. As mentioned earlier, six aspects related to the concept of shared-control are addressed: Definitions, metaphors, arbitration concept, levels of driving tasks, use cases, and control frameworks.

2.2.1 Definitions

In 1978, Thomas B. Sheridan and William L. Verplank defined shared-control for the first time. They considered it to be a particular form of a higher-level control scheme called supervisory control, consisting of a *"system ... capable of autonomous decision making and control over short periods of time and under constrained conditions, but monitored remotely and at times operated or reprogrammed directly by a person"*. In the context of this global control scheme, shared-control is defined simply as *"human and machine working on the same task at the same time"*. This interaction can be achieved in two different ways. First, when the machine can augment human capabilities (e.g., a robotic arm with haptic feedback that guides the human operator is a complex task). Second, when the machine can partially relieve the operator of the entire load of a task.

Later, Inagaki [57] considered shared-control as part of the partinioning scheme, in which a global task is divided into subtasks performed by individual agents, as a third type of shared-control. A clear example is the case of an automated vehicle L1, where a driver steers the vehicle and the automated system control the pedals. However, this view is not popular within the research community, but is more related to cooperative control, which includes a wider range of interactions.

Furthermore, these works distinguish between shared and traded control, where *"human and machine work on the same task but at a different time"*. In this type of interaction, the machine can either replace or back up the human. This distinction is relevant to the automotive sector because most advanced automated vehicles operate in traded rather than shared-control mode. The main disadvantage of traded control is that drivers usually have too much confidence in automation and are not able to take back manual control when needed.

In a 10-level scale (from manual control to full automation) Endsley [56] ranked shared-control at the fourth level of automation. Here, shared-control was defined as *"Both the human and the computer generate possible decision options. The human still retains full control over the selection of which option to implement, however, carrying out the actions is shared between the human and the system"*. This definition gives the human the ultimate authority over automation. It also portrays it as more than an active support system that helps the human perform an action, as the system has enough intelligence to generate possible decision options, but not enough authority to select the final action.

In addition to the works discussed above, the research of Abbink *et al.* [8] presents the more detailed definition of shared-control: *"human(s) and robot(s) are interacting congruently in a perception-action cycle to perform a dynamic task that either the human or the robot could execute individually under ideal circumstances"*. Based on this definition, Table 2.1 lists the arguments as to why various automated systems do not fall into the category of shared-control.

Tab. 2.1: Arguments to exclude common driving modes and system from the category of shared-control

System	Argument
Manual control	There is no automated system involved
Full autonomous	There is no driver involved
L3-4 vehicle	Automation and human drives at different periods
Warning systems	The perception-action cycle is not closed
Stability control	Not achievable by driver alone

2.2.2 Metaphors

It has been said that good design is sometimes preceded by a vision and mental model of the final product, rather than being based on selecting technologies and following procedures [59]. In this sense, metaphors are excellent descriptive tools that help to abstract from the technical problem and think at a high level, but they also help to move from pure theory to practical examples. Therefore, the use of metaphors is a promising approach to make shared-control a solid concept. Accordingly, some authors have used them to compare driver-automation interaction with real-world examples of agents cooperation to derive useful design concepts for the development of cooperative driving systems. In this section, four metaphors are described, as shown in Figure 2.2.

- **Rider-Horse**: Commonly referred to as the H-metaphor [59]. It was introduced by Flemisch in 2003 as a result of research collaboration between the German Aerospace Center (DLR) and the Langley Research Center (NASA) to investigate the similarities between driving an automated car and riding a horse. In horseback riding, the human controls the horse primarily through the reins. An interplay occurs in which the horse and rider perceive each other's actions through a haptic channel (e.g., the seat on the horse, the reins, or the spurs). In a shared-control situation, the rider may lead the horse on a tight rein to exert more direct control or use a loose rein to give the horse a greater degree of autonomy. The human uses

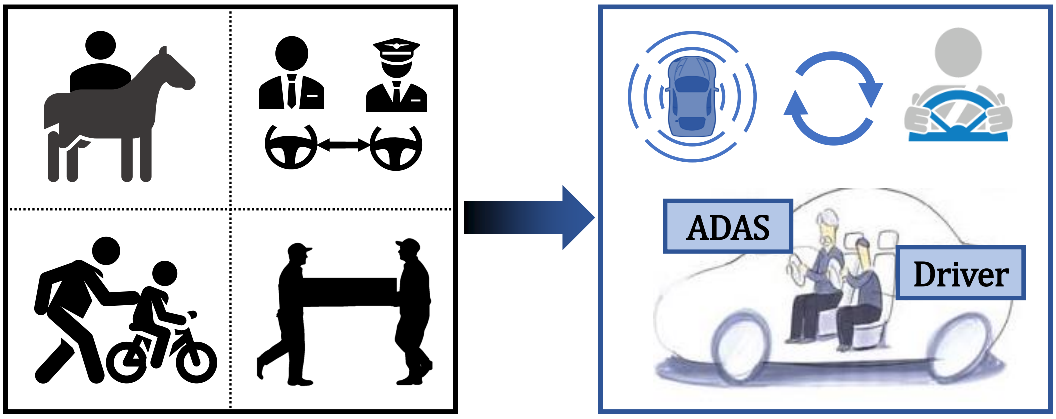


Fig. 2.2: Metaphors of shared-control for automated vehicles

the horse's field of vision and sense of security, but is still in control. Similarly, systems based on shared-control should provide support to the driver across the continuous spectrum of authority.

- **Flight lessons**: The example of the interaction between a novice pilot and an experienced pilot during flight lessons [62, 71, 73]. In this scenario, the control mechanisms of the pilot and the student pilot are coupled. The experienced pilot can assist the student pilot in two different modes. One, *active*, by applying forces to the control system to help execute maneuvers. And the other, *passive*, by holding the control system with different forces (variable stiffness [71]) to communicate agreement or disagreement with the commanded action to the student. Similarly, automation can assist a driver either actively or passively.
- **Joint-carrying**: It is another example of shared-control [69], with emphasis collaboration on a task between two agents who share a load and are responsible for its control and guidance. In this example, agents have different perceptual abilities, as one walks forward and the other walks backward. Yet both are needed to accomplish the task. The situation is similar in automated driving. An automated vehicle may have a better field of view than a human, but the driver still has better anticipatory situational awareness [74]. In both cases, the information perceived by each agent is complementary to achieve the task.
- **Parent-Child**: It is another example of shared-control [64]. A parent teaching a child to ride a bicycle is a good illustration. In this scenario, the parent is always in direct contact with the bicycle, but the child has most authority while maintaining balance. However, if the child starts to lurch, the parent intervenes with more authority to protect the child. Transferred to automated driving, the driver wants to feel that is in control of the vehicle. Therefore, automated systems must avoid overwhelming the driver while performing well. However, if the driver puts the vehicle under risk, the system must intervene accordingly to avoid accidents. Nevertheless, the intervention should be as gentle as possible.

From these four examples, the following principles can be derived for shared-control systems in automated vehicles:

- There should be a bidirectional communication channel.
- Automation should follow the driver's intention if not leading unsafety condition.
- Automated system should support the driver in proportion to the risk.
- The automated system can support the driver either actively or passively.

2.2.3 Arbitration

Shared-control and arbitration are closely related concepts, but they are not the same thing. From a higher-level perspective, a shared-controller applies control actions with the authority established by an arbitration system. Arbitration, simply put, is the division of control between humans and automation systems during their interaction [75]. In the context of cooperative vehicle control, it is a time-sensitive, structured negotiation between human and machine that achieves a clear and optimal goal for the overall system in a timely manner [58]. In traded control systems, arbitration is about who receives control and when, whereas in shared-control, it is about how much control authority is given to the driver and the automation. This means an arbitration system is needed to synchronize the control actions of the cooperative driving agents. [66].

This concept is represented by the Equation 2.1, as a combination of the driver input (u_d) and the automation command (u_a) with a variable authority ($\lambda \in [0, 1]$). In conventional steering systems, it is not possible to include the torques of the driver and the motor in the formula. However, the formula can be part of the driver's mental model [45] or can be interpreted as the system providing some of the torque (λ %) and the driver providing the rest ($(1 - \lambda)$ %) [76]. Conversely, using a steer-by-wire system allows the driver and automation to combine steering angle commands in parallel.

$$u = \lambda u_a + (1 - \lambda) u_d, \quad 0 \leq \lambda \leq 1 \tag{2.1}$$

The arbitration strategy may depend on several driving-related variables, such as the driver's state [77, 78], the time to collision [79], the time-to-lane-crossing [80], or the conflict between the driver and the automation [81, 82]. In these cases, the arbitration system acts as a decision strategy that manages the controller's authority (how strongly or how gently should the controller resist the driver's steering movements). In addition, a more general rule for arbitration systems has been proposed, according to which drivers should be strongly supported when they are under or overloaded, but receive less support when they are driving correctly [83, 84].

2.2.4 Driving Task Levels

Following the contribution of Michon [13], it can be said that a driver and an automated system can share the driving task at different levels of skill (or cognition): *strategic*, *tactical*, and *operational*. Petermeijer [39] refers to the latter two as *maneuvering* and *control*. Abbink [8] adds *execution* as a fourth level that complements the operational task.

- **Strategic**: In this level the issue is how to get from point A to point B (i.e., global planning). According to the standard SAE J3016[14], this level is not part of the dynamic driving task (DDT). For this reason, it is unusual to find an example of shared-control with the strategic component in automated vehicles. Some applications of longitudinal control, such as *eco-driving*, however, have a high strategic component [39].
- **Tactical**: This level is specific to driving maneuvers (e.g., lane changes) where the driving task contains a decision component intended to enable the strategic decision. Though, shared-control strongly relates to the operational level, there are some driving applications where separate tactical and operational shared-control modules coexist. An example is the work of Sentouh [44], which establishes a tactical decision law between the driver and the automated system to select which controller needs more authority at the operational level. It was a tactical shared-control because the decision depended on the torque difference between the driver and the automated system and therefore both were constantly involved.
- **Operational**: This level refers to the vehicle control, specifically the commands that the controller sends to the actuators to achieve the decision made at the tactical level. In parallel, the execution level is responsible for the low-level control actions required to achieve the operational set point. For example, in an automated lane-centering system, the lateral error controller finds the optimal steering angle to improve tracking performance (operational level). Then, this command must be executed by the steering motor, which has an internal position controller to execute the commanded steering angle (execution level). These two levels are usually considered together. In general, most work on shared vehicle control focuses on the operational execution level, i.e., the application of torque to the steering wheel.

With this taxonomy in mind, several frameworks for shared and cooperative control have been proposed. Flemisch [69] categorized shared-control as the sharp end of human-machine cooperation, considering only the operational level of a task, which is the usual approach in system applications based on haptic guidance. On the other hand, Abbink [8] proposed a general framework for sharing the control of a task at all skill levels that enables bidirectional learning and communication through knowledge-rule-skill behavior. These efforts were summarized in a joint publication by Abbink and Flemisch that considered shared-control as part of human-machine cooperation at all cognitive levels [9].

2.2.5 Use Cases

Considering that the driver is heavily involved in the driving task in shared-control, most system applications of automated driving involve driver assistance and partially automated vehicles. The most common applications are automated lane-centering, obstacle avoidance, and transition of control.

- **Lane-centering**: Commonly referred to as lane-keeping control, is the most well-known application of shared-control in automated vehicles. It is presented in the form of lateral vehicle control [85], which aims to improve lane-keeping performance with continuous and variable steering assistance. Specific applications can be found in the literature. One example is disturbance rejection, to keep the vehicle in the center of the lane after an unexpected lateral wind force [86]. Other examples include preventing the vehicle from leaving the lane [87], curve negotiation [88], and assistance for distracted and drowsy drivers [89]. These systems are closely linked to the operational level.
- **Lateral-maneuver**: In shared-control, it refers to the scenario in which the driver initiates a maneuver that intentionally diverts the vehicle from the desired trajectory. It can be performed in various forms, such as lane change [90], overtaking maneuver [91], unexpected obstacle avoidance [44], and avoiding road works [82]. In these scenarios, where the decision-making component is high, the tactical level of shared-control makes decisions based on the conflicts that arise when the driver and the automated system have different intentions [86], resulting in smooth and safe control transitions from automated to manual driving and vice versa. Other applications involve an active safety systems preventing the driver from performing a dangerous maneuver, such as changing lanes when a vehicle is in a blind spot [92, 93].
- **Control resumption**: Considers the scenario in which the driver resumes control of the vehicle and the system must smoothly return its authority to the driver [94, 95]. The difference with lateral maneuvers is that in this case the transition is not necessarily initiated by the driver and the automation plays a more active role during the transition. Such applications are relevant in automated L3-L4 vehicles, where the driver is not constantly involved, but can still intervene in the driving task when the automation requires it.

Other applications for shared-control of automated vehicles include reverse parking assistance [96] and roll stability of heavy vehicles [97].

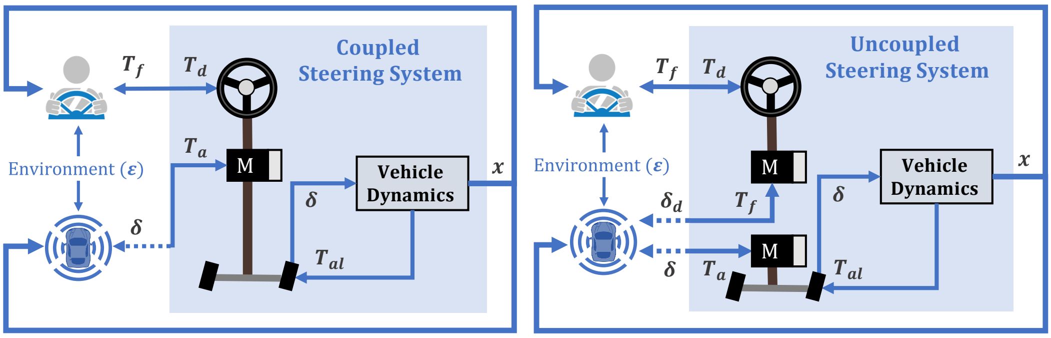
2.2.6 Control Frameworks

There are two clearly defined frameworks for shared-control in the literature. The difference between them lies in the control mechanism used to handle the vehicle.

The first is coupled shared-control, commonly found as haptic shared-control [34]. The second is uncoupled shared-control,which is referred to in the literature as indirect [98–100] or input mixing [34, 101]. In both cases, it is assumed that there is a control interface (e.g., steering wheel, accelerator pedal, or brake pedal) with an electronic actuator that allows the automation control system to steer, accelerate, or brake the vehicle.

- **Coupled shared-control**: The operator interface and the automation system are mechanically coupled. It is commonly associated with haptic control systems, where human and machine interact through force feedback. In this case, the control action performed by the operator directly affects the dynamics of the vehicle. Furthermore, the final control authority rests with the human operator (whenever the operator's force exceeds that of the automation). Through the actuator, the control actions of the automation assist the human and reduce his workload and control activity. In steering assistance systems, driver and automation interact through a motorized steering wheel that is mechanically connected to the vehicle's tires. In this case, the automation applies torque through the motor, while the driver applies torque with his hands and through neuromuscular adaptation to the perceived forces at the steering wheel [34]. Figure 2.3a shows the schematic diagram of coupled steering shared-control. It shows the torque applied by the driver's arms (T_d) along with the torque applied by the automated system (T_a) via the electric motor. These two together with the self-aligning torque T_{al} give a feedback torque T_f on the steering wheel. In manual mode, $T_a = 0$ and $T_f = T_{al}$, while in shared-control mode $T_a \neq 0$ and $T_d \neq 0$. In the case where $T_a \gg T_d$, the automation gets more authority than the driver and can override his maneuver intention.
- **Uncoupled shared-control**: Suitable for drive-by-wire systems in which the human control interface and the automated control system are mechanically decoupled. This mechanism allows the integration of an intermediate controller that post-processes the driver's commands and executes them according to the defined automation goals. Thus, the final control authority rests with the automation, although under normal circumstances the system must act as a virtually coupled system. Haptic feedback is always required to communicate the automation intent to the driver (consistent with the axioms presented by Abbink *et al.* [8] for the development of shared-control systems). In this case, there is a virtual (non-mechanical) combination of human and machine control commands. Applied to steering assistance, the driver indirectly controls the vehicle via a decoupled steering system (e.g., steer-by-wire or Active Front Steering (AFS)) that enables the virtual combination of driver and automation control actions before they are executed. In this method, the automated system includes two controllers (see Figure 2.3b). The first is responsible for controlling the vehicle by applying the automation torque (T_a). The second controller provides haptic feedback (T_f)

to the driver to inform him about the position of the wheels (self-aligning torque effect) and the automation intent. In manual mode, the system behaves like a conventional steer-by-wire system, the steering angle corresponds to the driver's intention ($\delta = \delta_d$) and $T_f = T_{al}$. In fully automatic mode, the driver's intention is ignored by the automated control system, while in shared-control mode, the driver's command influences the behavior of the automation with the degree of authority assigned by the arbitration system ($T_a = f(\delta_d, \lambda)$).



(a) Coupled steering shared-control framework **(b)** Uncoupled steering shared-control framework

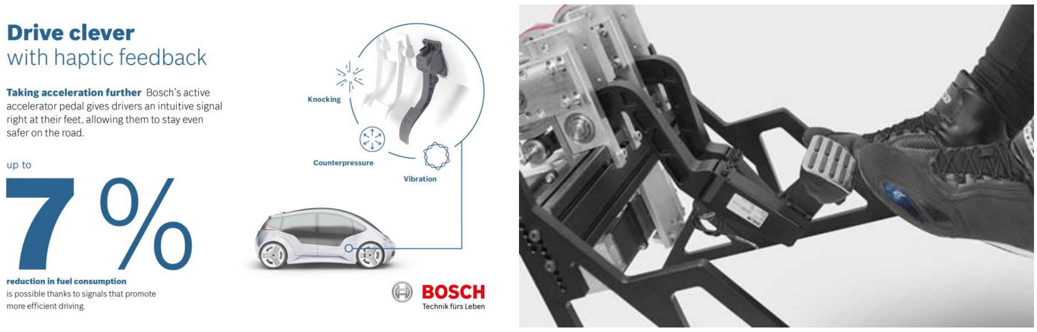
Fig. 2.3: Frameworks for steering shared-control based on control mechanism

2.3 Applications

This section analyzes the numerous shared-control applications available in the literature. First, the section opens with a summary of the applications of longitudinal shared-control. Then, it continous with a complete analysis on lateral shared-control systems. The analysis is organized according to the two control frameworks defined above (coupled and uncoupled), taking into account that there are relevant differences in design, implementation, evaluation, and results. In addition, the study of control strategies is further divided into model-based and model-free algorithms.

2.3.1 Longitudinal Shared-Control

In comparison with steering control, longitudinal vehicle control systems (acceleration and braking) are rare in shared-control applications. Nevertheless, relevant works exist, particularly for coupled systems. Abbink and Mulder made a major contribution in this field by using a haptic accelerator pedal to assist in a car following task [47–51]. Other examples include eco-friendly driving [53] and traction control on slippery surfaces [52]. In a separate study, Guo [54] integrated both a haptic brake and an accelerator to simulate a merging situation. Another work presents an uncoupled shared-controller that takes pedals and steering input into account when handling left turns in vehicles [41, 102]. With regard to an industrial perspective, Bosch introduced an active accelerator pedal which provides haptic feedback to limit speed, warns of sharp turns, and improves fuel efficiency. In addition, more haptic devices (accelerator and brake) are becoming available to continue research on applications related to haptic pedals in automated driving (see Figure 2.4b).



(a) Bosch active accelerator pedal[1] **(b)** Sensodrive active SENSO-Pedals pro[2]

Fig. 2.4: Haptic longitudinal actuators available for longitudinal shared-control applications

Meanwhile, over 100 articles address steering control. Therefore, the next two sections present a detailed analysis and evaluation of lateral control algorithms using coupled and uncoupled shared-control.

2.3.2 Lateral Shared-Control → Coupled

As mentioned earlier, in coupled shared-control, the driver and the automated system interact by applying continuous torque to the steering wheel [103]. The driver perceives the automation action through the haptic channel and then decides whether to override or accept it. Regarding the strength of the assistance, too little torque from the steering motor has no effect on the driver's behavior. Too much torque, on the other hand, can be oppressive, unsafe, and uncomfortable. Therefore, the strength of the torque is of great importance. However, this is not the only important aspect in developing shared-control strategies. Instead, four aspects should be considered [71]. The first is the design of the trajectory, and the rest is the decomposition of steering control into three components (see Figure 2.5).

- Human-Compatible Reference (HCR),
- Level of Haptic Support (LoHS),
- Strength of Haptic Feedback (SoHF), and
- Level of Haptic Authority (LoHA).

- **HCR**: The reference trajectory based on human driving patterns that is followed by the lateral shared-controller. It is especially pertinent when negotiating a curve since humans usually cut the curve rather than follow the centerline [88, 104, 105]. Consequently, a trajectory without consideration of driver profiles will result in conflicts regardless of the controller design. This criterion reflects the

[1]**Webpage**: Bosch Haptic Gas Pedal → https://www.bosch-press.nl/haptic-pedal
[2]**Webpage**: Sensodrive Haptic Pedals → https://www.sensodrive.de/feeback-pedal

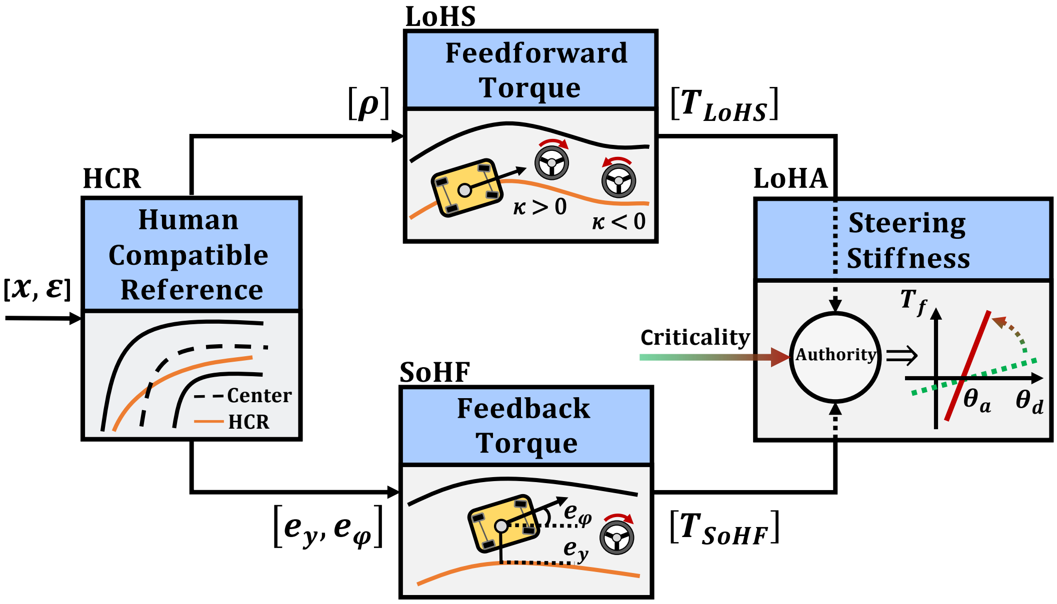


Fig. 2.5: Representation of vanPassen [71] four design aspects considered in coupled shared-control: HCR, LoHS, SoHF, and LoHA

axiom presented in [8], which indicates that automation under shared-control must follow human-centered design principles.

- **LoHS**: It depends on variables related to the shape of the trajectory, such as the curvature (ρ) [71] or the reference steering angle (δ_R) [106]. Rather than minimizing errors, this torque is applied in open loop and represents the feed-forward steering action. For example, as the vehicle approaches a turn, a force is applied to the steering wheel even if the driver remains in the centerline.
- **SoHF**: It refers to the control torque that minimizes the tracking errors with respect to the HCR. It is a feedback component instead of feed-forward steering action (LoHS). Its design is one of the biggest challenges in the development of driver-automation shared-control, as it has to reconcile several objectives: tracking performance, driver comfort, road safety, and control efficiency.
- **LoHA**: It is the magnitude of stiffness around the desired steering wheel angle calculated by automation (θ_a) [107]. In other words, it represents a variable impedance of the steering control [34]. Other works [40, 90] present this parameter under the name *stiffness feedback*. In [71], using the metaphor of flight instruction, it is described as the resistance force that the instructor exerts by holding the control interface to reject or approve the student pilot's actions. A high value of haptic authority makes it harder for the driver to move the steering wheel, so the automation is given more authority. In contrast, a low value gives the driver more freedom to control the lateral movement of the vehicle. Unlike the other torque components (LoHS and SoHF), the LoHA is passive in that it only takes effect when the driver deviates from the operational setpoint of the automation ($\theta_d \neq \theta_a$). One advantage of considering the LoHA separately

from the active steering torques is that the system authority can be decreased or increased without affecting the controller's scheme. Moreover, the LoHA (λ) is interpreted as a proportional gain applied to active torques ($\lambda(T_{SoHF} + T_{LoHS})$) [71, 106]. Some works present it as a proportional gain to the lateral error in the center of gravity (λe_y) [34, 40, 71, 90, 105, 107–110]. In [40], the LoHA multiplies the difference between driver and automation commands ($\lambda(\theta_d - \theta_a)$). Other works [44, 78, 89, 111, 112] considered the haptic authority at the tactical level to switch between two different control strategies ($\lambda T_{a1} + (1-\lambda)T_{a2}$). In [113], Balachandran evaluated LoHA in an obstacle avoidance scenario based on the MPC prediction index-i ($\lambda(\theta_d(i) - \theta_a(i))$). The modification of the prediction index, not the haptic authority gain, was responsible for increasing the haptic authority feedback torque in this case.

After the consideration of these concepts, the following subsections describe in detail the specific control algorithms used in the development of steering shared-control systems. In this context, the algorithms are either *model-free* or *model-based* controllers, as already mentioned in the methodology section.

2.3.2.1 Model-free

The distinctive feature of model-free controllers is the use of a feedback error signal. They do not include a driver-automation model in the design. It was the first type of haptic shared-control method used [114]. In this subsection, specific control algorithms, system variables, and experimental results are described. Two types of algorithms are found in the literature:

- **Steering angle difference**: In these controllers, the automation torque follows this formula $T_a = k\Delta\delta$, a proportional gain to the difference between the driver's steering inputs (δ_d) and the optimal automation command ($\Delta\delta = \delta_d - \delta_a$) calculated by a vehicle lateral controller (δ_a). Working with this method [85, 94, 95, 103, 114–119] requires the use of two different controllers. The first is a lateral controller that guides the vehicle in automatic mode. Examples include: heading calculation at a look-ahead distance with respect to a reference trajectory [85, 103], a dual PD controller based on the lateral and angular errors [117], a dual proportional controller [119], an artificial potential field [116], and a human remote control command [118]. The second controller is a feedback controller that receives $\Delta\delta$ as input. Most works use P or PD techniques for the feedback controller; one author uses a learning algorithm to adjust gains [117]. Gonzalez [119] has developed a variable proportional gain controller that accounts for maneuver risk in terms of time-to-collision (TTC) and time-to-lane-crossing (TLC).
- **Tracking errors**: Instead of two controllers, guidance and torque feedback are combined in a single controller. In this case, the control torque depends on the position of the vehicle with respect to the desired trajectory (e.g., lateral and

angular errors $[e_y, e_\psi]$) [34, 40, 65, 71, 88, 90, 104–110, 120–126]. A representative example for this controller would be $T_a = k_1 e_y + k_2 e_\psi$. In general, the error calculation is performed with a look-ahead time and assuming a constant speed and steering angle. The most common algorithms are P and PD controllers based on tracking error. One work includes an integral component [126] for the calculation of the support torque. In [106], the authors implement a combination of all four design aspects of shared-control using constant stiffness and incorporating a look-ahead component (LoHS) into the controller.

After analysing previous works in coupled shared-control under the model-free modality, some results are reported in terms of use cases, benefits, and drawbacks. Further information on haptic guidance system's effects on automated driving is available in Petermeijer's analysis [39], which includes specific results from some of the studies presented here.

- **Use-cases**: The lane-keeping task is the most common application, with an average speed of 65 km/h, but some tests have been conducted at 100 km/h [124]. There are several other applications of this technology, including obstacle avoidance [90, 108, 109, 116, 119, 122, 127], curve negotiation [88, 104, 105, 107, 120], and control authority transition [94, 95]. Interestingly, one work tested haptic shared-control for reverse parking assistance [96]. The usual test platform is a driver-in-the-loop (DiL) simulator for automated driving, except for one system that was tested on a real vehicle [94].
- **Results**: Overall, shared-control provides a positive improvement in the driving task, e.g. a better tracking performance [103, 114–116], a lower visual demand [103, 114, 115], a lower steering reversal rate [107] and lower driver torque [85, 88, 122], better driving performance in low visibility conditions [76], safer time-to-lane-crossing [125], smoother and more stable control transitions [82, 95, 128]. Also, fewer reported collisions during obstacle avoidance [108, 116]. One work proved that driver passive fatigue is reduced [125]. In addition, work by Scholtens [106] showed a reduction in driver-automation conflicts. Conversely, some disadvantages are also reported. Drivers are likely to misinterpret haptic feedback from automation [114], increase effort based on perceived feedback [103], feel disturbed by torque on the steering [34, 85], and experience undesirable steering conflicts [122].

Despite efforts to evaluate driver neuromuscular behavior in model-free control techniques [34, 129] and also consider various driver characteristics in their design [123], this method fails to incorporate a driver model in the calculation of optimal control torque. This is a limitation for the desired harmonious cooperation between the driver and the automation in shared-control. The model-based method described below incorporates this innovation into the controller design.

2.3.2.2 Model-based

A key aspect in model-based shared-control is the inclusion of the steering system model to use the steering torque as the control signal. Steering angle is often used because it provides robustness and compensation for nonlinearities [130, 131]. Yet, Negai *et. al.* [132] found that angle-based steering angle controllers perceive both driver torque and self-aligning torque (T_{sat}) as disturbances. Therefore, torque-based controllers are more suitable for coupling the driver and the automated system model. Accordingly, the steering model based on inertia and damping (J, b) enables the relationship between the steering wheel angle (θ) and the total steering torque ($T = T_d + T_a + T_{sat}$), as shown in Equation 2.2.

$$T_d + T_a + T_{sat} = J\ddot{\theta} + b\dot{\theta} \tag{2.2}$$

Another important consideration is the inclusion of a driver model. When the driver and the automated vehicle interact via the steering wheel, there is a bidirectional communication channel. On the one hand, the automation communicates its intentions to the driver through haptic feedback. On the other hand, the automation understands the driver's actions by reading the position of the steering wheel angle. The automation, however, needs to have a detailed understanding of the driver in order to cooperate more effectively with the driver. Therefore, many authors have included in the controller desing an integrated driver-road-vehicle (DVR) model to enable the system to predict the driver's behavior in different situations [36, 44, 45, 77, 78, 86, 87, 89, 111, 112, 131, 133–148]. With such mutual understanding, the controller can work to reduce conflict and consider the level of cooperation in the control algorithm. For a detailed summary of such systems, see Table 2.2. Only systems tested in DiL simulations or real vehicles were considered. This analysis provides information on the current state of this technology and its advantages. In the following, the main aspects listed in the table are analyzed in relation to the development and evaluation of coupled model-based algorithms for shared-control.

- **Driver model**: Initial driver model used in shared-control was presented in similar approaches by Sentouh, Saleh, and Mars [149, 150, 153, 156]. It takes into account the driver's cognitive, perceptual, and motor skills and assumes a dual control action by the driver in the lane keeping task. The first, compensatory (near angle θ_n), to maintain the centerline position. The second, anticipatory (far angle θ_f), to account for the curve ahead. The driver's neuromuscular system is also part of the model. Nguyen models the driver's torque as proportional to these variables ($\propto [\theta_n, \theta_f]$) [137]. Others have considered a proportional model in terms of tracking errors ($[y_L, \psi_L]$) [134, 140]. Moreover, this model is also used for other purposes, e.g., to simulate a driver agent in virtual tests [137]. Other authors use a driver model based on motion primitives (movemes) [151, 152] and a variable preview time model based on road curvature. A more complex solution is to

Tab. 2.2: Evaluation of model-based coupled steering shared-control algorithms

AUTHOR	VEHICLE MODEL	DRIVER MODEL	CONTROLLER	USE CASES	RESULTS
Saleh 2013 [135]	**Dynamic bicycle** Fixed speed **Vehicle** $= [\beta,\, r]$ **Steering** $= [\delta,\, d\delta/dt]$ **Road** $= [e_y,\, e_\Psi]$ $\boldsymbol{w}$ $= [\rho]$	**Sensorimotor** Saleh-Mars [149, 150] Simplified to 3 states Compensation θ_n Anticipation θ_f Driver delay	**Preview - $\mathcal{H}_2$** $J_t = min\ [e_y,\, e_\Psi]$ $J_s = min\ [T_d - T_a]$ $J_s = min\ [T_d \times T_a]$ **Stability**: μ-analysis	**DiL simulation** 1 participant $v_{max} = 65$ km/h **Lane keeping** Path following	**w.r.t. manual driving** ↓ 30% mean lateral error ↓ 25% STD lateral error ↓ 15% mean LDR ↓ 10% STD LDR + 18% conflict period
Soualmi 2014 [136]	**Dynamic bicycle** Variable speed **Vehicle** $= [v_y,\, r]$ **Steering** $= [\delta,\, d\delta/dt]$ **Road** $= [e_y,\, e_\Psi]$ $\boldsymbol{w}$ $= [\rho]$	**Lane keeping** Torque $\propto [e_y,\, e_\Psi]$ Torque derivative Eq.	**LMI - LQ** T-S fuzzy modelling $J_t = min\ [e_y,\, e_\Psi]$ $J_c = min\ [a_y,\, \ddot{\delta}]$ $J_s = min\ [T_d,\, T_d - T_a]$ **Stability**: Lyapunov	**DiL simulation** 1 participant $v_{max} = 54$ km/h **Lane keeping** Path following[1] **Obstacle avoidance** Transfer control[2]	**w.r.t. manual driving** ↓ 90% driver effort[1] ↓ 10% tracking errors[1] ↓ 65% driver effort[2] **w.r.t. no driver model** ↓ 80% driver effort[2] ↑ x4 driver goal[2]
Ercan 2017 [140]	**Dynamic bicycle** Fixed speed **Vehicle** $= [v_x,\, v_y,\, r]$ **Steering** $= [\delta,\, d\delta/dt]$ **Road** $= [e_y,\, e_\Psi,\, s]$ $\boldsymbol{w}$ $= [y_{Lref},\, \rho]$	**Lane keeping** Torque $\propto [e_y\ ,\, e_\Psi]$ T_{al} compensation Variable stiffness Variable damping	**MPC** $C_t = lim\ [e_y]$ $C_c = lim\ [\beta,\, \Delta T_a]$ $C_s = lim\ [T_a]$ $J_c = min\ [\Delta T_a]$ $J_s = min\ [T_a]$	**Real vehicle** 1 participant $v_{max} = 36$ km/h **Lane keeping** Road departure	**Achievements** + Avoid road departure + β constraints achieved + Return to lane center
Flad 2017 [142]	**Dynamic bicycle** Fixed speed **Vehicle** $= [\beta,\, r]$ **Steering** $= [\delta,\, d\delta/dt]$ **Road** $= [e_y,\, \psi]$	**Movemes [151, 152]** Movement primitives MPC switch control Inverse steering model	**Differential game** Stackelberg $J_t = min\ [e_y,\, e_\Psi]$ $J_c = min\ [T_a]$	**DiL simulation** 10 participants $v_{max} = 130$ km/h **Lane keeping** Path following	**w.r.t. manual driving** ↓ RMS lateral error **w.r.t. no driver model** ↓ Curve conflicts ↑ Driver acceptance
Sentouh 2018 [89]	**Dynamic bicycle** Fixed speed **Vehicle** $= [\beta,\, r]$ **Steering** $= [\delta,\, d\delta/dt]$ **Road** $= [e_y,\, e_\Psi]$ $\boldsymbol{w}$ $= [f_w,\, \rho]$	**Sensorimotor** Sentouh [153] Simplified to 2 states Compensation θ_n Anticipation θ_f Real driver data	**LMI - $\mathcal{H}_\infty$** $J_t = min\ [\theta_n,\, \theta_f]$ $J_c = min\ [a_y,\, r,\, \ddot{\delta}]$ $J_s = min\ [T_d - \lambda T_a]$ **Stability**: Lyapunov	**DiL simulation** 6 participants $v_{max} = 54$ km/h **Lane keeping** Disturbance rejection[1] Path following w/ST[2] Departure prevention[3]	**w.r.t. manual driving** ↓ 50% driver effort[1] ↓ 35% STD lateral error[2] ↓ 30% RMS lateral error[2] ↑ Driver acceptance[2] + Avoid lane departure[3]
Nguyen 2018 [77]	**Dynamic bicycle** Variable speed **Vehicle** $= [\beta,\, r]$ **Steering** $= [\delta,\, d\delta/dt]$ **Road** $= [e_y,\, e_\Psi]$ $\boldsymbol{w}$ $= [\rho]$	**Sensorimotor** Torque $\propto [\theta_n,\, \theta_f]$ Assistance law [154] Variable activity param.	**LMI - $\mathcal{H}_\infty$** T-S fuzzy modelling $J_t = min\ [\theta_n,\, \theta_f]$ $J_c = min\ [a_y,\, r,\, \ddot{\delta}]$ **Stability**: Lyapunov	**DiL simulation** 1 participant $v_{max} = 72$ km/h **Lane keeping** Disturbance rejection[1] Road departure[2]	**w.r.t. manual driving** ↓ 50% driver effort[1] + Reduce # sensors (-2) + Avoid lane departure[2] + Support distracted driver[2]
Yang 2019 [155]	**Dynamic bicycle** Fixed speed **Vehicle** $= [\beta,\, r]$ **Steering** $= [\delta,\, d\delta/dt]$ **Road** $= [y_{Lp},\, e_\Psi]$ $\boldsymbol{w}$ $= [T_{al},\, \rho]$	**Preview scheduler** Variable preview-time Function of ρ Real driver data	**LPV - $\mathcal{H}_\infty$** $J_t = min\ [y_{Lp},\, e_\Psi]$ Varying-param: $t_p(\rho)$ Pole placement **Stability**: Lyapunov	**DiL simulation** 8 participants $v_{max} = 72$ km/h **Lane keeping** Path following	**w.r.t. manual & LTI** ↓ Lateral error ↓ Driver effort ↑ Cooperative period ↑ TLC

AUTHOR	VEHICLE MODEL	DRIVER MODEL	CONTROLLER	USE CASES	RESULTS
Benloucif	**Dynamic bicycle**	**Sensorimotor**	**LMI - $\mathcal{H}_\infty$**	**DiL simulation**	**w.r.t. no driver model**
2019 [147]	Fixed speed	Sentouh [153]	T-S fuzzy modelling	8 participants	↓ Driver effort
	Vehicle $= [\beta, r]$	Simplified to 2 states	$J_t = min\ [\theta_n, \theta_f]$	$v_{max} = 90$ km/h	↓ Torque conflicts
	Steering $= [\delta, d\delta/dt]$	Compensation θ_n	$J_c = min\ [a_y, \ddot{\delta}]$	**Obstacle avoidance**	↑ Cooperative period
	Road $= [e_y, e_\Psi]$	Anticipation θ_f	J_s = Optimized trajectory based on driver state and torque effort	Transfer control	↑ Driver acceptance
	$\boldsymbol{w} = [\rho]$	Real driver data			
Ji	**Dynamic bicycle**	**Lane keeping**	**Differential game**	**DiL simulation**	**w.r.t. manual driving**
2019 [36]	Fixed speed	LQ problem	LQ problem	4 participants	↓ Lateral error
	Vehicle $= [\beta, r]$	$J_t = min\ [e_y, e_\Psi]$	Stackelberg	$v_{max} = ?$	↑ TLC
	Steering $= [\delta, d\delta/dt]$	$J_c = min\ [T_d]$	$J_t = min\ [e_y, e_\Psi]$	**Obstacle avoidance**	**w.r.t. no driver model**
	Road $= [e_y, e_\Psi]$	Driver uncertainty	$J_c = min\ [T_a]$	Double lane change	↓ Torque conflicts
		Real driver data			+ High cooperative ratio

Table notes: reduction (↓), increase (↑), additional benefit (+), proportional to (∝), standard deviation (STD), root mean square (RMS), driver in the loop (DiL), secondary task (ST), lane departure risk (LDR), model predictive control (MPC), linear parameter-varying(LPV), linear time-invariant (LTI), time-to-lane crossing (TLC), Takagi-Sugeno (T-S), Linear Quadratic (LQ)

model the driver as a linear quadratic problem with a path tracking optimization [36]. The main challenge in these models is to find the right parameters, which are usually determined in tests with real drivers [89].

- **Vehicle model**: It is common to incorporate the dynamics of the vehicle into the controller using the bicycle model [157], where the states correspond to the yaw rate (r) and sideslip angle (β). In addition, the single-track model includes equations for the lateral (e_y) and angular (e_ψ) errors. Furthermore, the second-order model, which includes the steering angle (δ) and angular velocity ($\dot{\delta}$) [156, 158] allows the torque equation to be included in the model. There are works that add a perturbation vector ($\boldsymbol{w}$) that accounts for variables such as road curvature (ρ), wind force (f_w), and road inclination angle [131]. In terms of longitudinal dynamics, it is common to linearize the driver-road-vehicle model around the vehicle speed (v_x), assuming that this value is constant. Another approach [133, 137] is to model the problem using the Takagi-Sugeno (T-S) identification technique [159], which allows other time-varying parameters such as driver activity to be considered in addition to speed [45].
- **Control algorithm**: Optimal control is the preferred option for model-based shared-control. An important work motivating the use of such a technique is presented by Sentouh *et al.* [86], where the authors developed a linear quadratic regulator (LQR) that optimizes steering input in cooperation with driver actions. Similar approaches followed this path with different algorithms such as $\mathcal{H}_2$ Optimal Control [44], $\mathcal{H}_2$ Preview Control [131, 135] and MPC [140, 158]. Also, LMI optimization becomes a popular technique [89], in combination with T-S fuzzy modeling to deal with the time-varying parameters [77, 136, 147]. To ensure the stability of the driver-automation interaction, the Lyapunov approach was

used. Another similar but different technique is steering control based on game theory. In this approach, the driver and automation are modeled using MPC or LQ methods along with a Stackelberg strategy to solve the optimal control problem [36, 142, 160]. Regardless of the control algorithm, the following objective minimization functions are standard for these methods:

→ *Tracking*: Lateral and angular errors ($[e_y, e_\Psi)$ or their equivalents ($[\theta_n, \theta_f]$).

→ *Comfort*: Sideslip angle, lateral acceleration (a_y), yaw rate and steering rate.

→ *Sharing*: Torque conflicts between the driver and the automated system ($T_{d,a}$).

- **Arbitration**: Various works [86, 87], have included the torque-based arbitration formula in their model ($T = \lambda T_d + (1 - \lambda)T_a$), where λ is associated with a Gaussian function depending on the lateral error. Moreover, Nguyen [45, 77, 137, 138] incorporated the arbitration law into the driver's mental model, taking into account that the driver should be assisted in case of underload and overload [154]. Other works [44, 78, 89, 111, 112] have included a conditional law that depends on a threshold for the driver's torque, combined with information about the risk of the current maneuver and the driver's state (in terms of drowsiness and inattention).
- **Results**: Overall, the integration of a driver-road-vehicle model along with the optimal control framework has resulted in safer and more convenient shared-control systems. The inclusion of the driver model has been shown to reduce driver torque effort, torque conflicts with automation, and the need for high visual attention. It has also led to improved tracking performance and harmonious control transitions. It also gives the driver a degree of freedom when steering, providing a subjective feeling of being in control while avoiding lane departure in the event of faulty steering. In addition, driver modeling is beneficial for reducing torque conflicts, especially when cornering. Further advantages arise when the driver's state (e.g., distraction or drowsiness) is taken into account, so that safety is enhanced when the driver's performance declines. Driver acceptance of such systems has been shown to be positive in several experiments [78, 142], but it is also clear that further research with more participants and scenarios is needed in this area. Most systems were evaluated in DiL simulators with an average speed of 70 km/h. Only one system [140] was tested on a real vehicle, but at a low speed (36 km/h). A first conclusion is that this technology is still in the simulation phase and is approaching the first implementations on real platforms, but still under controlled conditions.
- **Other works**: There are additional model-based shared-control works, where the driver model is not included and therefore cooperation is not considered in the model [76, 82, 101, 122, 128, 161, 162]. Some examples are: a robust lane departure control [101] and a gain-tuning control method for assisting the driver in lane change based on cooperative states and a preview model [128]. Iwano [122] calculated the optimal torque based on a dynamic bicycle model that

includes the steering system. Some authors also propose the use of optimal cotrol framework. Mars [76] applied a $\mathcal{H}_2$ optimization technique varying the level of haptic authority, and Guo [82, 163] designed a constrained model predictive control (MPC) to avoid off-road events with a variation of haptic authority depending on the driver's effort and intention to change lanes.

2.3.3 Lateral Shared-Control $\rightarrow$ Uncoupled

With a decoupled steering system, there can be a variable ratio between the steering wheel angle (δ_d) and the final steering command (δ_a). It opens new possibilities for shared-control that go beyond traditional haptic guidance systems. Here, the controller continuously receives the driver's input (θ_d) and then sends the last command to the wheel actuation mechanism. At that point, the vehicle's control is transferred to the automated system. Nevertheless, under ideal circumstances (i.e., when driving safety is not a concern) the controller should be designed to match the drivers' intentions. With regard this type of shared-control system, the literature search revealed about 30 related papers [37, 41–43, 88, 91, 98–100, 102, 113, 158, 164–181]. Similar to the previous section, the controller description is divided into model-free and model-based categories. Yet, the results analysis is done for the overall category of uncoupled steering shared-control, with some relevant works detailed in Table 2.3.

2.3.3.1 Model-free

This control scheme finds the final steering command using the arbitrage formula ($u = \lambda u_a + (1 - \lambda)u_d$) where $u = \delta$. Basically, the control command combines the driver input δ_d with the optimal automation signal δ_a, where λ is the authority gain. To properly design the λ, it is important to consider the driving context (e.g., environment, driver, and vehicle state). When $\lambda = 1$, the vehicle is in fully automatic mode, and when $\lambda = 0$, the system is in manual mode. Intermediate values represent the shared-control mode. Providing feedback torque by the automated system to the driver is another important aspect.

Fujioka [164] applied this technique for the first time in the literature, with fixed values for λ and haptic feedback proportional to the self-aligning torque. In addition, another work [165] used an authority law based on switching time (2 and 4 s) to provide a smooth transition between driver and automation during control transitions. In [166, 182], the authors implemented an artificial potential field method to compensate for driver actions for a lane keeping use case. They also present a successful validation of a robust controller to prevent lane departure[168].

Anderson *et al.* [42] introduced an MPC that was used as a path planner. It also served as a risk assessment because the threat depended on the sideslip angle of the calculated trajectory and was linearized with a piecewise linear function. The feedback torque was proportional to the difference between the driver and automation commands. This controller was implemented in a simulator for a dual lane change scenario to test different values of the threat thresholds for intervention and full autonomy. Later, as reported in [43, 170], experimental tests of obstacle avoidance were conducted in a teleoperated vehicle, resulting in a reduction in collisions and an increase in speed compared to manual driving.

Li [98–100] led a different approach that examined the effect of driver adaptation on shared-control. As part of the automation control command, the authors used an MPC, and the same optimization scheme was used to simulate the controller's internal model. In this work, λ static values were assigned for evaluation. As an alternative to this method, the system authority was determined by the driver's intent, which is calculated using a least squares estimator.

A fuzzy logic method was developed by M. Li *et al.* [175] to calculate λ based on the driver's intention and context. A linear time-varying MPC was developed for automation control. Validations were performed for both static and dynamic obstacle avoidance.

2.3.3.2 Model-based

Erlien [171, 172], Song [91], and Schwarting [41] have proposed a new control scheme in which the driver's steering command is considered in the cost function of an MPC optimization framework. Different optimization functions are used in fully autonomous MPCs in order to minimize objectives such as tracking performance (J_t) and comfort (J_c). In addition, a novel criterion is introduced to minimize the difference between driver and automation commands ($J_s = min\ [\delta_a - \delta_d]$).

Erlien [172] used wheel lateral force as a system input along with a dual safety envelope that depends on sideslip and yaw rate constraints. To select the optimal trajectory for the obstacle avoidance maneuver, a nonconvex optimization problem was solved by analyzing each possible trajectory individually with a convex optimization solver. Balachandran [113] continued this work and evaluated this controller with a predictive haptic torque based on future horizon error. Testing was conducted in a steer-by-wire test vehicle. This particular strategy is known as the control envelop approach[3], and is currently being investigated by Toyota Research Institute (TRI).

Song's work [91] considered a constrained MPC that optimizes the driver's steering angle and angular rate. In addition, vehicle dimensions were included in the system constraints to allow for a double lane change without leaving the safe corridor. Continuing this work, Liu [183] included a variable authority function based on fuzzy logic that considers the distance to leave the lane and an indicator of possible driver error. All tests were performed with numerical simulations.

A similar approach was used by Schwarting [41] by integrating the longitudinal acceleration command into the MPC problem. The uncertainty of the vehicle states was taken into account, and constraints on the road boundary and yaw rate were

[3] **Webpage**: Envelop Control Approach → *https://medium.com/toyotaresearch*

Tab. 2.3: Evaluation of uncoupled steering shared-control algorithms

STUDY	CONTROLLER	SCENARIO	RESULTS
M. Alirezaei 2012 [168]	**Robust control** Road departure avoidance controller with robustness ensured by H_∞ considering uncertainties. An increase in look-ahead time is used to balance stability and system intervention.	**Obstacle avoidance** DiL simulator 4 participants At 80 km/h Road departure	**Manual** 53% of departures **Assisted** 0.5% of departures
S. Anderson 2014 [170]	**Constrained MPC** Minimization of sideslip angle (β) and constraints on the free driving zone. The authority gain (λ) is a piecewise linear function depending on the threat calculated as the minimum β over the prediction horizon.	**Obstacle avoidance** Teleoperated vehicle 20 participants At 10 km/h	**w.r.t. manual** ↓ 78% collisions ↓ 34% driver effort ↑ 26% mean speed
S. Erlien 2014 [172] **Balachandran** 2016 [113]	**Nonlinear MPC** Optimization of an objective function designed to match the driver's command. The second objective includes two safety envelopes: one for the environmental constraints and the other limiting the yaw rate (r) and the sideslip angle (β).	**Obstacle avoidance** Experimental vehicle 11 participants At 28 km/h Single lane change	**w.r.t. no feedback** ↑ 70% TTC_{min} ↓ 33% a_{y-max} ↓ 40% δ_{max}
W. Wang 2017 - [173]	**Sigmoid function** A human-centered controller that allows the steering system ratio to be varied based on driver path-following characteristics. The variable gain depends on the lateral error, heading angle, longitudinal speed, and steering wheel angle.	**Obstacle avoidance** DiL simulator 20 participants At 70 km/h Double lane change	**w.r.t. manual** ↑ 7% tracking ↓ 50% driver effort ↓ 35% mental workload
M. Li 2019 [181]	**Differential game - DMPC** Non-cooperative Nash solution derived via distributed MPC (DMPC), considering an elliptic driving safety field. The driver state is considered in the dynamic authority allocation strategy.	**Obstacle avoidance** DiL simulation 6 participants At 72 km/h Straight/curvy road	**w.r.t. fixed** ↓ Driver effort ↑ Performance *lim* $[r,\ a_x]$

designed. The test included different driver profiles (passive and aggressive) and maneuvers with sharp turns. The results showed that the system follows driver inputs under safe conditions. A scenario for merging traffic after a left turn at an intersection was also presented, resulting in safe driving behavior without colliding with other vehicles. The tests were conducted in a simplified DiL simulator.

The technique of game theory also played an important role in shared-control for decoupled steering. Similar to Flad in coupled shared-control, Na [169, 176] and Ji [178, 184] presented a non-cooperative approach for a theoretical study of the interaction between the driver and an AFS. In this work, LQR and MPC techniques were used for modeling and control. The motivation for this approach is to avoid the drawbacks in terms of time and cost that occur in the experimental validation of steering assistance systems. Recent works have shown that game theory is increasingly being used to evaluate uncoupled shared-control [37, 180, 181]. One of these papers [181] was also tested in a DiL simulator, as indicated in Table 2.3.

Moreover, Wang *et al.* [179] presented an output feedback robust controller for trajectory tracking that includes the cooperative objective function (J_s). The results showed improved tracking performance and reduced physical workload. In addition, the controller remained robust to perturbations and variations in driver model parameters.

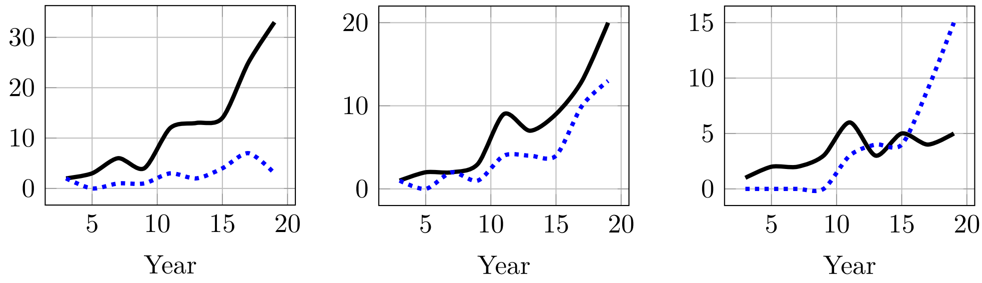
- **Results**: The main advantage of the decoupled steering system is that it requires less effort from the driver compared to coupled systems. This ability to reduce driver-automation conflicts makes lateral maneuvers (e.g., lane changes or obstacle avoidance) an attractive study case for the development of decoupled shared-control systems. However, the fact that the vehicle can move further than commanded by the driver creates an opaque effect that requires a learning and adaptation process [88]. Moreover, Table 2.3 shows that few works have considered experimental tests, even in DiL simulators. Of the tests that have been conducted in real vehicles, one [166] had a low cooperative component, and the second involved an experimental vehicle [172]. This observation suggests that the current state of this technology is one step behind that of coupled shared-control. Therefore, these systems need further evaluation, which seems to be the next clear step, building on the steady increase in related work in recent years.

2.4 Discussion and Perspective

The design, development and evaluation of shared steering control systems for automated vehicles is still a challenge. On the one hand, the concept of shared-control is not uniform in the research community and can be confused with other types of driver-automation interaction. On the other hand, the need to reconcile multiple goals at the control level poses a non-trivial problem in the development of steering controls. With this in mind, an extensive literature review, presented in this chapter, enabled a better understanding of the current state of this technology, both from a technical and a practical point of view. The most important aspects are discussed below:

- **Concept**: Although the term *shared-control* appears frequently in the scientific literature, it has not been precisely defined. Efforts in recent years, however, have led to a more detailed definition given by Abbink *et al.* [8]. In addition, a representation of shared-control in the context of Human-Machine Cooperation related to the levels of task support, has been presented by Flemisch *et al.* [9]. This definition can be applied to steering shared-control in automated vehicles as follows: *"The driver and the steering assistance system interact congruently in a perception-action cycle to execute a dynamic driving task that either the driver or the system could execute individually under idealcircumstances"*.

- **Control frameworks**: Two well-defined frameworks are recognized in the literature. First, coupled shared-control, where the driver and the automation interact exclusively via haptic feedback thanks to the mechanical coupling of the steering wheel and the automatic control. Second, uncoupled shared-control, where, thanks to the decoupling of the steering mechanism, the driver's inputs can be read, processed, and modified by the automation according to the goals of the control system. As can be seen from Figure 2.6b, there is a growing body of work on both systems, with the coupled strategy naturally receiving more attention since most commercial vehicles use a coupled steering system. The main disadvantage of a coupled steering system is the creation of torque conflicts between the driver and the automated system when they have different intentions, while an uncoupled system can cause the driver to feel a lack of control when the automated system does not closely follow the driver's intentions.
- **Control methods**: A first distinction was made between model-free and model-based shared-controllers. From this point of view, model-based optimal controllers such as MPC, LQR, and LMI have shown relevant advantages in incorporating driver models into problem formulation. This has reduced driver effort, improved performance, and minimized torque conflicts, which are one of the main causes of system rejection. As can be seen in Figure 2.6c, these benefits have led to increasing research interest in this control modality. In addition, much attention has been paid to game theory-based controllers for both coupled and uncoupled shared-control. A Lyapunov-based methodology was the preferred strategy to demonstrate system stability.
- **Arbitration**: The usual basis for the adaptive authority calculated by the arbitration system is vehicle tracking performance (e.g., lateral error). However, comfort parameters such as lateral acceleration and steering rate are also considered. However, recent work shows that it is important to include variables not directly related to control objectives in the calculation of system authority, such as driver state, e.g., fatigue and inattention. Also, some indicators of driving risk (e.g., TTLC, TTC) are relevant to modify the degree of intervention of the automated system, especially in tactical maneuvers, as well as the torque conflict between driver and automation. In addition, the driver's intentions and behavioral characteristics seem to be a next step that should be considered in the arbitration decision making process.



(a) Applications vs Theory **(b)** Coupled vs Uncoupled **(c)** Model-free vs Model-based

Fig. 2.6: Statistics on works addressing shared-control in automated vehicles: (a) numbers of system applications and theoretical works on shared-control in the automotive field, (b) numbers of works using coupled (black) and uncoupled (blue) steering systems, and (c) numbers of works on coupled shared steering control using model-free (black) and mode-based (blue) control methods

- **Use-cases**: Lane keeping and lateral maneuvers such as lane changes and obstacle avoidance are among the most common tasks in shared-control driving. Also of interest is the transition from manual to automated driving (or vice versa) when the driver regains control or when the automated system has a different intention than the driver. Partially automated vehicles could implement these applications, but highly automated vehicles could also be equipped with shared-control applications, especially for takeover requests.
- **Research community**: Institutions working in shared-control exist all over the world (Europe [44, 185], the USA [172, 186], China [99] and other regions). TU Delft [39, 48, 109] focus on coupled and model-free shared-control techniques. This institution participates in theoretical contributions with Flemisch *et al.* [9, 59, 69] regarding the conceptualization of shared-control. There is another relevant research group at IRCCyN in France [44, 87, 137]. This group specializes in coupled model-based control techniques that incorporate a driver model into a shared-control framework. In terms of industry partners, companies such as Renault, Nissan, and Toyota have been found to support academic research in shared-control.
- **Projects**: Moreover, automated driving applications based on shared-control has been considered within the frameworks of various european projects, such as Deserve [28, 66], HAVEit [187] the ABV Project [32], Prystine [188] and Hadrian [12, 189]. National funding programs were also involved in the development of such systems.
- **State of technology**: Many steering shared-control systems have been validated in virtual testing, a moderate number in DiL simulators and few with real vehicles. This situation reflects a technology under development for which appropriate tests have been performed, but only under controlled conditions. One can also conclude that shared-control for uncoupled systems is one step behind coupled shared-control in terms of its stage of development. In both cases, however, the research

community is showing increasing interest in this technology. In addition, driver acceptance studies show positive feedback and motivate further developments. The legal aspect will also be crucial for the transition to the commercial phase. The main challenge here is the variable assignment of authority in the dynamic driving task. Currently, the closest type of commercial ADAS to a shared-control-based system is a ALC. However, such a system lacks the continuous cooperative component that characterize shared-control. Therefore, an adaptive authority ALC based on driver state and maneuver risk is how shared-control is envisioned in a near future in the automotive domain.

- **Current trends**: The past two years have shown that interest in shared-control continues, with more than 40 relevant contributions in the literature [26, 190–232]. Several trends can be observed. For example, the evaluation of human factors in shared-control (e.g., trust) [196], the consideration of improved driver modeling for both lane keeping and lane changing [214, 227, 228, 230], and the comparison of the two main control frameworks (coupled vs. uncoupled [191]). In addition, there is an interest in studying shared-control ADAS, especially active safety systems [224, 226] and assistance systems that support drivers with limited capabilities (e.g., due to distraction or high workload) [198, 206, 218]. New scenarios are also explored, especially for evaluating shared-control strategies for system-initiated takeover requests [26, 192, 207, 225]. Complementary HMIs are being investigated to support the shared-control strategy with additional visual information [232]. Parameterization of torque values accepted by drivers is also the subject of research [220].
- **Future works**: Testing is expected to be conducted with real vehicles and experimental research platforms. Minimizing steering wheel conflicts during driving maneuvers is a priority to achieve good driver acceptance. In terms of application-oriented contributions, work on shared-control algorithms that take into account the driver's state is a clear future research direction. In addition, characterizing different driver behaviors and adjusting controller gains based on these factors is key to achieving acceptance of these systems among drivers with different driving styles. Finally, integration of shared-controllers with other modules such as driver monitoring systems, visual interfaces, adaptive HMIs, and collision detection systems is necessary for the creation of a complete collaborative framework [233, 234]. The inclusion of pedals with haptic feedback in combination with steering shared-controllers is a desired feature in future steps. Apart from these contributions, it is of great importance to evaluate the aftereffects of shared-control in automated driving, because it has been reported that people may lose their driving skills if they are constantly assisted by such systems [63]. Therefore, further studies on this aspect are needed. In this sense, shared-control has been promoted as a strategy that assists drivers when needed rather than all the time,

and future development of decision and control algorithms should take this into consideration.

2.5 Conclusions

In summary, this chapter provided an overview of shared-control as applied to automated driving, with particular emphasis on theoretical understanding of the concept and analysis of system applications of steering control. The results show an increasing interest and relevant technological advances in this area, motivating further developments and likely leading to experimental tests in real vehicles in the near future.

Shared-Control Framework for Automated Driving

3

This chapter presents a modular architecture used to develop shared-control strategies for automated vehicles. Special attention is given to the integration of the arbitration system and the steering shared-controller into a general framework for the development of Automated Driving (AD) functionalities [235]. Since this framework was originally developed for vehicles in which the human is the supervisor or passenger, the interaction between the driver and the automation system is not considered in its structure. In this context, the objectives of this chapter are:

- The integration of shared-control components into a general framework for automated driving applications, taking into account the hierarchical levels of the driving task (i.e., strategic, tactical, operational and execution).
- To perform a modular comparison of implementation requirements and challenges between traditional Automated Vehicles (AVs) and the shared-control approach.
- To describe the custom shared-control framework used in this dissertation, considering the hierarchical levels of the driving task, including the rationale for selecting the arbitration and steering control algorithms, along with their theoretical basis.
- To describe the software/hardware architecture for the DiL simulator platform used to develop shared-control applications in automated driving.

3.1 Automated Driving Framework

According to the general framework for automated driving presented in [235], the control architecture is divided into six main modules: Acquisition, Perception, Communication, Decision, Control and Actuation. In addition, other modules not directly related to automation control, such as HMI, supervision and database, are also considered. This framework has been used for several developments of automated driving applications in recent years, including optimal trajectory planning [236] and validation of model-based tracking controllers [17]. In this framework, however, the driver is considered a passenger and is excluded from the control loop. When the driver is included in the shared-control mode, additional considerations and sub-modules must be included in the framework, particularly related to human state assessment, inclusion of the arbitration system to harmonize driver and automation decisions, and adjustment of the automation controller's authority. In addition, driver interaction via the vehicle's human-machine interfaces must be considered. The integration of these submodules into the original architecture is shown in Figure 3.1 and represents the shared-control framework used in the Ph.D. Thesis. With this in mind, each module of the original architecture is described in the following subsections, along with a comparison between traditional automated driving (i.e., L2 to L5 capable vehicles) and shared-control for AVs, using a similar approach presented by Friedman [237] in relation to the concept of shared autonomy.

3.1.1 Acquisition

The focus of this level is on the sensors. On one side, the propioceptive sensors that relate to the state of the vehicle. On the other side are the exteroceptive sensors, which relate to sensing information from the vehicle's environment and may include sensors to monitor the driver (some propioceptive sensors may also be used for this task). The acquisition module has two main functions: collect data from sensors and process this data accordingly (e.g. filters and reference frame). General information about the state of the vehicle includes inertial variables coming from inertial measurement devices (IMU) and data provided by the low-level CAN (Controller Area Network) module, including information about the state of vehicle's actuation mechanisms and Electronic Control Units (ECUs). In terms of the environment, sensors such as radars, cameras, sonars, and LiDARs (Light Detection and Ranging) receive information from the road and road users in the vicinity. Both conventional automated driving and shared-control require accurate knowledge of the vehicle's state, but the main difference is in the detection of the environment. As for the driver sensing, both modes require knowledge of the driver's state, obtained through a variety of sensors including visual, IR, and thermographic cameras, sensors for physiological measurements (e.g., heart rate, temperature), and sensors in the control interfaces.

- **Automated driving**: To ensure proper operation, a large number of sensors are required to accurately map the road environment and detect road users. In [238], the authors provide an overview of perception sensors in AD, including the number of sensors in relevant demonstrators (e.g., Tesla, Waymo, Mobileye, and others). The average number of sensors in demonstrators between 2016 and 2019 (for environment detection only) is about 15, with architectures of up to 21 perception sensors. Regarding driver recognition, highly automated vehicles that do not consider the driver (i.e., L4-5) do not require extensive knowledge of the driver's state (here, the main challenge is environmental sensing). However, for AVs where the driver has a supervisory/fallback role, sensors are needed to detect involvement in the driving task, e.g., touch sensors on the steering wheel to detect the position of the hands, or cameras to verify that the eyes are focused on the road. However, to develop more advanced systems that help drivers maintain sufficient situational awareness to safely resume control, a deeper knowledge of the driver is needed, which would require more complex sensor technology[1].
- **Shared-control**: Environmental sensing is still important, but including the driver in the control loop reduces the required accuracy of the sensing system and thus the number of sensors needed. In this sense, sensors used for commercial

[1] **Video**: HADRIAN Driver Monitoring System → *https://hadrianproject.eu/dms*

Automated Lane Centering (ALC) and Adaptive Cruise Control (ACC) systems could be used as a basis for shared-control ADAS. In terms of human sensing, rather than just assessing the driver's condition, it is important to also consider the driver's control activity. This is measured by sensors integrated into the control mechanism, such as encoders, torque and force sensors, and others that would not be needed if the driver is out-of-the-loop.

Acquisition: Shared-control would require sensor technology similar to that used for environmental sensing in AVs, but with a much smaller number of sensors. Monitoring the driver requires a combination of sensors that assess the driver's state and those that assess performance at the control level. Yet, does not require extensive sensor structures to assess the driver's ability to safely resume control.

3.1.2 Perception

This layer focuses on algorithms that use data from the acquisition and communication modules to generate meaningful information about the environment, the vehicle, and other road users. This information includes localization of the ego-vehicle vehicle using techniques such as Simulataneous Localization and Mapping (SLAM). The perception module is also responsible for object detection and classification as well as road structuring. Artificial Intelligence (AI) is used for environment recognition and sensor fusion techniques are implemented for combining multisensor arrays to reduce measurement uncertainty. In addition, several aspects are of interest when monitoring the driver, such as the driver's state (e.g., drowsy, distracted, or stressed), the driver's activity, including performance of Non-Driving Related Tasks (NDRTs), and health condition, for example, heart-rate.

- **Automated driving**: Efforts are moving toward high-precision localization, combining stellite-based positioning with digital mapping and ego-vehicle sensors. Another goal is to improve the accuracy of object recognition for distinguishing road users (pedestrians, cyclists, and other vehicles), providing spatial, dynamic, and semantic information about external objects, and recognizing traffic signs (traffic lights, speed limits, pedestrian zones, and others). However, performing the task of perception with outstanding accuracy is complex, expensive, and time-consuming, not only because of the large number of sensors needed, but also due to the computational power required and the amount of training data. In terms of driver perception, the biggest challenge is to assess the driver's ability to safely take-over control. This would require assessing the level of situational awareness, emotions, and other variables that are not easily determined.
- **Shared-control**: Involving the driver gives the system an experienced pair of eyes and someone who can take back control if needed. In this sense, the need for precise localization and environmental recognition is less and could be compared to the perceptual capabilities of vehicles currently using ALC and ACC, which rely on detecting lane markings and recognizing other road

users in the vehicle's field of view without the need for detailed information. Nevertheless, the demands on the driver's sensing capabilities increase. In this sense, AI algorithms are working to obtain driver-related variables of interest [239], such as eyes gaze, position of the hands, head direction, physiological signals (e.g., breathing patterns), steering and pedaling activity, gestures, and others. Combining these variables can provide more meaningful driver-related information, such as distraction, workload, sleepiness, fatigue, in-cabin activity, health status, emotions, and others. Although, shared-control is less demanding in terms of specific driver information (compared to AVs), there are still some challenges ahead (e.g., adaptive recognition systems for drivers of different backgrounds, ages, driving profiles, etc.).

Perception: Shared-control would require the usual AI and sensor fusion algorithms used in AVs to perceive the environment and assess the driver's state, but with lower information accuracy requirements, reducing the computational power required, the amount of data to be trained, and the complexity of the algorithms.

3.1.3 Communication

The communication module provides information from other vehicles (Vehicle-to-Vehicle, V2V) or from a digital infrastructure (Vehicle-to-Infrastructure, V2I) to improve the scope and accuracy of the environment description. In addition, this module includes any type of communication between the vehicle and an external entity (V2X). This includes the Global Navigation Satellite System (GNSS), which enables the localization of the vehicle. But it also includes, for example, communication with the 5G mobile network. It is important not to confuse this layer with the communication layer of the sensors or the communication of the vehicle with the driver, which is handled in the HMI module.

- **Automated driving**: The challenge is to provide the automation system with additional information, particularly from other road users outside the vehicle's field of view and information about vehicles in the vicinity that are not accurately perceived by the ego-vehicle's sensors. However, improving perception for highly automated vehicles requires expensive vehicle and infrastructure adaptation, a large amount of data, and detailed information.
- **Shared-control**: Although this is highly desirable for proper implementation in AVs, it is an optional feature in shared-control. Even under these circumstances, it would require less information from other vehicles and also from infrastructure. Instead of a detailed description of objects and events, a simple description is already useful for the driver automation team. For example, if a smart infrastructure informs about an upcoming construction site, AVs needthe position of the zone, the time to arrive at this zone and other related information, but for the driver in shared-control mode the notification message is sufficient.

Communication: Shared-control does not rely on communication with other vehicles and infrastructure, although this would enhance functionality if available. In addition, the information required would be simpler in scope and detail.

3.1.4 Decision

This layer receives information from the perception and communication modules and decides on the trajectory (including path and speed planners) that the vehicle automation should follow. In this phase, safe trajectories are generated to react and interact with unexpected situations that typically affect the predefined driving style, such as: obstacles, road works, pedestrians, etc. This phase consists of three sub-modules. First, the *global planner*, which performs the initial planning process at the strategic level (how to get from A to B). It is responsible for creating an accurate global path by considering information from a map file and then finding the best path, usually by means of graph-search-based algorithms. Second, the *local planner*, which improves the smoothness of the trajectory and the comfort of the vehicle by using different types of curves, such as Bezier [240] and adding the speed profile of the longitudinal movement of the vehicle. Third and finally, the *behavior planner*, which selects the most appropriate maneuver depending on the dynamic road conditions (e.g. lane change, obstacle avoidance, overtaking, etc.).

- **Automated driving**: Real-time generation of safe and comfortable trajectories together with decision logic for vehicle maneuvers (e.g., when to overtake) is the main focus of the decision module. The approach is rather conservative in this sense, since safety must be ensured first and foremost.
- **Shared-control**: While trajectory precision and parameter fine-tuning is not a hard requirement, the development of personalized, human-centered trajectories is a must to avoid conflicts with drivers [71]. Moreover, the main challenge in shared-control is to design the right arbitration system to harmonize the driver and automation inputs (especially if they are different) in an understandable and optimal way based on the driving context (automation, environment, and driver state). In addition, a model of the driver's intentions must be considered to compare the driver's desired maneuver with that of the automation.

Decision: Real-time planning with optimal trajectories is a second priority compared to harmonizing driver and automation intentions through arbitration logic. In this context, personalized human-oriented trajectory references and driver intention models are of great importance.

3.1.5 Control

This module receives information from the decision level, in particular the optimal path and speed profile to follow. Then, the control algorithms compare the current vehicle states with those of the desired trajectory and makes appropriate lateral and longitudinal corrections by sending control commands to the actuation mechanisms (i.e., steering, accelerator, and brake).

- **Automated driving**: The controller's goal is to perfectly follow the calculated trajectory in the decision module. In addition, controllers are focused on goals such as tracking, stability, efficiency, and comfort, but drivers are considered a disturbance to the system. In this sense, most lateral controllers for automated driving are based on steering wheel angle and use position and speed controllers.
- **Shared-control**: The emphasis is on cooperation between the driver and the automation, so the main goal of the controller (in addition to the conventional goals of path tracking) is to avoid conflicts with the driver as much as possible. A unique feature of shared-controllers is that they use torque (for steering) and force (for pedaling) as control signals instead of position. In addition, the controller has adaptive haptic authority (whereas AVs controllers have fixed authority). This means that the arbitration system is able to determine the degree to which the controller assists the driver by providing gentler or stronger support, depending on the driving context.

Control: Instead of position-based controllers designed for accurate path tracking, the shared-controllers use torque/force as control signal and focuse on operational-level collaboration between the driver and automation. Its design incorporates adaptive haptic authority and aims to improme manual performance and safety, while reducing conflict with the driver and enabling seamless control transitions.

3.1.6 Actuation

The actuation module corresponds to the vehicle actuators such as the accelerator and brake pedals, and steering wheel. It also takes into account the low-level control of these vehicle control interfaces.

- **Automated driving**: The actuation mechanism has no significant effect on the operation of the control module, except for the setting of the low-level controller. Furthermore, the actuation module for AVs is almost irrelevant to the driver.
- **Shared-control**: The steering actuation system either the conventional coupled steering or the more modern steer-by-wire, affects the operation of the control module because the shared-control scheme changes depending on the actuation mechanism used (coupled or uncoupled shared-control, as explained in Section 2.2.6). In addition, each actuation system poses different challenges to the implementation and driver acceptance of shared-control. Appropriate instrumentation of the actuators is also required, as these sensors provide relevant information about the driver's control activity (e.g., the driver's torque effort when assisted by automation).

Actuation: The control mechanism is seamless in AVs, but in shared-control it determines the control scheme because it depends on whether the system is mechanically coupled or decoupled. It also affects how the driver perceives the assistance system, namely as a sense of control interaction.

3.1.7 HMI

Vehicle-oriented HMIs help the driver understand the intent, state, and actions of the automation and increase situational awareness and confidence in the automated vehicle. In this sense, the system can convey information to the driver through three main channels. First, a visual screen, through text or images, showing, for example, a representation of the environment with nearby vehicles. Second, via haptic interfaces, through vibration in the pilot seat, on the steering wheel, or on any other surface in contact with the driver. Third, using audio warnings, either through audible alerts or a tutorial voice. The design of such strategies should follow the principles of comfort and ease of use and avoid an excess of information so as not to overwhelm the driver.

- **Automated driving**: The interaction between the driver and the automation consists in the driver being sufficiently informed about the situation in case there is a request to intervene. In this sense, the continuous information consists in showing the operation of the system, and the alarms refer to the events of the control transition. In addition, AVs will benefit from external HMIs [241] that replace the interaction of the driver with other road users (e.g., pedestrian), and provide automation-related information to the outside of the vehicle.
- **Shared-control**: Because the driver is highly involved, the HMI strategy relies more on informing the driver of system status and issuing alerts that require quick responses. The fact that the human is at the wheel enhances the possibility of improved interaction via the control interfaces such as steering wheel and pedals through haptic feedback. With respect to eHMIs, they are not needed because the driver can interact directly with other road users, similar to manual driving.

HMI: Visualizing information to increase situational awareness and confidence is not the primary goal of HMIs in shared-control. Instead, it is worth exploring strategies that take advantage of the haptic channel of the control interface while leaving other interaction modalities available for information about system state. Furthermore, shared-control does not require eHMIs.

3.1.8 Supervision

The supervision module is responsible for detecting system failures and executing fallback and control transition strategies in the event that the automated system is limited or unable to operate. In comparison with the original framework [235], this module is intentionally integrated into the decision layer.

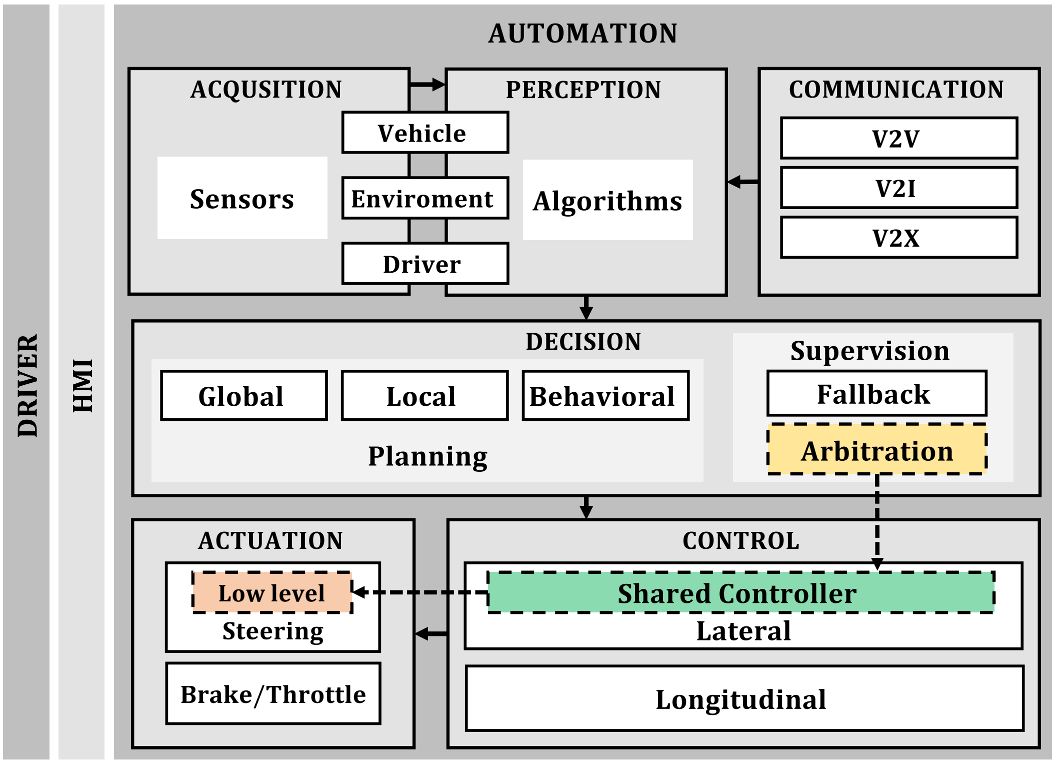


Fig. 3.1: Shared-control framework based on the automated driving architecture of Gonzalez *et al.* [235], including the neccesary components for steering shared-control applications

- **Automated driving**: The system should be fail-operational (i.e., able to maintain operation or perform a safe fallback maneuver after a system failure [242]). However, this requires complex perception technology, and in the event that the system cannot maintain normal operation, the strategy for returning the human to the control loop is also challenging, as the driver must regain good driving skills after a period of inactivity.
- **Shared-control**: In this case, the driver is the best fallback mechanism because s/he is already involved in the tactical-operational control of the vehicle. In this sense, the fallback strategy focuses on informing the driver in a simple way that the system is no longer providing support. It is important also to take the driver state into account to provide the appropiate feedback and sense of urgency. Also, as control transitions are managed in the arbitration system, it has been included as a submodule of the supervision layer, along with the fallback system.

Supervision: While in AVs the implementation of the fallback strategy is complex because the role of the human changes, in shared-control it mainly consists of informing the driver that the support system is no longer available, but the role is always that of the primary driver.

The previous modules are shown in Figure 3.1, including the new integrated components for shared-control applications, in particular those used in the steering control developments presented in the next chapters of this dissertation. In the next section, the new components of the shared-control framework are explained in detail, in particular the arbitration and shared-controller subsystems.

3.2 Shared-Control Framework

In addition to the aforementioned general AD architecture, this section presents the detailed framework for driver-automation interaction under shared-control in terms of cooperation levels (i.e., tactical, operational and execution). The representation of this framework along with its components is shown in Figure 3.2.

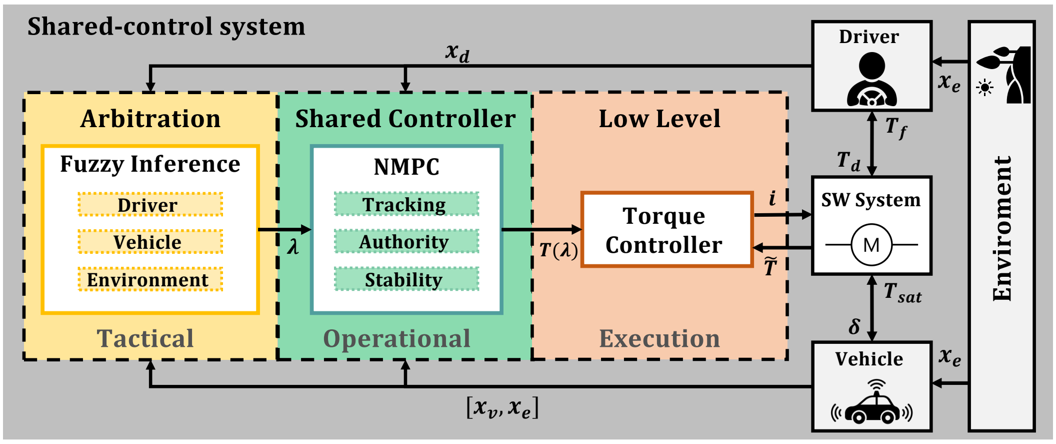


Fig. 3.2: Shared-control framework by driving task levels (tactical, operational, execution). It is an expanstion of the colored submodules of Figure 3.1

The operational level is responsible for the control task, the tactical level refers to the maneuvers and decisions, and the strategic level refers to the planning strategy to move from a starting point to a goal. An additional level, is sometimes considered, and is referred to as the execution level [8]. It relates to the operation of the low-level controller (in this case, the internal torque controller of the steering wheel system). In the context of shared-control of automated driving, some works use the three cognitive levels [9, 243], focusing on the tactical and operational phases, since the strategic part is a problem that has already been solved in intelligent vehicles and does not provide an enriched scenario for high cooperation between driver and vehicle. The next sections explain the specific algorithms used to develop the operational and tactical levels of the shared-control framework of Figure 3.2, focusing on applications for coupled steering systems. The execution level, on the other hand, is a torque controller that is integrated into the steering wheel device presented in Section 3.3.2 and supplies the system with the necessary current.

3.2.1 Operational Level → Shared-Controller

The operational level includes the ALC system, which is responsible for steering the vehicle and tracking the reference trajectory. However, it takes into account not only the tracking objectives, but also the application of the Level of Haptic Authority (LoHA, as described in Section 2.3.2) and the stability criteria. In order to select an appropriate control method, the next sections evaluate the controller requirements in the context of shared-control, then analyze the control methods available in the literature, and finally explain the selection of the most appropriate algorithm to accomplish the task along with its theoretical basis.

3.2.1.1 Requirements

The driver interacts with the controller through the steering wheel as part of the coupled shared-control scheme (driver and vehicle are mechanically coupled through the steering system). In this sense, the controller must meet a number of requirements that are not considered in conventional autopilots (which are designed for lateral vehicle control but do not consider interaction with the driver at the operational level). The most important requirements are listed below:

- The **control signal** must be the steering wheel torque. This is in contrast to autopilots, which typically control with steering wheel angle [244] or even angular velocity [245]. However, the driver controls the steering wheel by applying torque with the arm-hand mechanism, and steering angle control has been shown to limit the driver's ability to work harmoniously with the automation (since he must deal with the low lever position controller) [246]. Therefore, to couple the control signals of both agents, a torque-based lateral controller is developed. In this dissertation, the control signal is associated with the variable T.
- The **authority** of the controller (i.e., its stiffness) must be variable, because in shared-control the assistance required by the driver is not always the same, so it can be adapted to the driving context (i.e., driver, automation, and environmental conditions). This differs from traditional autopilots, which assign a single authority value to the controller that is either enabled or disabled. With autopilots, the change occurs at the decision level and in the trajectory planner, but the controller remains with the same authority, whereas with the shared-control approach, automation support can adjust its intensity based on various driving-related conditions. This means that the automation can assist the driver with different intensities, covering the whole spectrum from "no support" to "maximum support". In the literature, this intensity is referred to as Level of Haptic Authority (LoHA) [25, 247]. In this Ph.D. Thesis, it is associated with λ.
- The **control method** must be able to perform optimization of multiple objectives because the complex interaction between the driver and the automation creates a set of objectives such as tracking performance, driver comfort, driving effort, safety, and driver-automation conflict, that cannot always be achieved simultaneously. Therefore, a controller that can efficiently balance these goals is desired.

3.2.1.2 Rationale

Regarding the control method, classical controllers such as PID [248] and non-model based controllers such as fuzzy logic [249] are commonly used for autopilots. However, for shared-control applications, optimal control algorithms are more advantageous because they allow minimization of multiple objective functions and have the added benefit of managing the vehicle's dynamic states and control signals through system constraints. Another advantage is that optimal control works with a system model, and in this case, it is possible not only to model the vehicle system, but also to integrate a driver-vehicle model in the problem formulation, which allows better prediction of the driver-automation interaction [250, 251]. Moreover, the state-of-the-art in shared-control methods shows that more and more optimal controllers for shared-control applications have been developed in recent years [252, 253].

Moreover, previous works have used various optimal control methods for shared-control applications, such as Linear Matrix Inequalities (LMI) with Linear Quadratic Regulator (LQR) [254], and Game-Theory [142]. Nevertheless, the preferred control algorithm for this work is the MPC approach, due to the following advantages offered by this algorithm:

- Powerful approach to optimal control of multivariable systems with constraints on inputs and states.
- Enables easy integration of predicted information considered in the optimization problem, and therefore takes appropriate control actions.
- Allows to include constraints resulting from traffic or road geometry.
- Calculates a new solution at each time step.
- Acts as both a controller and a trajectory planner, as it is able to predict its states over a finite future horizon.
- Manages both hard constraints and a nonlinear systems moving away from its linearized operating point.
- Solvers are available in the microsecond range, making this technique suitable for a control loop of 1 to 10 ms, which is common in AD applications.

3.2.1.3 Model Predictive Control

Model Predictive Control (MPC) is a model-based optimization method that iterates over a finite prediction horizon to minimize an objective function. It is widely used in control processes [255] and has become a common planning and control strategy for automated driving applications [256, 257]. A general description is given by approaching the three main component: model, objective function, and constraints.

- **Prediction model**: The mathematical formulation of the system behavior using first order differential equations. The model contains the states of the system and the control inputs. To ensure precise control, the model must be as accurate as possible, especially in open-loop applications. In automated driving control, however, the closed-loop approach is preferred, allowing greater flexibility in identifying parameters.

- **Objective function**: It determines the behavior of the controller by minimizing a subset of the states and inputs of the system contained in the model, using a quadratic minimization approach. The minimization considers a weight matrix to balance the different objectives of the controller according to the desired behavior.
- **Constraints**: In addition to minimizing states and inputs, their values are also limited. For inputs, this is a simple task, since it is sufficient to saturate the output of the controller. However, the advantage of this feature is that the entire optimization framework aims to minimize the objective while maintaining the system's state constraints. This is particularly useful for incorporating safety and comfort considerations into the problem.

The mathematical representation of the controller scheme in its discrete form is shown in Equations 3.1a-3.1f:

$$\min_{U} \sum_{i=0}^{N_p-1} ||z_i - z_i^r||^2_{W_z} + \sum_{i=0}^{N_c-1} ||u_i - u_i^r||^2_{W_u} + \sum_{i=0}^{N_c-1} ||\Delta u_i - \Delta u_i^r||^2_{W_{\Delta u}} \tag{3.1a}$$

$$\text{s.t.} \quad s_0 = \bar{s}_o \tag{3.1b}$$

$$s_{i+1} = f(s_i, u_i, l_i), \quad i = 0, 1, ..., N_p \tag{3.1c}$$

$$\tilde{z}_{min,i} \leq \tilde{z}_i \leq \tilde{z}_{max,i}, \quad i = 0, 1, ..., N_p - 1 \tag{3.1d}$$

$$\tilde{u}_{min,i} \leq \tilde{u}_i \leq \tilde{u}_{max,i}, \quad i = 0, 1, ..., N_c - 1 \tag{3.1e}$$

$$\Delta\tilde{u}_{min,i} \leq \Delta\tilde{u}_i \leq \Delta\tilde{u}_{max,i}, \quad i = 0, 1, ..., N_c - 1 \tag{3.1f}$$

where $s \in \mathbb{R}^{N_s}$ is the state vector of the system with N_s elements, and initial state vector $\bar{s_0} \in \mathbb{R}^{N_s}$. It represents all measurable states, for example, the velocity, the position, or the yaw rate of the vehicle. The combination of the functions $f_i : \mathbb{R} \rightarrow \mathbb{R}$, with $i = 1, ..., N_s$ represents the model of the system and depends on the system states (s), the system control inputs (u), and the external inputs not considered in the model (l). For vehicle automation applications, for example, the function could be a kinematic or dynamic vehicle model. The vector $z \subseteq s$ is the vector of optimization states, a subset of the system state vector, and it represents the states to be optimized over the predictive horizon with length N_p, for example, vehicle position or velocity. The inputs (u) and the associated rate of change (Δu) are also optimized in the minimization function, over a finite control horizon of length N_c. The weight matrices $W_z, W_u, W_{\Delta u}$ balance the minimization of the objective functions (associated to the reference values $z_i^r, u_i^r, \Delta u_i^r$). This could, for example, help to increase the efficiency of the controller by minimizing the control signal as much as possible. The vector $\tilde{z} \subseteq s$, has $N_{\tilde{z}}$ states and contains those that are constrained, for instance, limiting the lateral vehicle position to avoid leaving the lane, is a common application in automated driving. The vectors $\tilde{u}$ and $\Delta\tilde{u}$, with $N_{\tilde{u}}$ and $N_{\Delta\tilde{u}}$ elements, respectively, add constraints to the control signals and their derivatives. The implementation of this optimal control framework for shared-control applications is presented in Chapter 4.

3.2.2 Tactical Level → Arbitration

The tactical level in AD refers to driving maneuvers. However, in shared-control, it is also responsible for calculating the haptic authority of the operational level controller. This is done through the decision system called Arbitration, which decides, depending on the different driving variables, whether the controller should be given high authority (the automation has the main control) or low authority (the driver applies most of the required torque). In this sense, this module is also responsible for control transitions. It can deactivate the controller and put the system in manual mode, or activate it and make the transition to automated mode.

3.2.2.1 Requirements

Calculating the optimal level of haptic authority is one of the most challenging aspects of shared-control, as it depends on multiple and complex conditions related to the environment, the vehicle, and the driver's state. In this sense, the decision algorithm must satisfy the following requirements:

- MIMO (Multiple Inputs Multiple Outputs) system to obtain the different driving conditions that affect the calculation of the authority, and to be able to complement the authority with other parameters of interest in the decision output.
- Intuitive incorporation of system variables into system behavior so that inputs and outputs are correlated in a straightforward manner.
- Flexibility in inputs and outputs values so that fine-tuning is not required.
- It must be a model-free technique, since the mathematical description of the calculation of authority is a difficult task.

3.2.2.2 Rationale

Concerning arbitration, previous works have implemented various algebraic functions that depend on one or two variables. In [258], linear, piecewise linear, and nonlinear functions are used to assign control authority based on a threat assessor. Other work has integrated driver state and torque conflict into gaussian [86] and exponential [84] functions to calculate authority. However, as systems become more complex, more inputs are required. Moreover, conventional functions require normalization and fine-tuning of parameters to fit the formula to the desired behavior. As previous works have shown [28, 259], decision-making methods based on Fuzzy Inference Systems (FIS) bring advantages to the arbitration task for these reasons:

- It does not require precise values for the inputs, but allows a simple description of each variable in terms of a range of values.
- Human knowledge can be easily integrated into logic by IF-THEN rules.
- Changing system behavior does not require re-setting the entire system.
- It is a flexible method in terms of the number of inputs and outputs.

- The continuity added to the system's inputs is reflected in the continuity of the output, resulting in a smooth decision surface.
- Low computational cost as it does not require complex numerical calculations.
- When using Mandami-type fuzzy systems, no model of the system is required.

3.2.2.3 Fuzzy Inference System

Fuzzy logic is an AI-based algorithm that provides a solution to complex, hard-to-model decision and control systems by incorporating human knowledge into the design of the logic. To do this, the system's inputs and outputs through a set of membership functions and linguistic IF-THEN rules [260]. The components of a Mandimi-type fuzzy system are described below:

- **Linguistic variables**: In fuzzy systems, it is necessary to give an understandable description of the inputs and outputs. For example, if the state of the driver is an input with two states, they can be labeled as *attentive* and *distracted*.
- **Fuzzyfication**: The process of assigning a degree of membership function ($\boldsymbol{M_k}$) for the numeric value of the input (x_k). Since this method does not use exact values for the set of inputs and outputs (y), it requires a description by ranges defined by membership functions (e.g., triangle, trapezoid or gaussian).
- **Inference engine**: Responsible for applying inference rules to the fuzzy input to produce the fuzzy output. It is the application of Boolean logic (e.g., AND, OR) and certain functions such as implication and aggregation to the inputs to obtain a fuzzy value for the output (between 0 and 1). This output is then passed to the defuzzification stage.
- **IF-THEN rules**: The design of the logic is done by simple IF-THEN rules (R_i) based on the previously defined linguistic variables as shown in Equations 3.2a-3.2b. For example, IF *Driver* = *Distracted* THEN *Controller* = *Active*.

$$\text{Rule } R_i: \quad \text{IF } x_1 \text{ is } \boldsymbol{M}_1^i,\ x_2 \text{ is } \boldsymbol{M}_2^i, ..., x_m \text{ is } \boldsymbol{M}_m^i \tag{3.2a}$$

$$\text{THEN } y \text{ is } \boldsymbol{H}^i,\ i = 1, 2, ..., n \tag{3.2b}$$

- **Defuzzyfication**: It does the opposite from fuzzyfication. In converts a fuzzy value in a classical value defined in the output membership function ($\boldsymbol{H_k}$).

The implementation of this technique is used in the validation of the steering shared-controller in Chapter 4 and in the experimental studies in Chapter 5.

3.3 Automated Driving Simulator

The shared-control system is implemented in Tecnalia's AD simulator shown in Figure 3.3. It is a static platform with immersive visual experience using three front screens (26 inches each). It consists of a cockpit, the driving actuators, the displays, the driving monitoring system and the control system PC. The cockpit includes both the structure of the simulator mounts and the driver's seat. The modular structure of the mounts allows the position of the pedals and steering wheel to be changed to mimic a normal driving position. The position of the seat can be adjusted as in a normal vehicle. The position of the screens is at a similar height to the windshield and rear windows to enhance the driving experience. See the following sections for details on the software/hardware architecture of the simulator.

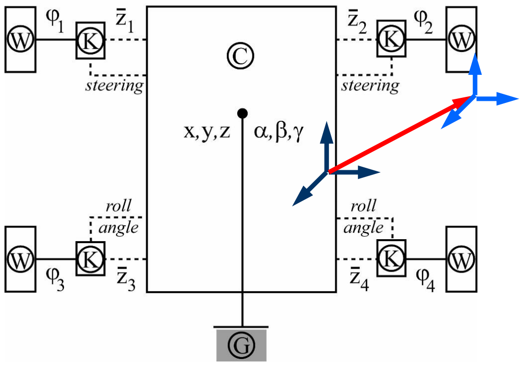
Fig. 3.3: Driver-in-the-loop AD simulator platform of Tecnalia

3.3.1 Software

The main components are the vehicle dynamics simulator, a Tecnalia proprietary software tool for validating vehicle systems, and the development environment in which the framework for automated driving is coded.

3.3.1.1 Vehicle Dynamics Simulator

The vehicle simulator is the software tool *Dynacar*, an integrated solution for the development of electric and hybrid vehicles that provides a physical model of the vehicle based on a multi-body formulation with relative coordinates and semi-recursive equations of motion based on a velocity transformation. The suspensions are considered as macro-joints and their behavior is modeled using lookup tables. As shown in Figure 3.4a, the local Cartesian coordinates of the chassis frame are located at the center of the front track width (C), cardan angles, which determine the orientation of the wheels with respect to the chassis frame, are located at the steering knuckles (K), and the kinematic expressions for the macro-joints take into account the position, velocity, and acceleration values of the wheels (W). The model allows users to develop or integrate their own control algorithms in the Matlab/Simulink environment. A detailed explanation of the model has been developed in previous publications [261]. In addition, the Dynacar software includes a visualization and road editor tool for driving simulations, as shown in Figure 3.4b.



(a) Vehicle multibody frame

(b) Dynacar visual simulator

Fig. 3.4: Dynacar simulator visualization

3.3.1.2 Development Enviroment

Automated driving algorithms are developed on Windows OS using Matlab-Simulink, a visual programming environment that operates at a higher level of abstraction than the Matlab interpreted language. The development of optimized code using S-function (C++ code integrated in Simulink) allows the integration of the Dynacar simulator software. For the development of the arbitration module, the integrated Matlab library for fuzzy logic systems was used. For the MPC controller, the ACADO toolkit [262], a software environment and algorithm collection for automatic control and dynamic optimization, was used as a problem solver for optimal control. It provides a general framework for using a variety of algorithms for direct optimal control, including model predictive The ACADO toolkit is implemented as stand-alone C++ code and has a user-friendly MATLAB interface. Steering control was achieved using the SimpleMotionV2[2] software library. For communication with the pedals, the general joystick library SLD [3] was used. The system for monitoring the driver, on the other hand, ran on a separate computer under Linux OS with ROS. The software architecture with the simulator components is shown in Figure 3.5.

3.3.2 Hardware

The hardware of the simulator consisted of the steering system, the accelerator and brake pedals, the controller PC, the driver monitoring system and the visual HMI. Various of the components are shown in Figure 3.6.

- **Steering-wheel**: It is part of Augury H Kit [4] and consists of a model 130ST servo motor (see Figure 3.6a) with a maximum rated torque of 15 Nm, with configurable damping and inertia via software (a key feature for the control algorithm). It is equipped with an incremental encoder and a current sensor used to calculate the applied torque. For safety reasons, there is an emergency button on the right side of the steering wheel.

[2] **Webpage**: Steering wheel library → *https://granitedevices.com/swlibrary*
[3] **Webpage**: Pedals library → *https://www.libsdl.org/release/*
[4] **Webpage**: Steering wheel hardware → *https://augurysimulations.com*

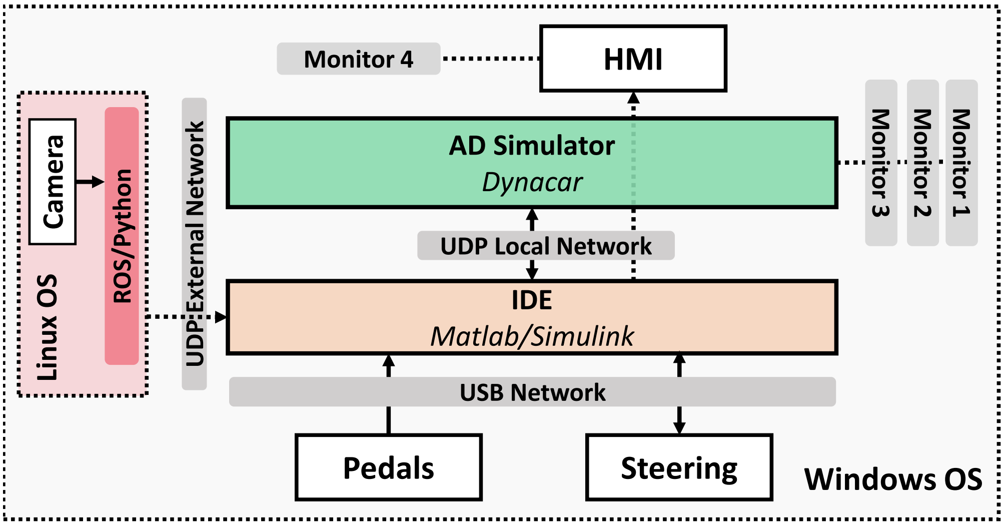
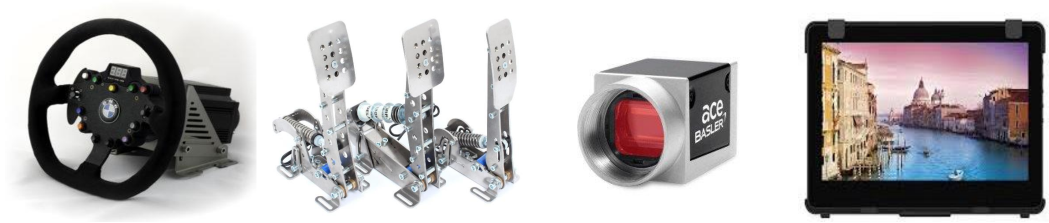


Fig. 3.5: AD simulator hardware/software architecture



(a) Steering-wheel (b) Accelerator-brake (c) DMS vision-camera (d) Visual HMI monitor

Fig. 3.6: AD simulator hardware components

- **Pedals**: Brake and accelerator pedals are Sim Pedals Pro - Heusinkveldare[5]. They can be configured with different pressure and damping coefficients that simulate the feel of some pedals in vehicles (see Figure 3.6b).
- **Control PC** : The control PC is a high-performance computer (Ryzen 2700x processor) with NVIDIA RTX 2080 GPU, with 32GB RAM memory and runs Windows 10 OS.
- **Driver monitoring camera**: The driver monitoring system uses an image processing-based camera (see Figure 3.6c) and is designed to measure the degree of driver distraction based on head position detection [263]. This system runs on Linux OS, with the software running in the Python and ROS environments. Data is transmitted to the main system over the UDP network. Images and video are captured using a Basler acA1920-40uc camera, which provides 41 frames per second at a resolution of 2.3 MP. The lens with a focal length of 12 mm was mounted on board behind the steering wheel.
- **Visual-HMI**: The visualization interface runs in a Windows application, and the hardware used for the display is an enhanced 11.6” touch monitor (GeChic

[5]**Webpage**: Pedals hardware → *https://heusinkveld.com/shop/sim-pedals/*

1102i[6]), as shown in Figure 3.6d. It is used for HMI visualization as well as for the execution of secondary tasks by the driver and is connected to the main computer via a mini-HDMI cable.

This AD simulator platform is the testbench of algorithms developed in Chapter 4 and experimental studies conducted in Chapter 5.

[6]**Webpage**: Visual-HMI hardware → *https://www.gechic.com/en/*

Steering Shared-Controller

4

SHared control in Automated Driving (AD) is intended to ensure that the driver and the intelligent vehicle drive as a well-coordinated team that achieves good performance, safety, and comfort on the road. To achieve this goal, progress is needed in the design and development of control and decision systems in this area. This is especially true for lateral control of the vehicle. The driver is more involved in the driving process through steering than through pedaling, and furthermore, lateral maneuvers remain a challenge for both the driver and the automation system, which is critical to maintaining driving safety.

In this context, this chapter presents the complete analysis for the development of a steering shared-controller for automated driving applications. In terms of the methodology for integrating variable authority into the control framework, two approaches are proposed (i.e., dual-level and unified). In addition, the controller development process is presented in four iterations. Each of these iterations includes a description of the system model, the optimization problem, consideration of adaptive authority, and finally validation of the system to test stability and performance. Some validations include the integration of an arbitration system to test the adaptive authority of the controller in real driving scenarios. The chapter concludes with a summary of the iterations and their results. In addition, the proposed shared-controller provides the following innovations and contributions:

- A torque-based lateral vehicle controller based on Non-Linear Model Predictive Control (NMPC) for shared-control applications in AD.
- A novel method for integrating the Level of Haptic Authority (LoHA) into the NMPC optimal control framework.
- A new stability criterion that ensure that system operation remains stable and maintains similar performance to the nominal controller, independently of the LoHA, and without the need to retune the weight matrices of the optimal control problem. Compared to similar works [81, 92, 264, 265] it is not only able to decrease nominal authority but also to increase it without losing stability.
- A multivariable arbitration system based on Fuzzy Inference System (FIS) for computing the appropriate LoHA for AD applications.

4.1 Dual-level Authority

As mentioned in the requirements for the shared-controller of the operational level (Section 3.2.1.1), it must be able to support the driver with a variable LoHA (different intensity of the control torque on the steering wheel). In this sense, the first approach of the NMPC-based shared-controller considers two levels of haptic authority.

First, the vehicle system has a natural haptic authority (λ_{sat}) as a product of the self-aligning torque that pushes the steering wheel toward the zero angle. The strength of this torque depends on some variables of the vehicle dynamics (e.g., longitudinal speed, sideslip angle, and others). This means that in manual mode, the total torque (T_{total}) is only the self-aligning torque. To simplify the design, T_{sat} is modeled with an elementary linear approximation shown in Equation 4.1, where θ is the steering wheel angle.

$$T_{total} = -\lambda_{sat}\theta \tag{4.1}$$

After the inclusion of a lateral vehicle control (in this case, the NMPC), a new haptic authority is added that is associated with the nominal authority of the controller (λ_{mpc}). In this case, the intensity depends on the controller's parameters (e.g., optimization weights and constraints). With the addition of the controller, the vehicle is now in automated mode. The total torque is represented in Equation 4.2, where θ_d is the desired steering wheel angle calculated by the controller.

$$T_{total} = -\lambda_{sat}\theta + \lambda_{mpc}(\theta_d - \theta) \tag{4.2}$$

The previous equation shows the natural (λ_{sat}) and nominal control authority (λ_{mpc}). In this context, shared-control applications require the integration of an adaptive Level of Haptic Authority (LoHA, λ). In some scenarios, the LoHA could be increased to correct the driver's steering movements (e.g., to avoid unsafe lane changes). In other cases, it would be necessary to decrease it to allow a transition to manual driving. On this basis, the dual-authority approach is based on the use of two variables that affect the nominal authority of the controller: one that increases it (λ_+) and one that decreases it ($\lambda_\_$). The first is represented as an additional haptic authority at the operational level (see Section 3.2.1), whose purpose is to increase the stiffness of the controller around the desired steering angle. This means that as $\lambda_+ \geq 0$ increases, it becomes more difficult for the driver to overcome the automation torque. In this sense, the new control authority is $\lambda = \lambda_{mpc} + \lambda_+$ as shown in Equation 4.3.

$$T_{total} = -\lambda_{sat}\theta + (\lambda_{mpc} + \lambda_+)(\theta_d - \theta) \tag{4.3}$$

The second instance of authority ($0 \leq \lambda_\_ \leq 1$) refers to the tactical level of the driving task (see Section 3.2.2), whose main purpose is to perform control transitions between the driver and the automation. When $\lambda_\_ = 1$ the automated steering system is active, and when $\lambda_\_ = 0$ the vehicle is in manual mode, at other values the system is switching from one operating mode to another. In this sense, the transition authority ($\lambda_\_$) can put the vehicle in manual mode regardless of the operational level authority (λ_+). Moreover, $\lambda_\_$ never exceeds the nominal control authority (λ_{mpc}) but can only decrease it, while λ_+ can never decrease the nominal authority but can only increase it. Equation 4.4 and Figure 4.1 provides the final representation of authorities.

$$T_{total} = -\lambda_{sat}\theta + \lambda_{-}(\lambda_{mpc} + \lambda_{+})(\theta_d - \theta) \tag{4.4}$$

This approach is implemented in two design iterations of the controller. Iteration 1 tests the system at low-speed (10 m/s) and uses a kinematic vehicle model. Iteration 2 operates at high-speed (20 m/s) and improves the vehicle equations using a dynamic vehicle model. Each iteration is presented by explaining the vehicle model, the optimization problem, the integration of the LoHA into the MPC framework, and finally the validation of the controller on the Driver-in-the-Loop (DiL) simulator.

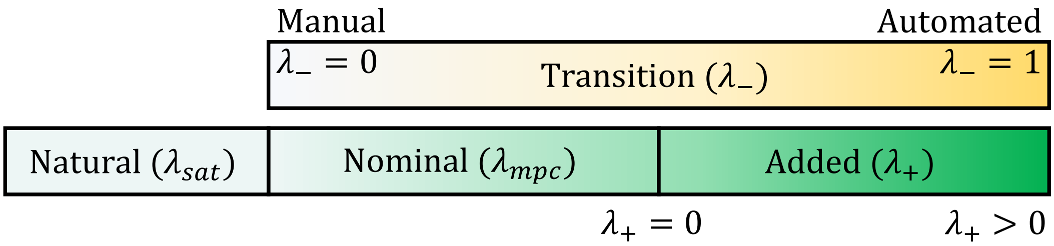


Fig. 4.1: Representations of the authorities at the steering wheel, with the dual-authority approach (λ_{-} at the tactical level, and λ_{+} at the operational level)

4.1.1 Iteration 1

The first iteration of the shared-controller consists of a low-speed (10 m/s) system using the dual-authority approach.

4.1.1.1 Model

The vehicle model is represented as a discrete differential equation system that depends on the vehicle states ($s_i \in \mathbb{R}^{N_s}$), the control inputs ($u_i \in \mathbb{R}^{N_u}$), and the exogenous variables ($l_i \in \mathbb{R}^{N_l}$), as shown in Equation 4.5. For simplicity, the representation of the automated vehicle system (f) is explained in terms of three submodels: vehicle model, lane keeping model, and steering system model. Their combination results in the integrated road-vehicle model. Table 4.1 contains the description of all related variables.

$$s_{i+1} = f(s_i, u_i, l_i), \quad i = 1, ..., N \tag{4.5}$$

The *vehicle* representation takes into account the bicycle kinematic bicycle model [266], as shown in Equations 4.6a-4.6f. In addition, Figure 4.2 contains a visual representation of the model.

Tab. 4.1: Kinematic bicycle model variable description

Var.	Description	Var.	Description
X	X coordinate in the global frame	$\bar{\kappa}$	Road curvature
Y	Y coordinate in the global frame	β	Side-slip angle
Ψ	Heading angle	L	Vehicle length
v_x	Longitudinal velocity	l_r	Distance CG to rear axle
v_y	Lateral velocity	δ	Steering angle
v	CG velocity	θ	Steering wheel angle
a_x	Longitudinal acceleration	w	Angular velocity
a_y	Lateral acceleration	k	Steering stiffness
e_y	Lateral error	b	Steering damping
e_ψ	Angular error	J	Steering inertial

$$\dot{X} = v\,cos(\Psi + \beta) \tag{4.6a}$$
$$\dot{Y} = v\,sin(\Psi + \beta) \tag{4.6b}$$
$$\dot{\Psi} = (v/l_r)\,sin(\beta) \tag{4.6c}$$
$$\dot{v_x} = a_x \tag{4.6d}$$
$$\dot{v_y} = a_y \tag{4.6e}$$
$$\beta = \tan^{-1}((lr/L)\,tan(\delta)) \tag{4.6f}$$

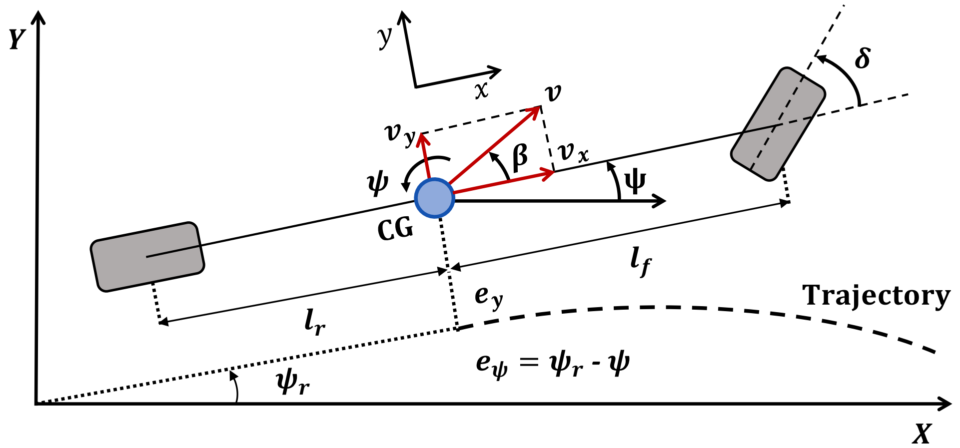


Fig. 4.2: Vehicle kinematic bicycle model

The *lane-keeping* model [157] is described using the lateral and angular errors, as in Equations 4.7a-4.7b. The road curvature ($\bar{\kappa}$), obtained from the reference trajectory computed offline with spline curves, is an exogenous input to the system.

$$\dot{e_y} = v_x\, sin(e_\Psi) + v_y\, cos(e_\Psi) \tag{4.7a}$$

$$\dot{e_\Psi} = \dot{\Psi} - \frac{\bar{\kappa}}{1 - \bar{\kappa}\, e_y}(v_x\, cos(e_\Psi) - v_y\, sin(e_\Psi)) \tag{4.7b}$$

The *steering* model makes it possible to add torque as the control signal instead of steering angle. It considers the second-order inertia, damping, and stiffness model of Equations 4.8a-4.8b. Furthermore, $\theta = n_s \delta$, where n_s is the constant steering ratio. In addition, a linear approximation of the self-aligning torque $T_{sat} = k\theta$ is included in the model, along with the steering control signal (T_{mpc}).

$$\dot{\theta} = w \tag{4.8a}$$

$$\dot{w} = \frac{-1}{J}\Big(bw + k\theta - T_{mpc}\Big) \tag{4.8b}$$

Based on the three submodels described above, the state vector is $s = [X,\, Y,\, \Psi,$ $v_x,\, v_y,\, e_y,\, e_\Psi,\, \theta,\, w]$, the input vector is $[u\ \Delta u] = [T_{mpc}\ \Delta T_{mpc}]$, and the exogenous vector is $l = [a_x,\, a_y,\, \bar{\kappa}]$.

4.1.1.2 Optimization

The design of the optimization problem consists in the selection of the controller's objectives to be minimized. There are three types of minimization functions: states, inputs, and rate of change of inputs, as shown in Equations 4.9a-4.9b.

$$\min_{U} \sum_{i=0}^{N_p-1} ||z_i - z_i^r||^2_{W_z} + \sum_{i=0}^{N_c-1} ||u_i - u_i^r||^2_{W_u} + \sum_{i=0}^{N_c-1} ||\Delta u_i - \Delta u_i^r||^2_{W_{\Delta u}} \tag{4.9a}$$

$$\min_{U}\ J_z + J_u + J_{\Delta u} \tag{4.9b}$$

The state optimization vector is $z \subseteq s$. In this case, $z = [e_y, e_\Psi]$, and represents the trajectory tracking objective. In addition, the input torque and its derivative are minimized to improve the efficiency of the controller and the interaction with the driver ($J_u + J_{\Delta u}$). All objective functions are minimized to 0. The weighting matrices of the optimization correspond to the tracking performance $W_z = \text{diag}(w_{e_y},\, w_{e_\Psi})$, the control torque $W_u = w_{T_{mpc}}$, and the torque rate of change$W_{\Delta u} = w_{\Delta T_{mpc}}$.

On the other hand, the state constraints vector $\tilde{z} = [e_y, \theta, w]$ imposes physical limits on the lateral vehicle position and steering wheel behavior. The input constraints limit the amplitude and the rate of change of the steering torque.

$$|T_{mpc_i}| \leq T_{max} \tag{4.10a}$$

$$|\Delta T_{mpc_i}| \leq \Delta T_{max} \tag{4.10b}$$

4.1.1.3 Authority → Operational

The challenge for the MPC-based shared-controller is to incorporate the dual-level authority ($[\lambda_+,\, \lambda_\_]$) into the problem formulation to enable a controller with variable authority that can be modified by a decision system at the tactical level (i.e., arbitration). Therefore, let us first consider the additional haptic authority at the operational level (λ_+). Previous works have considered a classical controller proportional to the lateral error [108]. In the case of the MPC controller, this means that w_{e_y} is increased. The problem with this approach is that changing the weights of the optimization problem may lead to an unpredictable behavior of the controller, in addition to changing its performance. The proposed solution is to include an additional term in the MPC torque (as in Equation 4.3). Thus, the control torque (T_λ) would satisfy Equations 4.11a-4.11b:

$$T_\lambda = T_{mpc} + T_{\lambda_+} \tag{4.11a}$$

$$T_\lambda = T_{mpc} + \lambda_+(\theta_d - \theta) \tag{4.11b}$$

In this approach, the MPC computes the prediction of its states and returns a vector of predictions for the optimal steering wheel angles $\theta_d(t+1) = [\theta_2(t), ..., \theta_N(t), \theta_{N+1}(t)]$. From this vector, the current desired angle is taken as the first prediction of the N available values ($\theta_d = \theta_2$), which according to the MPC sampling time configuration corresponds to the predicted angle value 50 ms ahead. In this strategy, the MPC torque and the additional haptic authority torque (T_{λ_+}) are related by optimizing the MPC goals. Apart from this calculation, a challenge in incorporating the operational authority is that the controller stiffness actually increases, but not without the risk of losing the stability achieved by tuning the weights of the MPC minimization function. Therefore, a stability consideration is presented that uses the sum of the torques and the steering system equation, where the driver's torque (T_d) is considered zero for the stability analysis since it is tested when the driver takes his hands off the steering wheel.

$$T_{mpc} + T_+ + T_{sat} + T_d = J\ddot{\theta} + b\dot{\theta} \tag{4.12a}$$

$$T_{mpc} + \lambda_+\theta_d = J\ddot{\theta} + b\dot{\theta} + (\lambda_{sat} + \lambda_+)\theta \tag{4.12b}$$

The new value of the equivalent stiffness around the center position is $k_e = \lambda_{sat} + \lambda_+$. In this sense, it is useful to consider the well-known formula for the damping ratio of the system in (4.8b) to obtain the parameter $\xi = b/2\sqrt{Jk}$, which gives information about the stability behavior [267]. Considering this, the strategy to maintain stability after incorporating the additional authority is to keep the same value of ξ. This is possible if a new equivalent damping ($b_e = b_{\lambda_+}$) is calculated and added to the steering system.

$$\xi = \frac{b_e}{2\sqrt{Jk_e}} = \frac{b}{2\sqrt{Jk}} \tag{4.13a}$$

$$\xi = \frac{b_{\lambda_+}}{2\sqrt{J(\lambda_{sat} + \lambda_+)}} = \frac{b}{2\sqrt{J\lambda_{sat}}} \tag{4.13b}$$

$$b_{\lambda_+} = b\sqrt{\frac{\lambda_{sat} + \lambda_+}{\lambda_{sat}}} \tag{4.13c}$$

In summary, the final additional authority torque has the form of Equation 4.14, which is a θ-dependent PD controller. The derivative term is integrated into the system by either configuring the steering wheel dynamic damping coefficient or by using a complementary torque signal with the appropriate filtering method. The major advantage is that the haptic authority of the controller is changed, stability is maintained and no change to the MPC weighting matrices was necessary.

$$T_{\lambda_+} = \lambda_+(\theta_d - \theta) + (b_{\lambda_+} - b)w \tag{4.14}$$

4.1.1.4 Authority → Tactical

Secondly, let us consider the transition authority ($\lambda_\_$) at the tactical level. The basic form to link the operational and tactical levels is by means of multiplication as in Equation 4.4. However, it is more advantageous to use the weights of the MPC to make the authority transitions, since it is able to perform the transition to manual mode while keeping the constraints of the MPC active. In previous work [82], this authority was included in the optimization function of the MPC states, as in Equation 4.15a.

$$J_{mpc} = J_z\lambda_\_ + J_u + J_{\Delta u} \tag{4.15a}$$

However, this function could include more states than just track errors, which could lead to unknown system behavior. In this context, the use of control input weighting ($w_{T_{mpc}}$) allows control transitions under a controlled behavior since it changes only one variable. A sufficiently high value of $w_{T_{mpc}}$ minimizes control torques to zero, which corresponds to manual mode. Therefore, the input optimization function should depend on $\lambda_\_$, as shown in Equation 4.16a. After some experimental tests and considering $w_{T_{mpc}}(\lambda_\_) = 10^{g(\lambda_\_)}$, with $g : \mathbb{R} \to \mathbb{R}$ and $0 \leq \lambda_\_ \leq 1$, it turns out that the system is in manual mode when $g(0) = 3$, and in automated mode (nominal controller active) when $g(1) = -0.5$. The mathematical representation can be found in Equations 4.16a-4.16d.

$$J_{mpc} = J_z + J_u(\lambda_\_) + J_{\Delta u} \tag{4.16a}$$

$$J_u(\lambda_\_) = \sum_{i=1}^{N} w_{T_{mpc}}(\lambda_\_)|T_{mpc_i}|^2 \tag{4.16b}$$

$$w_{T_{mpc}}(\lambda_\_) = 10^{g(\lambda_\_)} \tag{4.16c}$$

$$g(\lambda_\_) = -3.5\lambda_\_ + 3 \tag{4.16d}$$

4.1.1.5 Validation → Shared-Controller

The validation is performed by a driver using the driving simulator platform described in Section 3.3. The first test evaluates the stability of the steering torque controller with different λ_+ values. The vehicle has automatic longitudinal control at 35 km/h, and the driver interacts with the automation only at the steering wheel. The shared-controller is configured with the parameters given in Table 4.2.

Tab. 4.2: MPC parameters values for iteration 1 controller

Var.	Value	Var.	Value	Var.	Value
L	3.05 m	N	30	$w_{\Delta T_{mpc}}$	0.003
l_r	1.65 m	t_{mpc}	0.05 s	$[\theta_{min}, \theta_{max}]$	±7.85 rad
$k = \lambda_{sat}$	3 Nm/rad	t_c	0.01 s	$[w_{min}, w_{max}]$	±5.5 rad/s
b	0.75 Nm.s/rad	w_{e_y}	5000	$[e_{y_{min}}, e_{y_{max}}]$	[-2 , 6] m
J	0.075 kg.m^2	w_{e_Ψ}	30	T_{max}	10 Nm
n_s	8.45	$w_{T_{mpc}}$	0.3	ΔT_{max}	10 Nm/s

To test the stability of the controller, the driver performed an overtaking maneuver with automatic steering activated ($\lambda_- = 1$) and considering different values of λ_+. Initially, the driver starts with his hands on the steering wheel until the distance to the vehicle in front is 20 m. At this point, a vibration acts on the steering wheel to indicate the driver to start the overtaking maneuver. The controller remains activated to measure the effort. Once the driver has overtaken the other vehicle by 10 m, another vibration indicates that s/he should release the steering wheel and let the controller return to the lane independently.

In the first test, the driver completed five overtakes with $\lambda_+ = [0, 5, 10, 15, 20]$ and with a constant damping coefficient ($b = 0.75$), which corresponds to the standard damping of the steering system. Figure 4.3 (left side) shows the results of the tests. The increasing of the stiffness for the controller requires more effort from the driver to perform the maneuver. However, at higher authorities, the system loses stability when the driver releases the steering wheel. It is important to note that the nominal controller ($\lambda_+ = 0$) is stable and oscillations start when $\lambda_+ > 0$.

The second set of tests considers Equation 4.13c to preserve the stability of the controller. The damping coefficient of the steering system is varied by configuring the steering motor parameters. This allows the damping ratio (ξ) of the original stable configuration to be maintained as the stiffness increases. Figure4.3 (right side) shows that driver effort increases and vehicle stability is maintained for various values of λ_+.

In addition, Figure 4.4 shows the torque behavior of the controller when the variable damping formula is applied. It can be seen that the additional authority helps to almost double the stiffness of the controller when comparing the nominal

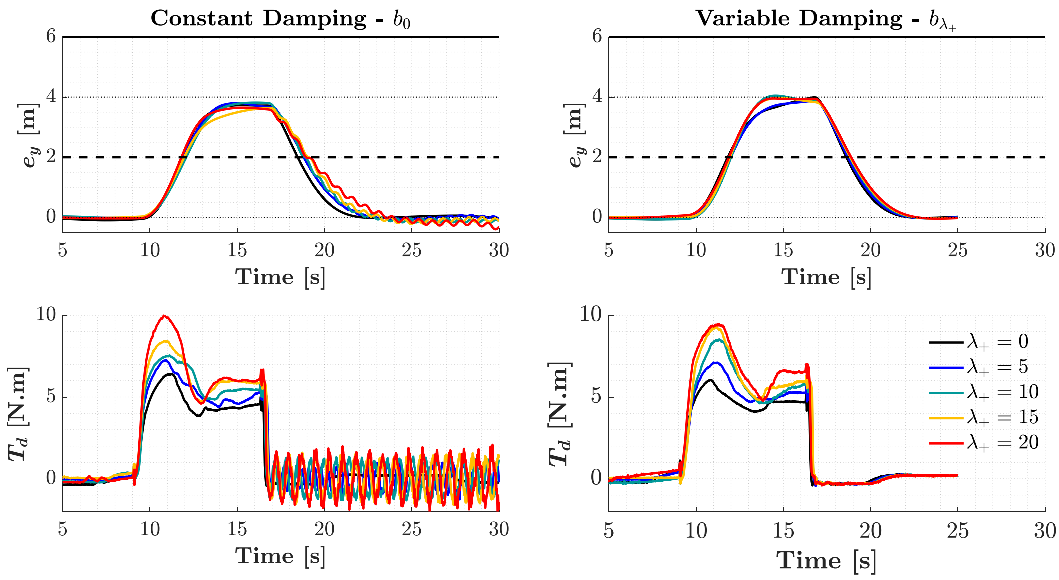


Fig. 4.3: Operational authority (λ_+) tests with constant and variable damping

($\lambda_+ = 0$) to the higher authority ($\lambda_+ = 20$), where the driver's force was increased from just over 5 Nm to almost 10 Nm.

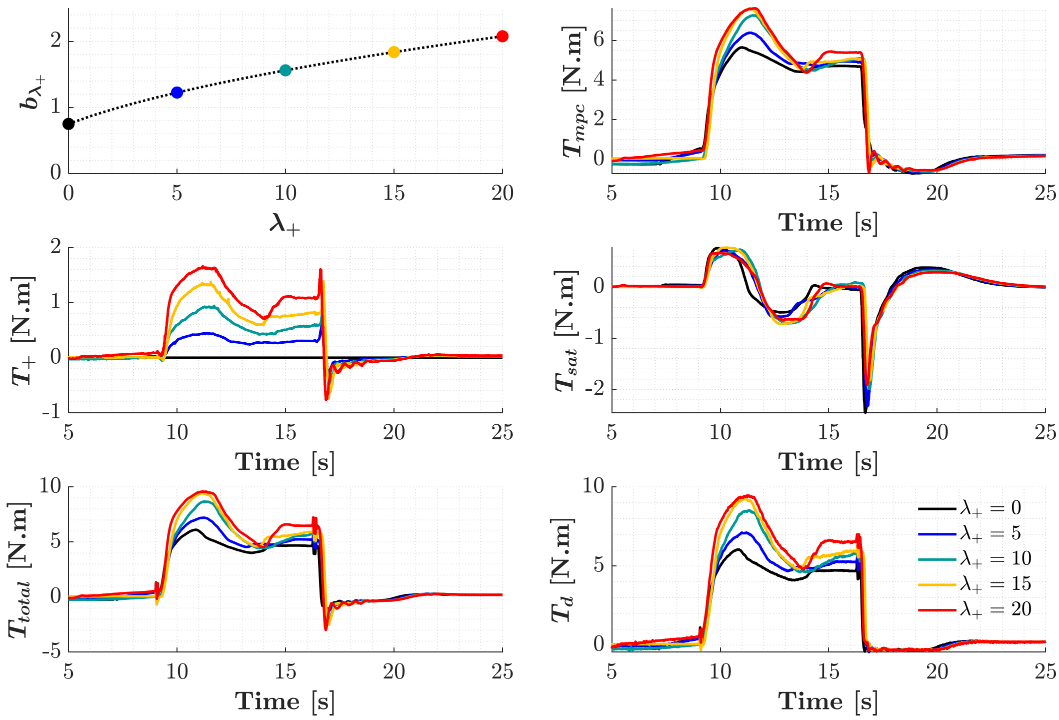
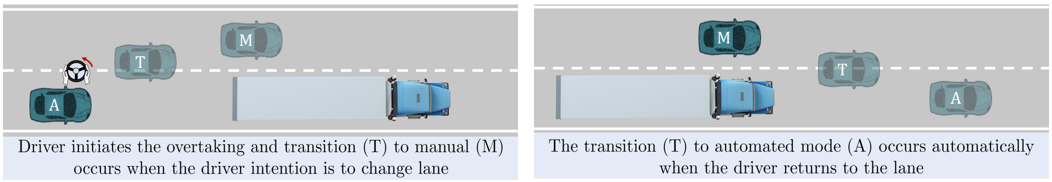


Fig. 4.4: Torques of the operational authority ($\lambda\_$) tests with variable damping

4.1.1.6 Validation → Arbitration

The validation of the tactical level considers the transition authority. For this purpose, the controller is tested in the use case of an overtaking maneuver (see

Figure 4.5), which involves different authority transitions. First, the automated system assists the driver in maintaining the lane. In the second phase, the driver performs a lane change and there is a gradual transition from automated-to-manual (see Figure 4.5a). Once the vehicle is in the left lane, the driver has full control. Then, when it returns to the right lane, authority is gently increased from manual-to-automated (see Figure 4.5b). Finally, the driver automation system returns to the initial state.



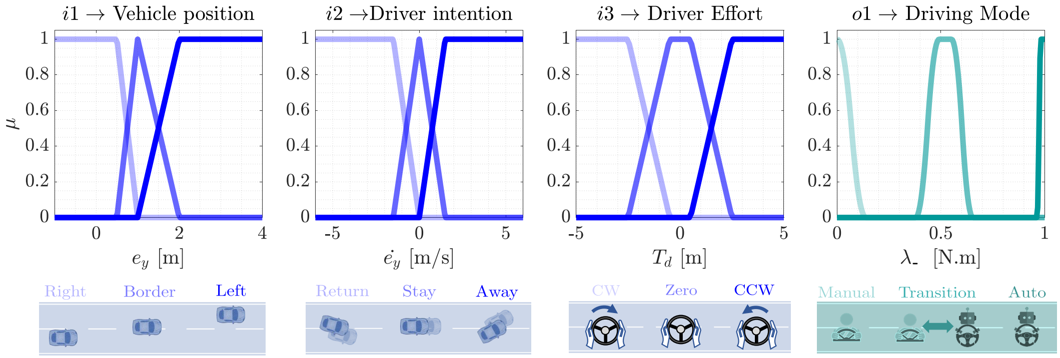
(a) Lane change maneuver **(b)** Lane return maneuver

Fig. 4.5: Control transitions during overtaking maneuver

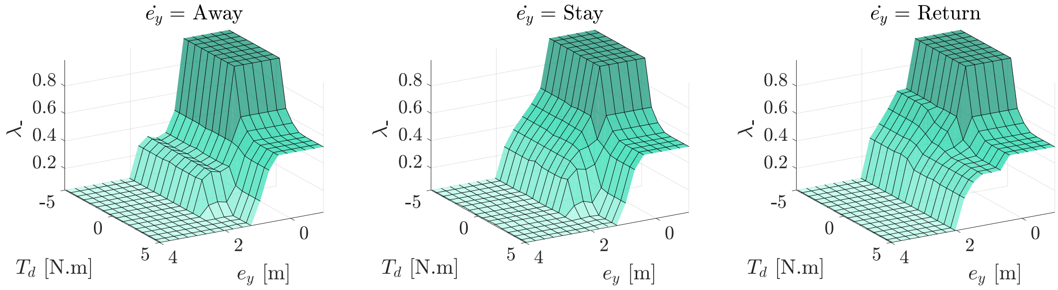
The decision algorithm for performing the transitions is a fuzzy logic-based arbitration system (see Section 3.2.2) and is shown in Figures 4.6a and 4.6b. The arbitration module proposed in this section consists of three inputs $(e_y, \dot{e}_y, T_d)$ representing the driver's intention and one output (λ_-), which is a continuous value from 0 (manual mode) to 1 (automated mode). The design rules are shown in Table 4.3. The description of the system can be found below.

- $i1$ - **Vehicle position**: Represented as the lateral error of the vehicle with respect to the center of the right lane (e_y). The labels of the membership functions ([Right - Border - Left]) represent the different positions of the vehicle on a two-lane road.
- $i2$ - **Driver intention**: Represented as the derivative of the lateral error of the vehicle $(\dot{e_y})$. The labels of the membership functions ([Away - Stay - Return]) represent the driver's intention to leave the lane, stay in the same direction, or return to the lane. This intention is combined with the lateral error and the direction of driver effort to obtain an estimate of the lane change intention.
- $i3$ - **Driver effort**: Represented as the driver's torque measured by the steering wheel torque sensor. The labels of the membership functions ([CW - Zero - CCW]) represent the steering direction (clockwise and counterclockwise) and the force exerted by the driver.
- $o1$ - **Transition authority**: Represented as a dimensionless value indicating the driving mode. The labels of the membership functions ([Manual - Transition - Automated]) are the three possible states for the driver-automation interaction.

The tests for evaluating authority transitions include four modalities for switching from manual to automated and from automated to manual using the variable parameter λ_- calculated by the arbitration system, and considering the nominal controller $(\lambda_+ = 0)$. These modalities are described in Table 4.4.



(a) Inputs/Output description



(b) Decision output surface

Fig. 4.6: Representation of the arbitration system for transitions during overtaking

Tab. 4.3: Fuzzy logic IF-THEN rules for Iteration 1 shared-controller validation

$i1 - e_y \rightarrow$	Right			Border			Left		
$i2 - \dot{e_y} \rightarrow$	Return	Stay	Away	Return	Stay	Away	Return	Stay	Away
CCW	T	T	T	T	M	M	M	M	M
Zero	A	A	A	T	T	M	M	M	M
CW	A	A	A	A	T	M	M	M	M
$i3 - T_d \uparrow$	$o1 - \lambda\_ \uparrow$								

Tab. 4.4: Mode of transitions for validation of the tactical authority

Transition mode	Description
No transition	The system is always in automated moded, with controller enabled during the entire overtaking
On/Off	Controller disabled if $T_d > 4$ [Nm] when leaving the lane and enabled if $\dot{e_y} < 0$ and $e_y < 2$, when returning to the lane
On/Off*	The transitions are the same as in on/off mode, with a first order filter with $\tau = 2$ s
Fuzzy logic	The transition considers the three-input fuzzy system presented in Figure 4.6

The driver performs three tests in each mode. Figure 4.7 shows the results of the tests comparing the authority transition strategies. The test procedure is the same

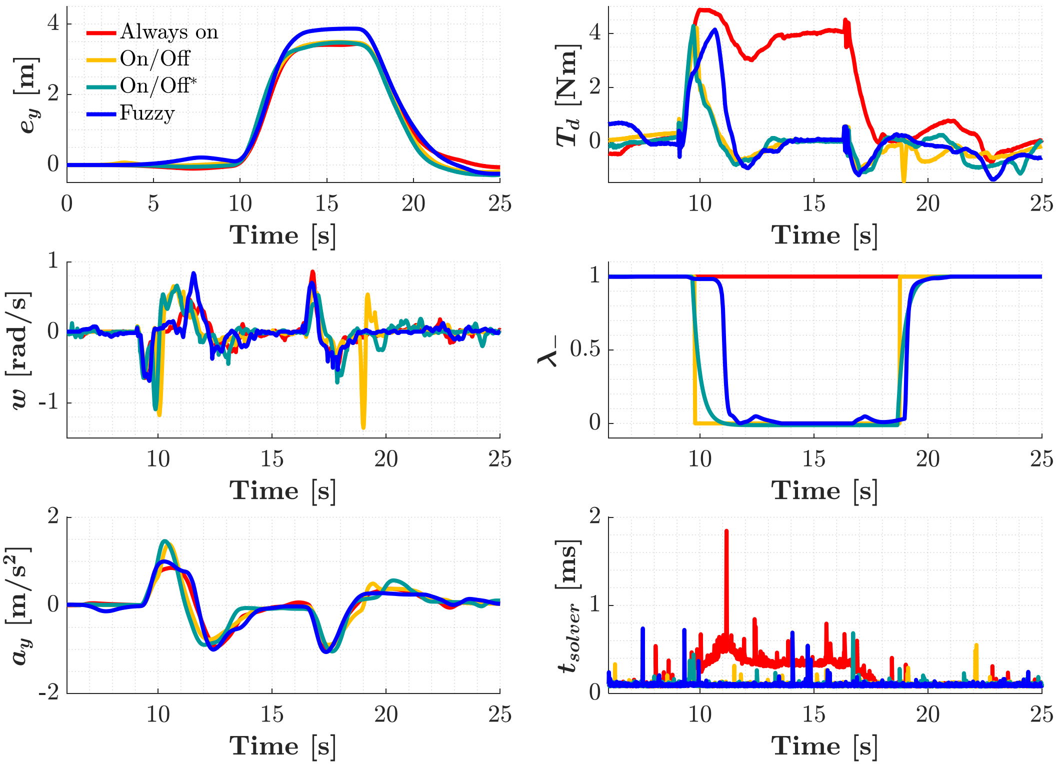


Fig. 4.7: Transition authority tests with four strategies

overtaking maneuver as described earlier. The vibration in the steering wheel tells the driver when to change lanes to overtake, but in this case the driver does not take his hands off the steering wheel and steers the vehicle back to the lane.

The first mode (no transition) requires more torque input from the driver, but shows the best results in terms of comfort when analyzing lateral acceleration and steering angular velocity. In contrast, the on/off mode requires less driver effort, but the sudden deactivation of the controller shows the largest peaks in steering wheel speed and lateral acceleration. Adding a 2-second filter does not reduce the peaks during the first transition, but improves comfort when the driver returns to the lane.

The fuzzy arbitration system shows the best compromise between driver effort and comfort. The torque felt at the steering wheel is lower than in automated mode, although slightly higher than in the on/off strategy, which is a good indicator as it helps avoid unintended transitions. In addition, the comfort parameters for both types of transitions (activation and deactivation) are close to the automated mode.

The results also show that changing $w_{T_{mpc}}$ for the authority transitions does not affect the computation time (t_{solver}) needed to find the optimal MPC solution. However, in automated mode, this time increases because the solver cannot minimize the tracking objective function when the driver is in the left lane. Nevertheless, $t_{solver} < 1$ ms is suitable for a control loop of 10 ms.

4.1.2 Iteration 2

The second iteration of the shared-controller consists of a high-speed (70 km/h) controller using dual-authority mode.

4.1.2.1 Model

Similar to the section 4.1.1.1, the vehicle model consists of three submodels: vehicle, lane-keeping, and steering system. The only difference between the two models is in the vehicle equations, which now use a dynamic bicycle model (rather than a kinematic one) that allows the driver to reach higher speeds by accounting for the slip angle and forces acting on the tires. In addition, these equations allow for a nonlinear representation of the self-aligning torque. Figure 4.8 shows the representation of the model Equations 4.17a-4.17f in the global coordinate frame.

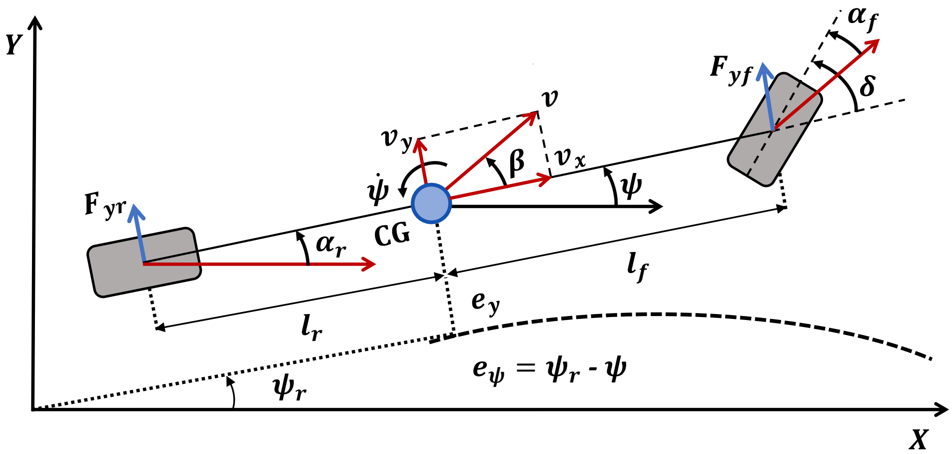


Fig. 4.8: Vehicle dynamic model

Table 4.5 describes the additional variables included in the vehicle dynamic model of the vehicle.

Tab. 4.5: Dynamic bicycle model variable description

Var.	Description	Var.	Description
m	Vehicle mass	F_{yr}	Rear axle lateral force
I_z	Yaw inertia	C_{α_f}	Front axle cornering stiffness
l_f	Distacen CG to front axle	C_{α_r}	Rear axle cornering stiffness
ψ	Yaw rate	α_f	Front axle slip angle
F_{yf}	Front axle lateral force	α_r	Rear axle slip angle

$$\dot{X} = v_x cos(\Psi) - v_y sin(\Psi) \tag{4.17a}$$
$$\dot{Y} = v_x sin(\Psi) + v_y cos(\Psi) \tag{4.17b}$$
$$\dot{\Psi} = \psi \tag{4.17c}$$
$$\dot{v_x} = (ma_x - F_{yf} sin(\delta) + mv_y\psi)/m \tag{4.17d}$$
$$\dot{v_y} = (F_{yr} + F_{yf} cos(\delta) - mv_x\psi)/m \tag{4.17e}$$
$$\dot{\psi} = (l_f F_{yf} cos(\delta) - l_r F_{yr})/I_z \tag{4.17f}$$

the lateral forces F_{yf} and F_{yr} acting in the front and rear tires respectively, are included as algebraic states of the model, as defined in Equations 4.18a-4.18b:

$$F_{yf} = C_{\alpha_f}\alpha_f \tag{4.18a}$$
$$F_{yr} = C_{\alpha_r}\alpha_r \tag{4.18b}$$

where $C_{\alpha f}$ and $C_{\alpha r}$ are the front and rear cornering stiffness constants calculated by the estimation method presented in [268]. The formulas for the sideslip angles are presented in Equations 4.19a-4.19b:

$$\alpha_f = \delta - (v_y + l_f\psi)/v_x \tag{4.19a}$$
$$\alpha_r = (v_y - l_r\psi)/v_x \tag{4.19b}$$

These considerations allow the self-algning torque to be expressed in terms of the lateral force on the front axle, as in Equation 4.20a, where k_{sat} is a gain to tune the feel when using the steering wheel in the simulator platform. Furthermore, compared to the linear Equation 4.20b, as in the first iteration, the stiffness gain of the self-aligning torque is calculated in real time as $\lambda_{sat} = T_{sat}/\theta$, where $2 \leq \lambda_{sat} \leq 5$.

$$T_{sat} = k_{sat} F_{yf} \tag{4.20a}$$
$$T_{sat} = \lambda_{sat}\theta \tag{4.20b}$$

The final state vector of the road-vehicle model is $s = [X,\, Y,\, \Psi,\, v_x,\, v_y,\, \psi\ e_y,\, e_\Psi,\, \theta,\, w]$, the input vector is $[u\ \Delta u] = [T_{mpc}\ \Delta T_{mpc}]$, and the exogenous vector is $l = [a_x,\, \kappa,\, \lambda_{sat}]$.

4.1.2.2 Optimization

The design of the optimization problem follows the same structure as the first iteration of the controller, according to Equations 4.9a-4.9b. The difference is based on the optimized state vector $z \in s$, which is now composed of two sub-objective vectors such that $z = z_{tracking} \cup z_{comfort}$, where $z_{tracking} = [e_y, e_\psi]$ and $z_{comfort} = [v_y, \psi, w]$. The state optimization weights correspond to the diagonal matrix and its eigenvalues $W_z = \text{diag}(w_{e_y},\, w_{e_\Psi},\, w_{v_y},\, w_\psi,\, w_w)$. The input optimization and system constraints remain the same as in iteration 1 ($W_u = w_{T_{mpc}}$, $W_{\Delta u} = w_{\Delta T_{mpc}}$, and $\tilde{z} = [e_y, \theta, w]$).

4.1.2.3 Authority → Operational

The added authority (λ_+) is included in the problem formulation in the same way as in the first iteration (Section 4.1.1.3), following the added torque formula and the corresponding damping to preserve stability, as in Equations 4.21a-4.21b. This variables are included in the MPC problem thorugh the exogenous vector $l = [a_x,\ \kappa,\ \lambda_{sat},\ \lambda_+,\ \theta_d]$.

$$T_{\lambda_+} = \lambda_+(\theta_d - \theta) + (b_{\lambda_+} - b)w \tag{4.21a}$$

$$b_{\lambda_+} = b\sqrt{\frac{\lambda_{sat} + \lambda_+}{\lambda_{sat}}} \tag{4.21b}$$

4.1.2.4 Authority → Tactical

The transition authority ($\lambda\_$) is also the same as in iteration 1. After some experimental tests and considering $w_{T_{mpc}}(\lambda\_) = 10^{h(\lambda\_)}$, with $h : \mathbb{R} \to \mathbb{R}$ and $0 \le \lambda\_ \le 1$, it turns out that the system is in manual mode when $h(0) = 7$, and in automated mode (nominal controller active) when $h(1) = 3$, resulting in Equation 4.22.

$$h(\lambda\_) = -4\lambda\_ + 7 \tag{4.22}$$

4.1.2.5 Validation → Shared-Controller

One driver performs the validation in the DiL simulator. The test evaluates the tracking performance of the controller for different values of λ_+. The vehicle has automatic longitudinal control at 70 km/h, and the driver interacts with the automation only at the steering wheel. The shared-controller is configured with the parameters given in Table 4.6.

Tab. 4.6: MPC parameters values for iteration 2 controller

Var.	Value	Var.	Value	Var.	Value
L	3.05 m	C_{α_f}	88000 N/rad	$w_{T_{mpc}}$	100
$[l_f, l_r]$	[1.40, 1.65] m	C_{α_r}	110000 N/rad	$w_{\Delta T_{mpc}}$	100
λ_{sat}	5 Nm/rad	w_{e_y}	5e4	$[\theta_{min}, \theta_{max}]$	±7.85 rad
k_{sat}	1/750	w_{e_Ψ}	70e4	$[w_{min}, w_{max}]$	±5.5 rad/s
b	0.75 Nm.s/rad	w_{v_y}	10	$[e_{y_{min}}, e_{y_{max}}]$	[-2 , 6] m
J	0.075 kg.m^2	w_ψ	10	T_{max}	10 Nm
n_s	8.77	w_w	1000	ΔT_{max}	3 Nm/s

The tracking performance results of the shared-controller in automated mode are shown in Figure 4.9. The controller shows stability on roads with different curvature ratios. The lateral error is less than 0.2 m for all values of λ_+. The angular error remains small, below 3° indicating a positive index of tracking performance for a torque control signal below 2 Nm. It is also shown that the solution of the MPC controller is calculated in less than 2 ms, which is a good indicator of the control loop of 10 ms. These results confirm that the performance of the shared-controller in automated mode does not depend on the choice of authority (λ_+) and that this method is effective to change the stiffness of the controller without affecting the performance and without redesigning the MPC parameters.

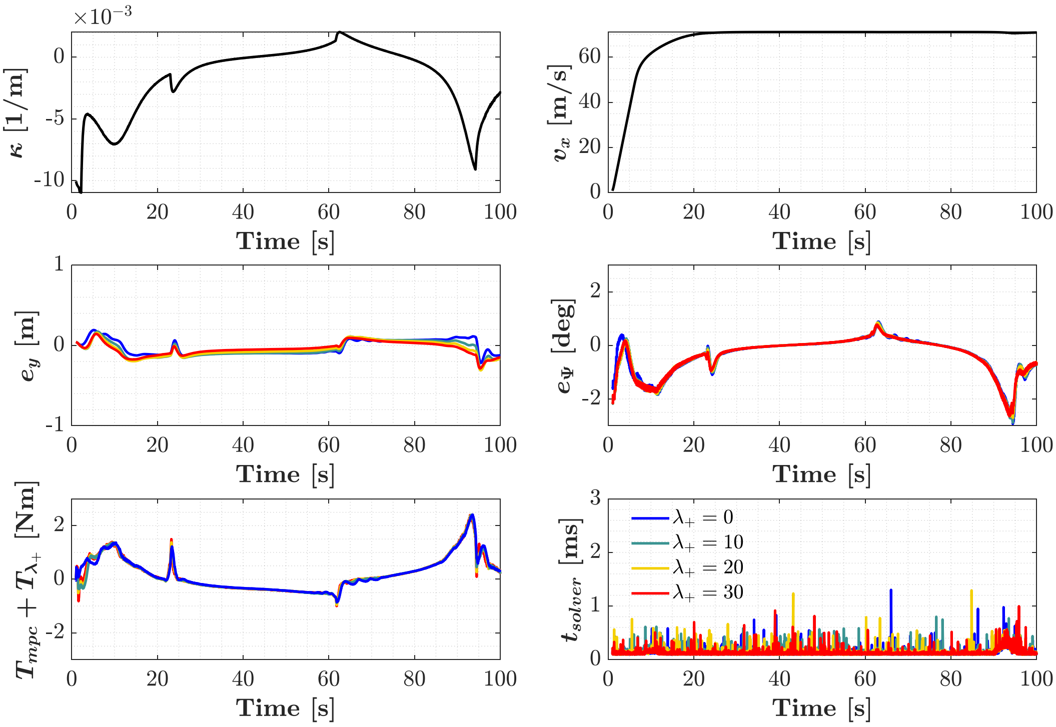
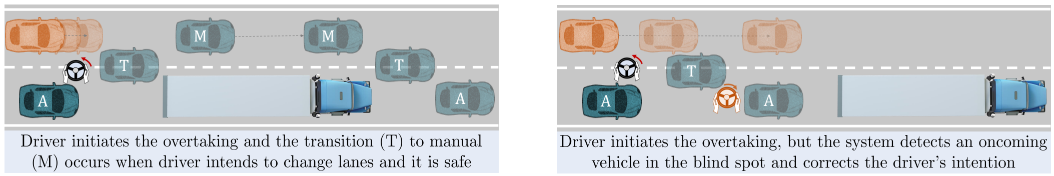


Fig. 4.9: Tracking performance with different values of λ_+

4.1.2.6 Validation → Arbitration

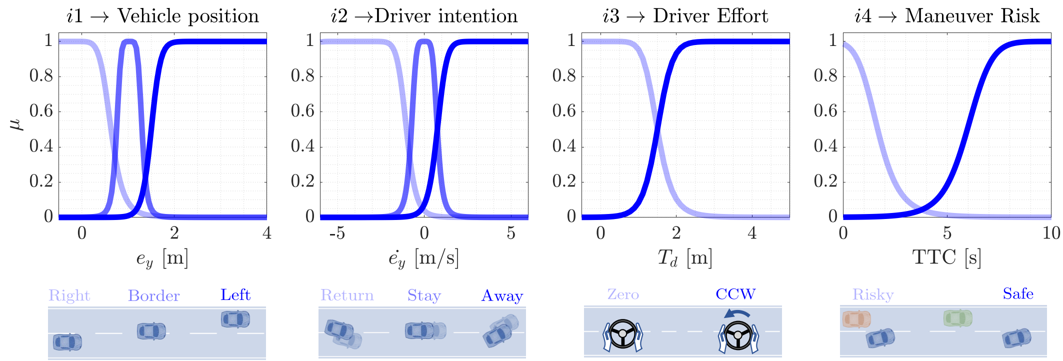
Tactical-level validation tests the performance of the transition authority ($\lambda\_$). For this purpose, the controller is tested in the use case of an overtaking maneuver, similar to the validation of iteration 1, except that the maneuver now considers a vehicle coming through the blind spot. First, when the driver initiates the overtaking maneuver and there is no risk of collision, the transition from manual to-automated is performed, the driver assumes manual control during the overtaking maneuver, and the system is reactivated when the driver returns to the original lane (see Figure 4.10a). In the second scenario, the driver wants to change lanes to overtake the vehicle ahead, but there is a vehicle in the left lane with which a collision could occur. In this case, the automated system intervenes appropriately and avoids the maneuver to ensure safety (see Figure 4.10b).

A fuzzy logic algorithm with four inputs ($[e_y, \dot{e}_y, T_d, TTC]$) and two outputs ($[\lambda_+, \lambda\_]$) is used for validation. The membership functions of the inputs and outputs of the system are shown in Figures 4.11a-4.11b, and are described below.

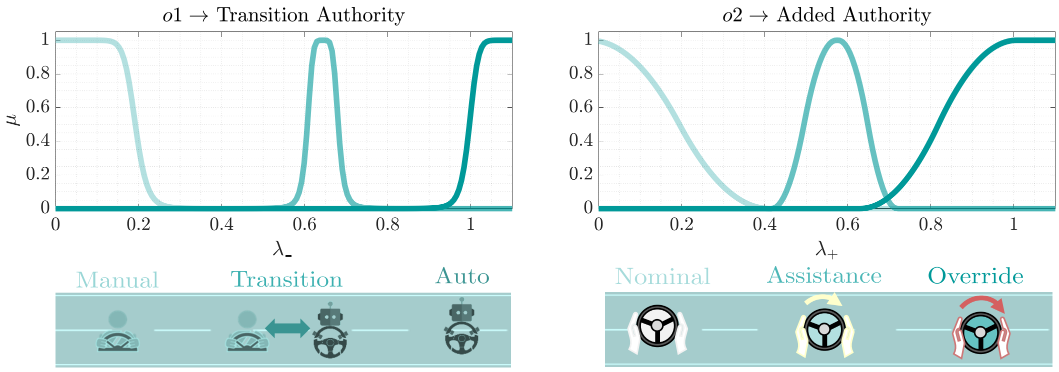


(a) Safe overtaking maneuver **(b)** Unsafe overtaking maneuver

Fig. 4.10: Control transitions during overtaking maneuver



(a) Inputs $\rightarrow$ vehicle, driver, and enviroment states



(b) Outputs $\rightarrow$ operational and tactical authorities

Fig. 4.11: Membership functions of the fuzzy-logic-based arbitration system

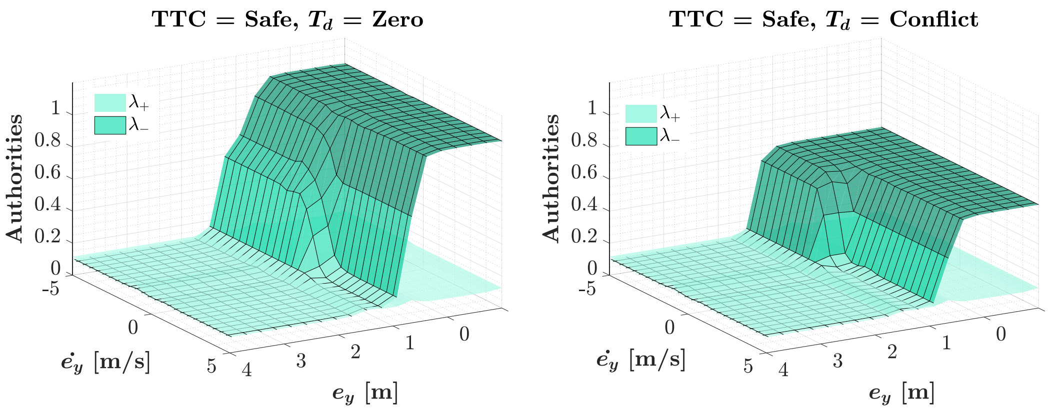
- $i1$ - **Vehicle position**: Represented as the lateral error of the vehicle with respect to the center of the right lane (e_y). The labels of the membership functions ([Right - Border - Left]) represent the different positions of the vehicle on a two-lane road.
- $i2$ - **Driver intention**: Represented as the derivative of the lateral error of the vehicle ($\dot{e_y}$). The labels of the membership functions ([Away - Stay - Return]) represent the driver's intention to leave the lane, stay in the same direction, or return to the lane. This intention is combined with the lateral error and the direction of driver effort to obtain an estimate of the lane change intention.
- $i3$ - **Driver effort**: Represented as the driver's torque measured by the steering wheel torque sensor. The labels of the membership functions ([Zero - CCW]) indicate if there is a conflict between driver and automation during the maneuver.

- $i4$ **- Maneuver risk**: Computed as the time-to-collision with the vehicle in the left lane ($\mathrm{TTC} = \frac{d}{v_{xl}-v_x}$), with v_{xl} being the longitudinal speed of the second vehicle. The labels of the membership functions ([Risky - Safe]), represents the possibility of collision.
- $o1$ **- Transition authority**: Represented as a dimensionless value indicating the driving mode ($\lambda_{\_}$). The labels of the membership functions ([Manual (M) - Transition (T) - Automated (A)]) are the three possible states for the driver-automation interaction.
- $o2$ **- Added authority**: Represented as a normalized value indicating stiffness of the controller ($\lambda_+ = \bar{\lambda}_+ o_1$), with $\bar{\lambda}_+ = 30$. The labels of the membership functions ([Nominal (No) - Assistance (As) - Override (Ov)]) denote the strength of the steering controller.

The decision system depends on whether the overtaking maneuver is safe or risky. If the maneuver is safe, then the arbitration behaves according to the IF-THEN rules of Table 4.7. The values of the authorities are shown in Figure 4.7.

Tab. 4.7: Fuzzy logic IF-THEN rules for Iteration 2 shared-controller validation (Safe)

TTC = Safe									
$i1 - e_y \rightarrow$	**Right**			**Border**			**Left**		
$i2 - \dot{e_y} \rightarrow$	**Return**	**Stay**	**Away**	**Return**	**Stay**	**Away**	**Return**	**Stay**	**Away**
CCW	**T**	**T**	**T**	**T**	**M**	**M**	**M**	**M**	**M**
Zero	**A**	**A**	**A**	**T**	**T**	**M**	**M**	**M**	**M**
$i3 - T_d \uparrow$	$o1 - \lambda_{\_} \uparrow$								
CCW	**Nominal Authority**								
Zero									
$i3 - T_d \uparrow$	$o2 - \lambda_+ \uparrow$								



(a) No driver-automation conflict **(b)** With driver-automation conflict

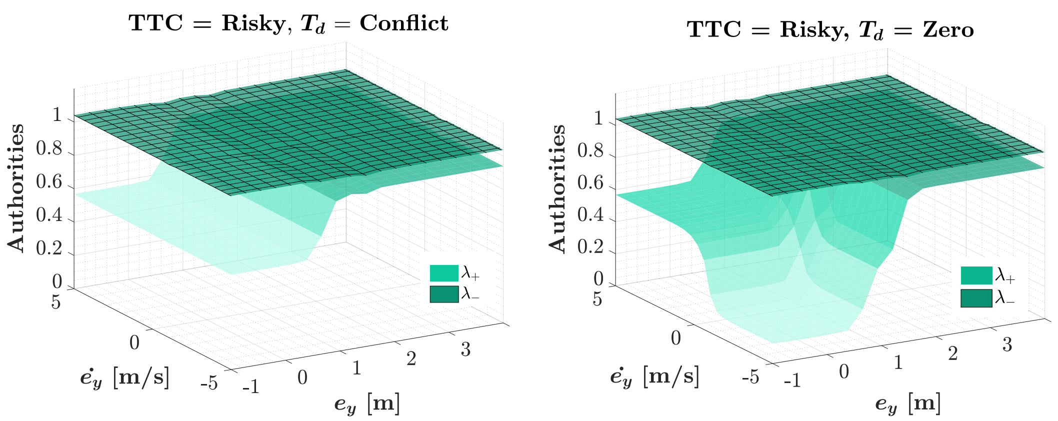
Fig. 4.12: Decision surfaces when the overtaking is safe

It shows that the controller retains its nominal authority on a safe lane change without the need to add a new authority ($\lambda_+ = 0$, nominal). Instead, the transition authority kicks in, either to keep steering assistance active or to transition to manual mode. If there is no conflict with automation (Figure 4.12a), the system reaches maximum authority (λ_-) when driving in the right lane. When there is a conflict (Figure 4.12b), the maximum transition authority is decreased to reduce the torque conflict. In both cases, the transition occurs after a deviation of 1 m from the center of the lane and it can be observed that it is a smooth surface that represents a harmonious transition from automated to manual driving and vice versa.

On the other hand, if overtaking is unsafe because a vehicle enters the blind spot, the arbitration system behaves according to the IF-THEN rules of Table 4.8. The values of the authorities are shown in Figure 4.13.

Tab. 4.8: Fuzzy logic IF-THEN rules for Iteration 2 shared-controller validation (Risky)

TTC = Risky									
$i1 - e_y \rightarrow$	**Right**			**Border**			**Left**		
$i2 - \dot{e_y} \rightarrow$	**Return**	**Stay**	**Away**	**Return**	**Stay**	**Away**	**Return**	**Stay**	**Away**
CCW	**Automated**								
Zero									
$i3 - T_d \uparrow$	$o1 - \lambda_- \uparrow$								
CCW	**No**	**No**	**No**	**No**	**As**	**Ov**	**Ov**	**Ov**	**Ov**
Zero	**As**	**As**	**As**	**As**	**As**	**Ov**	**Ov**	**Ov**	**Ov**
$i3 - T_d \uparrow$	$o2 - \lambda_+ \uparrow$								



(a) No driver-automation conflict **(b)** With driver-automation conflict

Fig. 4.13: Decision surfaces when the overtaking is risky

In this case, the transition authority is always at its maximum value ($\lambda_- = 1$, automated), while the additional haptic authority is increased to correct the lane change maneuver with greater force. As long as the driver is within 1 m of the lane center, the authority is not significantly increased, even when a vehicle approaches in the left lane. However, when the intention to change lanes is detected, the stiffness of the controller increases proportionally to the distance from the lane center. Comparing Figures 4.13a and 4.13b, lateral error affects the choice of authority, and also when the driver is in conflict with the automation (i.e., when the driver does not accept being guided to the center by the automation). In this sense, authority is higher when there is conflict than when there is not. This suggests that safety is a more important variable in design considerations than comfort. The results of the arbitration system validation are shown in Figure 4.14.

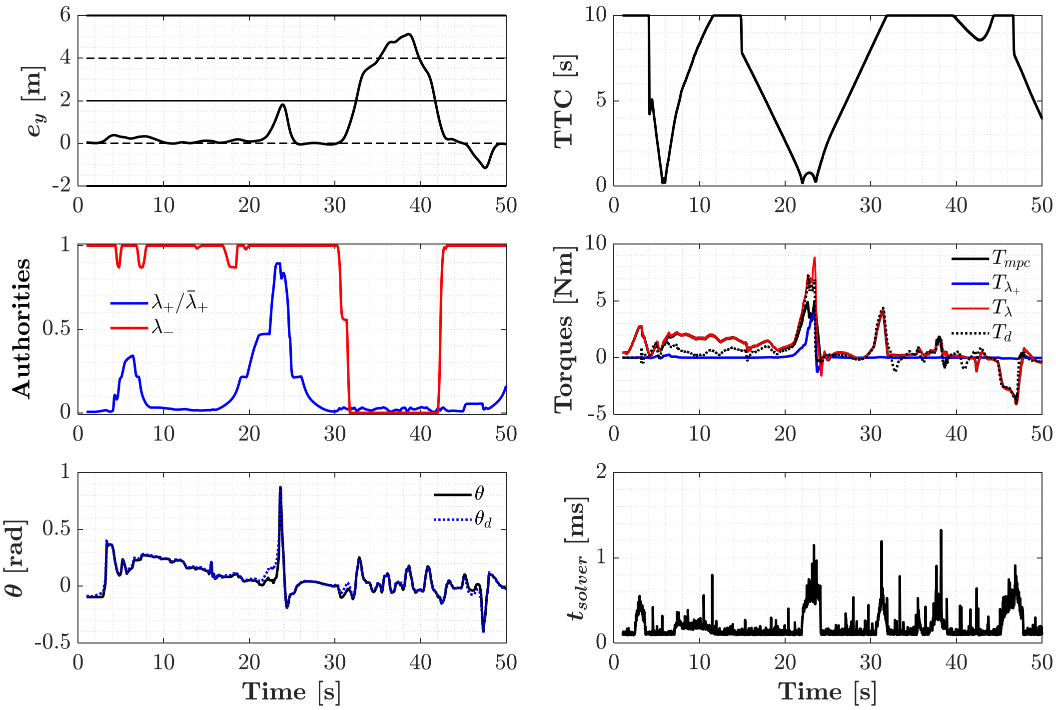


Fig. 4.14: Validation of the arbitration system during an overtaking maneuver

The analysis is divided into four stages, the first two of which evaluate the performance of λ_+, while the rest evaluate the behavior of $\lambda\_$. In the first stage, between 0 and 10 s, the vehicle is in automated mode ($\lambda\_ = 1$) and follows the center of the lane. The test is performed on a curvy road and therefore $T_\lambda = T_{mpc} + T_{\lambda_+} \approx 2$ Nm, but the driver's torque is close to zero. At this moment, a vehicle approaches in the left lane and the stiffness of the controller is preemptively increased ($\lambda_+ \approx 0.3$) to avoid a lane change. It is noted that the driver's torque does not increase together with the authority, since the driver follows the controller's commands. In the second phase, between 15 and 30 s, the driver intends to overtake, but the TTC is low and the additional authority increases the risk. The driver comes into conflict with the controller to test the maximum correction torque. It can be seen that the additional torque (T_{λ_+}) helps the controller to increase from the nominal 5 Nm to 9 Nm. At second 25, the driver releases the steering wheel to test the stability of the system, and he succeeds, as shown by the evolution of the lateral error. It is worth noting that the steering wheel angle is always very similar to the desired steering wheel angle, except when the driver drives off and the controller's intention is different. In this case, the difference increases the additional torque correction.

To analyze the transition authority, stages 3 and 4 were studied. In the third, between 30 and 42 s, the driver intends to change lanes, which the system has recognized as safe, and the transition to manual driving occurs. The driver performs the overtake in manual mode, and during this period it is determined that $\theta = \theta_d$, confirming the design consideration that if $\lambda_{\_} \rightarrow 0$ then $\theta_d \rightarrow \theta$. As soon as the driver returns to the right lane, the steering assistance is automatically activated. In the last phase, the driver swerves to the right edge of the lane and the assistance of the nominal controller is activated ($T_{mpc} \approx 5$ Nm), which proves that the arbitration system distinguishes between the direction of the lane change to know whether a transition or a correction must be made. Overall, the solution time for the optimal control problem of MPC is less than 1.5 ms, which is satisfactory for a control loop of 10 ms.

4.2 Unified Authority

The previous section has shown that dual-level authority approaches provide a good framework to increase the stiffness of the steering assistance system without changing the parameters of the original controller. In addition, transition authority has been shown to be effective in transitioning from automated to manual control and vice versa. However, this approach also has some disadvantages. First, adding torque outside of the MPC problem formulation is a problem for maintaining the designed constraints, since the total control torque does not come from the MPC, but only a part of it ($T_\lambda = T_{mpc} + T_{\lambda_+}$). In this sense, it is necessary to include the authority in the MPC formulation and have only one torque from the control. Second, the use of two authorities requires the development of two sub-decision systems, which makes the development of the arbitration system even more complex. Third, the value of θ_d must be computed as an additional input to the system, and finally, also related to this, the possible effect of the discontinuity of the $\theta_d - \theta$ term, which may affect the driver's feel on the steering wheel.

For these reasons, the unified authority approach proposes to have only one authority, called the haptic authority (λ), which serves both to increase the stiffness of the controller (as λ_+ before) and to enable driving mode transitions (as the $\lambda_{\_}$). The final algebraic representation of the authority can be found in the Equations 4.23a-4.23c and also in the Figure 4.15.

$$T_{total} = T_{mpc} + T_{sat} + T_d \tag{4.23a}$$

$$T_{total} = \lambda T_{mpc} + T_{sat} \tag{4.23b}$$

$$T_{total} = \lambda \lambda_{mpc}(\theta_d - \theta) - \lambda_{sat}\theta \tag{4.23c}$$

$$\tag{4.23d}$$

It is clear that when $\lambda = 0$ the system is in manual mode and feels only the self-aligning torque. And when $\lambda = 1$, the MPC controller is active with its nominal

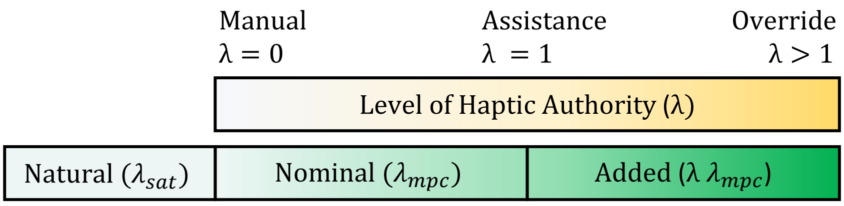


Fig. 4.15: Representations of the haptic authority (λ) at the steering wheel, with the unified approach

authority. For all values of $\lambda > 1$, the haptic authority of the system increases beyond the nominal value, so that the controller not only assists the driver in the steering task, but can also override him. The controller development is now moving into a third and fourth iteration using this approach for haptic authority, all designed for high speeds.

4.2.1 Iteration 3

The third iteration continues to use the high-speed dynamic vehicle model, but incorporates the unified authority approach into the controller design.

4.2.1.1 Model

The system model is similar to the dynamic bicycle model used for iteration 2, shown in Figure 4.8 and Equations 4.17a-4.20b. The only difference is the inclusion of haptic authority in the equation for torque input, as in Equation 4.24. This allows the controller output T_{mpc} to already account for the authority effect.

$$\dot{T}_{mpc} = \lambda \Delta T_{mpc} \tag{4.24}$$

The final state vector of the road-vehicle model is $s = [X,\, Y,\, \Psi,\, v_x,\, v_y,\, \psi\ e_y,\, e_\Psi,\, \theta,\, w]$, the input vector is $[u\ \Delta u] = [T_{mpc}\ \Delta T_{mpc}]$, and the exogenous vector is $l = [a_x,\, \kappa,\, \lambda_H]$.

4.2.1.2 Optimization

The same optimization design approach as in iteration 2 is maintained with $z = z_{tracking} \cup z_{comfort}$, except that the tracking function now uses the coordinates of the vehicle position (since better performance was observed). In this sense, $z_{tracking} = [X - X_r, Y - Y_r, \Psi - \Psi_r]$ and $z_{comfort} = [\psi, w]$. The state optimization weights correspond to the diagonal matrix and its eigenvalues $W_z = \mathrm{diag}(w_X,\, w_Y\ w_\Psi,\, w_\psi,\, w_w)$. The input optimization to reduce driver effort remains the same as in the previous iteration ($W_u = w_{T_{mpc}}$, $W_{\Delta u} = w_{\Delta T_{mpc}}$. In addition, safety considerations are taken into account by applying a yaw rate constraint (ψ) to prevent the vehicle from drifting unsafely and by limiting the maximum allowable lateral deviation (defined as about half the lane width to prevent the vehicle from drifting off the lane). The vector of state constraints is $\tilde{z} = [e_y, \psi, \theta, w]$, and the vector of input constraints is $\tilde{u} = [T_{mpc}, \Delta T_{mpc}]$.

4.2.1.3 Authority

This iteration improves the design of the controller by including haptic authority as a factor in the equation deriving torque (see Equation 4.24), so that the full contribution of torque (including the effect of authority) is included in the control signal. However, similar to the dual-level authority approach, increasing the haptic authority causes the system to become susceptible to instability, so an appropriate stability criterion must be developed.

$$\lambda T_{mpc} + T_{sat} + T_d = J\ddot{\theta} + b\dot{\theta} \tag{4.25a}$$

$$\lambda\lambda_{mpc}(\theta_d - \theta) - \lambda_{sat}\theta = J\ddot{\theta} + b\dot{\theta} \tag{4.25b}$$

$$\lambda\lambda_{mpc}\theta_d = J\ddot{\theta} + b\dot{\theta} + (\lambda\lambda_{mpc} + \lambda_{sat})\theta \tag{4.25c}$$

When $\lambda = 1$, the nominal MPC controller is active and it is known to be a stable controller since the MPC weight matrices are chosen to be so. Therefore, similar to the dual-level authority approach, the stability criterion is based on the damping ratio ($\xi = \frac{b}{2\sqrt{Jk}}$) of the second-order steering system using the rotational inertia (J), damping (b), and stiffness (k). The strategy for the stability criterion is to keep the damping ratio of the nominal controller (ξ_1) and make it equal to the one with haptic authority greater than 1 (ξ_λ). In this sense, the Equations 4.26a-4.26f show how to find the equivalent damping that allows to keep the stability:

$$\xi_\lambda = \frac{b_\lambda}{2\sqrt{J(\lambda\lambda_{mpc} + \lambda_{sat})}} \tag{4.26a}$$

$$\xi_1 = \frac{b}{2\sqrt{J(\lambda_{mpc} + \lambda_{sat})}} \tag{4.26b}$$

$$\xi_\lambda = \xi_1 \tag{4.26c}$$

$$\frac{b_\lambda}{2\sqrt{J(\lambda\lambda_{mpc} + \lambda_{sat})}} = \frac{b}{2\sqrt{J(\lambda_{mpc} + \lambda_{sat})}} \tag{4.26d}$$

$$b_\lambda = b\sqrt{\frac{\lambda\lambda_{mpc} + \lambda_{sat}}{\lambda_{mpc} + \lambda_{sat}}} \tag{4.26e}$$

$$b_\lambda = b\sqrt{\frac{\lambda + r}{1 + r}}; \quad r = \frac{\lambda_{sat}}{\lambda_{mpc}} \tag{4.26f}$$

and assuming $r \approx 0$, that $\lambda_{mpc} \gg \lambda_{sat}$ under the logic that the controller is more noticeable in steering than the self-aligning torque, which is more subtle. With this consideration, the final equivalent damping is represented in Equation 4.27:

$$b_\lambda = b\sqrt{\lambda} \tag{4.27}$$

This variable damping can be easily introduced into the system via a linear term or by adjusting the motor damping via software configuration. This guarantees stable and comfortable system behavior over the entire range of variable authority range without having to fine-tune the MPC again.

4.2.1.4 Validation → Shared-Controller

Validation of the shared-controller is performed by a driver using the driving simulator platform. The first test evaluates the stability of the steering torque controller with different λ values. The vehicle has automatic longitudinal control at 90 km/h, and the driver interacts with the automation using only the steering wheel. The second test evaluates the tracking performance with different values of λ at two longitudinal speeds (70 km/h and 120 km/h). The shared-controller is configured with the parameters given in Table 4.9.

Tab. 4.9: MPC parameters values for iteration 3 shared-controller

Var.	Value	Var.	Value	Var.	Value
b	0.65 Nm.s/rad	$w_x = w_y$	40	$w_{\Delta T_{mpc}}$	0.02
J	0.1 kg.m^2	w_Ψ	80	$[\theta_{min}, \theta_{max}]$	± 2 rad
n_s	8.77	w_ψ	1000	$[\psi_{min}, \psi_{max}]$	± 0.2 rad
C_{α_f}	94000 N/rad	w_w	0.03	T_{max}	15 Nm
C_{α_r}	118000 N/rad	$w_{T_{mpc}}$	0.02	ΔT_{max}	1.9 Nm/s

Figure 4.16 shows the results of the stability test of the controller with and without the designed stability criteria. To perform the test, the driver moves about 2 m away from the center of the road with steering assistance activated and different values for λ. After a few seconds, the driver releases the steering wheel to test the stability performance when the controller tries to return to the center of the road.

The results show that increasing the haptic authority increases the stiffness of the controller, as shown in the control torque graph. It is also shown that increasing the authority makes the system unstable. It is important to note that the nominal controller was stable from the beginning (looking at the constant damping graph of both the lateral error and the control moment). It was also proved that the stability criterion of Equation 4.27 keeps the system stable for different values of the haptic authorities.

In addition, the inclusion of a system state constraint for the controller is also being tested. A yaw rate constraint was introduced in the design to avoid unsafe dirfting of the vehicle. Figure 4.17 shows the value of ψ for the same variable damping test in Figure 4.16. The results show the performance of the controller without the constraint (left side) and with the $|\psi_{max}| < 0.2$ rad/s constraint (right side). The outcome is that for different values of λ the designed controller is able to

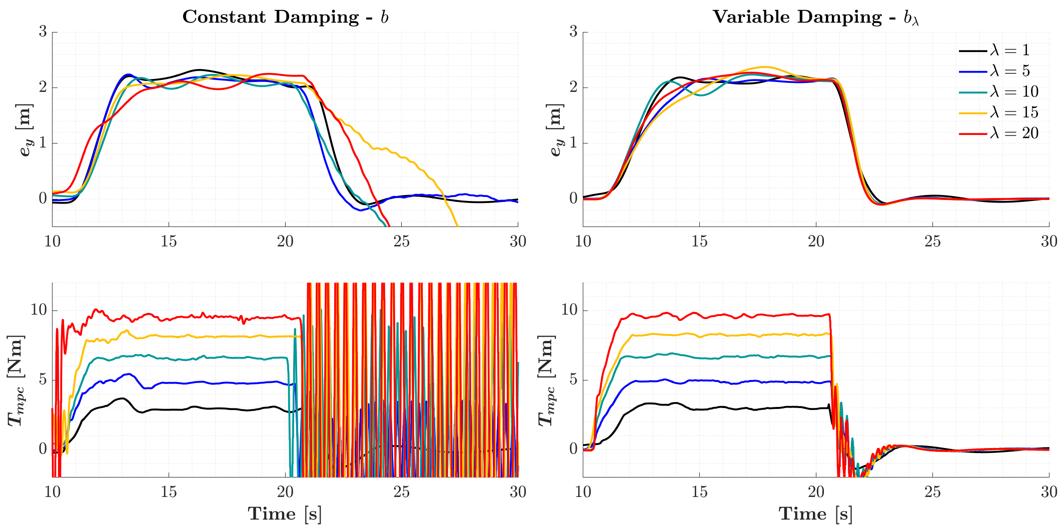


Fig. 4.16: Stability test of iteration 3 controller at 90 km/h

satisfy the constraint very accurately, and both plots show the effect of introducing the constraint into the MPC problem.

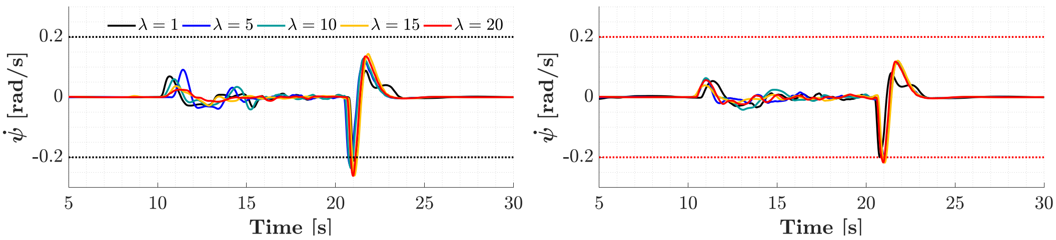


Fig. 4.17: Yaw rate constraint for iteration 3 controller at 90 km/h

The second validation of the controller is to test the tracking performance with the controller alone (without interaction with the driver). This is done at 70 and 120 km/h to evaluate the ability of the controller to maintain performance under different longitudinal speed conditions. Both are tested for different values of λ. Figure 4.18 shows the results of the tests. From the results, it can be seen that neither longitudinal speed nor haptic authority changes the performance of the controller. This shows its robustness under different conditions. The only difference is that at 120 km/h the angular error is even smaller than at 70 km/h and the control torque is larger. This is to be expected since the self-aligning torque increases with speed and the controller must overcome this torque to maintain tracking performance. Overall, the controller shows good tracking performance with a lateral error below 5 cm and an angular error below 2°. The computation time to solve the optimal control problem is positive as it is kept below 1 ms.

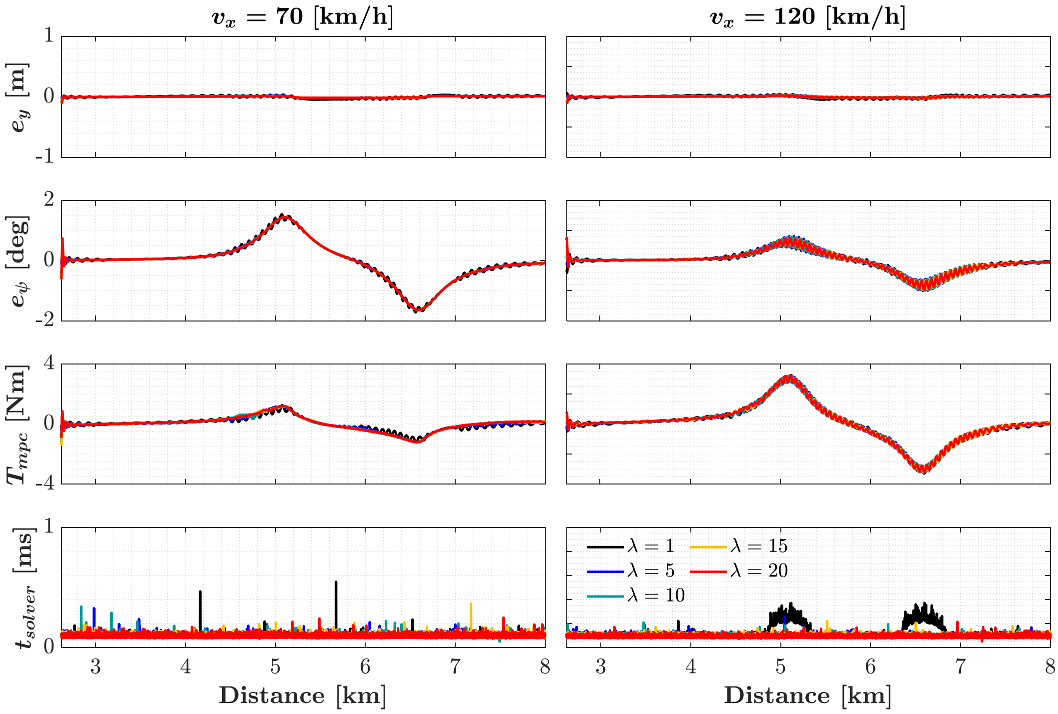


Fig. 4.18: Yaw rate constraint for iteration 3 controller at 90 km/h

4.2.2 Iteration 4

The final iteration of the controller consists of the same dynamic vehicle model as in the previous iteration. In addition, two changes are made to the haptic design. First, the authority is no longer dimensionless, but refers to the maximum torque output by the controller. Second, a new stability formula is introduced to optimize the λ/b_λ ratio and find the most efficient damping formula (the smaller the damping, the better).

4.2.2.1 Model

The system model is similar to the dynamic bicycle model used for iteration 3, shown in Figure 4.8 and Equations 4.17a-4.20b. The haptic authority is included in the model through the equations of the steering system.

$$\dot{T_{mpc}} = \lambda \Delta T_{mpc} \tag{4.28a}$$

$$\dot{w} = \frac{-1}{J}\left(b_\lambda w + T_{sat} - T_{mpc}\right) \tag{4.28b}$$

The final state vector of the road-vehicle model is $s = [X,\ Y,\ \Psi,\ v_x,\ v_y,\ \psi\ e_y,\ e_\Psi,\ \theta,\ w]$, the input vector is $[u\ \Delta u] = [T_{mpc}\ \Delta T_{mpc}]$, and the exogenous vector is $l = [a_x,\ \kappa,\ \lambda_H]$.

4.2.2.2 Optimization

The formulation of the optimal control problem is the same as in Iteration 3, with the only difference that the formula for the system's input constraint is now associated with haptic authority. In the next section, a new conceptualization of authority ($\hat{\lambda}$) is introduced, which adds a representative value related to the maximum torque on the steering wheel. In this sense, the new constraint is represented in Equation 4.29.

$$|T_{mpc}| \leq \hat{\lambda} \tag{4.29}$$

4.2.2.3 Authority

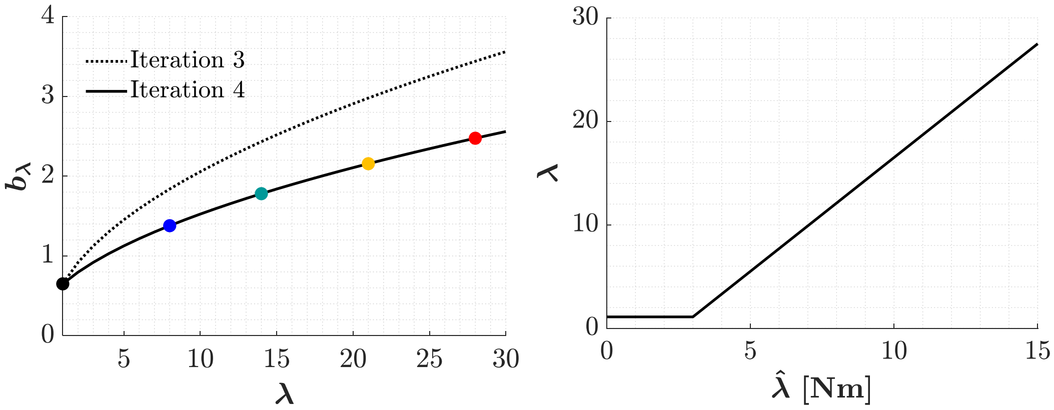
In the third iteration, the assumption that $r = \frac{\lambda_{sat}}{\lambda_{mpc}} \approx 0$, led to the damping formula $b_\lambda = b\sqrt{\lambda}$. In this case, it was assumed that $\lambda_{mpc} \gg \lambda_{sat}$. However, this was a conservative assumption since $r = 0$ leads to a larger damping value according to the formula. In this sense, the damping formula does work to maintain controller stability, but it is also true that adding damping to the system is not in vain, as it makes the steering wheel feel harder. So it is important to find not only the value that maintains stability, but also the one that is optimal. With this in mind, a further approximation is made by assuming that $\lambda = \lambda_{sat}$. It is assumed that the controller should be at least equal to the magnitude of the self-aligning torque felt by the driver at the steering wheel. Taking this consideration into account, $r = 1$ leads to the new damping formula of Equation 4.30:

$$b_\lambda = b\sqrt{\frac{\lambda + 1}{2}} \tag{4.30}$$

Figure 4.19a shows the relationship between the haptic authority and the equivalent damping of the stability criteria. Compared to iteration 3, it can be seen that the damping is reduced by 25% on average, showing that the new formula optimizes the system parameters.

However, although the stability problem is solved, the choice of the value of λ is an ambiguous process. In this sense, a system identification process was performed by forcing the vehicle to move 2 m away from the center of the road and reporting the maximum torque measured by the torque sensor. In this sense, a linear relationship was established between λ and the reported maximum torque. For this relationship, a new instance is defined, $\lambda = q(\hat{\lambda})$ with $q : \mathbb{R} \to \mathbb{R}$ and $\hat{\lambda} \geq 0$. To guarantee that the maximum torque is indeed $\hat{\lambda}$, the system constraint of the previous Equation 4.30 was added. The linear relation is given in Equation 4.31 and shown in Figure 4.19b. Now the choice of haptic authority makes more sense, since one can choose the one that assigns the maximum required torque (which is reached at a maximum deviation of 2 m from the center of the road).

$$\lambda = 2.2 \max(3, \hat{\lambda}) - 5.5 \tag{4.31}$$



(a) Damping Iteration 3 vs Iteration 4 (b) Linear relationship $\hat{\lambda} = q(\lambda)$

Fig. 4.19: Relationship between haptic authorities and steering control system damping

To switch to manual mode, it is also necessary that $\hat{\lambda} < 3$. In this case, the haptic authority is always $\lambda = 1$ to maintain the damping formula, and does not reduce the natural damping of the steering system. The actual transition then occurs thanks to the constraint explained in Equation 4.29, i.e., nominal control with variation of the constraint on the control torque, which may include $T_{max} = 0$ for the transition to manual driving.

4.2.2.4 Validation → Shared-Controller

Since this controller is an extension of iteration 3, whose main change is the optimization of the damping formula, the evaluation of the tracking performance is done for a typical behavior of the controller at 80 km/h, the speed for the experimental studies conducted in Chapter 5. The validation is performed by a driver using the DiL simulator platform. The vehicle has automatic longitudinal control and the driver interacts with the automation only through the steering wheel. The first test evaluates the stability of the steering torque controller with different λ values, along with the system state constraints. The second test evaluates the tracking performance at different values of λ. The shared-controller is configured with the parameters given in Table 4.10.

Tab. 4.10: MPC parameters values for Iteration 4 controller

Var.	Value	Var.	Value	Var.	Value
b	0.65 Nm.s/rad	$w_x = w_y = w_\Psi$	50	$[\theta_{min}, \theta_{max}]$	$\pm\pi$ rad
J	0.1 kg.m^2	w_ψ	100	$[w_{min}, w_{max}]$	± 4 rad/s
n_s	8.77	w_w	0.1	$[\psi_{min}, \psi_{max}]$	± 0.4 rad
C_{α_f}	94000 N/rad	$w_{T_{mpc}}$	0.01	T_{max}	$\hat{\lambda}$
C_{α_r}	118000 N/rad	$w_{\Delta T_{mpc}}$	0.1	ΔT_{max}	0.2 Nm/s

To test this design, several experiments were conducted with a driver who had his vehicle about 2 m from the center of the roadway using five different values of $\hat{\lambda}$.

The driver was then asked to take his hands off the steering wheel to observe the performance and stability of the controller. Figure shows that driver effort equals haptic authority and maintains the system constraint $|T_{max}| \leq \hat{\lambda}$, but also that increasing authority leads to oscillations in the system response. In contrast, Figure shows the effect of the optimized variable damping formula in maintaining stability and control performance with low tracking error. Moreover, the yaw rate constraint is also maintained for different gains.

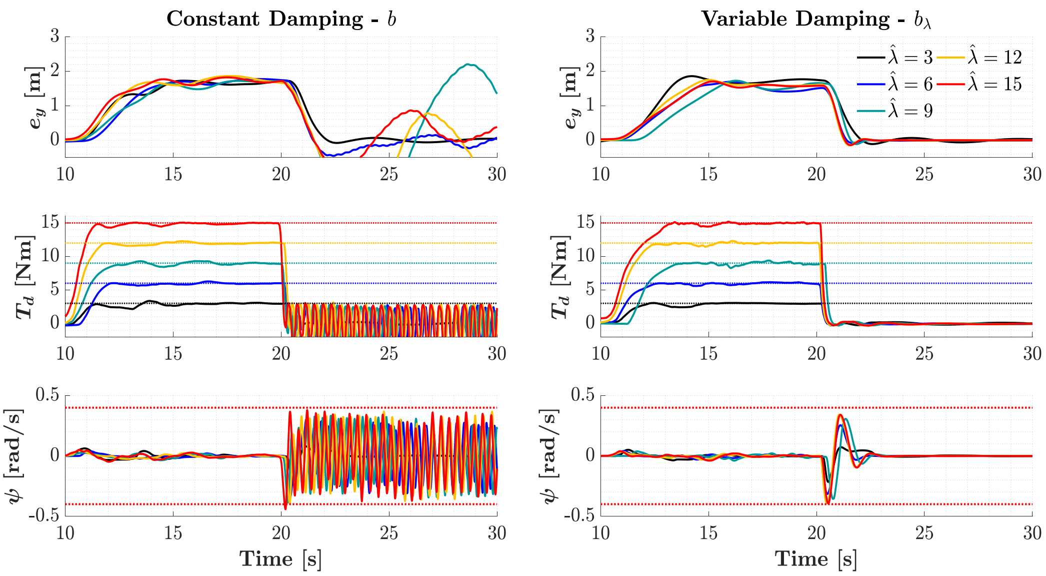


Fig. 4.20: Stability results for for Iteration 4 controller at 80 km/h

Figure 4.21 shows the tracking performance of the controller with respect to lateral and angular errors when driving in automated mode at 80 km/h on a road with a maximum curvature of 0.0024 1/m. Controller performance is evaluated for different levels of haptic authority. For all values of $\hat{\lambda}$, the lateral error is kept below about 10 cm, while the angular error is below 2°. A more detailed analysis of the performance can be found in Table 4.11. It is interesting to note that increasing the haptic authority leads to improved lateral error reduction, with the controller with the highest authority ($\hat{\lambda} = 15$) showing a maximum value of 1.5 cm. Angular error, on the other hand, shows performance that does not depend on authority.

This controller is the final version developed as part of this Ph.D. Thesis and will be validated in real-world scenarios and along with an arbitration system in the simulator studies presented in Chapter 5. The representation of the controller scheme is shown in Figure 4.22.

4.3 Conclusion

This chapter presented the design and development of a steering shared-controller based on torque and considering variable haptic authority with stability criteria.

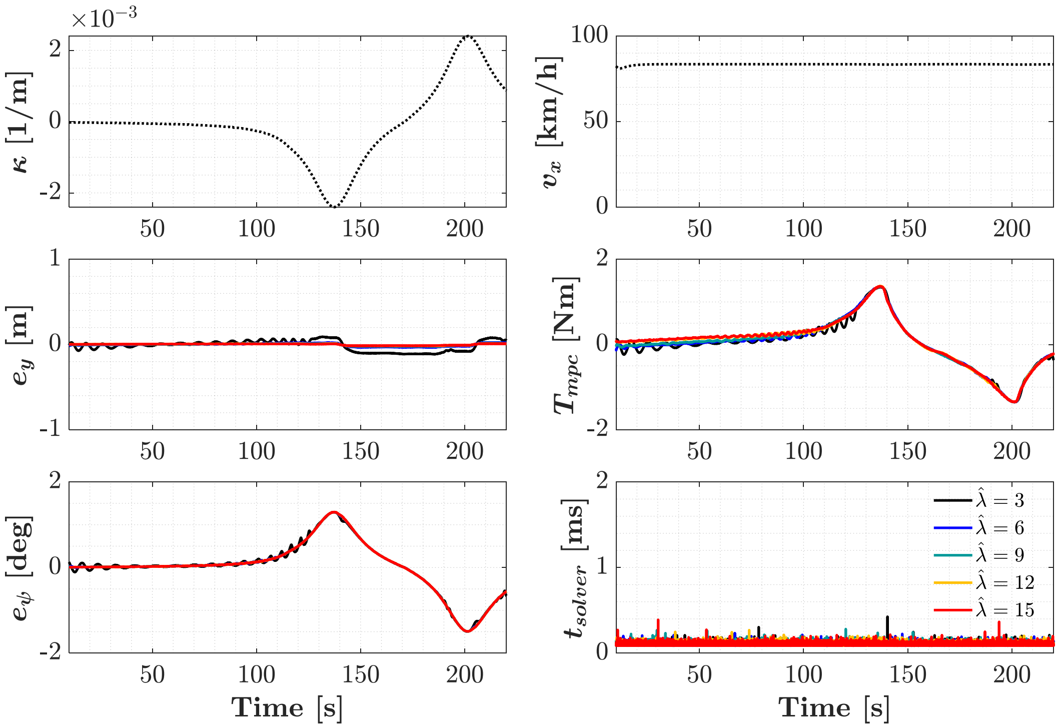


Fig. 4.21: Performance results for for Iteration 4 controller at 80 km/h

Tab. 4.11: Final shared-controller tracking performance

$\hat{\lambda}$	mean(e_y)	rms(e_y)	max($\lvert e_y \rvert$)	mean(e_Ψ)	rms(e_Ψ)	max($\lvert e_\Psi \rvert$)
3	0.049 m	0.061 m	0.112 m	0.404 º	0.594 º	1.493 º
6	0.015 m	0.018 m	0.033 m	0.403 º	0.597 º	1.492 º
9	0.010 m	0.012 m	0.022 m	0.403 º	0.598 º	1.492 º
12	0.009 m	0.010 m	0.018 m	0.403 º	0.598 º	1.492 º
15	0.008 m	0.008 m	0.015 m	0.403 º	0.598 º	1.493 º

The controller was developed in four iterations, moving from a dual-level authority approach to a unified approach. Each of the iterations of the controller was presented in terms of the system model, optimization problem, inclusion of variable authority, and validation. The following is a summary of the conclusions.

- Iteration 1 consisted of a low-speed (35 km/h) controller and consideration of two haptic authorities. The first to increase the stiffness of the controller (λ_+), and the second to perform control transitions ($\lambda\_$) from automated to manual and vice versa. The stability criterion proved successful and the arbitration system for an overtaking maneuver was validated.
- Iteration 2 improved the controller by incorporating a dynamic vehicle model that allowed the controller to be tested at 70 km/h. A more complex arbitration

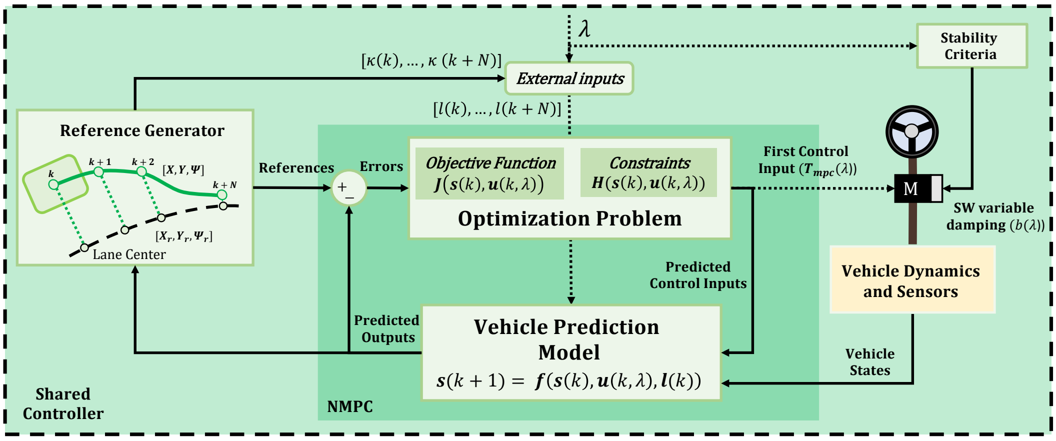


Fig. 4.22: NMPC-based shared-controller architecture

system validated the use of the dual-level authority approach for a steering correction maneuver.

- Iteration 3, the unified authority approach was introduced, which allowed the haptic authority (λ) to be included as part of the MPC problem so that only one control signal was needed, thus allowing for system constraints on different values of the authorities. The new stability criterion was found to eliminate oscillations and the tracking performance of the controller was satisfactory (with a lateral error of less than 5 cm for speeds of 70 km/h and 120 km/h).
- Iteration 4, the design was improved by introducing a more intuitive authority $\hat{\lambda}$ with respect to the maximum torque of the controller. An optimized damping formula was introduced, and both the stability and tracking performance of the controller were found to be of high quality (with performance in lateral error below 1.5 cm for the higher authority). System constraints on torque and yaw rate were maintained as intended, demonstrating the versatility of the MPC controller.
- The end result is a torque-based shared steering controller with a novel method of increasing controller stiffness (haptic authority) without having to retune the parameters of the nominal MPC controller, while maintaining stability, tracking performance, and system constraints.
- The controller is useful for various scenarios where the interaction between the driver and automation requires adaptive authority that depends on the constantly changing conditions of the driver, automation, and environmental conditions. Validation in real-world use cases is presented in Chapter 5.

Experimental Studies 5

Shared control is a promising approach to drive the development of automated driving systems that improve road safety. However, to become a successful solution, it is important to know how drivers accept such systems. In this sense, the contribution of this chapter is to conduct two experimental studies to evaluate ADAS based on the shared-control and arbitration system developed in Chapter 4. The validation is performed by real drivers in the Driver-in-the-Loop (DiL) simulator platform described in Chapter 3. The two scenarios under investigation were chosen to support the driver on demand rather than continuously, as this strategy has been shown to be best suited for shared-control systems to avoid aftereffects when the driver is continuously assisted [63]. In this sense, the main contributions of this chapter are the following:

- Development and evaluation with real drivers of an ADAS based on shared-control that provides **assistance during short distraction events**. The evaluation includes both objective and subjective assesment and is compared against manual driving performance and two commercial ADAS.
- Development and evaluation with real drivers of an ADAS based on shared-control that provides **assistance during overtaking maneuvers in roads with oncoming traffic**. The evaluation includes both objective and subjective assesment and is compared against a vehicle with L2 capabilities.

The next sections describe the studies in terms of the specific use cases (proposed in the framework of the PRYSTINE project [188]), the methodology used for the experiments, the design of each experimental condition, the performance of each system, and then the quantitative and qualitative analysis of the results. Each experiment concludes with a brief description of the main findings.

5.1 Support to Distracted Driver

5.1.1 Use Case

To settle the driving conditions in the scope of the test, the following use case (UC) has been defined, highlighting a scenario where the driver–automation system would be benefited from their cooperation as a “team”.

5.1.1.1 User Story

"A mother is driving in a highway/extra-urban road with her baby at the back, in the right passenger seat. From time to time, the baby starts crying and catching her attention. The position of the baby is completely out of her scope, so she has to turn in order to take care of the child. She is driving an L1 automated vehicle with the adaptive cruise control function activated. This implies that she is only taking

care of the lateral control of the vehicle (however, she is not allowed to release both hands from the steering wheel). This driving scenario presents several safety issues regarding vehicle control loss. Nevertheless, steering automated driving functions can prevent potential dangers, in cooperation with driver interventions"

5.1.1.2 Motivations

Driver distraction is known to be one of the leading causes of traffic crashes and has serious consequences, not only for the driver, but also for passengers, other vehicles, and Vulnerable Road Users (VRUs). According to NHTSA[1], distracted drivers cause an average of about 3000 deaths, 280000 injuries, and nearly 1 million crashes each year. Because of these alarming numbers, this institution has set some goals for the Distraction Plan Program to reduce accidents caused by distracted drivers. The plan includes actions from different angles: 1) collect more data to better understand the problem, 2) new vehicle technologies, either by developing vehicle interfaces with less driver workload or by developing active safety systems to prevent the consequences of driver distraction, and 3) make drivers aware of the risk and consequences of their distracted driving. In this sense, new vehicle technologies seem to be a promising solution to reduce the consequences of distractions, especially the development of active safety systems. Although the development of less distracting interfaces can help solve the problem, there are many sources of distraction, not just in-vehicle interfaces (e.g., as in the proposed use case, when a mother is distracted because the baby is crying and needs attention).

Safety systems exist today to prevent accidents due to driver distraction, but they provide either little or excessive assistance. On the one hand, there are already Driver Monitoring Systems (DMS) in commercial vehicles that can detect driver distraction (using detection cameras or by detecting abnormal steering patterns), but they do not assist the driver at the control level. These systems provide visual or audible warnings to the driver to prompt s/he to regain attention. On the other hand, there are two approaches for ADAS to assist distracted drivers. The first is the Lane Keeping Assist System (LKAS), which ensures that the automated system applies torque to the steering wheel when the driver leaves the lane due to inattention. The problem with this system is its reactive nature, as it protects as soon as the unsafe event occurs and does not take into account the driver's condition for the intervention. The second approach is Automated Lane-Centering (ALC), which corresponds to an autopilot assistance that always steers the vehicle to the center of the lane. While this system allows the driver to be distracted without greater risk, it also leads to lower driver engagement in the driving task and thus overreliance on the system, which can lead to other problems (e.g., not continuing to drive safely when the system fails).

In this sense, a shared-control strategy is suitable approach for an active safety system that supports the driver in case of distractions. It is based on the principle

[1] **Webpage**: NHTSA Distracted Driving Statistics → *https://www.nhtsa.gov/distracted-driving*

that the driver should be assisted only when necessary (e.g., when distracted)[83]. In this sense, the shared-control system will act earlier than the LKA (since it takes into account the driver's state) and be active for less time than the ALC (since it assists the driver only when necessary), resulting in improved safety while maintaining the right level of driver engagement.

5.1.1.3 Current Research

Previous works on shared-control have examined driver assistance in various scenarios such as lane keeping, obstacle avoidance, and resumption of control, according to the state-of-the-art described in Chapter 2. In these scenarios, the adaptive authority of shared-controller depends on several variables (e.g., time- to- lane-crossing [269], the lateral error [270], driver effort [271], driver intention [82], and others).

However, there is limited work examining the effects of shared-control support, with authority varying by driver state. One work evaluated the benefits of shared-control for fatigued drivers [272] improving the tracking performance and safety. However, driver fatigue is not as common as driver distraction, which almost always occurs when people are driving. A recent work by Wang [273] presented an adaptive authority controller based on driver distraction level measured by forearm surface electromyography. In this study, distraction was induced by asking drivers to calculate the cumulative sum of numbers given every three seconds while performing a lane change maneuver. While doing so, drivers kept their eyes on the road at all times. Sentouh and Benloucif [274, 275] present a more realistic scenario with two studies of a system that assists distracted drivers (measured with a visual camera). The secondary task involved reading a text with one hand and writing on a tablet while driving. In [274], the shared-control strategy was compared to manual driving (by 7 participants), with improvements in tracking errors and subjective measurements. A more comprehensive study was presented in [275] with 15 participants, also compared to a ALC system (fixed authority). In both experiments, the results indicated that shared-control is a promising strategy for helping distracted drivers. In these works, the duration of the secondary task (reading and writing) was high, about 10 s. However, in everyday life, drivers are usually distracted for shorter periods of time, e.g., changing the radio, looking at the instrument cluster, or briefly glancing at the back seat. In this sense, the investigation of support for shorter distraction events is of interest for this Ph.D. Thesis, where the driver is asked to perform a distraction task of 2-5 seconds.

5.1.2 Method

5.1.2.1 Participants

A total of 5 participants (1 female and 4 males), took part in the pilot expert studies (all were related to automated driving research activities), aged between 21 and 49 years with mean = 35.6 years and Standard Deviation (SD = 13.0), all of them with at least 3 years holding a driving license (mean = 11.8, SD = 10.9).

5.1.2.2 Apparatus

The DiL simulator shown in Figure 5.1a is the experimental platform for the study. The custom configuration for the scenario of the distracted driver consists of 1) a steering wheel to control the lateral motion of the vehicle, 2) a vision-based camera (Basler ACE acA1920—40uc camera with a Sony IMX249 CMOS sensor) to estimate the driver distraction level, and 3) a touch-screen that serves to execute the secondary task.

(a) Simulator set-up **(b)** Steering wheel and driver monitoring camera

Fig. 5.1: DiL simulator for expert study of distracted driver

5.1.2.3 Experimental Conditions

Four test conditions consisting of driver assistance systems to help drivers with distractions are evaluated. Three of them are baseline conditions, including manual driving (i.e., no assistance) and two commercially available ADAS such as Lane-Keeping Assistance (LKA) and Automated Lane-Centering (ALC) [16]. The other is the shared-control-based system developed in Chapter 4. The description of the experimental conditions is as follows:

- **Manual (MAN)**: No automated steering support to the driver. Only the CC longitudinal control function is active.
- **Lane Keeping Assistance (LKA)**: The automated system applies a momentary torque to the steering wheel when the vehicle is leaving the lane. However, if the vehicle is within the lane, there is no automation assistance.
- **Automated Lane-Centering (ALC)**: Automation provides lateral vehicle control that always keeps the vehicle in the center of the lane. Under this condition, the driver must still keep at least one hand on the steering wheel. This mode considers a fixed authority ($\lambda = 3$ Nm).
- **Shared-control (SC)**: The proposed system depends on the state of the driver. When the driver is concentrated, the system is in manual mode, but when

distracted, the ALC is activated during the distraction event. This mode considers a variable authority depending on a fuzzy logic-based arbitration system.

5.1.2.4 Procedure

Figure 5.2 shows the experiment design for this use case. Before the official test, each driver sat in the driving simulator. After calibrating the driver monitoring camera, they drove one lap to familiarize themselves with the simulator and the four experimental conditions. Each driver received a thorough explanation of the driving modes during the familiarization session. For the official test, participants drove an automated vehicle with longitudinal control set at 85 km/h in each session. The duration of each session was 6 minutes in a highway scenario (with 420 m minimum curve radius).

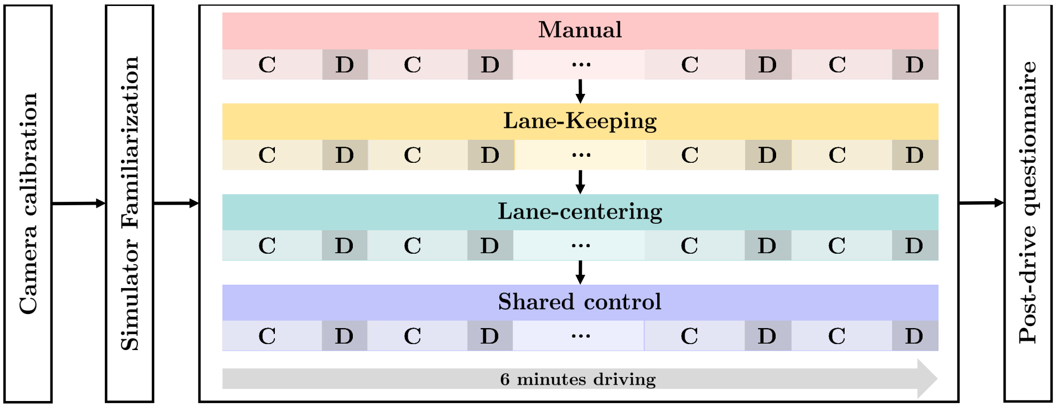


Fig. 5.2: Within-experiment design description of use-case 1 (C: concentrated phase, D: distracted phase)

Periodic distraction events (every 20 s) occurred during the trip. An audible warning signal alerted the driver to start the distraction task. The distraction consisted of pressing a button on the touchscreen (changing from gray to red) and paying attention for 2 s (until the change from red to gray). Then the driver pressed the button a second time (changing from gray to green) and returned to the normal driving task. During this activity, the driver deviated from looking at the road, turned the head to the right, and interacted with a touch monitor with the right hand, while the other hand always remained on the steering wheel. Figure 5.3 shows the distraction sequence. This applies to all driving modes tested in the following order: 1) MA, 2) LKA, 3) ALC, and 4) SC. To add more realism to the scenario, the simulator environment additionally includes other vehicles (one driving ahead and one passing in the same direction but in the left lane, repeatedly).

5.1.3 System Design

The setup of the system for each experimental condition consisted of configuring the arbitration and shared-controller modules explained in Chapter 4. Under all conditions, the automated system controls the vehicle speed within the cruise control

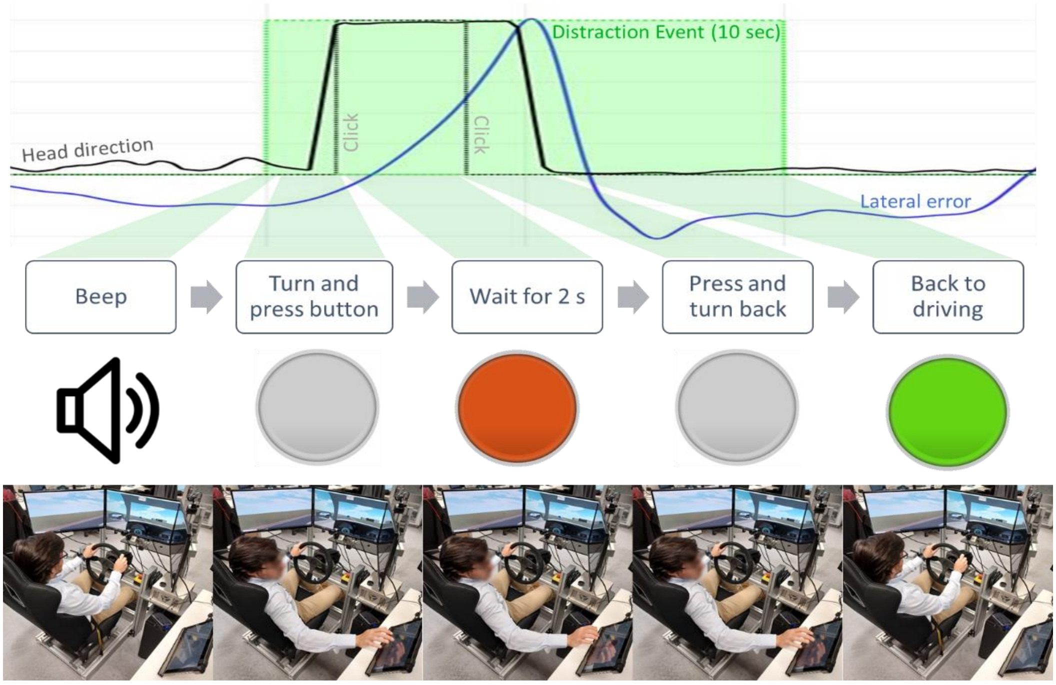


Fig. 5.3: Experiment procedure with the sequence of distraction event

mode set to 85 km/h. The driver does not interact with the pedals, only with the steering wheel.

5.1.3.1 Baseline #1 - Manual

There is no steering assist for the Manual state because lateral vehicle control is disabled ($\lambda = 0$).

5.1.3.2 Baseline #2 - LKA

For the LKA system, lateral vehicle control is disabled ($\lambda = 0$), but NMPC lateral error constraint is active ($T_{mpc} \leq 3$ Nm and $e_y \leq 1.5$ m). When the vehicle is close to the edge of the road, the system applies an instantaneous torque of up to 3 Nm.

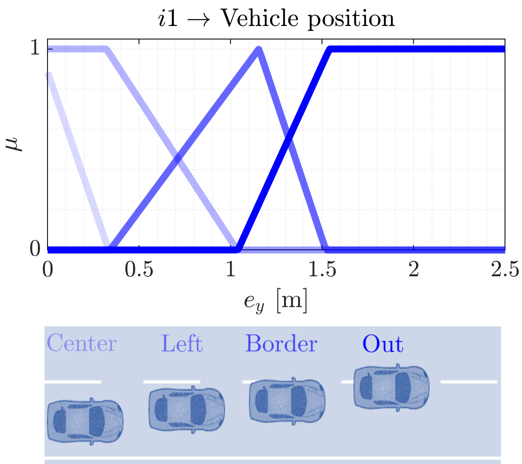
5.1.3.3 Baseline #3 - ALC

For the ALC system, the lateral vehicle controller is always active with fixed authority ($\lambda = 3$ Nm), with no lateral error constraints. The controller torque is strong enough to steer the vehicle to the center of the lane, but low enough to allow the driver to steer the vehicle.

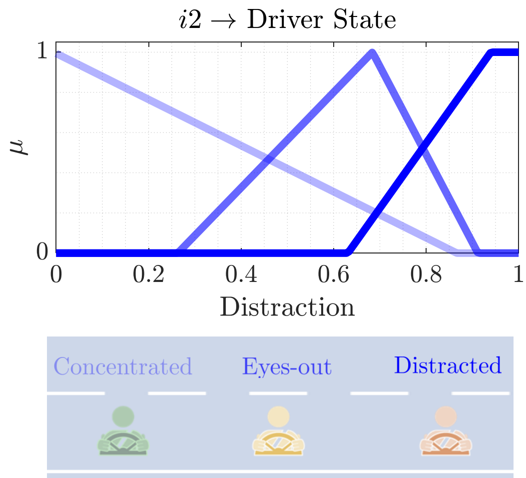
5.1.3.4 Shared-Control System

Unlike ALC, the shared-control mode applies variable authority computed by the arbitration module based on the fuzzy logic system described in Figures 5.4 and 5.5. It represents the behavior of the lateral shared-control system by defining membership functions with representative values (since defining the value in fuzzy logic systems is similar to how humans assign values to categories). The fuzzy system consists of two inputs and one output, as described below:

- $i1$ - **Vehicle position**: Represented as the lateral error of the vehicle with respect to the center of the right lane (e_y). It has 4 membership functions labels ([Center - Left - Border - Out]) representing the different positions of the vehicle on the right lane. The 1.5 m (Border-Out) is the distance where the vehicle is at the edge of the lane, and 0.3 m (Center-Left) gives the driver the freedom to deviate from the center without receiving automation assistance.
- $i2$ - **Driver state**: Represented as the level of driver distraction. The membership functions ([Concentrated - Eyes out - Distracted]) represent the driver with eyes on the road, eyes off the road, and definitely engaged in another task. The values reflect the behavior of the raw distraction signal.
- $o1$ - **Level of Authority**: Represented as maximum steering torque of the correction (λ) in Nm. Figure 5.5a shows that the labels of the membership functions ([Manual - Assistance - Correction - Override]) represent the full range of automation steering assistance. The values reflect how the driver feels the assistance: a) no torque corresponds to Manual, b) with 2 Nm the driver hardly feels the steering assistance (Assistance), c) between 6 and 10 Nm corresponds to strong assistance (Correction) and d) 15 Nm is the maximum torque of the steering motor.



(a) Vehicle position - Lateral error

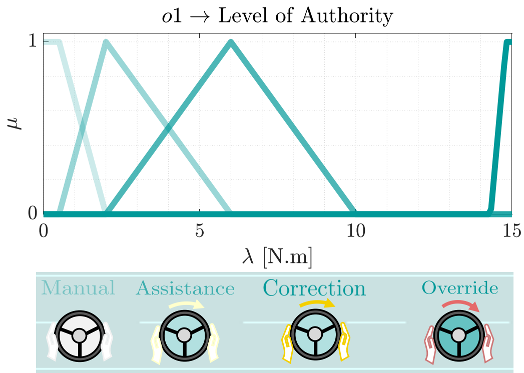


(b) Driver state - Distraction level

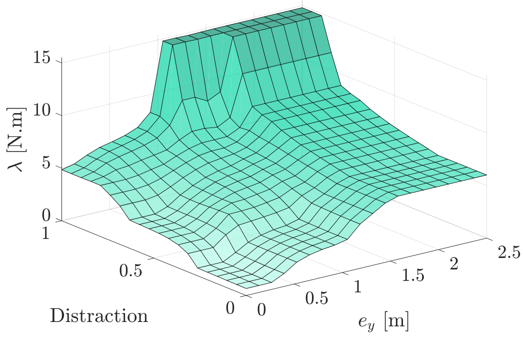
Fig. 5.4: Inputs description of the arbitration system based on fuzzy logic

Tab. 5.1: Fuzzy logic rules for the distraction support system

$i1 - e_y \rightarrow$	**Center**	**Left**	**Border**	**Out**
Concentrated	Manual	Manual	Assistance	Correction
Eyes-out	Assistance	Assistance	Correction	Override
Distracted	Assistance	Correction	Correction	Override
$\uparrow i2 - dms$	$\uparrow i1 - \lambda$			



(a) Level of authority



(b) Decision surface

Fig. 5.5: Output description of the arbitration system based on fuzzy logic

Table 5.1 shows the IF-THEN rules of the arbitration system. Its structure consists of the application of two main principles. First, the principle of *minimal intervention* follows the idea that drivers need help only under certain circumstances [63]. On the contrary, automation could lead to unnecessary conflicts, making drivers feel that they are constantly being contradicted and reducing the acceptance of the system by drivers. Moreover, not intervening when drivers are capable of driving themselves aims to increase the sense of responsibility and avoid overreliance on automation. In this sense, automation support is very low during concentration, but increases (with gentle gradients) in proportion to the risk (either from deviation from center or from distraction), as shown in Figure 5.5b. The second principle is *safety before comfort*, which gives higher priority to safety than to parameters that increase comfort while driving. In this sense, the system intervenes not only when the driver is no longer able to drive and performs an unsafe action, but also when the probability of risk increases, which gives the system a preventive safety. Under this principle, automation can override the driver's intent, but at the cost of inconvenience (e.g., abrupt accelerations or strong steering corrections).

5.1.4 System Performance

Figure 5.6 shows the performance of the developed systems (the three initial conditions and the shared-control system). The results are from the data of one of the participants and represent the overall behavior of the system under these conditions. The performance metrics are the lateral error, driver torque, and the automation control torque, along with the description of the distraction event and the authority signal in each of the conditions.

5.1.4.1 Baseline #1 - Manual

The vehicle leaves the lane beyond the limits during the distraction events, especially in the zones with higher curvature. As for the driver's torque, some peaks result from the effort the driver makes to bring the vehicle back to center after the deviation. There is no automation support, and therefore the authority λ is always zero.

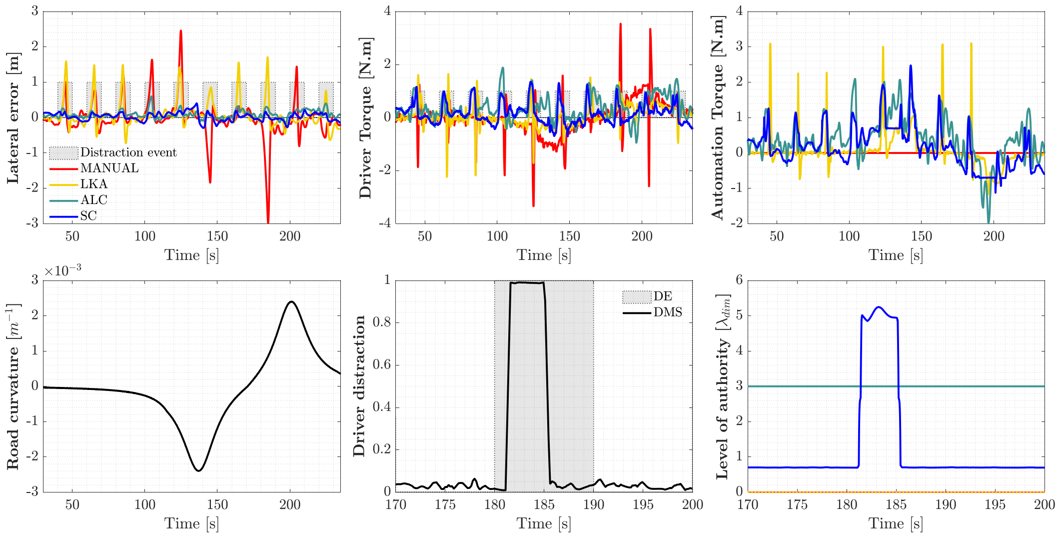


Fig. 5.6: Performance of baseline conditions and shared-control systems in terms of lateral error, driver torque and automation torque command

5.1.4.2 Baseline #2 - LKA

The vehicle constantly deviates from the center of the lane during distraction maneuvers, but the LKA system effectively prevents the driver from leaving the lane (the lateral error is less than 2 m) after applying a bump torque of up to 3 Nm when the lane limit is reached. Driver effort is less than in manual mode thanks to LKA assistance. The automation torque also shows that the LKA has a non-zero assistance component in cornering areas, thanks to the predictive behavior of the NMPC controller, which acts as a power steering system in these circumstances. There is no continuous automation (only assistance to keep the lateral limit), and therefore the authority λ is always zero.

5.1.4.3 Baseline #3 - ALC

The vehicle does not deviate significantly from the center of the lane (even in areas with strong curvature), thanks to the automation assistance, which is always active with an authority $\lambda = 3$ Nm. The driver's torque is reduced compared to Manual and LKA, and the automation torque is stronger in areas with strong curvature.

5.1.4.4 Shared-Control System

Similar to ALC, the SC system keeps the vehicle in the center of the lane, except that authority is lower under concentration ($\lambda \approx 0.6$ Nm) and higher under distraction ($\lambda \approx 5$ Nm). At first glance, SC seems to result in lower driver effort, but since there is no significant difference, the analysis is performed quantitatively. Automation torque of $T_{max} = \lambda$ is shown in Figure 5.6, where it is saturated and smaller than in ALC. These initial results suggest that SC and ALC are the safer systems, but SC achieves this with less driver and automation effort.

5.1.5 Quantitative Results

The quantitative evaluation of the systems takes into account various Key Performance Indicators (KPIs) that were developed in the framework of the PRYSTINE project [188] (after conducting special workshops with experts in the field) and taking into account previous works in shared-control [276]. The evaluation considers three categories of KPIs, as shown in Table 5.2. First, tracking performance, to measure the ability of the systems to follow the expected trajectory. Second, safety-related indicators to find the system that is safest (the one with a lower probability of unsafe events). Finally, driver and automation torques serve as indicators of the conflict between the driver and the automated system.

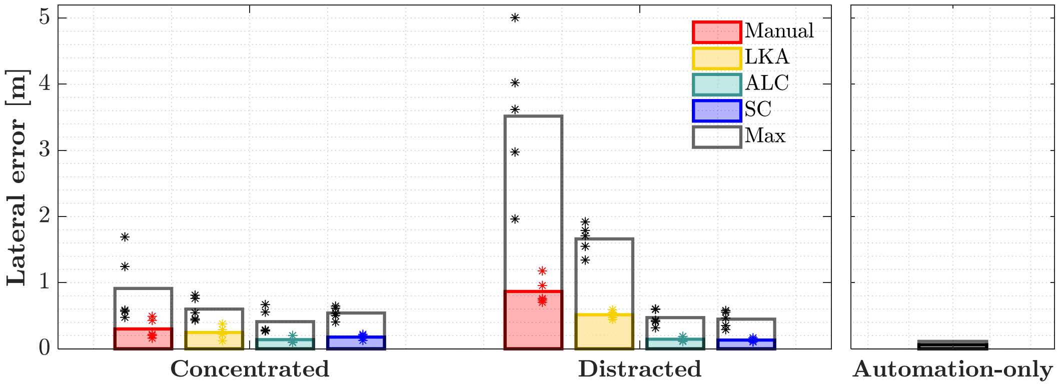
Tab. 5.2: KPIs description for the overtaking scenario

KPI		Tracking
1.1	Lateral error RMS (LE-RMS)	Mean of participants RMS of the lateral error
1.2	Lateral error MAX (LE-MAX)	Mean of participant's maximum value of the lateral error
1.3	Angular error RMS (AE-RMS)	Mean of participant's RMS of the angular error
1.4	Angular error MAX (AE-MAX)	Mean of participants maximum value of the angular error
		Safety
2.1	# Time-to-lane-crossing RMS (TLC-RMS)	Mean of participants RMS of the TLC
2.2	# Time-to-lane-crossing MIN (TLC-MIN)	Mean of participant's minimum value of the TLC
2.3	# Time-to-lane-crossing period (PTLC)	Mean of participants period of time when TLC < 3.8 s
		Effort
3.1	Driver torque RMS (DT-RMS)	Mean of participants RMS of the driver torque
3.2	Driver torque MAX(DT-MAX)	Mean of participant's maximum value of the driver torque
3.3	Automation torque RMS (AT-RMS)	Mean of participants RMS of the NMPC torque command
3.4	Automation torque MAX (AT-MAX)	Mean of participants maximum value of the NMPC torque

Figures 9-14 show the results for each experimental condition considering the two states of the driver (concentrated and distracted). Figures 9, 10, 13, and 14 show the Root-Mean-Square (RMS) and the maximum values of the tracking errors (lateral and angular). The individual values for each driver (* symbol) help to evaluate the dispersion of the data. Figures 11 and 12 show the safety indicators. Figure 11 shows RMS and the minimum value of Time-to-Lane-Crossing (TLC). Figure 12 shows the percentage of time that TLC is below a safe threshold. In addition, each figure includes the performance indicators of the automated system driving alone (i.e., without driver intervention), which is referred to as “Automation- only”. This serves to validate the controller and compare the entire spectrum from manual to purely automated operation.

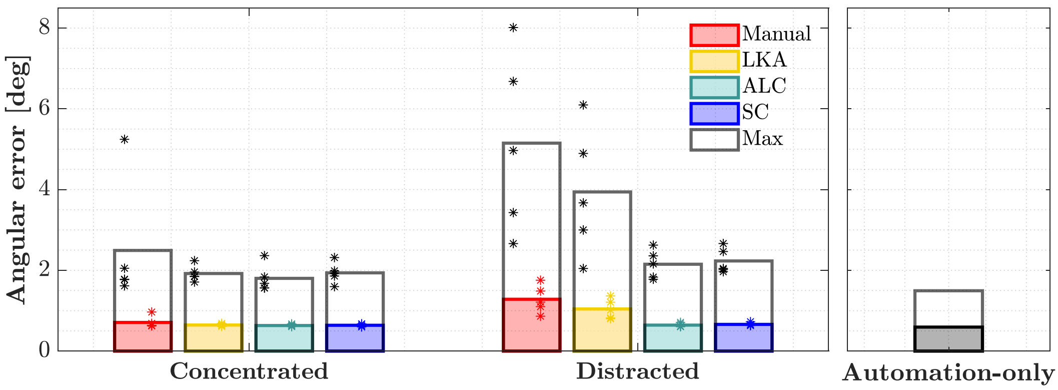
5.1.5.1 Tracking

To evaluate the tracking performance under all conditions, the analytical procedure uses two main variables, the lateral error (e_y) and the angular error (e_{psi}). Figures 5.7 and 5.8 show the results of RMS and the maximum value for these two variables.



	Concentrated				Distracted				Automation-only
RMS	0.30	0.25	0.14	0.18	0.87	0.51	0.15	0.13	0.06
MAX	0.91	0.60	0.41	0.54	3.52	1.66	0.47	0.45	0.11

Fig. 5.7: Lateral error comparison



	Concentrated				Distracted				Automation-only
RMS	0.71	0.64	0.63	0.64	1.28	1.04	0.64	0.66	0.59
MAX	2.49	1.92	1.80	1.94	5.15	3.94	2.15	2.23	1.49

Fig. 5.8: Angular error comparison

- **KPI 1.1 - LE-RMS**: Analysis of Figure 5.7 shows that under all conditions the average deviation from center remains below 30 cm. The three driving aids improve the ability to follow the center of the road compared to MAN. The improvements in following the center of the road by ALC and SC are very similar and much better than LK (including lower dispersion between participants). However, SC has lower authority ($\lambda \approx 0.6$ Nm) compared to ALC ($\lambda = 3$ Nm), suggesting that the same tracking performance is achieved with less automation intervention. However, when the driver is distracted, the differences become larger. Manual and LK exceed the mean deviation of 50 cm, while ALC performs very similarly regardless of the driver's condition. On the other hand, SC improves performance when distracted, which can be attributed to the increased authority in this condition. Comparing SC with automation-only, the vehicle moves 10 cm more from the center of the lane on average, but with the advantage that the driver cooperates with the automation.

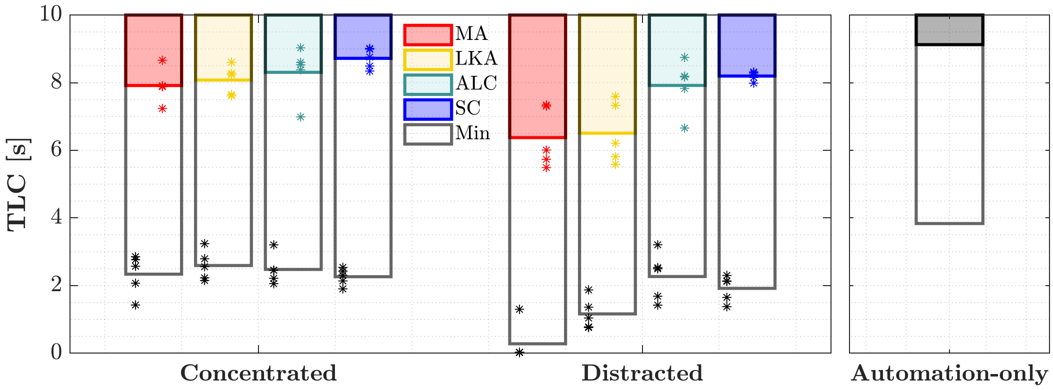
- **KPI 1.2 - LE-MAX**: As the maximum values show, all drivers stay within the lane most of the time even in manual mode when they are focused. However, when distracted, all drivers in manual mode deviated from the lane at least once, which is enough to cause an accident. The LKA feedback helps to completely avoid these unsafe events thanks to the correction torque when reaching the limit (the maximum error is less than 2 m). Nevertheless, the ALC and SC systems show the best performance when it comes to keeping the vehicle within 50 cm from the center.
- **KPI 1.3 - AE-RMS**: In terms of angular error, the RMS value at concentration is similar for all driving modes (below 1 degree), but during distraction events it follows the same pattern as lateral error. When the driver has continuous steering assistance (ALC and SC), the overall angular error does not change as much as in manual and LKA modes.
- **KPI 1.4 - AE-MAX**: The highest values occur in manual and LKA modes during distraction maneuvers, while ALC and SC do not show large changes compared to normal driving.

5.1.5.2 Safety

To evaluate the safety performance, the analysis procedure uses the Time-to-Lane-Crossing (TLC) variable, which indicates how close (in time) the vehicle is to leaving the lane boundary. The estimation assumes that the steering angular velocity remains unchanged. The analysis takes into account the average of the RMS values of TLC during the driving session and also the minimum values (see Figure 5.9). The higher the TLC value is, the safer the vehicle is (if TLC $= 0$, the vehicle has crossed the lane). The results include a global safety indicator that calculates the time that the TLC is below a threshold, as shown in Figure 5.10. The threshold was chosen based on the performance of pure automation, which results in a minimum TLC of 3.8 s. Therefore, it is of interest to calculate the time period when the TLC is below this value (considering only the moments when the TLC is not infinite).

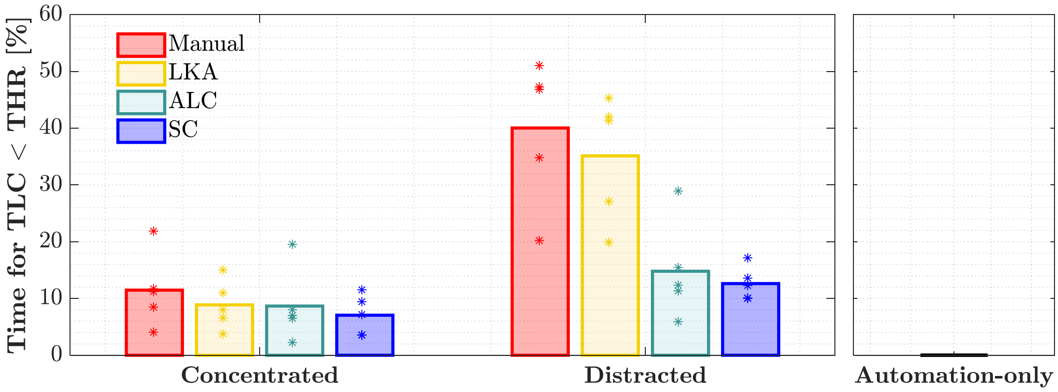
$$\mathrm{PTLC} = \frac{\mathrm{time}(\mathrm{TLC} < 3.8\ \mathrm{s})}{\mathrm{time}(\mathrm{TLC} \neq \mathrm{inf})} \tag{5.1}$$

- **KPI 2.1 - TLC-RMS**: In Figure 5.9 all driving modes show high and safe TLC when the driver is focused, with performance proportional to the level of support (more support, better safety indication). This tendency is maintained when the distraction events occur, with SC showing the safest performance and the lowest dispersion between participants.



RMS	7.92	8.08	8.31	8.72	6.38	6.51	7.92	8.20	9.22
MIN	2.34	2.59	2.48	2.26	0.28	1.16	2.27	1.92	3.84

Fig. 5.9: Time-to-lane-crossing comparison for safety performance evaluation



Time %	11.47	8.88	8.67	7.05	40.04	35.13	14.80	12.63	0.00

Fig. 5.10: Time-to-lane-crossing period (%) comparison

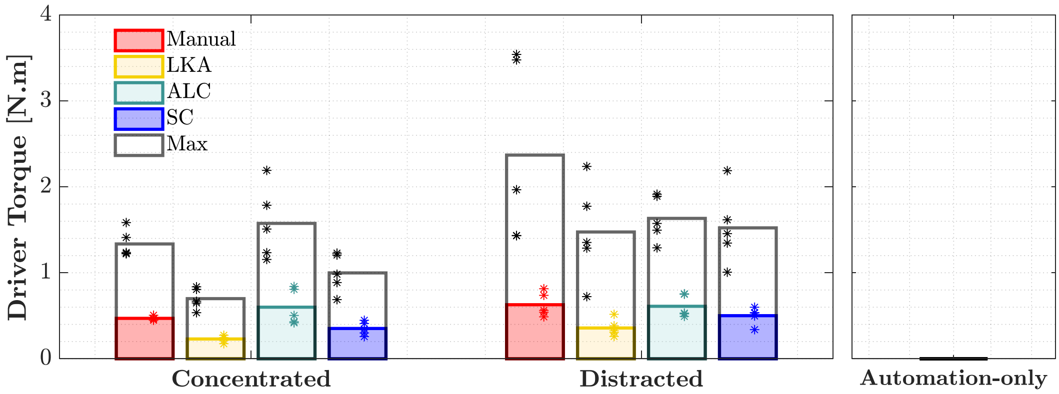
- **KPI 2.2 - TLC-MIN**: The average of minimum TLC was very similar across conditions (all above 2 s). During distracted driving, 4 out of 5 drivers in manual mode crossed the lane at least once (TLC $\approx$ 0), while the LKA system was able to prevent any lane crossing (with a minimum TLC of 0.76 s). The average minimum values of ALC and SC are above 1.5 s, which is a safety threshold below which it can be considered an unsafe event [277]. The minimum values for ALC and SC are not significantly different when comparing the two driver states.
- **KPI 2.3 - PTLC** : The period of TLC as a global indicator shows the same progressive pattern in both concentrated and distracted events (see Figure 5.10). SC is the safest in both conditions (with a small difference from ALC and a significant difference from Manual and LKA) and again shows not only the best values but also the least dispersion. Moreover, this indicator helps to show the advantages of LKA, as PTLC is significantly lower compared to Manual (although it should be similar). This effect seems to be reinforced by the fact that when entering a curve (or rather, approaching a curve change), the NMPC

controller predicts that the vehicle will approach the lane boundaries at a later time, providing the driver with anticipatory haptic torque.

In terms of safety indicators, SC moves further away from the disadvantages of manual driving and closer to the lower TLC of pure automation, both for normal driving and for distraction events. This underlines the advantages of the "team" approach.

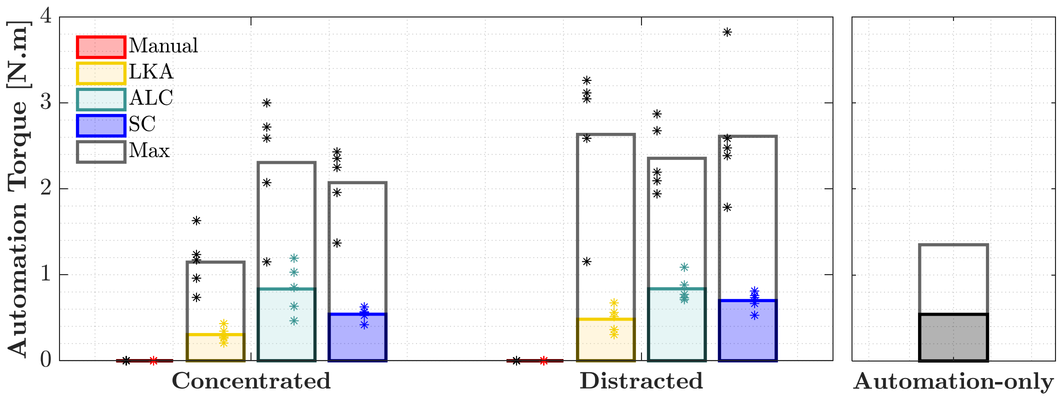
5.1.5.3 Effort

Figures 5.11 and 5.12 show the results of driver effort (DE) and automation effort (AE), so it is possible to determine how much torque conflict exists between them. It is assumed that systems with less conflict are more likely to be accepted by drivers.



RMS	0.47	0.23	0.6	0.35	0.63	0.36	0.61	0.50	0.00
MIN	1.34	0.70	1.58	1.00	2.37	1.48	1.63	1.52	0.00

Fig. 5.11: Driver torque effort applied to the steering wheel



RMS	0.00	0.30	0.83	0.54	0.00	0.48	0.84	0.70	0.54
MIN	0.00	1.17	2.31	2.07	0.00	2.63	2.36	2.61	1.35

Fig. 5.12: Automation torque effort applied to the steering wheel

- **KPI 3.1 - DE-RMS**: In Automation-only mode, there is no torque for the driver. When concentrated, expectations were for manual mode to be the least taxing, however, LKA shows the least conflict of the four modes (nearly half of manual mode, as shown in Figure ¦reffig:chap-v:effortdriver), confirming previous results indicating LKA's behavior as a steering aid in curvy zones. As expected, ALC shows the most conflict considering that automation is always active. This situation shows how the system provides unnecessary torque. During the distraction maneuvers, torque increases in all driving modes except ALC, where there is no change. Again, LKA shows the least conflict even when the driver is distracted. SC shows the second best performance in terms of effort.

- **KPI 3.2 - DE-MAX**: While focused, the higher efforts are observed in manual mode (the driver is struggling to take the turn) and in ALC (the driver is struggling with the system). At SC the conflict does not exceed 1 Nm, which is still an acceptable (comfort-related) value. In distracted maneuvers, the high effort of almost 4 Nm in manual mode is due to the driver's steering corrections to bring the vehicle back on track. In LKA mode, the highest effort is due to the roadside corrections to avoid leaving the lane. Interestingly, the maximum torques are similar between SC and ALC, although the authority of SC is higher.
- **KPI 3.3 - AE-RMS**: In manual mode, there is no support for automation ($T_{mpc} = 0$). Figure 5.12 shows that the results for the concentrated segments follow the logic. Smaller average torque commands for LKA, which is active only during short periods, and larger torque for ALC, which is always active. When distracted, torque increases for all modes except ALC, which has fixed authority. Interestingly, SC is more efficient than ALC, even though it has a higher authority.
- **KPI 3.4 - AE-MAX**: The maximum torque applied by the automation with ALC is the highest, showing the disadvantage of conflicts between the driver and the system when approaching a fixed authority. During distraction maneuvers, SC exhibits larger torque peaks due to the higher authority, but overall the effort is less than ALC, showing that SC is the more efficient control after LKA.

In summary, if the driver is attentive, he can maintain a very small deviation from the lane in all modes. In these cases, the SC mode provides very little assistance, and the driver feels very close to manual driving, being able to drive freely within a narrow band around the center. Only when a larger deviation occasionally occurs does SC provide feedback on centering. On the other hand, LKA gives feedback even for small tracking errors when the steering is heading for a possible lane crossing (i.e., when the TLC is small). ALC always gives feedback, even for small lane errors. Thus, the ALC and SC modes seem to give the best results in terms of lane keeping. In terms of safety indicators, SC shows the highest performance, closely followed by the ALC mode. In terms of effort, the lowest effort for the driver is observed in LKA mode, followed by SC, while ALC presents the highest torque conflict for the driver. Overall, the SC mode seems to offer the best compromise among the tested modes. It is the furthest from manual control and the closest to pure automation, supporting the idea that the "team" approach can offer the best of both worlds (manual and automated). In addition, it seems worthwhile to combine the benefits of SC with the predictive torque of LKA mode.

5.1.6 Qualitative Results

The subjective evaluation helps to understand the driver's perception of the system. After completing all tests, participants were asked to rate each driving mode in this particular scenario by answering the questions in Table 5.3. Punctuation varied from 1 (no/bad) to 10 (yes/good). The questionnaire targets four categories of questions: 1) monitoring, to measure the driver's perception of his or her need to engage with the driving task (Q1-Q2), 2) safety, to assess the driver's feeling of being protected (Q4), 3) comfort, to understand the driver's feeling of whether the system is harmonious or too intrusive in its interaction (Q3-Q5), and 4) overall perception of the systems (Q6). Figure 5.13 shows participants' scores in response to the custom questionnaire. Individual scores (+) are connected with a line to understand the overall perception of each driver.

Tab. 5.3: Driver acceptance customized questionnaire

#	Category	Question
Q1	Monitoring	Did you have the feeling that you were free to perform the secondary task?
Q2	Monitoring	Did you feel the system required your continuous monitoring of the situation?
Q3	Comfort	Did you have the feeling that the system was too intrusive?
Q4	Safety	Did you feel that your security was ensured by the system?
Q5	Comfort	Did you feel that your interaction with the system was harmonious?
Q6	Overall	Provide an overall evaluation of the system.

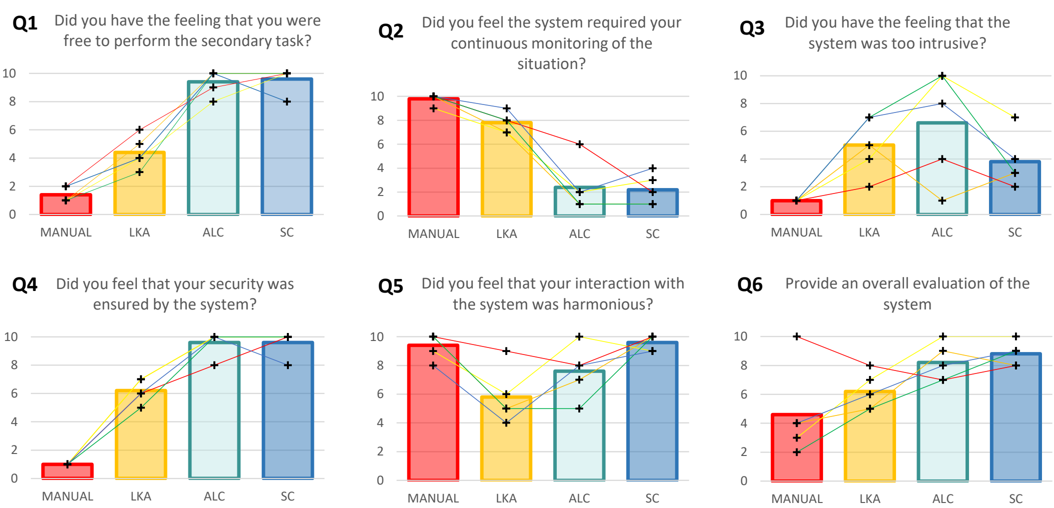


Fig. 5.13: Subjective evaluation of assistance systems for the distracted driver use case

5.1.6.1 Monitoring

As it is shown in left upper part of Figure 5.13, questions 1 and 2 correlate very well with each other. The results show that when driving with SC and ALC, drivers feel they have a lot of freedom to perform a secondary task, while when monitoring the system, they do not have much responsibility. Although the ratings of these two modes are similar, only one driver felt that SC required less monitoring of the automated system. However, the goal of SC is to keep driver involvement lower than in manual driving, but not as low as in driving with an autopilot (to avoid the out-of-the-loop problem). To achieve this goal, it is proposed for the future to warn the driver if the Secondary Task (ST) takes longer than expected or if the frequency of ST is high, so that the driver knows that he has the main responsibility for driving the vehicle.

5.1.6.2 Safety

Question 4 assesses the drivers' perception of safety in relation to the systems. The manual mode is absolutely not perceived as safe. LKA mode is perceived as reasonably safe, and ALC and SC are perceived almost identically as very safe.

5.1.6.3 Comfort

Questions 3 and 5 also correlate well, indicating that the interaction between Manual and SC is very harmonious and SC is not perceived as an intrusive system. On the other hand, ALC is perceived as the most intrusive of all modes tested (although the results show a high dispersion), consistent with the highest level of conflict discussed above, while LKA is perceived as less intrusive but also less harmonious, most likely reflecting the freedom to wander within small trajectory deviations characteristic of human drivers (low intrusiveness), in combination with momentary corrections or "bumps" that disrupt the harmony of the interaction.

5.1.6.4 Overall

Finally, after considering the three evaluation categories, participants were asked to provide an overall rating for each mode, forcing them to reconsider their system rating under each criterion. A clear trend emerged in the responses in favor of SC. Again, the response of one participant is noteworthy, who gave a perfect score to manual mode. He obviously prefers the independence of the driver in this mode, but acknowledges that it cannot provide additional protection in the event of a distraction. Not surprisingly, this answer came from the driver who never crossed the lane during the tests.

It is also clear from the driver perception information that a combination of SC with LKA is worth testing. LKA's predictive torque could not only help improve the dynamic parameters of the already favored SC mode, but also make it feel more harmonious. If needed (depending on automation capabilities), it could allow a reduction in authority during normal driving (attentive driver), forcing the driver to continue to observe the environment and avoid secondary tasks without compromising additional safety.

5.1.7 Conclusion

The first experimental study of this chapter explored human-automation cooperation (as a team) when one of the members has limited resources, in particular, when the human driver is inattentive. The NMPC-based shared-controller developed in Chapter 4 was used to conduct experiments on a driving simulator with real users. The scenario considered an appropriate methodology for sharing the driving task, which is important for effective vehicle control. In doing so, the arbitration module presented two design considerations (i.e., minimal intervention and safety over comfort). The summary of the results and lessons learned are presented below.

- SC proved to be the best solution to support the driver during short distractions. Objective results showed that good tracking performance and safety were achieved, similar to ALC, but at the cost of lower driver-automation conflict.
- The combination of the SC and the LKA mode seems promising for future work, as the LKA mode could further support the driver by reducing more conflicts with the automation.
- Compared to similar work that also investigated shared-control for the distracted driver scenario [274, 275], the quantitative results show overall consistency. In the tests with real drivers, both works show an improvement in lateral error RMS during distracted driving when SC is used. Regarding driver effort, the cited work shows the highest effort at SC during the execution of the secondary task, while the results of this dissertation show a lower effort at SC compared to ALC and Manual. In addition, qualitative analysis shows that SC performs better in terms of safety and comfort, which is consistent with the subjective results of previous work.
- The study needs to be improved by increasing the number of participants, selecting people who are not experts in automated driving development, and adding a more complex simulated test track.
- An interesting KPI to measure in future experiments is the quality of the takeover request, which assesses the driver's ability to regain manual control of the vehicle under shared-control after an automation failure.

5.2 Support in Overtaking

The second use case relates to an overtaking maneuver in a 2-ways road when driving an automated vehicle with L2 capabilities. The focus of the use case is on the cooperation between the driver and the automation. The idea is that the team performance (shared-control mode) will surpass the individual performance. The safety indicators of the maneuver will compose the quantitative analysis, together with an evaluation of the time in each operation mode. For the subjective evaluation, two standardized questionnaires measure the participant's perception of the automated system.

5.2.1 Use case

As part of setting up the driving conditions in the scope of the test, the following use case was created with the Prystine project consortium, showing a situation where the driver and automated system can work together as a "team".

5.2.1.1 User Story

"On an extra-urban road, Silvano is driving in AD mode (L2) to come back home, when the vehicle approaches a big and slow tractor ahead. The automation cannot overtake due to the limited perception (it cannot "see" and check if other vehicles are coming in the opposite direction and thus if the left-lateral lane is free for the maneuver). In such a situation, the automated vehicle can only slowly follow the truck in front, waiting until it changes its route. However, Silvano is in a hurry due to an appointment for dinner and thus, he is getting nervous. In this sense, the system based on shared-control, ask Silvano for support in case he wants to overtake"

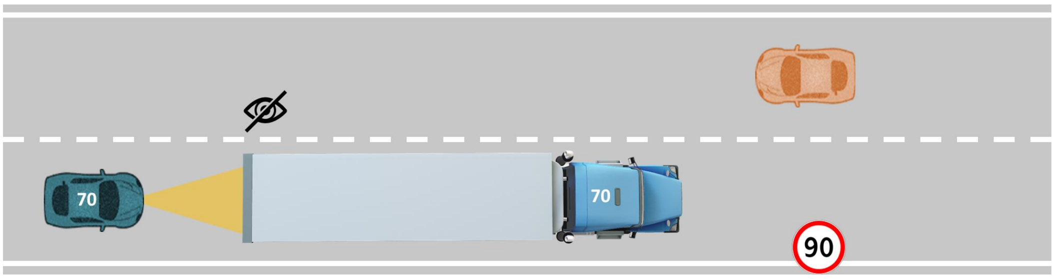


Fig. 5.14: Driving scenario of use case 2: overtaking a slow truck in a two-ways road

5.2.1.2 Motivations

The first use case focuses on automation assistance due to driver limitations (e.g., distraction). The second use case focuses on driver assistance due to automation impediments (e.g., low sensor visibility). Therefore, the overtaking maneuver in the oncoming lane is a suitable scenario for evaluating the shared-control interaction initiated by the driver. In this scenario, the collaboration between driver and automation is active only for a limited period of time. This is the ideal situation to benefit from shared-control while avoiding the disadvantages of strong continuous support [63]. The scenario is also relevant to safety, because when accidents occur during overtaking, the likelihood of serious injuries and fatalities is high (especially in head-on collisions). Improper overtaking is also an important cause of accidents on interurban roads with lanes in both directions (which represent about 90% of the Spanish road network [278]).

5.2.1.3 Current Research

Various systems supporting this maneuver can be found in the literature. The See-Through-System [279] presents a solution based on augmented perception, where the driver can see the view of the vehicle in front (equipped with a vision camera and screens in the rear). Samsung has implemented this solution in real trucks in Argentina[2]. There are also systems based on driver automation at the tactical level (decision), such as the one presented by Walch [280], used in the same overtaking scenario. In this work, the collaboration is done through a Human-Machine-Interface (HMI) to approve or reject the overtaking operation, but the automation performs all the control actions [3]. As for shared-control based solutions that involve the driver at the operational level, few works address this scenario. Ercan [281] and Muslim [93] present collision avoidance systems for dangerous lane changes, but consider a vehicle coming from the same direction. Nishimura [282] evaluates the situation of overtaking, but with a focus on the control transitions from automated to manual and vice versa. In another paper, Dillman [283] presents a comparison of overtaking modes, including a semi-automated one based on shared-control, where the automation performs an overtake as soon as the driver has hands on the steering wheel and confirms the intention to overtake.

However, the literature does not present a system based on shared-control that handles control transitions and avoids dangerous overtaking maneuvers in roads with oncoming traffic. The following sections describe the developed driver assistance system with these features.

5.2.2 Method

5.2.2.1 Participants

A total of 13 participants (6 females and 7 males), took part in the experimental studies, aged between 23 and 64 years (mean = 35.6, SD = 13.0), all of them with at least 2 years holding a driving license, and with an overall driving experience around 5 years or higher.

5.2.2.2 Apparatus

The DiL simulator presented in Section 3 is the experimental platform for this study. The custom configuration for the overtaking scenario consists of: 1) steering wheel and pedals to control the vehicle motion, 2) a Bluetooth button to activate the automated functionalities (integrated in the steering wheel of Figure 5.15a), 3) a visual HMI (developed by RE:Lab[4], as part of the Prystine project collaboration [210]) that serves as an instrument cluster to display the automation status information, but also to inform the driver about overtaking events. The DMS is not part of this study, as only the environmental risks are of interest. Figure 5.15 shows the aforementioned configuration.

[2] **Video**: Samsung Safety Truck → *https://www.youtube.com/watch?samsungsafety*
[3] **Video**: Cooperative Overtaking System → *https://www.youtube.com/watch?cooperativeovertaking*
[4] **Webpage**: RE:Lab → *https://www.re-lab.it/*

(a) Simulator set-up

(b) Visual HMI - automation off

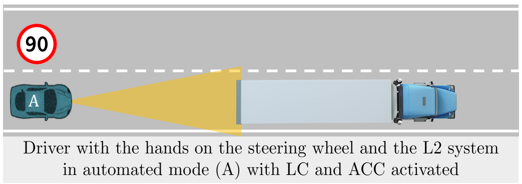
(c) Visual HMI - automation on

(d) Visual HMI - automation ask for support

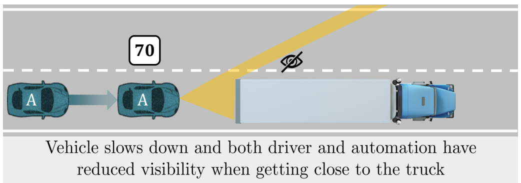
Fig. 5.15: DiL simulator for experiment and visualization of the RE:Lab HMI states [210]

5.2.2.3 Experimental Conditions

The participants start driving in manual mode and activate the system after reaching a speed of 50 km/h. Automated functions include Adaptive Cruise Control (ACC) and ALC (longitudinal and lateral control of the vehicle). The system is activated by pressing a button on the steering wheel, and the driver receives confirmation on the visual HMI (the active lane is highlighted in green, as in Figure 5.15c). The automated controller sets the speed to 90 km/h until a slow truck appears in front, and the vehicle slows down to follow it using the ACC function. At this point, the driver is in a situation where an overtaking maneuver is desired (Figure 5.16 shows this sequence). In this context, the participants tested the following two overtaking assistance systems:



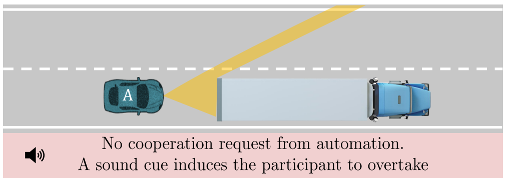
(a) Driving in automated mode at 90 km/h



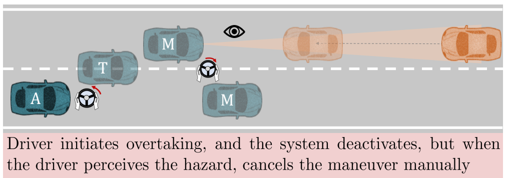
(b) Approaching the slow truck at 70 km/h

Fig. 5.16: Description of the initial conditions of the driving experiment

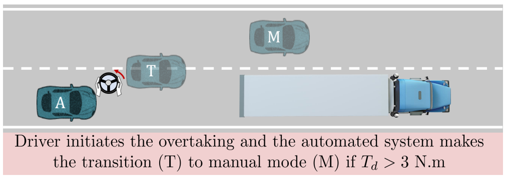
- **L2 automated vehicle** as the baseline condition. Participants drive the vehicle with ALC and ACC enabled. The automated vehicle is responsible for lateral and longitudinal control, but the driver must keep his hands on the steering wheel and monitor the system. To manually overtake a slow truck, the driver must deactivate the L2 driving mode by applying torque to the steering wheel (Figure 5.17c), perform the maneuver in manual mode, and manually reactivate the L2 functions after completing the overtake (Figure 5.17d). If the overtaking is dangerous, the system does not make any correction (Figure 5.17b). Figure 5.17 illustrates all the functionalities.



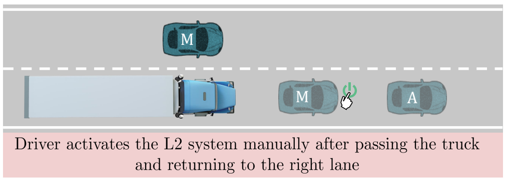
(a) Support request



(b) Lane change - Unsafe

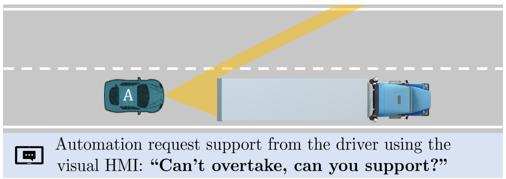


(c) Lane change - Safe

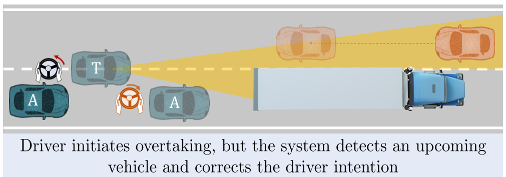


(d) Lane return

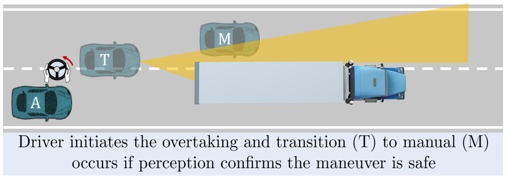
Fig. 5.17: L2 driving mode



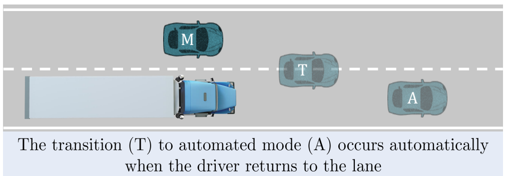
(a) Support request



(b) Lane change - Unsafe



(c) Lane change - Safe



(d) Lane return

Fig. 5.18: Shared-control mode

- **Shared-control** functions are added to the L2 baseline. For the lane change indicator, the visual HMI asks the driver for assistance (Figure 5.18a). In addition, the automated functions are deactivated only when there is a sufficient field of view to watch for upcoming vehicles (and not only when the driver exceeds the torque threshold, as in Figure 5.18c). In the event of an unsafe lane change, the ALC controller increases authority relative to collision risk to avoid accidents (Figure 5.18b). During the overtaking phase, the shared-control mode includes a lane departure system to avoid a lateral collision with the truck or the departure from the left lane. Finally, the automated functions are automatically activated when the driver approaches the right lane and completes the overtaking maneuver (Figure 5.18d). Figure 5.18 shows all the functionalities.

5.2.2.4 Procedure

Before the test, participants completed a questionnaire related to demographic data and driving profiles. Also, they familiarized with the simulator, taking a driving session in manual mode. The study was a within-subject experiment. For each experimental condition (L2 and SC), there was a practice session before the official test. The design of the experiment consisted of two groups that differed in the order in which they tested the two systems (as shown in Figure 5.19).

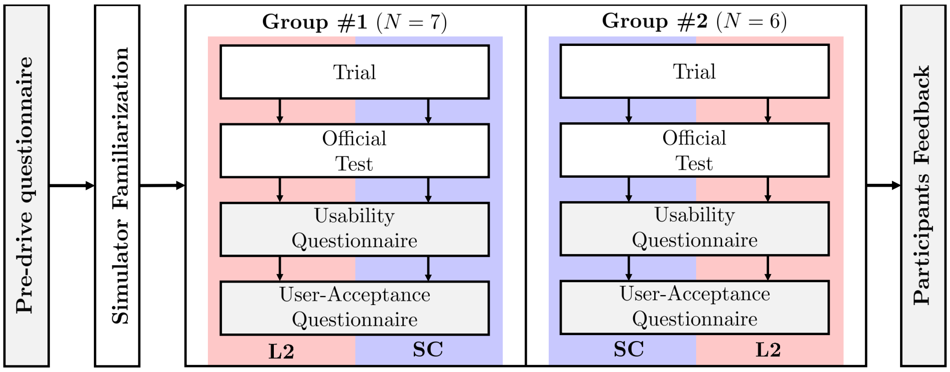


Fig. 5.19: Within-experiment design description

In the official test, participants drove on a straight road. The scenario involved one overtaking maneuver after another. To avoid learning patterns, the vehicles in the other lane appear at different distances (very close, close, far, and very far as in Figure 5.20), so that each maneuver is different from the others. The speed of the truck is 70 km/h, while the speed of the vehicle is 90 km/h (the maximum speed on the road). In addition, the system does not limit the vehicle speed above 90 km/h, so the driver can exceed the limit if necessary for safety reasons. The driver was instructed that the goal was to maximize the distance traveled (i.e., overtake as fast as possible, but without accidents) for the duration of the test.

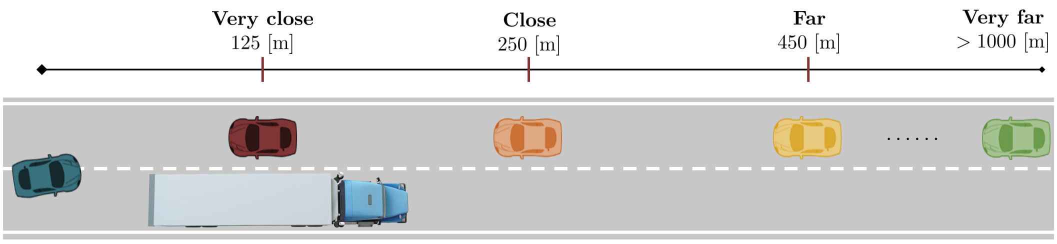


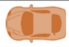
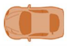
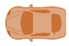
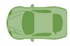
Fig. 5.20: Vehicles appearing in the left lane at different distances

Table 5.4 shows the order of appearance of the coming vehicles. If after the first overtaking intention the driver or the system aborts the maneuver, another vehicle will appear on the next attempt. The experimental design does not guarantee more than three overtaking intentions per truck, since the vehicle that appears "very far" always allows the maneuver to be completed. The test duration was 9 minutes per experimental condition, which allowed participants to overtake more than 10 trucks. After completing the official test for each experimental condition, participants filled out three questionnaires (customized, usability, and user-acceptance). At the end of the entire test, they also provided feedback to the instructors with general comments about the two systems.

5.2.3 System Design

The setup of the system for each experimental condition consisted of the configuration of the arbitration and shared-controller modules explained in Chapter 4.

Tab. 5.4: Sequence of vehicles appearing in the left lane when overtaking the truck

	Truck to overtake										
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11
Intent #1											
Intent #2											
Intent #3											

5.2.3.1 Baseline # 1 - L2

For the baseline condition (i.e., automated vehicle L2), the ALC controller is the torque-based NMPC developed in Chapter 4 (configured with $\lambda = 3$ Nm), while the ACC function uses a variable speed reference fuzzy logic controller. No arbitration module is used, because the ALC controller always works with a fixed authority.

5.2.3.2 Shared-Control Sytem

The controller used for this experimental condition is the torque-based NMPC shared-controller. Unlike the baseline (fixed authority), the shared-control mode applies a variable authority calculated by the arbitration module. Due to the aggressive nature of the maneuver, the NMPC design also includes a yaw rate constraint (ψ) to prevent excessive vehicle drift that could lead to instability and accidents. The ψ constraint follows the reference value of a related work based on shared-control for obstacle avoidance [172].

$$-0.5\,\frac{\text{rad}}{\text{s}} < \psi < 0.5\,\frac{\text{rad}}{\text{s}} \tag{5.2}$$

The arbitration module works with the fuzzy logic system described in Figure 5.21. It represents the behavior of the lateral shared-control system. It consists of three inputs and one output, as described below:

- $i1$ - **Vehicle position**: Represented as the lateral error of the vehicle with respect to the center of the right lane (e_y). The labels of the membership functions ([Right - Border - Left]) represent the different positions of the vehicle on a two-lane road.
- $i2$ - **Driver intention**: Represented as the derivative of the lateral error of the vehicle ($\dot{e_y}$). The labels of the membership functions ([Away - Stay - Return]) represent the driver's intention to leave the lane, stay in the same direction, or return to the lane. This intention is combined with the lateral error to obtain an estimate of the lane change intention.
- $i3$ - **Maneuver risk**: Represented as the distance to collision (dtc) between the vehicle and the following vehicle in the left lane. The labels of the membership functions ([Far - Close]) represent the relative distance between the two vehicles, indicating low and high collision risk, respectively.
- $o1$ - **Level of Authority**: Represented as the maximum steering torque of the correction (λ) in Nm. The labels of the membership functions ([Manual -

Assistance - Override]) represent the full range of automation steering assistance from none, to gentle corrections, to maximum assistance that can even exceed the force exerted by the driver.

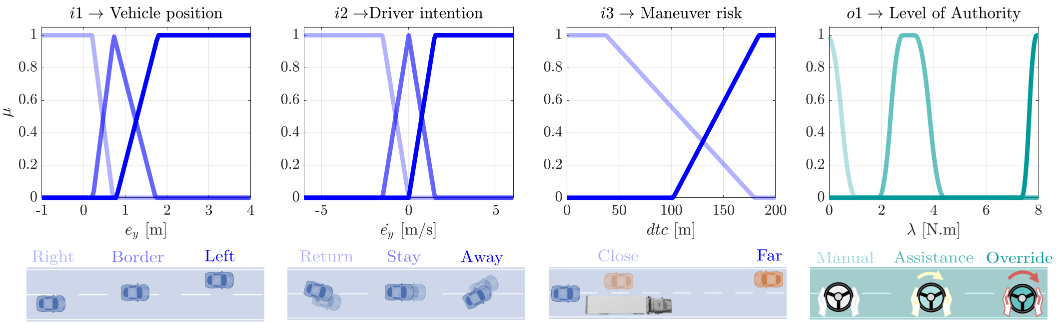


Fig. 5.21: Inputs/Output description of the arbitration system based on fuzzy logic

Tab. 5.5: Fuzzy logic IF-THEN rules of the arbitration system

$i1 - e_y \rightarrow$	Right			Border			Left		
$i2 - \dot{e_y} \rightarrow$	Return	Stay	Away	Return	Stay	Away	Return	Stay	Away
Close	Assist	Assist	Assist	Assist	Assist	Override	Override	Override	Override
Far	Assist	Assist	Assist	Assist	Assist	Manual	Manual	Manual	Manual
$\uparrow i3 - dtc$	$\uparrow o1 - \lambda$								

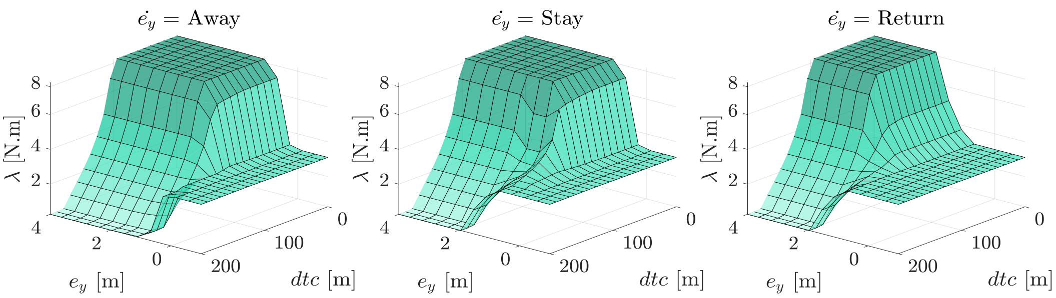


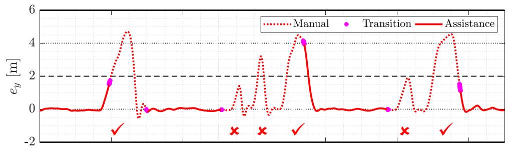
Fig. 5.22: Decision surface of the arbitration system for the level of authority (λ)

Table 5.5 contains the IF-THEN rules of the arbitration system. The high-level logic is as follows: 1) as long as the vehicle is in the right lane, the system operates as an L2 system with ALC enabled (Assist), 2) when the driver intends to change lanes (i.e., vehicle at the edge of the lane moving away from the right lane), the system performs the control transition (Manual) if there is no risk in the maneuver (far vehicle), 3) if there is a risk in the maneuver (close vehicle), the authority of the ALC controller increases (Override), 4) the left lane is designed for manual driving unless there is a risk, and 5) if the driver intends to return to the right lane (vehicle at the edge of the lane approaching), the system returns to L2 mode (Assist).

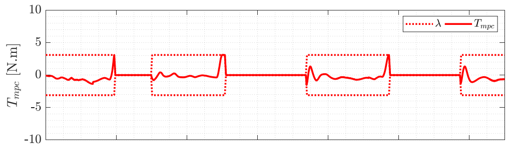
Figure 5.22 shows the decision surfaces resulting from the above IF-THEN rules. The surfaces show no discontinuity and the behavior is coherent with the designed rules. The maximum authority is set to $\lambda = 8$ Nm and is reached when the distance to the collision is at least 100 m (which corresponds to a TTC ≈ 1.8 s, considering the speeds of the two vehicles traveling in opposite directions). In addition, the default haptic authority of the system (driving in the right lane) corresponds to $\lambda = 3$ Nm. Moreover, the manual mode is active when the vehicle is at least 1 m away from the center of the right lane and when overtaking is safe.

5.2.4 System Performance

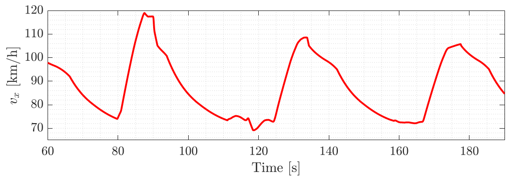
Figures 5.23 and 5.24 show the performance of the developed systems (L2 driving mode and shared-control). The results are from the data of one of the participants and represent the overall behavior of the system under these conditions.



(a) Successful (✓) and failed (x) overtakings, with the corresponding assistance mode

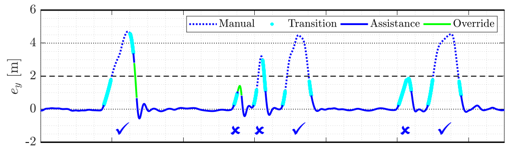


(b) MPC torque with the constraint established by the valye of λ

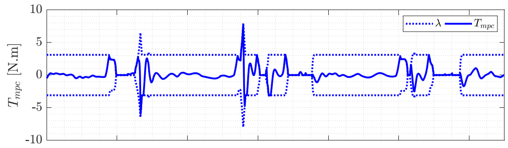


(c) Vehicle speed

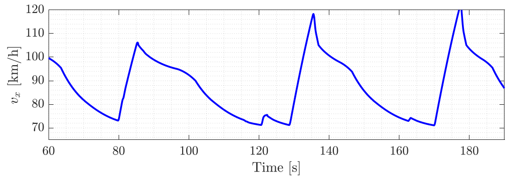
Fig. 5.23: Performance - L2



(a) Successful (✓) and failed (x) overtakings, with the corresponding assistance mode



(b) MPC torque with the constraint established by the valye of λ



(c) Vehicle speed

Fig. 5.24: Performance - SC

5.2.4.1 Baseline #1 - L2

Figure 5.23 shows the behavior of the system after three successful overtakes. It shows that the system operates mainly in two states (assistance and manual), without maneuver correction support. It is also clear that the transition process from manual to automated and vice versa is very short (activated by exceeding a torque threshold). The maximum assistance torque is 3 Nm, and the vehicle speed reaches up to 120 km/h when overtaking the truck.

5.2.4.2 Shared-Control System

Figure 5.24a shows the additional features of the shared-control mode. The system now shortens the time in manual mode, and there is support for correcting maneuvers with additional steering torque for critical situations. In addition, the transition process from assistance to manual mode and vice versa is longer because it depends not only on torque but also on vehicle position, driver intent, and field of view.

Figure 5.24b illustrates that the torque constraint ($T_{mpc} < \lambda$) applies and that the correction torque can reach up to 8 Nm. The vehicle speed in Figure 5.24c shows no difference compared to the baseline.

5.2.5 Quantitative Results

Similar to the first use case, the definition of the KPIs comes from the context of the PRYSTINE project. In addition, many of the quantitative indicators come from the state-of-the-art developed in the HADRIAN project for safety assessment of automated driving functions [277, 284].

This scenario has a strong safety component, since the main objective is to avoid accidents and unsafe events during the overtaking maneuver. In this sense, the first category of quantitative KPIs focuses on the safety evaluation of the system. Since the developed systems can operate in different modes during driving (assistance, manual, transition), the second category of KPIs evaluates the proportion of time the system operates in the different driving modes. Table 5.6 shows a summary of the KPIs considered for this use case.

Tab. 5.6: KPIs description for the overtaking scenario

KPI		Safety
1.1	# Crashes (NC)	Events of collision w.r.t left side vehicle
1.2	# Near misses (NNM)	Events when $0 < \mathrm{TTC}_{min} < 0.5$ s w.r.t left side vehicle
1.3	# Unsafe events (NUE)	Number of times when $0.5 \leq \mathrm{TTC}_{min} < 1.5$ s w.r.t left side vehicle
1.4	Proportion of TTC (PTTC)	% Time when TTC is lower than a threshold
1.5	# Left road departures (LRD)	Events when the vehicle wheel touches the left lane border ($e_y > 5$ m)
1.6	# Center Road departures (CRD)	Events when the vehicle surpasses the center line before corrections ($e_y > 2$ m)
1.7	# Right road departures (RRD)	Events when the vehicle wheel touches the right lane border ($e_y < -1$ m)
1.8	# Lane return peaks (LRP)	Lateral error peaks when returning to right lane (peak(e_y) > 0.4 m)
		Mode of operation
2.1	% Time in automated (PTA)	% Time when the vehicle is in automated mode ($\lambda \geq 3.1$ Nm)
2.2	% Time in manual (PTM)	% Time in manual mode ($\lambda = 0$ Nm)
2.3	% Time transitioning to automated (PTMA)	% Time transitioning transitioning to automated ($0 < \lambda < 3.1$ Nm and $\dot{\lambda} \geq 0$)
2.4	% Time transitioning to manual (PTMM)	% Time transitioning to manual ($0 < \lambda < 3.1$ Nm and $\dot{\lambda} < 0$)
2.5	Time of transition to automated (TTA)	Quartile analysis of transition time to manual
2.6	Time of transition to manual (TTM)	Quartile analysis of transition time to manual

5.2.5.1 Safety

To evaluate the safety indicators of the two systems, the analysis procedure uses two main variables, time-to-collision (TTC) between the vehicle in the right lane and the vehicle in the left lane, and secondly, vehicle position measured as lateral error with respect to the center of the right lane (e_y).

Figure 5.25 shows the TTC values for the 13 participants in each of the tested experimental conditions. This information is useful in determining the values of

KPIs 1.1 through 1.3. The calculation of TTC takes into account that the speed of the vehicle remains unchanged and is not infinite when part of the vehicle being driven is in the left lane ($e_y > 1.5$ m). In addition, the analysis distinguishes between events that occur behind the truck (a corrective maneuver) and those in which overtaking is completed and the vehicle quickly returns to the right lane to avoid collisions (truck ahead)

- **KPI 1.1 - NC**: Two accidents were reported after the experiment, one in L2 driving mode and one in shared-control mode. Both occurred after overtaking the truck (truck ahead) and returning to the lane (i.e., due to a misjudgment of the time available to overtake). One lesson from these results is that the shared-control system needs to be more cautious when deactivating assistance (i.e., deactivating at a greater distance).
- **KPI 1.2 - NNM**: Although there is no definitive threshold for considering near misses, the overall value is between 0.5 s and 1 s [285]. Since the scenario already considers a critical situation with the appearance of unexpected vehicles, the threshold of 0.5 s was preferred to capture a better difference between the systems. There were 7 events of this type for the L2 mode and only 1 for SC. The most valuable result is that no near miss behind the truck was reported for SC (compared to 6 for L2), which means that the correction of the shared-control aid not only reduces but eliminates the near misses.
- **KPI 1.3 - NUE**: These are the events with a high probability of collision (excluding accidents and near-misses). The safety threshold for this KPI is 1.5 s, which is half of the minimum TTC that naturally occurs when the left vehicle appears at a very close distance (125 m), and this is also a value used as a safety threshold in the literature [277]. The results show that SC has a better safety indicator than L2 by reducing the number of events during corrective maneuvers by 85 % (5 versus 38). In addition, the support of SC after overtaking the truck, which guides the vehicle back to the right lane, affects the safety indicator and reduces the unsafe events by more than 90 % compared to the return to the lane in manual mode (1 vs. 13).

Figure 5.26 shows the proportion of TTC (PTTC) as a percentage of time (KPI 1.4). This is a global safety indicator for the systems. The percentage takes into account only the time in which both vehicles would cross if they follow their current course (i.e., the total time for the calculation is not the time of the driving session but the time in which TTC $\neq$ inf). In this sense, the following Equation 5.3 applies.

$$\text{PTTC} = \frac{\text{time}(\text{TTC} < \text{Threshold})}{\text{time}(\text{TTC} \neq \text{inf})} \tag{5.3}$$

- **KPI 1.4 - PTTC**: Overall, SC shows safer performance compared to L2 based on quartile analysis (median, maximum, and minimum values). The most remarkable result is how SC ensures a TTC $<$ 1.6 s for all participants, except for the two

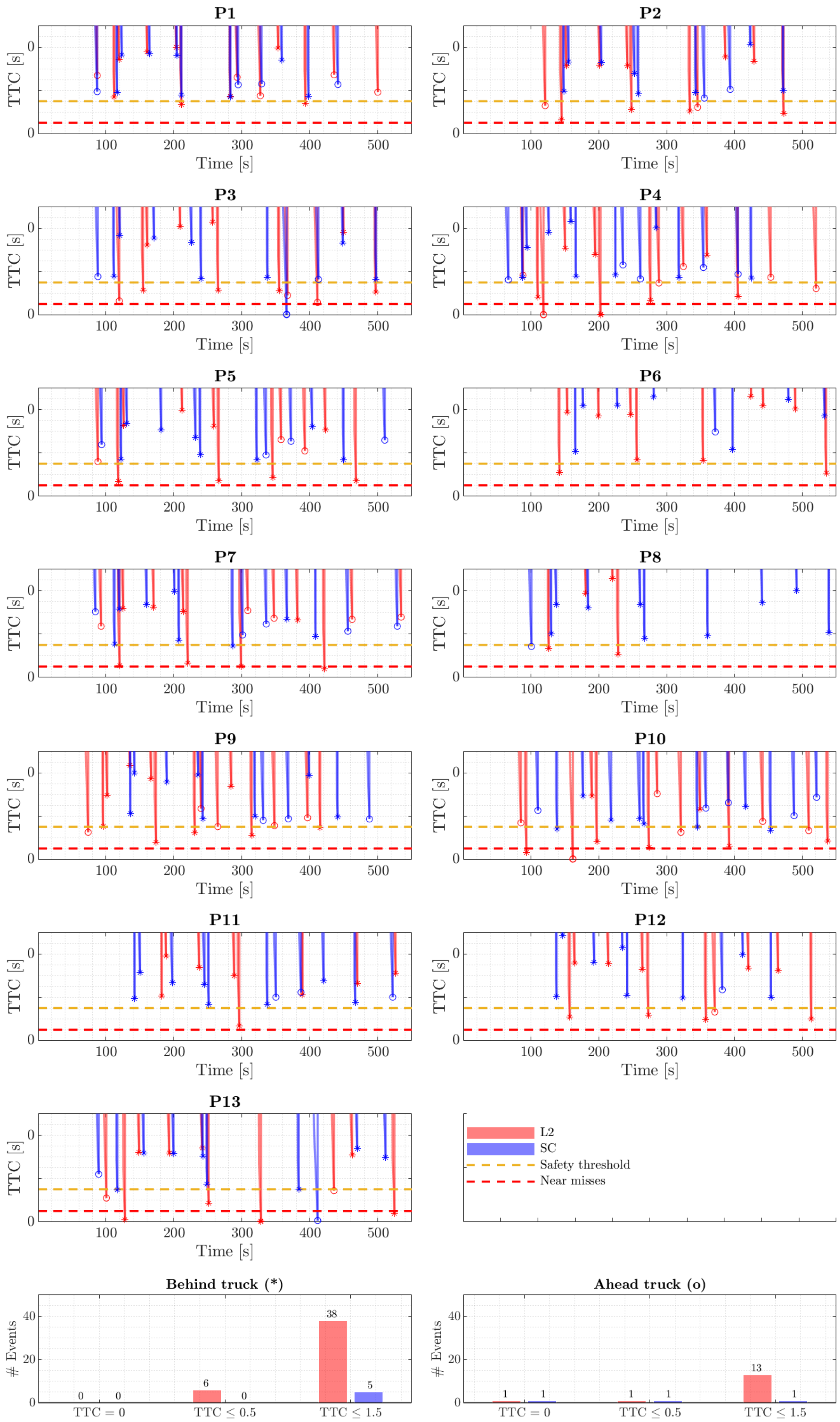


Fig. 5.25: TTC and thresholds of safety events

outliers representing the two previously reported unsafe events (1 accident and 1 near miss that occurred after overtaking the truck). This means that the SC mode maintains the safety of the vehicle in terms of the protective function of the system correction when a sudden vehicle appears, according to the design of the shared-controller and the arbitration system. For the L2 system, on the other hand, the percentage is above the threshold of 0.7 seconds for most participants.

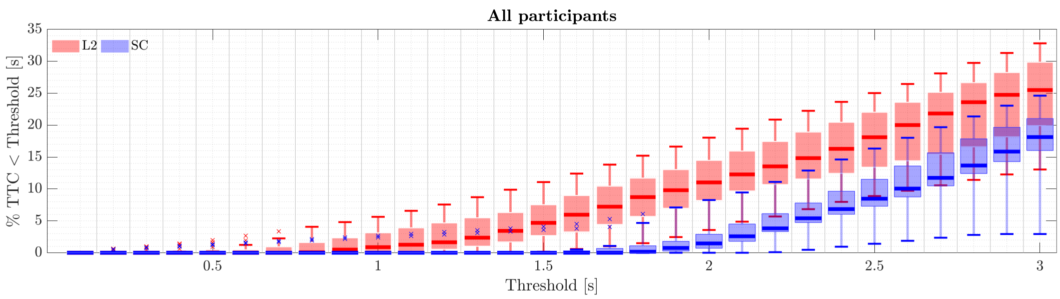


Fig. 5.26: TTC and thresholds of safety events

In addition to safety indicators related to TTC, other unsafe events can be determined based on vehicle position by analyzing lateral error (e_y). Figure 5.27 shows three types of road departures: 1) left (RDL), when the vehicle crosses the left lane boundary (when changing lanes to overtake), 2) center (RDC), when most of the vehicle is in the left lane before a correction is made (i.e., events that generate TTC $\neq=$ inf), and 3) right (RDR), when the vehicle crosses the right lane boundary (after a correction or after an overtake and return to the right lane).

- **KPI 1.5 - LRD**: The analysis of overtaking events in Figure 5.27 shows that the number of successful overtaking maneuvers is almost the same for both conditions, but the events involving lane departure in the left lane are half for SC compared to L2 (8 versus 16). Also, looking at the boxplot analysis, all of the data for SC except for the outliers are below the lane departure threshold, while some of the Q4 from L2 exceeds the threshold. The longer and smoother transition in SC could lead to a better adaptation to the left lane before overtaking the truck.
- **KPI 1.6 - CRD**: Regarding the vehicle position before correction to avoid a crash, the results show that the median position of SC is below the departure threshold, while L2 is above. In terms of numbers, more than 50 % of SC corrections are not counted as deviations, while 65 % of L2 events are center departures.
- **KPI 1.7 -RRD**: When returning to the right lane, either by correction or driver intent after passing the truck, there are possible road departures in the right lane. The lane return graph in Figure 5.27 shows that when the driver returns to the lane after overtaking the truck on L2, there are 6 departure events, but no departure event for SC. This is a result that can be attributed to the advantage provided by the automatic transition to automated driving on SC rather than manual activation. On the other hand, when corrected, the results show a similar

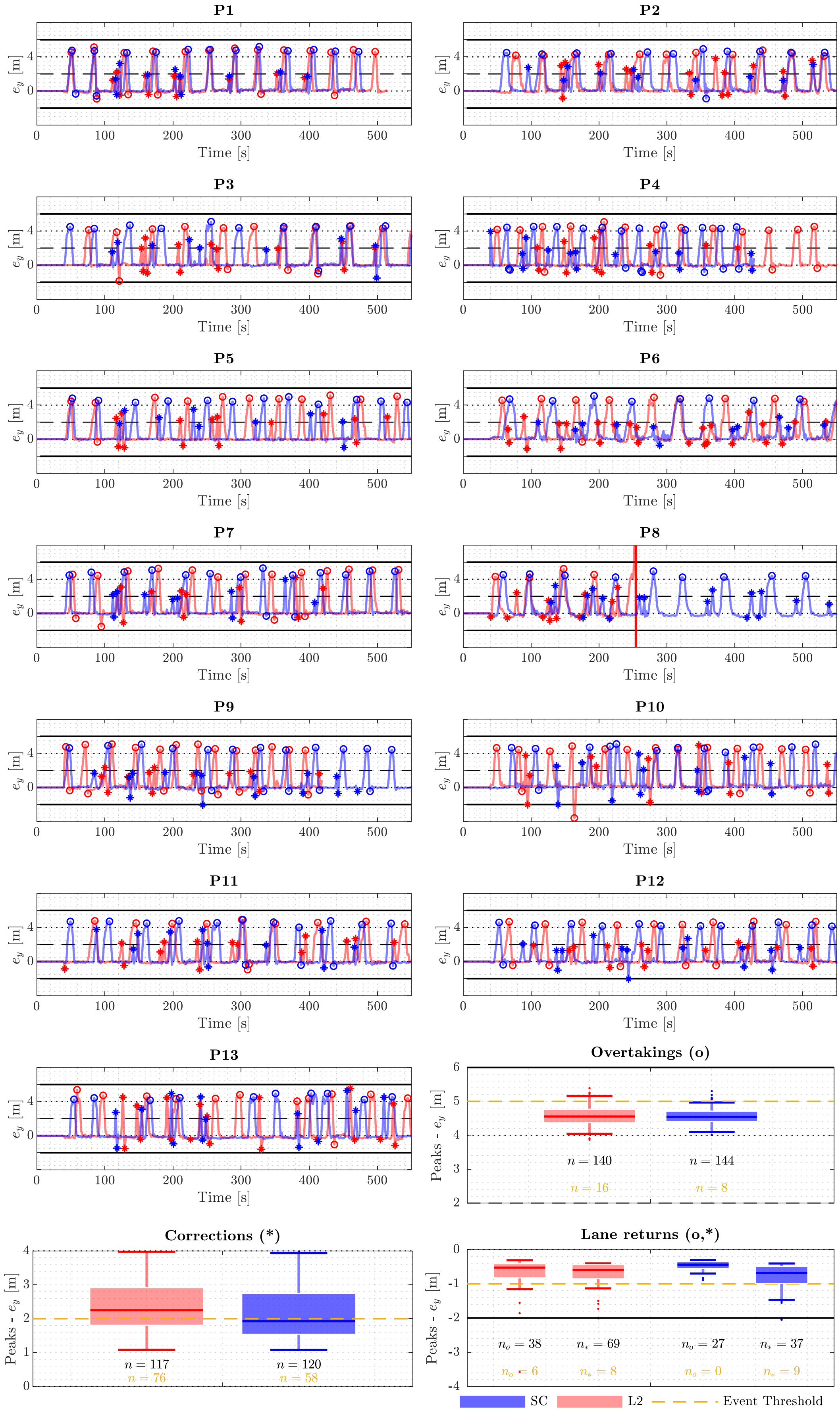


Fig. 5.27: Vehicle position during overtakes, corrections, and lane returns

number of lane deviations between L2 and SC (8 vs. 9), suggesting that the corrections of SC do not increase the risk of departure.

- **KPI 1.8 - LRP**: Consistent with the previous analysis, it is important to count the number of peaks related to the center of the lane when returning to the lane to understand the quality of the return maneuver (how well the driver returns to the lane). Valid peak counts are 0.4 m or greater. The return after an overtaking maneuver shows a 30% reduction in LRP in favor of SC. On the other hand, returning after a correction shows larger peaks for SC, but almost half the events compared to L2 (37 vs. 69). This result also shows the advantages of automatic transition compared with manual activation.

Tab. 5.7: Summary of safety KPIs

KPI	Name	L2	SC
-	# Km driven	154	161
-	# Attempts to overtake	257	264
-	# Successful overtakes	140	144
-	# Corrected overtakes	117	120
1.1	NC	1	1
1.2	NNM	7	1
1.3	NUE	51	6
1.5	LRD	16 (11%)	8 (6%)
1.6	CRD	76 (65%)	58 (48%)
1.7_o	RRD_o	6 (4%)	0 (0%)
1.7_*	RRD_*	8 (7%)	9 (8%)
1.8_o	LRP_o	38 (27%)	27 (19%)
1.8_*	LRP_*	69 (59%)	37 (31%)

5.2.5.2 Mode of Operation

This KPIs analysis considers three modes of operation: 1) manual mode ($\lambda = 0$ Nm), 2) automated mode ($\lambda \geq 3.1$ Nm), which includes overriding actions, and 3) transition mode ($0 \leq \lambda \leq 3.1$), when going from manual to automated mode or vice versa. Figure 5.28 shows the percentage of time for each of the operating modes, along with the boxplot analysis of the transition duration.

- **KPI 2.1 - PTA** : Time in automated mode reflects that both systems were active for most of the driving session, with SC operating for 10% more time in this state. This is due to assistance with corrective maneuvers not present in L2, as well as faster activation during lane returns (due to automatic transition instead of manual activation via button press).

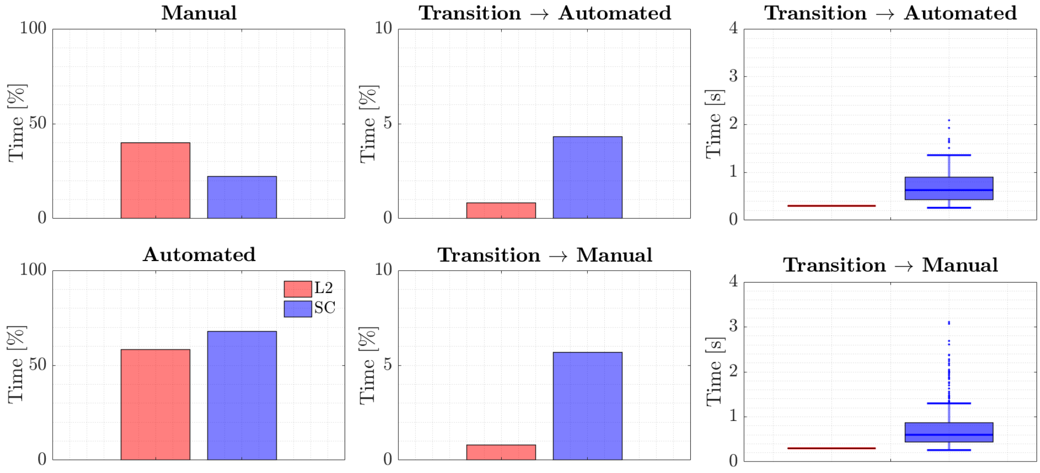


Fig. 5.28: Analysis of modes of automated vehicle operation

- **KPI 2.2 - PTM**: Figure 5.28 shows that L2 mode takes twice as long to operate in manual mode compared to SC mode. This time saving is important for safety because the preferred state is to drive automated and use manual mode only when necessary (overtaking the truck).
- **KPI 2.3 - PTTA**: The percentage of time needed to transition to automated is almost 5 times longer on SC than on L2. Longer transitions are smoother and reduce the number of peaks when returning to the lane.
- **KPI 2.4 - PTTM**: The percentage of time switching to the manual is almost 4 times longer on SC than on L2. Longer transitions are smoother and avoid sudden lane departures.
- **KPI 2.5 - TTA**: There is no significant difference between TTA and TTM, as the same values apply to L2 and SC (0.3 vs. 0.6 s). However, there are more outliers in TTA, suggesting that the activation of the system is slower than its deactivation, which is consistent with the design expectations.
- **KPI 2.6 - TTM**: Boxplot analysis shows that all transitions in L2 mode take 0.3 s, while there is a variation in transitions in SC that depends on several factors. The median as a global indicator shows a transition duration of 0.6 s, which is twice as long compared to L2.

5.2.6 Qualitative Results

For the subjective evaluation of the developed systems, participants received a brief description and had to answer both a pre-test (to characterize their demographic data and background relevant to the study) and various post-test questionnaires. This section focuses on the results of the subjective evaluation of the three post-test questionnaires that drivers answered after testing each of the systems (L2 and SC). A summary of the questionnaires can be found in Table 5.8.

Tab. 5.8: Summary of questionnaires used for the subjective evaluation of UC2

Name	Description
CSA	36 questions grouped by categories (Desirable, Harmonious, Involvement, Safe, Understable), with a 5-point-rating likert scale
SUS	10 questions to accurately asses the usability of the system [286], with a 5-point-rating likert scale
UA	9 questions related to satisfaction, usefulness, and overall evaluation of the system [287], with 5-point-rating scale between antonyms words.

5.2.6.1 Custom System Assesment - CSA

This questionnaire aims to obtain a score from 1 (strongly disagree) to 5 (strongly agree) on 36 questions (see Table 5.9). For a technical evaluation of the system, responses are grouped into five categories to describe the following: Desirability (DES), Harmony in Operation (HAR), Driver Involvement (INV), Safety (SAF), and Understandability (UND). Figure 5.29 compiles the responses given by drivers after testing both the L2 (baseline) and SC systems. The results show the averaged responses for each category after taking into account that some questions were asked in a positive sense and some in a negative sense, defined as the positive scale factor (PS) of Table 5.9. Below is an analysis of the qualitative results per category:

Tab. 5.9: Custom System Assesment questions per category

Name	Cat	Assesment questionnaire	PSF
CSA-01	DES	I think that I would like to use this system frequently	1
CSA-02	DES	I would use this system if it was in my car.	1
CSA-03	DES	I would buy the system.	1
CSA-04	DES	The cost of the system would be the most important thing I would consider before purchasing one	-1
CSA-05	DES	The benefits of the system would be the most important thing I would consider before purchasing one	1
CSA-06	DES	I would recommend the system to others	1
CSA-07	DES	I would use the system during my everyday trips	1
CSA-08	DES	Using the system on motorways was fun.	1
CSA-09	DES	I would make more trips if I had the function in my car.	1

CSA-10	DES	I would select destinations further away if I had the function in my car	1
CSA-11	HAR	I found the various functions in this system were well integrated	1
CSA-12	HAR	I thought there was too much inconsistency in this system	-1
CSA-13	HAR	Sometimes the system behaved unexpectedly.	-1
CSA-14	HAR	Driving with this system was demanding.	-1
CSA-15	HAR	Driving with the system was stressful.	-1
CSA-16	HAR	The system acted appropriately in all situations.	1
CSA-17	HAR	Driving with the system active was comfortable.	1
CSA-18	HAR	Driving with the function on long journeys would make me tired.	-1
CSA-19	HAR	The system worked as it should work.	1
CSA-20	INV	I would want to monitor the system's performance.	1
CSA-21	INV	I would use the time the system was active to do other activities.	-1
CSA-22	INV	I trust the system to drive on motorways.	1
CSA-23	INV	During driving with the system active, I monitored the surrounding environment more than in manual driving.	1
CSA-24	INV	During driving with the system active, I was more aware of hazards in the surrounding environment than in manual driving.	1
CSA-25	SAF	I felt very confident using the system	1
CSA-26	SAF	I felt safe when driving with the system active.	1
CSA-27	SAF	During the takeover I always felt safe.	1
CSA-28	UND	I found the system unnecessarily complex	-1
CSA-29	UND	I thought the system was easy to use	1
CSA-30	UND	I think that I would need the support of a technical person to be able to use this system	-1
CSA-31	UND	I would imagine that most people would learn to use this system very quickly	1

CSA-32	UND	I found the system very cumbersome to use	-1
CSA-33	UND	I needed to learn a lot of things before I could get going with this system	-1
CSA-34	UND	Driving with this system on motorways was difficult.	-1
CSA-35	UND	It was obvious to me why takeover suggestions occurred.	1
CSA-36	UND	I would have liked more information about why a takeover suggestion was triggered.	-1

- **Desirable**: Overall, the SC system is about 15 % more desirable than the L2 system. Although drivers would not make more trips or drive farther because of the SC system, they would like to use it more often in their cars.
- **Harmonious**: Drivers perceived both systems as harmonious, with appropriately integrated functions, low stress levels, comfortable, and with low chances of inducing sleep. The SC system gave the feeling of behaving unexpectedly, probably because of the sudden corrections to avoid accidents. In addition, although both systems were not very demanding, L2 demanded more from the driver than the SC mode.
- **Involvement**: Both systems required active driver involvement, but without high scores, suggesting that drivers are part of the driving task, but not with the same intensity as when driving manually. They show confidence in both systems and comment that other activities were unlikely while driving with L2 and SC.
- **Safe**: The SC mode proved to be almost 10% safer than L2 in the driver's perception. Overall, drivers felt safe with both systems.
- **Understandable**: Both systems were very understandable to drivers, low in complexity, and it was felt that they would quickly learn to use them. The takeover suggestions adequately informed drivers (more in SC because of the HMI information), but they would like more information.
- **Overall**: Both systems were perceived positively by drivers, with SC mode being more accepted by participants by 5%. Drivers rated the SC mode as safer than the L2 mode, while being equally easy to understand, maintaining harmony with the driver, and reducing driver involvement, resulting in greater appeal. When looking at the individual questions, one stands out where the difference is greatest: drivers find that the SC system sometimes behaves unexpectedly, and much more so than the L2 system. As expected in advance and later confirmed in the oral debriefings, this is related to the fact that the SC intervenes in risky situations and corrects the driver, even if the driver was aware of it. However, the participant estimated that this was compensated by the improvement in safety,

with significant differences in the other two items indicating that they felt safer and more confident.

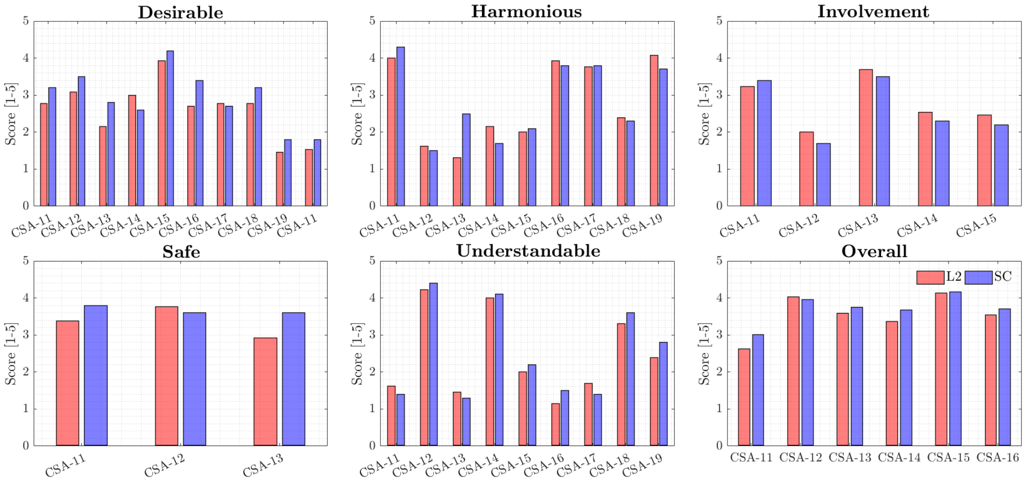


Fig. 5.29: Custom System Assesment results per category

5.2.6.2 System Usability - SUS

The Sauro-Lewis (SUS) scale [286] consists of 10 questions (shown in Table 5.10) related to the usability of the system. It is a quick and efficient tool to assess the extent to which drivers are willing to use the automated systems presented in this section.

Tab. 5.10: Questions of SUS scale for usability assesment

Name	Assesment questionnaire
SUS-01	I think that I would like to use this system frequently
SUS-02	I found the system unnecessarily complex
SUS-03	I thought the system was easy to use
SUS-04	I think that I would need the support of a technical person to be able to use this system
SUS-05	I found the various functions in this system were well integrated
SUS-06	I thought there was too much inconsistency in this system
SUS-07	I would imagine that most people would learn to use this system very quickly
SUS-08	I found the system very cumbersome to use
SUS-09	I felt very confident using the system
SUS-10	I needed to learn a lot of things before I could get going with this system

Figure 5.30 shows the averaged results of the 13 participants for each of the questions. Higher scores are better for the odd-numbered questions, and lower scores are better for the even-numbered questions. A first look shows that SC has a better usability score than L2 for 8 of the 10 questions. At SUS-08 and SUS-10, the L2 system is perceived as less cumbersome to use and less learning intensive, which is to be expected since the SC mode integrates more features. Nevertheless, the ratings for SC are positive.

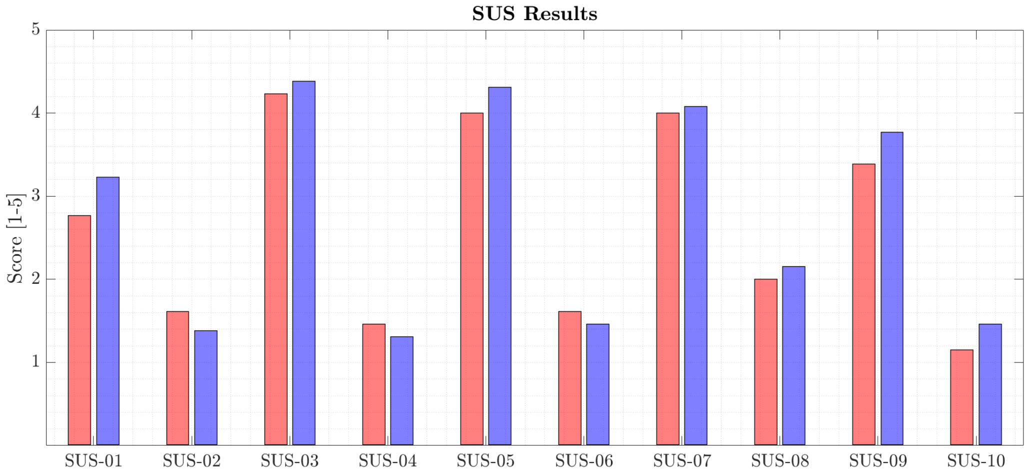


Fig. 5.30: SUS average scores

Beyond the preceding analysis, the SUS scale has a process for assigning a score to each system evaluated to give it a range from A+ to F [286]. Table 5.11 shows the SUS scores for the 13 participants. The SUS score is calculated as SUS = 2.5(20 + SUM (even) - SUM (odd)). These scores are then averaged, resulting in $L2_{SUS}$ = 76.3 and SC_{SUS} = 80. The normative mean is 68 (percentile rank above 50 %), so both systems are well above average. The L2 system has a score of B on the curved Sauro-Lewis rating scale. The confidence interval ranges from 85.1 (A) to 67.0 (C), so it is fairly certain that it will not end up with a D or F. SC, on the other hand, has a grade of A- on the Sauro-Lewis curved grading scale. The confidence interval ranges from 86.3 (A+) to 73.7 (B-). Thus, it is highly unlikely that an increase in the number of participants will degrade to a C, D, or F.

The confidence interval around the difference between the means of the 2 systems (3.7) does not rule out 0, and the p-value (p=0.33) is not below the 95% confidence level ($p < 0.05$), so the results cannot say that there is a significant difference between the 2 systems. A look at the confidence intervals of the 2 systems shows that they have common ranges. With these means (80 and 76.3), increasing the number of samples to 51 would result in a p-value of 0.0488, which means that a higher number of samples could result in a significant difference between the 2 systems. In this case, both confidence intervals would have no common range, and the confidence interval of the difference would exclude 0.

5.2.6.3 User Acceptance - UA

To assess user acceptance of the system, the evaluation method uses the questionnaire proposed in [287], which is based on a 5-point scale with 9 fields labeled with antonymous words, as shown in Table 5.12.

The improvement in user perception (from B to A- in SUS) is also evident when looking at the items of the acceptance scale in Figure 5.31a. In all items, the SC system is rated equal to or better than the L2 system, being perceived as more

Tab. 5.11: Score for the SUS analysis of the participants

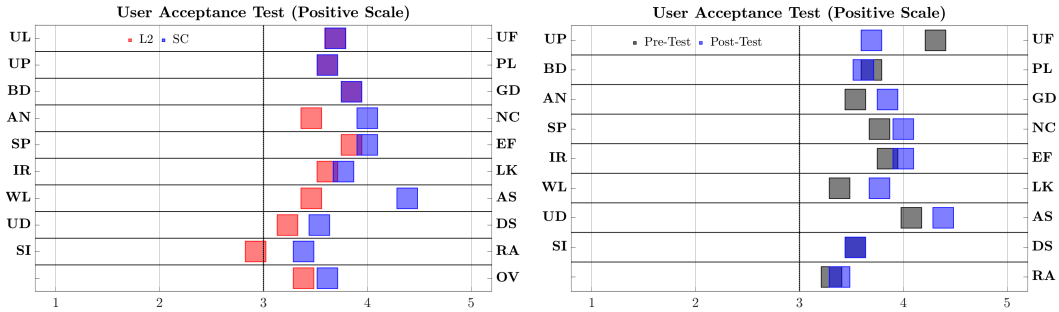
Participant	SUS01	SUS02	SUS03	SUS04	SUS05	SUS06	SUS07	SUS08	SUS09	SUS10	SUS
1	3	1	5	1	5	1	4	1	5	1	92,5
2	1	1	5	2	4	2	4	3	1	1	65,0
3	5	2	5	2	4	2	4	2	4	2	80,0
4	4	2	5	1	4	2	4	2	4	1	82,5
5	1	3	3	1	4	2	5	3	2	1	62,5
6	2	4	2	2	4	1	3	3	3	1	57,5
7	3	2	4	2	4	2	3	2	3	1	70,0
8	2	1	4	2	2	2	3	2	1	2	57,5
9	3	1	5	1	5	1	5	2	4	1	90,0
10	5	1	5	1	5	1	5	1	5	1	100,0
11	3	1	5	1	5	1	5	1	4	1	92,5
12	2	1	5	1	3	3	5	2	4	1	77,5
13	2	1	2	2	3	1	2	2	4	1	65,0

Tab. 5.12: Questions for the user acceptance test

	1	2	3	4	5	
Useful (UF)						Useless (UL)
Pleasant (PL)						Unpleasant (UP)
Bad (BD)						Good (GD)
Nice (NC)						Annoying (AN)
Effective (EF)						Superfluous (SP)
Irritating (IR)						Likeable (LK)
Assisting (AS)						Worthless (WL)
Undesirable (UD)						Desirable (DS)
Raising alertness (RA)						Sleep-inducing (SI)

assisting, less distracting, more attentive, and more desirable. Interestingly, SC is also perceived as less annoying even when unexpected and strong interventions occur. As mentioned earlier, the improvement in safety offsets this, but the automatic transitions also offer advantages over manual activation of L2 mode. In addition, a look at Figure 5.31b shows that the comparison between the pre and post-test questionnaires indicates that the SC system exceeds users' expectations, apart from the fact that they found it more useful.

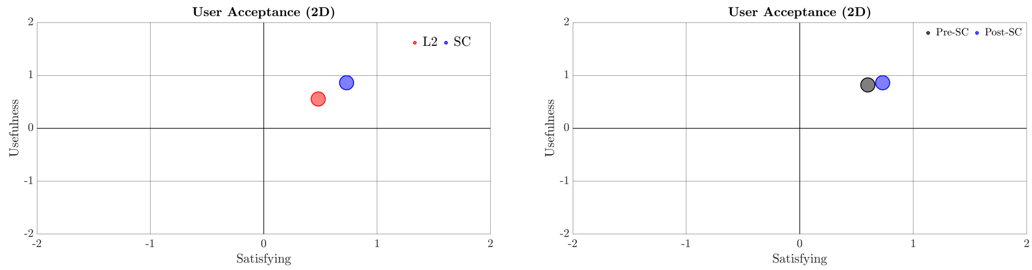
In addition, for a more summary evaluation of the results, odd fields are grouped as usefulness indicators, and even fields represent the user satisfaction after testing the system. The scores range from -2 to 2, with 2 being the better result. The 2D graph shows the overall results of user acceptance, as shown in Figure 5.32a. The SC system has better acceptance in both usefulness and satisfaction, with an overall score of 1.12 (compared to 0.73 for the L2 system). In addition, the comparison



(a) Comparison between L2 and SC systems **(b)** Expectation vs Reality of SC system

Fig. 5.31: Average scores for the user acceptance questionnaire

between the pre and post-test questionnaires shows that the SC system exceeds the users' expectations in both satisfaction and usefulness.



(a) Comparison between L2 and SC systems **(b)** Expectation vs Reality of SC system

Fig. 5.32: Average scores for the user acceptance questionnaire

5.2.7 Conclusion

This use case explores collaboration between humans and automation (as a team) when one (or two) of the members has limited resources (e.g., when the human and automation have limited visibility for the overtaking maneuver). The approach uses an NMPC technique as the torque controller and a fuzzy logic decision system for the arbitration module. Experiments were conducted to evaluate the advantages of SC compared to a commercial L2 autopilot function. After analyzing the results, the following conclusions were drawn:

- SC proved to be the best solution for assisting the driver during the overtaking compared to the L2 vehicle. Although none of them resulted in lane departure accidents, SC significantly reduced the number of near misses and unsafe events.
- The SC longer and smoother control transitions are one of the factors that help the system better protect the driver, because it does not deactivate immediately on the driver's command, but only when it is safe to do so.
- The SUS questionnaire shows that the SC system is rated A-, while the L2 system is rated B-. However, for the results to be meaningful enough, the number of participants needs to be increased to 50 or more drivers.

- Future experiments could compare the SC mode with other overtaking aids, such as Automatic Lane-Change Assistance for L3 vehicles or steering assistance during the overtaking maneuver for L2 functions.
- Further experiments should find the optimal level of authority for drivers to feel the balance between safety and steering conflict. The user acceptance test shows that the assistance function of the system is well perceived, but the scores for ease of use and comfort were not the best.

Conclusions 6

This chapter summarizes the main findings of this Ph.D. Thesis, based on the systematic state-of-the-art in shared-control of automated vehicles presented in Chapter 2, the shared-control Framework ellaborated in Chapter 3, the experience gained in designing, developing, and testing a steering-based shared-controller described in Chapter 4, and the results of two experimental studies evaluating ADAS based on shared-control in a DiL simulator presented in Chapter 5. The chapter concludes with recommendations and future work in this area.

6.1 Concluding Remarks

Automated vehicles are a promising solution to reduce traffic fatalities and serious accidents on the road. However, after an initial rush to self-driving cars (i.e., L4/5 vehicles) that no longer require humans to be behind the wheel, it became clear that technology, society, and governments were not ready for such implementation on the daily roads in the short term. In this context, highly automated vehicles where the driver can still intervene (i.e., L2/L3 vehicles) have been the subject of research for a decade. However, new challenges are emerging. For L2 vehicles, the problem is that the driver overtrust automation and stops monitoring the environment and being ready to take control at any time (accidents involving autopilots have been reported). For L3 vehicles, the problem is that the driver loses situational awareness and can become drowsy, which can lead to an inability to respond to a vehicle takeover request with good performance. On the other hand, driver assistance systems for L1 vehicles are already part of private vehicles, but the support is simple compared to the available technology that can be used to develop more advanced systems.

In this context, experts in the field have worked towards two main strategies. One is to improve the HMI interaction between the driver and the vehicle to ensure a safe takeover maneuver when the system prompts the driver. This includes continuous monitoring of driver status, including secondary tasks performed in the vehicle. However, there is still the problem that vehicles cannot guarantee a time to take over in all scenarios. In this sense, this technology can be used in the short term for controlled scenarios such as traffic congestions or highways. However, accidents also occur in more complex scenarios. Therefore, another opportunity is to better support manual driving and enhance collaboration between drivers and automation at the control level. To this end, shared-control is an attractive approach to improve driver performance and road safety through the use of new sensor technologies and advanced control techniques, while avoiding the out-of-the-loop problems that occur with higher levels of automation. In this context, shared-control refers to the idea that the driver and automation are a well-coordinated team working continuously on the driving task at both the tactical and control levels.

Based on these premises, this Ph.D. thesis ellaborated on the issue of shared-control for automated vehicles, both theoretically and practically. The theoretical approach first consisted of a systematic review to evaluate the state-of-the-art and common methods for shared-control strategies. In practice, the development of a novel control system for shared-control was presented along with various arbitration systems used for specific use cases. Finally, two experimental studies were conducted to evaluate ADAS based on shared-control in the scenarios of a distracted driver and in an overtaking maneuver. In the following sections, conclusions on the main results are presented.

6.1.1 Lessos from the State-of-the-Art

In **Chapter 2**, the literature on shared-control of automated vehicles was thoroughly reviewed, with more than 150 papers on the subject. The review covered both the theory and current applications developed specifically for steering assistance systems. The key findings are summarized below.

- The **concept** of *shared-control* has been at the center of debate for decades. In recent years, collaboration among various experts in the field has led to a more precise definition and differentiation from other types of cooperation. In automated vehicle systems in particular, it has become well understood in practice, as continuous haptic feedback in steering or pedals.
- The **numbers of works** in the research community is increasing every year as more and more researchers conduct research in this area, especially with applications for steering assistance systems.
- **Automotive manufacturers** are still focusing on increasing the level of automation, but relevant vehicle demonstrators and prototypes from automakers are improving the collaboration between drivers and automation at the wheel. Although many of them operate under the traded control scheme, at least one automaker (Toyota) is applying the shared-control concept to its research vehicles.
- Many **experimental studies** have been conducted testing shared-control ADAS with DiL simulators. The objective and subjective results are overall positive and encourage to improve the quality of the studies. Nevertheless, only a few real vehicle implementations are available, which shows that the technology is still under development and a big step needs to be taken towards implementation in relevant demonstrators.
- Several **projects** are funded by public and private institutions to study human-machine cooperation in automated driving. However, most strategies are based on the design of the human-machine interface (HMI) to allow the driver to play a safe monitoring/fallback role in highly automated vehicles. Although many of these projects offer shared-control-based solutions, more projects that focus exclusively on shared-control systems are needed to advance these developments and see multiple relevant vehicle demonstrators.

- Applications based on shared-control for automated driving mainly focus on using the steering wheel as the **control mechanism** to cooperate with. Haptic pedals, on the other hand, have been studied to a lesser extent.
- In terms of **control algorithms**, torque-based controllers using optimal control frameworks are the trending option for the development of ADAS with shared-control functions, as they outperform position-based controllers in terms of cooperation with the driver. Furthermore, optimal control is an appropriate technique to balance the different control objectives that this cooperation strategy requires (performance, safety, comfort, conflict).
- The **challenge** in developing the controller is to find a balance between safety and comfort. Here, torque conflict is the desired target to be minimized so that drivers do not feel inconvenienced by the system, but instead feel comfortably supported. This conflict is easier to resolve with steer-by-wire (uncoupled shared-control) systems, but at the cost of introducing a new paradigm of vehicle control where the driver might observe the vehicle doing something not commanded at the steering wheel.
- A **desirable feature** is to have a driver model included in the road-vehicle system. This has proven helpful in reducing conflicts and allowing seamless collaboration. However, modeling the driver is not an intuitive task and presents additional challenges. Another recommendation for resolving driver-automation conflicts is to use a human-centered design for the reference trajectory followed by the controller (i.e., not just having the controller follow the center of the lane).
- As for the decision algorithms related to the **arbitration** system, there are some relevant variables that need to be considered. On the one hand, the common approach is that the driver must be assisted only when necessary, either because s/he is overloaded or underloaded by the driving activity. This logic must be part of the arbitration system. On the other hand, the inclusion of certain variables is of interest. The TTC seems to be a promising option to consider both the driver's performance and safety, instead of considering only the driving errors. Driver state is also an important consideration in decisions for shared-control algorithms, especially the level of distraction. In addition, for more complex maneuvers, a module for risk assessment of the whole environment is needed, and finally, the degree of conflict or cooperation should be considered. In summary, the arbitration system must consider the driving state from three perspectives: driver, vehicle, and environment.
- To properly evaluate systems based on experimental studies, it is important to consider the axiom of evaluation for shared-control presented by Abbink [8]. The recommendation is that the **design of the experiment** must include baselines at both extremes of automation, the manual mode on the one hand, and current solutions for highly automated vehicles (especially L2 and L3 or any traded control scheme) on the other. The metric of takeover performance is one that has

been studied only to a limited extent, but is an important variable for comparing the performance of shared-control systems with that of traded-control systems.

6.1.2 Lessons from the Integration of the Framework

Chapter 3 presented the shared-control framework used in this dissertation. It consisted first of integrating the components of shared-control (mainly arbitration and haptic authority control) into a general framework for the development of automated driving. A modular analysis was conducted comparing the challenges of implementing shared-control versus highly automated vehicles. A summary of the key findings can be found below:

- In terms of **implementation requirements**, in commercial vehicles shared-control would require less effort and complexity for the sensor/perception system, but it would direct efforts toward HMI collaboration strategies and steering control strategies that are both effective in terms of safety and performance and easily accepted by drivers.
- A clear distinction between the tactical and operational modules of shared-control is beneficial to the design of such a system. In this way, this architecture allows for the design of an **scalable controller** (i.e., designed as a black box) and the arbitration system adapted to fit any scenario.

6.1.3 Lessons from the Development of the Controller

Chapter 4 describes in detail the design, development, and validation of the steering shared-controller used in this Ph.D. Thesis. The development was carried out in a process that consisted of four iterations. The main results are listed below.

- The final developments resulted in a **robust controller** is able to support the driver with different levels of haptic authority (any torque greater than 0 and less than 15 N.m), without losing stability and performance, at different speeds (tested up to 120 km/h).
- The novelty of this controller is the included stability criterion (which found an optimal steering damping value) where not a single parameter of the nominal NMPC needs to be reset.
- The controller is also able to **meet the constraints**, such as the yaw rate and the maximum torque. However, it is necessary to evaluate the torque derivative constraint on a larger scale.
- The choice of fuzzy logic as the algorithm for the development of the arbitration system has proven to be advantageous, as it provides easy-to-program rules and adapts different driving variables to real-world scenarios in an intuitive way. It has also proven to be a **versatile decision-making tool**, as it has been possible to develop a system with 4 inputs and 2 outputs.

- In terms of **hardware**, steering wheels that can input and output data at a frequency of 1 ms are desirable not only for control but also for hand feel. Steering motors with the ability to electronically change damping are also desirable, since the stability criterion proposed in this dissertation relies on additional steering damping. In addition, robust torque sensors are an important sensor that should be considered in algorithms for steering shared-control.
- The ACADO toolkit proved to be a reliable option for **solving the NMPC controller** optimal problem, finding solutions under 2 ms.

6.1.4 Lessons from the Conducted Studies

Chapter 5 presented the objective and subjective evaluation of two ADAS based on shared-control. The first assisted the driver during distracted driving maneuvers and was compared to three baseline models (manual driving, LKAS, and ALC). The second supported the driver during an overtaking maneuver on a road with oncoming traffic and was compared with a conventional L2 autopilot. The main results of the studies conducted are presented below.

- The shared-control system to **assist distracted drivers** was shown to improve tracking performance and safety among distracted drivers. It also showed a reduction in driver-automation conflicts compared to ALC. In addition, the results suggest that a combination of the adaptability of the shared-control system and the supportive behavior of the LKAS when turning is a good combination for future developments. Overall, drivers rated the shared-control system positively. To improve this pilot study, it is necessary to increase the number of participants (5 in this case) and add new metrics to the experiment. For example, include the situation where the system fails when distracted and the driver must take full control of the driving task.
- The shared-control system for **overtaking a slow truck** was found to promote safety after evaluating various metrics compared to the L2 autopilot. In addition, the longer control transitions proved beneficial to safety and driver acceptance. Overall, drivers rated the new features added by shared-control higher when analyzing three subjective evaluation methods. In addition, the results of the SUS scale recommended increasing the number of participants from 13 to 51 to obtain a result with sufficient significance in terms of outcome probability.

6.2 Research Perspective and Future Works

This dissertation has comprehensively and deeply addressed the area of shared-control in automated vehicles from both theoretical and practical perspectives. In this sense, researchers can use this document as a reference for future developments to extend the studies, improve the robustness of the controller, and promote new scenarios in which shared-control is a solution to achieve safer roads. In this context, the proposed future perspective in this area are:

- **Systematic review for evaluation of shared-control**: The state-of-the-art presented in this paper addresses shared-control mainly in terms of control algorithms. However, it is not only important to know how to develop the system, but also how to validate and properly evaluate it. In this sense, a comprehensive overview of the methods used to evaluate shared-control systems in automated driving, including the ideal basis of comparison for each scenario, and the publication of the relevant metrics in terms of performance, safety and comfort would be of great benefit.
- **Advance the shared-controller**: The NMPC-based shared-controller developed in this work could be improved by adding a driver model to the proposed road-vehicle model. On the other hand, the inclusion of power steering behavior to cover the full range of assistance is a desired feature for future developments. Also, it would be useful to integrate the longitudinal control in the optimization NMPC framework, even considering other modalities such as torque vectoring [288] that involves lateral and longitudinal corrections.
- **Torque values parametrization**: Controller design requires prior knowledge of how the driver perceives steering torque. With this in mind, further experimentation is needed to determine the values of the torques that fall into the categories of no assist, smooth assist, medium assist, correction, and override. With this in mind, the HADRIAN project is working to determine the optimal torque values for an evasive maneuver.
- **Haptic icons**: The interaction between the driver and the vehicle control interfaces during shared-control enables an enriched communication channel via the steering wheel. The so-called haptic icons are a promising communication strategy that overlays the steering of the vehicle to convey driving-related information to the driver.
- **Driver-by-wire**: The implementation of shared-control in vehicles using steer-by-wire technology is a promising solution that is currently being investigated. It has the advantage of reducing the conflict between driver and automation. However, the driver's reaction to the new control paradigm, where the automation can perform an action that is contrary to the commands given by the driver via the steering wheel, still needs to be studied in detail.
- **Multimodal HMIs**: Shared-control will benefit from other HMI strategies that improve cooperation between drivers and automation at the tactical and control levels. The combination of multiple HMIs in an active safety system scenario based on shared-control is being investigated as part of the HADRIAN project.
- **New scenarios**: Shared-control can improve manual driving in scenarios that involve following the lane, performing a lateral maneuver, or even helping the driver regain manual control of the vehicle. However, there are other interesting scenarios where shared-control can be useful in difficult conditions. For example, in poor visibility conditions due to rain or in slippery snow. Physically impaired

drivers can also benefit from this mode and have a safer and more comfortable driving experience.

- **Experimental studies**: Overall, studies conducted in DiL simulators include fewer than 20 participants. Therefore, studies with a larger number of participants are needed to validate such systems. In addition, assessment of driver takeover performance during expected and unexpected control transitions is an important metric that is critical to promoting shared-control systems as a safer option over traded control.
- **Moving to real platforms**: Most of the implementations have been done in numerical simulations and DiL simulators. Few works have demonstrated shared-control in experimental vehicles. To make further progress in this area, it is important to work towards implementing shared-control algorithms in real vehicles to demonstrate the benefits of such a system in real platforms and to evaluate the acceptance of drivers when testing such systems in real scenarios.
- **Legal framework**: It is well known that an appropriate legal framework for highly automated vehicles is difficult, as some issues, such as responsibility in case of accidents, need to be addressed. For vehicles with shared-control functions, this problem is easier to solve because the driver is responsible for the driving task. However, the fact that in some cases the system can overrule the driver or induces the driver to perform certain maneuvers is an aspect that needs to be considered in future legal frameworks for these types of systems

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