Deliverable D2.1

WP2 Report on case studies and analysis of transferability from other sectors

Project acronym:	RAILS
Starting date:	01/12/2019
Duration (in months):	43
Call (part) identifier:	H2020-S2R-OC-IPX-01-2019
Grant agreement no:	881782
Due date of deliverable:	Month 22
Actual submission date:	November 2nd 2021
Responsible/Author:	Stefania Santini (CINI)
Dissemination level:	Public
Status:	Final

Reviewed: no

Document history		
Revision	*Date*	*Description*
1	October 11th 2021	First issue for internal review
2	October $29th$ 2021	Second issue after internal review
3	January $14th$ 2022	Final version after JU revision

Report contributors		
Name	Beneficiary Short Name	Details of contribution
Francesco Flammini	LNU	Task Leader
Stefania Santini	CINI	Contributor
Lorenzo De Donato	CINI	Contributor
Valeria Vittorini	CINI	Contributor

Advisory Board Reviewers	
Name	*Company or Institution*
Pasquale Donadio	Comesvil
Claudio Mazzariello	Hitachi Rail STS

Funding

This project has received funding from the Shift2Rail Joint Undertaking under the European Union's Horizon 2020 research and innovation programme under grant agreement n. 881782 Rails. The JU receives support from the European Union's Horizon 2020 research and innovation program and the Shift2Rail JU members other than the Union.

Contents

Executive Summary

This Deliverable reports activities and results related to relevant AI applications in other sectors, and a preliminary study about their transferability to the rail domain, with a special focus on safe rail automation. Two main case studies are also identified and introduced, that will provide the context for the development of proof of concepts throughout WP2. Hence, this Deliverable defines the scope and the boundary of the ongoing research carried out in WP2.

Specifically, the document addresses the following main themes: i) the definition of a methodological framework for transferability, ii) a review of the most relevant AI applications in automation from other relevant sectors, iii) the identification of directions for transferability, and iv) the selection of case studies that can encompass a broad area of investigation, because they are conceived as containers in which several research directions can be explored.

It is worth noting that this deliverable contains high-level transferability guidelines, while more specific analyses would require as many in-depth studies as the number of the relevant applications reported in the other sectors and enter into the substance of technical characteristics of both AI techniques and the systems under study, also including the technologies involved (e.g., IoT devices, communication means, cloud resources, and the like).

Among the objectives of the case studies, one is to provide *the context* for specific transferability analyses, selected from the directions identified in the document, and further develop and assess the transferability framework introduced herein.

Abbreviations and acronyms

Abbreviations / Acronyms	Description
3GPP	3rd Generation Partnership Project
5G	Fifth Generation
5G-R	Fifth Generation for Railway
A3C	Advantage Actor-Critic
ACC	Adaptive Cruise Control
ACF	Aggregate Channel Features
ACS	Adaptable Communication System
ADAS	Advanced Driver-Assistance Systems
ADSs	Autonomous Driving Systems
AI	Artificial Intelligence
AID	Automatic Incident Detection
AoI	Age of Information
ANN	Artificial Neural Network
ATIS	Advanced Traveler Information Systems
ATs	Autonomous Trains
AVs	Autonomous Vehicles
BEV	Battery Electric Vehicle
BS	Base Station
BSC	Base Station Controller
CACC	Cooperative Adaptive Cruise Control
CAD	Connected Autonomous Driving
CAMs	Cooperative Awareness Messages
CAN	Controlled Area Networks
CAS	Collision Avoidance Systems
CAVs	Connected and Autonomous Vehicles
CNN	Convolutional Neural Network
CBTC	Communications-Based Train Control
CRF	Conditional Random Field
C-V2X	Cellular V2X
D3QN	Dueling Double Deep Q-Networks
DAS	Driver Assistance Systems
DCNN	Deep Convolutional Neural Network
DDPG	Deep Deterministic Policy Gradients
DDQN	Double Deep Q-Network
DEC-POMDP	Decentralized Partially Observable Markov Decision Process
DeepDCA	Deep Learning and Dendritic Cell Algorithm
DF	Data Fusion
DL	Deep Learning
DN	Deconvolutional Network
DNN	Deep Neural Networks
DPGA	Deterministic Policy Gradient Algorithm
DQN	Deep Q-Learning Network

DRL	Deep Reinforcement Learning
DS	Driving Style
DSRC	Dedicated Short-Range Communications
E2E	End-to-End
ECUs	Electronic Controller Units
eMLPP	Enhanced Multi-Level Precedence and Preemption
ETCS	European Train Control System
FCN	Fully Convolutional Network
FCW	Forward Collision Warning
GPS	Global Positioning System
HAPS	High Altitude Platform Stations
HEV	Hybrid Electric Vehicle
HSRs	High-Speed Railways
I-ADAS	Intersection Advanced Driver-Assistance Systems
IDS	Intrusion Detection Systems
IIoT	Industrial Internet of Trains
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
IS	Instance Segmentation
ITS	Intelligent Transportation Systems
KELM	Kernel-based Extreme Learning Machine
LiDAR	Light Detection and Ranging
LSTM	Long Short-Term Memory
LTE	Long Term Evolution
LTE-A	Long Term Evolution Advanced
MAC	Medium Access Control
MACAD-Gym	Multi-Agent Connected, Autonomous Driving agent learning platform
MADDPG	Multi-Agent Deep Deterministic Policy Gradient
MARL	Multi-Agent (Deep) Reinforcement Learning
MAS	Multi-Agent Systems
MCWA	MLPNN-based rear-end collision Warning Algorithm
MIMO	Multiple-Input-Multiple-Output
ML	Machine Learning
MLPNN	Multi-Layer Perceptron Neural Network
mmWave	millimeter-Wave
MSC	Mobile Switching Centre
NGP	Next Generation Positioning
NGSIM	Next Generation Simulation
NLOS	Non-Line-Of-Sight capability
NMFNet	Navigation Multimodal Fusion Network
NR	New Radio
NR-V2X	New Radio V2X
MTL	Multi-Task Learning
OFDM	Orthogonal Frequency Division Multiplexing
OTA	Over-the-Air

PHEV	Plug-in Hybrid Electric Vehicle
PHY	Physical
PL	Platoon Leader
POMDP	Partially Observable Markov Decision Process
POSG	Partially Observable Markov Games
Q0E	Quality of Experience
QoS	Quality of Service
Radar	Radio Detection and Ranging
RAT	Radio Access Technologies
RCNNs	Recurrent Convolutional Neural Networks
RefineNet	Multi-Path Refinement Network
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RoI	Region of Interest
RPN	Region Proposal Network
RSU	Road-Side Unit
RVM	Relevance Vector Machine
R-CNN	Region-based CNN
SAE	Society of Automotive Engineers
SCN	Single Convolutional Network
SDN	Software-Defined Networking
SegNet	Deep Semantic Segmentation Network
SI	Swarm Intelligence
SLAM	Simultaneous Location and Mapping
SS	Semantic Segmentation
SUMO	Simulation of Urban MObility
SVM	Support Vector Machine
SWA	Side Warning Assist
TGbd	IEEE Task Group 802.11bd
T2X	Train-to-Everything
TTA	Terrain Traversability Analysis
UEs	User Equipments
UAVs	Unmanned Aerial Vehicles
UIC	International Union of Railways
UGVs	Unmanned Ground Vehicles
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-everything
VBS	Voice Broadcast Service
VC	Virtual Coupling
VGCS	Voice Group Call Service
WSNs	Wireless Sensor Networks
YOLO	You Only Look Once

1. Background

The present document constitutes the Deliverable D2.1 “WP2 Report on case studies and analysis of transferability from other sectors” of the S2R JU project “Roadmaps for AI integration in the Rail Sector” (RAILS). The project is in the framework of Shift2Rail’s Innovation Programme IPX. As such, RAILS does not focus on a specific domain, nor does it directly contribute to specific Technical Demonstrators but contributes to Disruptive Innovation and Exploratory Research in the field of Artificial Intelligence within the Shift2Rail Innovation Programme. The RAILS research is structured in three main phases:

- DISCOVER, covering all the preliminary survey and analysis activities.
- ASSESS, covering all the core development and experimentation activities.
- LEARN, covering all the follow-up and knowledge dissemination activities.

The work carried out in WP1 (State-of-the-art of artificial intelligence in railway transport) achieved the following objectives: i) to provide an in-depth review of the current research on the application of Artificial Intelligence (AI) in railways and of AI techniques and methods, ii) to build a first map of AI technologies to solve railway problems or improve performance in railway scenarios, iii) to identify specific needs and railway application areas for future research, iv) to point out the major open problems and challenges for AI adoption according to the current research and the railway stakeholders, v) to determine some priority directions and provide preliminary recommendations.

Starting from the findings and the application areas identified in WP1, the objective of the ASSESS phase is to define pilot case studies and develop proof of concepts leading to a technology roadmapping for an effective pick-up of AI in the rail sector. To this aim, the ASSESS phase includes three technical workpackages that investigate different railway domains but have the same task structure. The first step of the ASSESS phase is an analysis of AI applications from other sectors in order to enable transferability studies, and the identification of possible case studies. The case studies are not specifically aimed at transferability but they are the context of the technical activities carried out in the workpackages. Transferability is just one of the aspect that will be addressed.

Deliverable D2.1 describes the work carried out in task 2.1 of Work Package WP2 that investigates the adoption of learning techniques and other AI methods for **enhanced safety and rail automation**. WP2 specific objectives are:

- To study the transferability of classical and novel approaches basing on the available results from rail as assessed in WP1 and from other transportation sectors.
- To develop pilot case studies in specific operational scenarios, according to the outcomes of WP1 and exploiting the support of the RAILS Advisory Board.
- To develop AI-based approaches and solution to address the problems and the challenges proposed in the case studies.
- To define evaluation criteria for the specific operational scenarios.
- To ensure a deep insight into the possible use of AI for future railway applications.

This document reports about relevant AI applications in other sector, poses the basis for developing transferability studies, and introduces the possible case studies in the area of railway safety and automation.

2. Objective

The main objectives of this document are: 1) to identify and describe AI applications from other sectors that potentially may be generalised/modified to some extent to be applied to railway problems, 2) provide some guidelines for the development of transferability studies, 3) identify relevant case studies to be developed through the WP activities. Therefore, this deliverable reports of the analysis carried on in Task 2.1 with the objective to:

- assess the open problems, research challenges, methods and tools from others transportation/relevant sectors;
- analyse the available results for identifying a set of learning methods and application in rail automation, with a special focus on unmanned vehicles and automotive;
- define pilot case studies by instantiating the application areas identified in WP1 to specific uses cases and operational scenarios in rail automation.

In order to provide a transferability framework for discussion and investigation, a methodological approach is proposed before reporting about the review of AI applications in relevant sectors other than railways. The proposed approach is introduced in this document and it needs to be further developed and assessed by discussing with the railway stakeholders and applying it to the concrete transferability analyses that will be conducted in WP2, WP3 and WP4. For this reason it is briefly presented in the Introduction and it is not given more emphasis in a separate chapter.

AI applications from Robotics and Automotive are surveyed and analysed: The focus is on **vehicle automation**, therefore key topics of the study are AI applications for autonomous control in Automotive and **Unmanned Vehicles** in Robotics, including both Areal and Ground vehicles. *Special emphasis is given to Automotive*, because the wide research effort that has been spent currently and the past years in the development of AI-based solutions for autonomous driving. For this reason, this document provides an in an-depth assessment of the current state of research as well as of the current or emerging technologies technologies for vehicles control.

Further, according to the results of WP1, attention is payed to **trustworthiness and explainability**, as well as to existing applications of AI to **risk assessment**. Techniques for coping with limited data are also considered, due to the importance of this topic when coming to data-driven AI approaches. These research directions will be addressed by specific proof of concepts in the context of the case studies.

3. Introduction

Transferability studies aim at investigating the extent to which research findings or new technologies can be applied in other contexts. As such, this document reports the activities carried out in this direction by:

- proposing guidelines for carrying out transferability studies;
- identifying relevant AI-based approaches developed in sectors different than railways;
- providing *indications* about transferability directions towards railway systems, focusing on railway safety and automation.

Determining whether research findings or technologies can actually be transferred from one context to another is a complex activity that cannot be performed within the time span of a limited analysis. Therefore, here we report the work performed to take a first step towards such an objective. This first step will help to design proper roadmaps to transferability scenarios.

The structure of the document reflects the process we made to carry out the study. First, we present some preliminary criteria for transferability, then, chapters 4 and 5 report on research findings and technologies currently available in related sectors other than railways. Chapter 6 proposes transferability directions and establishes relationships between the findings of WP1 and the proposed directions. In particular the review done in WP1 supports the discussion provided in Sections 6.5 and 6.6.

The results of this analysis are still *perceptions* of transferability/applicability, they provides indications but need to be verified through proper research.

Chapter 7 identifies possible pilot case studies, taking into account both the potential that emerged by the activities carried out in task 2.1 and the needed expressed by the railway community according to the outcomes of WP1. The primary objective of the case studies is not tranferability, because they are meant to be the testbench for the research of the project, but they provide the context in which some transferability activities can be developed.

3.1. Transferability Criteria

In this Section we give some dimensions for the transferability of AI-based applications from other sectors to railways. We only focus on scientific and technical aspects. Social, political, and legal dimensions are not considered at this level. The definition of the preliminary criteria for transferability is based on: a) the outcome of the DISCOVER phase conducted in WP1, because that work provide us with indications from all the relevant stakeholders and from the analysis of the railway problems related to safety and automation; b) the transferability analyses conducted in other sectors. Although these studies are tailored to other scientific areas and other objectives, they provide some general indications.

According to the related literature, transferability primarily involve the perception of who is interested in assessing the applicability of the research findings or technology that can be of potential use (e.g., see [1]). The factors affecting this perception are based both on general considerations, i.e. dimensions that are generally valid, and domain-based concerns that are important in the specific target sector. Hence, to set **a framework for transferability**

in the critical area of railway safety and automation, we start from general dimensions that help to identify useful criteria.

In doing so, we take a first step to define a transferability methodology that will be further developed in the next project tasks, supported by a discussion with the railway stakeholders within Advisory Board meetings and intermediate project workshop.

Transferability refers to the possibility of transferring the results or findings of research from one domain (*source*) (e.g., automotive), to another domain (*target*) (e.g., railways).

In the following, the research is intended to be related to the development and usage of AI-based solutions, findings and results of the research are intended to cover a wide spectrum of possible outcomes, whose transferability we are interested in, including AI-based methodologies, approaches, methods, techniques, and technologies. We will refer to all them with the generic expression of *AI applications*.

Some general transferability dimensions and some derived criteria for their application to the railway context in WP2 are introduced herein:

- Congruence;
- Significance;
- Preservation;
- Similarity;
- Maturity;
- Implementability.

Congruence is the adherence of the AI application we want to transfer to the *mission, aims and scope* of the target domain/system and to *previous experiences* (if any). For example, the general mission of the target domain system in our context is *the safe transportation of passengers and freights for a better society*, thus excluding military purposes. As such, AI-based solutions for defence or other military targets could be not congruent with this mission and should be carefully examined.

Therefore, *Congruence* also includes values and principles that have to be fulfilled. In the specific case of safety or security critical railway applications, the degree in which *trustworthiness* and its attributes are considered in the source domain is an important evaluation criteria of transferability. As for the innovative nature of the studied AI applications, this criterion will often refer to the *expected* trustworthiness.

Significance is a measure of the benefits that the adoption the of the AI application we want to transfer may bring in the target domain, regardless of its maturity. This includes the *potential effectiveness* of the application and its (positive) *impact*. In other words, the degree to which the application is expected to produce the desired results if successfully transferred, and the impact this result may have on the target domain (for example, higher level of safety, increased line capacity, etc.).

Preservation says if the adoption of the AI application in the target domain may affect relevant properties of the target system, and to what extent. In this context we consider that *safety* and *security* of the system must be preserved. In case they are affected, this may also be due to the technologies required to deploy the AI application, and not to the AI application itself. If the safety or security state of the system may be affected, a risk analysis process could be required for safety/security critical systems or functions, which enable to assess the safety/security properties granted, for example, by cloud-based (AI) applications. Therefore,

careful attention should be paid to the level of **Preservation** of *safety* and *security*. Please note that this is different from trustworthiness, that is a quality of the AI techniques employed.

Similarity includes two aspects: a) the similarities between the specific goal of the AI application we want to transfer and the *goal* we want to achieve in the target domain (for example, a given level of autonomy), and b) the similarities between those characteristics of the target and source domain on which the AI application is based (for example the presence or the absence of a control infrastructure). Therefore, similarity provides a measure of the distance between the source and target applications.

Maturity is the maturity level of the AI application in the target domain. It can be measured using the TRL (Technology Readiness Level) if this makes sense for the specific study, or other evaluation criteria can be used for decide if the maturity reached in the source domain is sufficient for transferability. The maturity of an AI-based *technique* used to achieve a given results in the target domain, and the results itself (i.e., the AI application) can be considered separately. For example, an AI-based obstacle detection approach can be well assessed but the outcomes obtained by applying it to a specific purpose in the target domain may not have not be fully assessed yet.

Implementability is related to the easy of implementation of the AI application and its sustainability. It is a measure of the effort and cost needed to implement the AI application in the target domain, taking into account the required technologies, skills and the possibility to maintain the application over time.

As explained before, these dimensions are suggested by the literature (e.g., see [1], [2]) and by the perception of the stakeholders, as it emerges from WP1 (including the perception of those who are carrying out this research). The order used to list them is not casual. They are sorted in descending order according to their importance for the realisability and purpose of transferability. The order may change for different analyses/contexts, but it should be clearly stated at the beginning of the analysis. In the context of railway safety and automation we primarly consider the congruence with the system mission and the expenditure of the intervention, that should be proportional to the benefits, i.e. its significance, followed by the preservation of safety and security. Nonetheless, it must be considered that dimensions and criteria are not independent in the transferability analysis: for example, a low level of trustworthiness or maturity may lower the capability of preserving the safety and security of the system.

			Very High	High	Medium	Low	Very Low
Dimension	Criterium	Domain Specific					
Congruence	mission/aim/scope						
	trustworthiness						
	previous experience						
Significance	potential						
	impact						
Preservation	safety						
	security						
Similarity	objective/goal						
	domain characteristics						
Maturity	AI technique						
	AI application						
Implementability	technology						
	sustainability						

Fig. 3.1. Transferability Table (TTable)

Fig. 3.1 shows a Transferability Table (TTable) that can support the analysis. The TTable can be customised, and be part of a worksheet to contain more information for a qualitative approach to transferability.

The column ”criterium” allows the specialisation of the related dimension to the target domain, nonetheless further levels can be considered if necessary, so adding one or more ”Domain Specific” columns to detail more specific criteria.

The levels used in the TTable (Very High, High, Medium, Low, Very Low) specify *at what extent the transferability criteria are met* by the AI application under study for the specified objective in the source or target domain (accordingly to the definition of the dimension/criterium).

Although the method could appear intuitive, the assessment of these levels is subjective (as in many other qualitative analysis) and a way to establish the thresholds for their evaluation must be provided case by case. Therefore, the TTable must be accompanied by further tools or studies. For example, proper **checklists** can be developed in order to collect information and support the assessment of transferability.

It is worth noting that the goal of the TTable is to provide *indications* about the transferability of a given AI-based approach to the railway sector for a specific objective: it says if it makes sense to take further steps in that direction.

On the contrary, if the values in the TTable are all ”Very High”, including the level of ”previous experience”, this might be an indication that a similar AI application has been already implemented in railways.

A **quantitative approach** can also be developed by defining proper *Transferability Indicators* on the basis of available data and information. For example, under the hypothesis that the TTable allows to identify the relevant factors (through the evaluation of dimensions and criteria) that can significantly influence the transferability of the AI application under study, it could be possible to identify the relationships between such factors and exploit appropriate metrics to calculate the feasibility of a successful technology transfer, by also identifying the most important contributing factors or how specific factors influence the probability of success.

4. AI-based Emerging Technologies in Unmanned Vehicles

4.1. Unmanned Aerial Vehicles

Unmanned Aerial Vehicles (UAVs) have been extremely useful in different scenarios as they allow us to reach remote areas [3], poorly predisposed for human access, and to deal with more sensitive (or critical) situations such as military operations [4], surveillance [5, 6], and systems/infrastructures health monitoring [7, 8]. In addition, studies in the literature provide notions about how effective UAVs could be for wireless network communication, also integrating AI-based solutions [9, 10]. Besides the countless scenarios in which UAV-aided applications could be exploited, the purpose of this document is to understand to which extent AI-based solutions for UAV's application can be leveraged in the context of train autonomous driving and control. This involves both AI applications for UAVs operation and the integration of AI and UAVs to tackle relevant problems in this context. Therefore, given this purpose, we focused our attention on three main aspects related to the unmanned aerial world: i) AI-aided communication in UAV's fleets for coordinated flight; ii) intelligent path planning and autonomous flight; iii) AI-aided UAVs as enabling technologies to support and/or improve operations such as obstacle detection and wireless network communication.

4.1.1. AI-aided communication for UAVs coordination

In the context of wireless communication, we can consider two possible scenarios: UAVs communicating with each other (namely UAV networks), and a broader scenario in which UAVs communicate also with other entities (e.g. UGV, ground base stations). In the last decade, there have been different studies approaching both these scenarios by implementing AI solutions to maintain efficient and reliable communication [11–13]. As reported by [11], some attempts were performed by leveraging Reinforcement Learning (RL), nevertheless, it may not find a suitable solution in a proper time frame when it comes to large-scale networks; therefore, Deep Reinforcement Learning (DRL) was introduced to overcome such an issue. Interestingly, Deep Q-Networks (DQN) have been applied to preserve the connection between two UAVs [14] (a leader and a follower) or between multiple leaders and multiple followers [15]. Here, the system is modelled as a Markov Decision Process and the dynamic is handled by a ground base station that, leveraging a DQN, manages the action space and the velocity of the follower(s); however, the authors did not consider the minimum distances between UAVs which may collide.

Mostly the same problem was faced in [16] where the authors implemented a Q-Learning approach to allow a fleet of followers to follow an independently-controlled leader and keep the same flight formation, defined a-priori, throughout the schedule simulation. The base concept was to minimise the Euclidean distance between the real position of the followers and the position in which they should be to be compliant with the given formation by leveraging the Received Signal Strength (RSSI) values of the neighbour UAVs, a partial history of these data, and the previous actions; the connection network was created ad-hoc exploiting the IEEE 802.11.

Regarding collision avoidance, very recently (January 2021), the authors in [17] proposed a complex Multi-Agent (Deep) Reinforcement Learning (MARL) architecture based on the actor-critic model [18] to allow UAVs to reach a given point without colliding with others

UAVs along routes; the simulation was performed considering a 2D airspace. Since the number of UAVs in the airspace was not fixed a-priori and that UAVs exchange information (e.g. position, speed), the authors proposed a RNN (based on LSTM cells) to encode the varying size of input states that each UAV receives; then, each UAV takes its own decision based on the computation of its local actor NN.
Besides RL and DRL, also swarm intelligence (SI) and genetic algorithms have been used to deal with multiple UAVs coordination: the Particle Swarm Optimisation algorithm was used in [19] to coordinate a swarm of UAVs in patrolling operations; an immunology-inspired swarm intelligence algorithm was proposed in [20] to deal with intruders in a monitored area, UAVs communicating with each other were able to autonomously decide whether attack the intruder (when next to them) or continuing their patrolling activity. Then, in 2019, the authors in [21] proposed a comparison between an approach based on swarm intelligence (a modified version of the bee algorithm) and another based on Q-learning aiming to coordinate unmanned aerial systems (UAS) at high altitude to optimally provide a global communication area coverage to mobile users. Performances were evaluated in terms of the number of subscribers (connected users) to each UAS: the SI-based solution resulted to be more reliable but with less area coverage, whereas the RL-based one achieved a better area coverage but with the risk of unpredictable occasional dips due to the individual exploration strategy.

Lastly, what is also of interest is the applicability of Machine Learning (ML) to ensure reliable wireless connectivity in cellular-connected UAVs widely discussed by Challita et al. [22]. The authors deeply investigated three UAV-aided scenarios (i.e. UAV-based delivery systems, UAV-based real-time multimedia streaming, and UAV-enabled intelligent transport systems) and arose, among other challenges, some network security issues possibly mitigable through ML-based solutions. UAVs might be subject to cyber-physical (CP) attacks; in this case, CNNs might be used to create CP threat maps in real-time and classify high-risk locations by exploiting images of the UAV's surroundings, whereas RNNs could be exploited to analyse time-series data (e.g. speed, position, acceleration) and identify whether an UAV is behaving correctly or unnaturally as a consequence of a CP attack. Another possible scenario involves attackers taking the place of some UAVs by stealing and reusing their credentials to transfer malicious data. In large-scale networks, it would be not feasible for base stations (BS) to implement an identification phase each time they receive data from UAVs, therefore, a possible solution lies in the usage of DRL applications based on Long Short-Term Memory (LSTM) cells; in such a way, it would be possible to learn a sequence of future authentication decisions for each UAV based on a sequence of previous security states and UAVs vulnerability. Lastly, swarms of UAVs are susceptible to Adversarial ML attacks (an attacker joins the swarm and affect data sharing); in this scenario, federated learning might be a suitable solution as each UAV, instead of transmitting data to other UAVs, locally processes them and updates a shared ML model, then, a summary of this update is shared with the other components of the fleet.

4.1.2. Intelligent path planning and autonomous flight

Intelligent UAV path planning deals with the design, possibly online, of a suitable flying path aiming to reach a target position with minimal costs taking into account the physical limitations of the UAVs and the requirements of the specific mission [23]. It is almost 20 years now that intelligent path planning has caught the attention of scholars (e.g. in 2003, an evolutionary algorithm was proposed for offline/online path planning [24]), and different AI-based solutions have been presented during this time period. A survey on AI solutions for UAVs

path planning covering the period from 2013 to 2017 was proposed in reference [23]. The authors surveyed different approaches including: i) genetic algorithms (GA), which have the advantage of not falling into local optima and having a high processing capability; ii) Swarm Intelligence approaches such as the Particle Swarm Optimisation (PSO), which even falling much easier into local optima leads to lower complexity and could be combined with GA to achieve faster convergence, and the Ant Colony Optimisation (ACO), which is more robust and can be easily implemented in a parallel fashion; iii) ML approaches such as Artificial Neural Networks (ANN), which are capable of finding safe and optimal solutions with fast convergence, RL approaches, which evolve the selection strategy based on the environmental response, and Deep Learning (DL) approaches, through which the constraints of complex environments can be potentially reduced and the path planning process simplified. The reported trends show a particular increasing interest over the years in applying ML techniques rather than Evolutionary Computing approaches.
Concerning Swarm Intelligence solutions, [25] surveyed some of the latest exploited approaches to cope with intelligent path planning: an improved Gray Wolf Optimisation (GWO) algorithm has been implemented to find the optimal path in a 3D environment and realise obstacle avoidance [26]; reference [27] combined the Pigeon Inspired Optimisation (PIO) to find the initial path and the Fruit Fly Optimisation Algorithm (FOA) to perform local optimisation and avoid obstacles; lastly, an improved PSO algorithm is implemented to solve the path planning problem described as a three-objective optimisation problem [28]. In addition, a hybrid algorithm combining improved PSO and modified symbiotic organisms search (MSOS) had been presented in [29] for cooperative multi-UAV path planning in a three-dimensional environment. The aim was to generate paths for each UAV while assessing safety and cooperation requirements. Lastly, as a notable hybrid solution, the Gray Wolf Optimisation algorithm was combined with RL to overcome the GWO limitations which involve the dropping of the performance in high dimension optimisation problems and the fact that the characteristics of each individual are not considered as all the wolves are forced to perform the same behaviour during the search process [30]. In this context, RL is introduced to treat each wolf as an individual agent. The optimal path planning is then computed off-line (in a 3D environment) and the cubic B-spline curve is used afterwards to smooth the path. Nevertheless, despite being interesting approaches, these are evaluated in 3D environments where each entity has six degrees of freedom (i.e. it can move in any direction), which is a completely different scenario from the railway one.
Regarding ML, we found that DRL approaches have been the most exploited. Recalling again the work carried out in [11], deep Q-Learning methods allow designing model-free schemes capable of adapting to the evolution of the scenario. A DQL approach based on the actor-critic method was proposed by the authors in [31] to minimise the network delay and dynamically adapt to the traffic conditions which showed high real-time performances as it could achieve a near-optimal in a single step. An actor-critic-based DRL method was also proposed by [32] to cope with the autonomous navigation of a single UAV, also taking into account the distance to nearby obstacles as to avoid them while flying; here, the continuous control was performed through a Recurrent Deterministic Policy Gradient (RDPG) and RNNs were used to approximate the actor and the critic. However, what generally emerged in [11] is that most of the works relied on simulated data generated through stochastic models representing a simplification of the real problem which may lead to biased or not fully compliant solutions. This seems not to be changed also in the recent studies, where algorithms are tested through pc-based simulations.

Intelligent path planning can be exploited for countless applications; it is not only a matter of reaching a target point, but to provide services or achieving goals while heading towards a specific position and, in doing that, UAVs might communicate with each other, with base stations, or with ground users (GU). In the last years, the involvement of cellular networks has been revealed to be a win-win technology for UAV communication as cellular-connected UAV can integrate cellular signals to support GPS information to achieve robust navigation, and they are also cost-effective as, instead of building new infrastructures, already deployed BSs can be exploited [33], nevertheless, it is not exempt from challenges including mutual communication interference between GUs and UAVs, range limits, the limited battery capacity could affect the connection, rapid channel variation [22, 33, 34]. In this context, a DRL solution based on echo state networks (ESN) was presented to cope with cellular-connected UAV (over 5G) path planning while maximising energy efficiency and minimising communication latency and the interference caused by UAVs on the ground network [22]; a dueling double deep Q network (dueling DDQN) was exploited to design an optimal trajectory while optimising the trade-off between the communication quality of service (QoS) and on-board energy consumption [33]; in addition, a DQN was implemented to design an optimal path for a cellular-connected UAV within the covered area of a fixed base station [34]. In the latter case, a millimeter wave (mmWave) communication following the 5G protocol is considered, and the BS aims to guide the UAV along the optimal path while providing better connectivity at every instant.
For the sake of knowledge, it would be worthwhile to mention that DRL approaches have also been used to achieve optimised path planning in other kinds of scenarios including area coverage path planning (CPP) [35], object tracking [36], real-time adaption in dynamic environments [37], and for mobile edge computing (MEC) [38]. For example, the authors in reference [35] proposes a DDQN to achieve coverage goals under varying constraints in the context of area CPP; an improved version of the Deep Deterministic Policy Gradient (DDPG) algorithm, which combines DQN with the actor-critic method, was proposed in [36] to track and follow ground moving objects while ensuring collision avoidance with environment obstacles; the authors in [37] proposed a dueling DDQN to guide an UAV towards a destination location while avoiding dynamic threats along the path (e.g. other surveillance drones, radars, etc.) in real-time; in addition, a DDQN was implemented in [38] to design a suitable path for UAVs as to increment the QoS of the MEC network from the perspective of the mobile users while meeting the constraint of limited UAV energy.
To conclude, the main problem with almost all the mentioned approaches is that they have been tested in simulated environments (e.g. STAGE [37]) or considering synthetic data. Moreover, the UAV and the rail scenario are at the opposite ends when it comes to the degrees of freedom: UAVs are free to move in any direction, whereas trains run on predetermined routes (i.e. rails). Nevertheless, it is not said that some of the aforementioned approaches could not be adapted (or re-designed) to solve routing problems in wide railway networks or to deal with dynamic train control policies. As an example, a DQL was implemented to optimise the performances in communication-based train control (CBTC) systems to minimise the profile tracking error and energy consumption [39].

4.2. Unmanned Ground Vehciles

Unmanned Ground Vehicles (UGVs) are robotic systems operating on land without an on-board human operator. Navigation in unstructured environments is a great challenge in

mobile robotics, as the domain of UGVs has added complexity compared to UAVs. This is due to the need to deal with changing and challenging ground, different kinds of obstacles and limited manoeuvrability. In the following we will show the relevant AI-based challenges in the field.

4.2.1. Navigation for Ground Vehicles in Unstructured Environments

Much of the works already done in UGVs considered structured environments, wireless interfaces from a centralised control station an easy environments. These prior methods allowed the robot to maintain an internal map of the surrounding environment and then to use a localisation and planning method to navigate through the internal map.
Since autonomous vehicles technology is extended to UGVs for their deployment in unstructured environments, AI methods for fully autonomous control on embedded platforms and vision systems for enhanced perception will play a fundamental role. It is clear that, in order for the UGVs to reach full autonomy, they must be able to detect objects around them. In the view of this, cameras are a natural choice as the primary sensor for autonomous vehicles, because they provide data for a great number of tasks, as 3D mapping, visual localisation, and 3D obstacle detection.
In this field, the use of DL methodologies can offer the advantage of continuous improvement as the robot learns. Indeed, DL has been applied to tasks concerning the navigation of a UGV exploiting data from vision sensors, but also supported by sensors such as Inertial Measurement Units (IMUs) and LiDAR, while 3D depth sensing cameras are being used as a distance measurement between objects and the camera [40].
End-to-end (E2E) methods allow to fuse perception and control of the navigation framework into a single block through a direct mapping of raw environment perception and/or vehicle state (i.e., sensory data) to navigation control actions. They can indeed considered as a particular case of Terrain Traversability Analysis (TTA)-based methods, as they include both TTA and control.
In the field of unstructured environments, only a few solutions have been developed exploiting standard ML techniques [41, 42]. Moving on to recent DL solutions, [43] adopted a DRL method based on the Asynchronous Advantage Actor-Critic (A3C) approach. The A3C architecture network processes the depth images, the elevation map and the robot orientation on three different branches, through convolutional layers and fully connected layers. These branches are then concatenated and fed into a LSTM recurrent network, which is used to better deal with the partially observed environment. The outputs are provided as commands for a low level controller (forward/backward motion, or turning right/left). The robot's direction depends on the target location: a high reward is provided if the robot gets closer to or reaches the target location; conversely, a negative reward is related to undesirable final states. [44] proposed a CNN method for autonomous crop row-following. The authors used at first a large-scale forest trail dataset; then, they tuned their model on smaller custom datasets from agricultural environments. In [45], instead, an imitation learning-based procedure for high-speed off-road driving tasks has been addressed. The policy to be imitated is provided by a model predictive controller, while the learned control policy is composed by two sub-networks: a CNN, which uses RGB images as inputs, and a feedforward network with a fully connected layer (fed with wheel speeds). [46] proposed a method to directly map the multi-modal input sensory data to the output steering commands. In this method, a three-branched network architecture is leveraged to process three visual modalities (laser, RGB images, and point cloud data). Namely, laser scans are processed to provide a 2D

occupancy map. Both the RGB images and the 2D occupancy map are given to two parallel residual net branches for visual features extraction, whereas the third branch processes the point cloud data for geometric features extraction. Then, the geometric features are concatenated with those from the RGB image branch, fed to convolutional layers and finally combined with the 2D occupancy map branch output. The steering angle is predicted from a final fully connected layer. The training is made through the simulation of large-scale dataset, capable of reproducing complex environments. The authors of [47] proposed a sort of self-supervised multi-task RL problem, combining generalised computation graphs [48] and composable action-conditioned predictors [49]. Namely, a planning strategy is completely defined: a sequence of reward-maximising actions can be planned by leveraging current observation, the trained event-predictive model, and the reward function. In particular, the vehicle collects and labels, through IMU, LiDAR and wheel odometry, off-policy data experienced in the real world. These data are used to train a predictive model of navigation relevant events (i.e., collision, terrain bumpiness, and so on) from the current on-board camera image and a sequence of future actions (linear and angular velocity commands). The model is based on a recurrent LSTM unit: the current RGB image, passing through convolutional and fully connected layers, forms the initial hidden state of the LSTM. The recurrent unit takes as input a sequence of actions, and produces a sequence of outputs which are passed through further fully connected layers in order to predict all the events for all the future time steps. The trained model is combined with a user-defined reward function related to the task required to the robot. [50] introduced a local planner based on DRL approach in unknown rough terrain. Different E2E architectures are proposed depending on the available range sensing system. The solution is tested in a dynamic simulation environment, proving the capability of planning safe local paths over surfaces with different levels of friction. The work proposed in [51] is similar to the one in [47], as it addressed the prediction of terrain classes (smooth, rough or obstacle) over an horizon of planned future actions, with the aim to avoid obstacles and prefer smoother terrain areas. In particular, current images are fed to a CNN, thus forming the initial hidden state of an LSTM RNN. The model is fed with both first-person and overhead aerial images, which follow two different convolutional branches. The input-output pairs of the LSTM are given by steering actions and predicted terrain class probabilities. A high reward function is related to running on smoother terrains, thus allowing the planning of action trajectories that maximise the expected reward.

4.2.2. Obstacle Detection and Avoidance

The detection of obstacles in a robot's path in real-time is a crucial requirement from a safety point of view. CNNs has been recently adopted to accomplish the task of pedestrian detection, as this methodology has achieved success in classification, localisation and detection tasks [52]. The recent challenges in the field of object detection are reviewed in [53].
The current studies on 3D object localisation have been developed exploiting 3D vision systems including stereovision [54], RGBD cameras [55] and 3D LiDAR [56]. Object detection algorithms often use different metrics for evaluation; thus, it is sometimes difficult to compare their performances. However, they usually use a standard benchmark dataset in the domain of self-driving cars, the KITTI dataset. Among the proposed 3D object detection algorithms, best performance has been achieved by techniques taking stereovision as input [54]. Indeed, CNNs taking data from inputs different by camera data still have to be fully optimised. When developing object detection systems for specific domains, it could be useful to leverage the classical CNNs, such as Faster-RCNN for better accuracy [56] and Mobilenets for

better speed of inference [57] and then to tune them on a custom dataset for the application. Object tracking is based on associating detection related to the same object between successive frames over time: this allows the estimation of the object's direction and velocity of movement relative to the vision system. Tracking is another critical issue for UGVs for the prediction of the path of moving obstacles. This allows the robot to make better decisions regarding its own trajectory. Tracking can be used, for instance, for person-following [58]. It can be carried out exploiting a combination of data association methods, such as Nearest Neighbour for associating detection and Kalman filters for the estimation of direction and velocity [52].

4.2.3. Semantic Segmentation

Semantic Segmentation (SS) has been exploited for many applications, such as free space detection [59], understanding of indoor [60] and outdoor scenes [61], segmentation of path proposals for autonomous driving [62, 63] and in visual SLAM [64]. Identifying the object class of each pixel in an image is indeed fundamental in applications, as it reduces the ambiguity related to drawing a rectangular bounding box around object proposals in traditional object detection.
The SS-based methods aims at improving performance in applications through sensor fusion of monocular cameras with LiDAR, aameras, IMU/LIDAR and IMU/GPS.
The most recent SS techniques, such as Dilated Convolutions [65], DeepLab [66], and RefineNet [67], exploit Fully Convolutional Networks (FCNs). The latters avoid the use of fully connected layers which allows segmentation maps to be directly translated to the output for images of any size. Moreover, they are faster than the patch classification approach [40].
Instance Segmentation (IS) combines both object detection and SS to segment different instances of classes, in order to localize object instances with pixel-level accuracy and solve both object detection and SS simultaneously. This is actually a complex task, as bounding boxes are now irregular shapes which must overlap with the shape and the detection proposal for each object. The most popular IS algorithm is Mask-RCNN [68]. It is an extension of Faster R-CNN with the addition of a branch for predicting an object mask in parallel with the existing branch for bounding box recognition.
The main issue of SS/IS is providing pixel-wise annotations, which is a time-consuming operation. In order to overcome this problem, the methodology "ScribbleSup" has been proposed [69]. It leverages "scribbles" (lines drawn over each shape while remaining within its boundary) to annotate images, and uses these images to train CNNs for SS. Additionally, "Deep Extreme Cut" [70] is another approach which exploits extreme points in an object as input to get precise object segmentation. It guarantees the most precise results so far.
In table 4.1, we summarise the main existing works on AI-based applications in the unmanned vehicle sector.

Ref.	Objective	Application	AI Technique
		UAVs	
[17]	Collision avoidance	Fixed-Wing UAVs	RL
[19]	Coordination and energy consumption minimisation	Multiple UAVs	Particle Swarm optimisation
[21]	Coordination	Unmanned HAPS	RL & SI

[22]	Interference management	Cellular-Connected UAVs	DRL
[24]	Path planning	UAVs navigation	Evolutionary algorithm
[27]	Path planning	Aerial inspection	Pigeon-inspired optimisation
[28]	Path planning	Rotary UAVs	Particle Swarm optimisation
[31]	Routing optimisation	Agent control	SDN & DRL
[32]	E2E driving	Autonomous navigation	POMDP
[34]	Trajectory optimisation	Cellular-connected UAVs	DQN
[35]	Coverage path planning	Power optimisation	DDQN
[36]	Path planning	Ground target tracking	DDPG & DRL
[37]	Path planning	Virtual testing	D3QN
[38]	Path planning	QoS-based action selection policy	DDQN
		UGVs	
[41]	Obstacle avoidance	Off-road mobile robot navigation	E2E learning
[42]	Path tracking	Off-road mobile robot navigation	Iterative learning control
[43]	Vision-based driving	Off-road mobile robot navigation	DRL
[44]	Vision-based driving	Off-road mobile robot navigation	DCNN
[45]	Vision-based driving	Off-road mobile robot navigation	E2E imitation learning
[46]	Vision-based driving	Mobile robot navigation	NMFNet
[47]	Vision-based driving	Off-road mobile robot navigation	E2E learning
[48]	Vision-based driving	In-door mobile robot navigation	Self-supervised DRL
[49]	Vision-based driving	Indoor mobile robot navigation	Multi-task learning & RL
[50]	Path planning	Off-road mobile robot navigation	DRL
[51]	Path planning and tracking	Off-road mobile robot navigation	Hybrid model-free & model-based RL
[52]	Pedestrian detection	Out-door robot navigation	ACF & DCNN
[54]	Path planning and tracking	3D object detection	CNN
[56]	LiDAR-based navigation	3D vehicle detection	FCN

[59]	3D-2D navigation	Road segmentation and free space detection	SLAM & CNN
[60]	Indoor navigation	3D semantic scene segmentation	3D-multi-view prediction network
[62]	Object detection and tracking	Weakly-supervised segmentation	SegNet
[64]	Vision-based vehicle validation	SS	SLAM & DL
[66]	Vision-based navigation	SS	DCNN & Fully connected CRF
[67]	Vision-based navigation	SS	RefineNet
[68]	Vision-based navigation	2D detection	R-CCN
[69]	Vision-based navigation	SS	Supervised CNN
[70]	Vision-based navigation	Object segmentation	CNN

Table 4.1: Summary of the existing literature on the main AI-based applications for unmanned vehicles

5. AI-based Technologies for Vehicle Control in Automotive

Artificial Intelligence in cars currently powers a great revolution in the Auto Industry. The pioneering idea goes under the name of ”Intelligent Drive” where the vehicle becomes a ”thinking partner”: it detects hazards and supports the driver with a visual, acoustic and/or haptic warning - in an emergency, it can also take corrective action, for example in order to avoid an accident or reduce its severity. The basis is the intelligent linking of cameras, sensors, and control units.
Then this concept is evolved, leading to the self-driving cars, i.e., able to cooperate exploiting a communication network according to the IoV (Internet-of-Vehicles) paradigm.
According to the level of automation, autonomy and connectivity the following basic concepts arise:

- *Automated Driving*: Automation deals with the execution of processes and procedures without human intervention. Hence, automated driving implies driving without the intervention of human drivers. A further differentiation between fully automated driving and the different automation levels according SAE is done.
- *Autonomous Driving*: Autonomy means that one is able and allowed to make decisions independently and on one’s own mind. In the case of autonomous driving, a single vehicle can make its own driving decision independently. Autonomous driving can be performed by highly-automated cars.
- *Connected Driving*: Information is exchanged between automated as well as non-automated vehicles and other traffic participants and/or infrastructure in an automated way.
- *Cooperative Driving*: Cooperative driving means that single vehicles and drivers act cooperatively within traffic. This implies that single traffic participants are coordinating actions in the light of improved overall macroscopic effects.

Note that autonomy is not equivalent to automation and connectivity is not equivalent to cooperativeness. Indeed, connected driving itself does not necessarily imply cooperative driving. Single traffic participants can theoretically use the additional information for their own individual advantage at the cost of others. On the other end, automated driving often depends on valid decisions, which rely on information that could be provided with or without connectivity. However, connected driving can accelerate the introduction of automated driving significantly, because it enables approaches for collective learning to identify and resolve inappropriate behaviour and driving strategies quickly. Furthermore, autonomous driving does not intrinsically cause improved traffic. If everybody decides on his own without cooperative coordination with other traffic participants, then chaos and traffic collapses may be a consequence. Normally autonomy is only appropriate in the case of low densities. In the case of saturated and crowded traffic situations in fact the improvements may come from the reduction of autonomy and increase in coordinated cooperation.
In what follows we review the most relevant and recent use of artificial intelligence systems for automated, autonomous, connected, cooperative cars, which employ ML techniques to collect, analyse and transfer data, in order to make decisions that in conventional cars are currently taken by humans.
The aim of is to identify which AI-based tool could be transferred from Automotive to the

Railway sector.

5.1. Enabling Technologies: the Role of Sensors

Standalone devices are currently the most used in the majority of vehicles in production. In general, a IMU is used as source of information [71–75]. It can be either the vehicle speed, or the throttle pedal position, or the acceleration, etc. Moreover, low-cost accelerometers can be used in order to provide additional information [76]. Global Positioning System (GPS) is able to achieve vehicle localisation; it is also an indirect measurement of speed and acceleration [77, 78].
Some innovative devices are installed on the last generation vehicles, such as the Geographical Information System (GIS), which is able to detect the driver behaviour under specific manoeuvres, and thus used, for instance, for the detection of the roundabouts [78]. Moreover, Radio Detection and Ranging (radar) or Light Detection and Ranging (LiDAR) sensors, necessary for the use of parameters related to the car-following, are already installed on the vehicles equipped with Adaptive Cruise Control (ACC) [74, 79, 80]. Eventually, smartphones could replace the other devices, when the related required signals are not available [81–84]. Indeed, smartphones are increasingly enclosing additional devices, such as accelerometers, gyroscopes and geomagnetic field sensors [84], GPS and cameras [82]. Thus, the widespreading of smartphones could ensure the availability of these devices at any time.

5.1.1. Data Fusion

In the field of transportation modelling, a recurrent issue is represented by multi-source processing, as planning problems, traffic estimation, demand estimation, and so on. [85]. In the view of this, Intelligent Transportation Systems (ITS), in which transportation infrastructure is integrated with information and communication technologies, aims at guarantee passenger safety, reduce transportation time, fuel consumption and vehicle tear [86]. With the widespreading of modern communication and computational devices and inexpensive sensors, it is possible to collect and analyse data from different sources. Data fusion (DF) is indeed a collection of techniques which allows to merge and combine information from different sources in order to reach a better inference. Among such techniques, the mainly exploited in ITS are: Advanced Traveller Information Systems (ATIS), Automatic Incident Detection (AID), Advanced Driver Assistance Systems (ADAS), network control, crash analysis and prevention, traffic demand estimation, traffic forecast and monitoring and accurate position estimation. Additionally, DF techniques can be combined with each other to obtain better results.

5.1.1.1. Data Fusion for ADAS

As mentioned above, passenger safety represents one of the main tasks of ITS. Over the years, a great deal of progress has been made for that purpose, starting from the introduction of passive devices, such as belts, air bags and lighting, up to the development of driver assistance techniques. However, despite the huge reduction of the gravity rate related to car accidents, the trend in demand for transportation safety is constantly increasing. In the view of this, the spreading of active safety devices in addition to the passive ones is taking place. The huge diffusion of ADAS and Collision Avoidance Systems (CAS) are an evidence of such trends. The main task of these systems is to collect information in order to provide a reliable description of the traffic scene in the surrounding environment of the vehicle, specifically in a pre-crash situation. The technique of simultaneous localisation and mapping can

be used to gain the static map of the surrounding environment and the vehicle position in the map [87].
In the field of DF, another important research topic is represented by the automated highways. The diffusion of autonomous vehicles is indeed taking place, also because of their potential use in unsafe or unknown situations. In order for the autonomous vehicles to be efficient, they need to detect the environment with a collection of sensors; then, the sensory information need to be effectively analysed in order to provide decision support. The main issues of this task are related to the heterogeneity of the collected data and the extraction of relevant information from them. In general, sensors of different types are used to obtain complementary information. In this framework, Simultaneous Localisation and Mapping (SLAM) represents a current research area in robotics. SLAM technique consists of multiple functions: landmark extraction, data association, state estimation, state update and landmark update. However, since individual goals can be achieved using a multitude of algorithms, a universally accepted algorithm for SLAM is still missing.
Detection and tracking of moving objects represents another set of techniques whose objective is to get information from the dynamic environment in which the vehicle is operating [88, 89]. Many commercial products, capable of alerting drivers about lane changes, are spreading. In such systems, artificial intelligence (AI) techniques are used together with image processing tools, able to get data from 2D and 3D cameras. The first techniques were based on edge lane detection, thanks to the good contrast between the road and lane markings. The next step would be a perceptual grouping of the edge points to detect the lane markers of interest. [90–92]. More enhanced techniques have been proposed in [93], in which one-dimensional edge detection is complemented by a least median squares technique in order to detect the curvature and orientation of the road. Moreover, individual lane markers are directly recognised through a technique based of the segmentation of the row-averaged image intensity values. Another technique [94] is based on the frequency domain for lane extraction. It uses several sensor systems which are complementary and redundant. The collected information are then analysed by a DF process which merges the data coming from the different sensors and provides an accurate description of the traffic scene. The crucial step of this process is represented by the association of the sensor data with the environment description, which is based on the synchronisation of information and the associated object state. Consequently, when different sensors are used to detect multiple objects, an association between the measurements and the individual objects is required [95]. Once such association is completed, the sensor bias has to be removed through a sensor registration procedure. Eventually, through the use of Kalman filter or its variants, such as the particle filtering, all the fused measurements are manipulated to detect the objects [96]. In this field, the role of the sensor fusion for vehicle localisation has been discussed in [97], by suggesting general methods for fusing data, and sensor-fusion activities within a robot architecture. [98] proposed a 3D vehicle motion estimation by the fusion of multi-source information, based on image point and line features, while [99] proposed DF systems for ACC with stop and go phenomenon, and [100] showed a DF framework for obstacle detection and tracking.

5.1.1.2. Data Fusion for Accurate Position Estimation

The main task od DF is the accurate estimation of the position and the orientation of a vehicle. The first techniques which have been proposed in the navigation field are Inertial Navigation Systems (INS), based on dead-reckoning. Unfortunately, this technique is af-

fected by the so called integration drift, that is the accumulation of measurement error for both acceleration and angular velocity, which leads to a greater error in the estimation of the vehicle position [86]. Another well known tool for position estimation, GPS, which had been firstly developed for military purposes, has become of common use in the last decades. It is composed of three main functions: satellites moving around the Earth, stations for their control and monitoring, and the GPS devices used by people. These components work together in order to provide an accurate estimation of the position. Namely, GPS satellites send signals from space that are received and identified by GPS devices, which are able to provide 3D location (latitude, longitude, and altitude), and the time [95]. However, when the satellite signals are stopped because of buildings or electromagnetic interference, GPS is unable to provide the position, due to the lack of reference signals. In the view of this, DF could effectively be used as a valid alternative to overcome the limitations of both the INS and GPS techniques. Namely, a combined usage of GPS together with an INS may lead to several benefits. For instance, the INS may be calibrated by the GPS signals, so that INS can provide position updates faster than GPS. Indeed, for high dynamic vehicles, such as missiles and aircraft, INS complements the gaps between GPS positions. Moreover, INS can compensate the contingent lack of signal of GPS, by continuing to compute the vehicle position and angle. For these reasons, the two systems, being complementary, are often developed together. One of the first attempts in the employment of GPS with INS leveraged the Kalman filter. Namely, [101] proposed a decentralised filtering strategy for the integration of GPS and INS systems. In particular, a Kalman smoother has been used to integrate the different range and phase measurements with the data coming from INS. Variants of Kalman filter are often employed to reach a more accurate integration: a constrained Kalman filter algorithm has been proposed in [97] to integrate data from GPS, INS and digital map to obtain a precise localisation of vehicles for ITS applications. However, a correct usage of Kalman filter requires accurate stochastic models of the sensors, which could be achieved through AI techniques for GPS/INS integration. To that purpose, different types of neural networks have been proposed to merge the GPS and INS information: multi layer perception and radial basis function neural networks have been addressed in [102]. GPS/INS integration has also been reached leveraging adaptive neurofuzzy techniques [103], which simulate the vehicle dynamics by training the AI modules when the GPS signals are available.

5.2. Enabling Technologies: V2X Communication

In the last decades, the increasing interest in autonomous driving led to the development of Radio Access Technologies (RATs), able of guaranteeing reliable and low latency vehicular communications. The current technologies capable of enabling Vehicle-to-everything (V2X) communications are Dedicated Short-Range Communications (DSRC) and Cellular V2X (C-V2X). However, RATs fail to fully support the communication requirements of the most advanced vehicle applications. As these requirements are necessary to enable fully autonomous vehicles, both the DSRC and the C-V2X are undergoing huge improvements to support advanced vehicular applications characterised by high reliability and low latency. This RAT developments, designed to support autonomous and cooperative driving, are compliant with the IEEE 802.11bd protocol for DSRC and the NR-V2X for C-V2X [104]. In the following, both the DSRC and C-V2X are briefly described.
As to DSRC, it is designed to mainly work in the 5.9 GHz band, which has been designated for ITS applications in many countries. On the other hand, C-V2X can also operate in the 5.9

GHz band as well as in the authorised carrier of cellular operators [105]. DSRC is based on the IEEE 802.11p standard for its physical (PHY) and medium access control (MAC) layers. It uses a simple and well-characterised MAC protocol, capable of distributed operations. However, the adoption of DSRC in vehicles may be limited due to its poor scalability with respect to the challenges posed by high-mobility scenarios. In the meantime, the C-V2X, Long Term Evolution RAT based on LTE, has been developed by the 3rd Generation Partnership Project (3GPP), in order to allow vehicles to operate in a distributed manner even without a cellular infrastructure, while exploiting the infrastructure for the efficient allocation of resources when vehicles operate within its coverage [106]. Existing literature shows that C-V2X can offer better performances than DSRC, in terms of higher interference resilience and better non-line-of-sight capability (NLOS) [107]. Namely, both DSRC and C-V2X can reliably and securely support applications that require E2E latency of approximately 100 milliseconds as long as the vehicular density is not very high [108]. However, because the QoS requirements of V2X can be very strict for several advanced V2X applications, both technologies, in some use cases, seem unable to ensure the desired performance [109]. In the view of this, a new Study Group called IEEE 802.11 Next Generation V2X was formed in March 2018 [110], in order to let DSRC and C-V2X support additional operating modes and increase the offered throughput. This led to the formation of the IEEE Task Group 802.11bd (TGbd) in January 2019. 3GPP is also working on the development of the so called New Radio (NR) V2X (3GPP Rel. 16) stating from 5G NR, which has been standardised in 3GPP Rel. 15. It seems that NR-V2X is able to guarantee stricter requirements than C-V2X: in some use cases, E2E latency is only 3 msec with 99,999% reliability [109]. Thus, it could support advanced V2X applications.
802.11bd and NR-V2X show some similarities in terms of design goals. Both have been indeed designed with the aim of improving the reliability of the offered services, reduce E2E latency, and support applications requiring high throughput. Nevertheless, their design methodologies are quite different. Namely, TGbd requires the new 802.11bd standard to be backward compatible with 802.11p. To do this, the devices based on 802.11bd and 802.11p must guarantee a communication with each other when operating on the same channel. Conversely, 3GPP does not impose such constraint on NR-V2X. In any case, vehicles equipped with NR-V2X based devices will still be able to communicate with traditional C-V2X based devices using a dual-radio system.

5.2.1. Current Technologies

5.2.1.1. Dedicated Short Range Communication

The PHY and MAC levels of DSRC are defined by the IEEE 802.11p standard, which is mostly derived from IEEE 802.11a, for highly mobile environments. The DSRC leverages a PHY based on Orthogonal Frequency Division Multiplexing (OFDM) with a channel bandwidth of 10 MHz. Hence, the DSRC sub-carrier spacing, compared to that of Wi-Fi, is reduced by a factor of two. The MAC protocol used in DSRC is instead Carrier Sense Multiple Access [111]. Since the DSRC is mainly designed for broadcast-based systems, there is no recognition of the frame returned to the transmitter and high latencies can be observed in some use cases.

5.2.1.2. Cellular V2X

C-V2X is a V2X RAT developed by 3GPP. C-V2X users can take advantage of the already existing cellular infrastructure. However, as the presence of this kind of infrastructure is not

always reliable, C-V2X defines some transmission modes enabling direct V2X communication. To do this, it leverages a sidelink channel on a PC5 interface. 3GPP introduced two new sidelink transmission modes (modes 3 and 4) to support low latency [112]. The basic structure of C-V2X is similar to that of LTE (smallest unit of allocation in time: one subframe - 1 msec comprising of 14 OFDM symbols; smallest frequency-granularity: 12 subcarriers of 15 kHz each) [113]. Since C-V2X is able to work both in coverage and out of coverage environments, C-V2X can operate using both traditional LTE air interfaces and sidelink air interfaces. In particular, the V2X via the so-called LTE-Uu air interface exploits an advancement of LTE-Uu optimised for the vehicle [106], while the V2X via PC5 air interface enables direct communication between the User Equipments (UEs).

5.2.2. Performances of the Current V2X Technologies

DSRC performance is acceptable for most vehicular security applications requiring E2E latency of approximately 100 msec until the vehicle density is controlled [111]. Hence, if the traffic density exceeds a certain limit, DSRC performance grows quickly worse due to two main reasons:

- packet collisions due to simultaneous transmissions;
- packet collisions due to hidden nodes.

In order to compensate the low scalability of DSRC, a congestion control mechanism may be leveraged, such as the one standardised in [114]. Such mechanisms usually employ controlling transmission parameters, such as transmission power, or message transmission speed (packets/second), or both [106]. Compared to DSRC, C-V2X is a newer and less studied technology. Most of the analysis on the performance of C-V2X are based on simulation platforms. These studies show that the performance of C-V2X sidelink mode 4 is better that DSRC in terms of higher link budget [108], as confirmed by experimental results [107]. Moreover, better performances are obtained by leveraging a centralied control of resources in the 3 sidelink C-V2X mode, which leads to an efficient use of the spectrum [115]. However, in some critical situations, the performance of C-V2X rapidly decreases, too [108]. Namely, when traffic density is high, the reuse distance is reduced, thus increasing the interference between C-V2X users.

5.2.3. Requirements of Advanced V2X Based Applications

DSRC and C-V2X support a basic set of vehicle applications which are able to provide driver warnings to indicate potentially dangerous situations, thus being compliant with the QoS requirements about autonomous and semi-autonomous safety driving applications [108, 116, 117]. Such applications are basically designed as an help for the driver to facilitate safety driving. To do this, they mainly need the deliverable of a periodic message characterised by rates ranging from 1 to 10 Hz and E2E latency from 50 to 100 msec. Hence, an evolution of RAT is necessary to improve the reliability of use cases that require an exchange of information packets with a low latency. Autonomous driving requires applications to be useful in safety critical situations, thus able to transmit messages in case of changes and manoeuvres, alignment of trajectories, formations of platoons, exchange of data from heterogeneous sensors, etc. [109]. Existing applications, however, such as left turn assistance and electronic emergency brake lights, although useful for vehicle safety, can't be exploited in safety critical situations. Furthermore, even for human-driven vehicles, the processing of data received by sensors from the surrounding environment (for example, a vehicle sharing its camera) requires performances in sharing information which should

be higher than the ones ensured by the basic safety applications. To improve such performances, 3GPP addressed the requirements of some advanced vehicular applications [109]. These advanced use cases not only improve road safety, but also allow a better traffic management and satisfaction of the passenger infotainment needs. These applications may be classified in four categories:

- vehicle platooning;
- advanced driving;
- extended sensors;
- remote driving.

The requirements of the over mentioned categories are summarised in Fig. 5.1.

Use Case Group	Max. Latency (msec)	Payload Size (Bytes)	Reliability (%)	Data Rate (Mbps)	Min. Range (meters)
Vehicle Platooning	10 - 500	50 - 6000	90 - 99.99	50 - 65	80 - 350
Advanced Driving	3 - 100	300 - 12000	90 - 99.999	10 - 50	360 - 500
Extended Sensors	3 - 100	1600	90 - 99.999	10 - 1000	50 - 1000
Remote Driving	5	-	99.999	UL: 25 DL: 1	-

Fig. 5.1. Qos requirements of advanced V2X applications [104]

5.2.4. Emerging V2X Technologies

5.2.4.1. IEEE 802.11BD: the Evolution of IEEE 802.11P

The main task of IEEE 802.11p was to develop a vehicular communication standard which could give a huge contribution to vehicular safety, traffic management and control and other related applications, such as parking and vehicular diagnostic. In particular, the requirements of this standard were developed with the aim of supporting, for instance, relative velocities up to 200 km/h, response times of about 100 msec, communication range up to 1000 m. The 802.11p standard adopted its PHY and MAC layers from 802.11a; after this, the latter has been replaced by its successors, namely 802.11n and 802.11ac, while 802.11ax is in its final steps of standardisation. Thus, the MAC techniques introduced in 802.11n/ac/ax can be exploited to improve 802.11p. This is indeed the main task of the IEEE 802.11 Next Generation V2X Study Group, which was formed in March 2018, and of the IEEE 802.11bd Task Group, born in January 2019. The main goals of 802.11bd are to double the MAC throughput of 802.11p up to relative speeds of 500 km/h, double the communication range of 802.11p, support vehicle positioning [118]. One of the task of 802.11bd is indeed to enable vehicle positioning. For this purpose, 802.11bd should employ the positioning scheme provided by IEEE802.11ax, also known as Next Generation Positioning (NGP), which is able to provide location accuracy up to 1 meter. Additionally, 802.11bd should support the following features:

- Interoperability: 802.11p devices should be able to decode transmissions from 802.11bd devices and vice versa;

- Coexistence: 802.11bd should be able to detect 802.11p;
- Backward Compatibility: at least one 802.11bd mode must be compliant with 802.11p;
- Fairness: In the co-channel scenarios, 802.11bd and 802.11p should get the same channel access opportunities.

Fig. 5.2 shows a comparison between 802.11p and 802.11bd.

Feature	802.11p	802.11bd
Radio bands of operation	5.9 GHz	5.9 GHz & 60 GHz
Channel coding	BCC	LDPC
Re-transmissions	None	Congestion dependent
Countermeasures against Doppler shift	None	Midambles
Sub-carrier spacing	156.25 kHz	312.5 kHz, 156.25 kHz, 78.125 kHz
Supported relative speeds	252 kmph	500 kmph
Spatial Streams	One	Multiple

Fig. 5.2. Differences between 802.11p and 802.11bd standards [104]

5.2.4.2. New Radio-V2X: Evolution of Cellular V2X

The main goal of NR-V2X is not to replace C-V2X, but to complement C-V2X in the use cases that the latter is unable to support [119]. As C-V2X is already standardised and its use in commercial applications is spreading [120], C-V2X and NR-V2X could coexist in the same geographic environment, as the new generation vehicles will be equipped with both C-V2X and NR-V2X functionalities. In this way, use cases or guide features supporting C-V2X will leverage it, while NR-V2X will enable the remaining use cases. However, in order for NR-V2X to provide unified support for all V2X applications in the future, it should be compliant not only with advanced V2X applications, but also with the basic safety applications already supported by C-V2X.

The main task of NR-V2X is to support V2X applications having varying requirements in terms of latency, reliability and throughput. In fact, while some use cases require periodic transmission of information, others require reliable although aperiodic delivery of messages. Furthermore, some use cases involve a broadcast transmission of information; in others, such as vehicle platooning, the transmission of messages must be only addressed to a specific subset of vehicles (UEs); eventually, 3GPP also takes advantages in transmitting packets to a single vehicle (UE) [109]. In order to be compliant with this variety of use cases, NR-V2X must support both unicast and groupcast communications, other than broadcast. Eventually, like IEEE 802.11bd, NR-V2X, too, requires the use of mmWave bands for V2X applications, particularly for the ones involving a short range and high throughput. Specifically, NR-V2X outlines the following objectives [104]:

- improved sidelink design to support advanced V2X applications;
- Uu interface improvements;
- allocation/configuration/optimisation of sidelink resources;
- identification of the best interface among LTE sidelink, NR sidelink, LTE Uu and NR Uu, for the transmission of a given V2X message;

- QoS Management;
- feasibility analysis and technical solutions for the coexistence of C-V2X and NR V2X within a single communication device.

Further information are detailed in Fig. 5.3. Finally, in Fig. 5.4 the main features of the emerging V2X technologies are summarised.

Feature	C-V2X	NR V2X
Comm. types	Broadcast	Broadcast, Groupcast, Unicast
MCS	Rel. 14: QPSK, 16-QAM Rel. 15: 64-QAM	QPSK, 16-QAM, 64-QAM
Waveform	SC-FDMA	OFDM
Re-transmissions	Blind	HARQ
Feedback channel	Not Available	PSFCH
Control & data multiplexing	FDM	TDM
DMRS	Four/sub-frame	Flexible
Sub-carrier spacing	15 kHz	sub-6 GHz: 15, 30, 60 kHz mmWave: 60, 120 kHz
Scheduling interval	one sub-frame	slot, mini-slot or multi-slot
Sidelink modes	Modes 3 & 4	Modes 1 & 2
Sidelink sub-modes	N/A	Modes 2(a), 2(d)

Fig. 5.3. Comparison between C-V2X and NR V2X [104]

Feature	IEEE 802.11bd	NR V2X
Base Technology	IEEE 802.11n/ac	5G NR
PHY layer	OFDM	SC-FDMA, OFDM
MAC layer	CSMA	Mode 1: gNodeB scheduling Mode 2: Flexible sub-modes
Interoperability	Yes	Non co-channel
Backward compatibility	Co-channel	Not backward compatible
mmWave support	Yes	Yes

Fig. 5.4. Comparison between IEEE 802.11bd and NR V2X [104]

5.3. Advanced Driver-Assistance Systems

ADAS belong to ICT technologies enabling Intelligent Driving. Their main task is to help drivers in driving functions. Indeed, they are developed to automate and enhance vehicle technology for safety and better driving in order to minimise human error, thus reducing road fatalities [121]. To this aim, they leverage automation technology and sensors to detect obstacles or driver errors in the surrounding environment, allowing the driver a safely reaction to these contingencies, also thanks to a human-machine interface.
More recently, since the V2X communication is ready to support cooperation, classical ADAS

functions have been extended for receiving vehicles' intentions and thus explicitly negotiating a common driving manoeuvre. In this perspective, the more recent ADASs, often named cooperative driver assistance (CoDASs), are designed for integrating cooperation leveraging V2X communication.
ADAS technology is devoted to alert the driver to problems implementing safeguards and taking control of the vehicle, if necessary, in order to prevent or mitigate accidents and collisions. So, some adaptive features are commonly exploited to provide different services (such as, for example, ACC, collision avoidance and automate lighting) by incorporating satellite navigation and traffic warnings, navigational assistance, and so on.
ADAS differ from Driver-Assistance Systems (DAS): while the first leverage data coming from the surrounding environment of the vehicle, the second just use internal data. Thus, ADAS are based on inputs from multiple sources, such as automotive imaging, computer vision, LiDAR, radar, image processing, in-car networking, etc. Indeed, they can also exploit additional inputs from other sources, such as Vehicle-to-Vehicle (V2V) communication and Vehicle-to-Infrastructure (V2I) communication. In new generation vehicles, ADAS are integrated in their electronics and so they are real-time systems capable of processing multiple inputs, selecting the priority ones to prevent accidents, allowing the vehicle to react in order to guarantee safety. To this aim, they use preemptive priority scheduling, which requires a correct assignment of the priorities to avoid bad consequences.
Over the last years, the trend to embed ADAS in vehicles has grown up. In this technological scenario, the exploitation of AI-based technologies in the automotive field is mainly focused on personalisation. Namely, ADAS observe user situation-dependent interaction behaviour and adapt themselves according to the driver practices and preferences [122]. In particular, the main task of current personalisation approaches in the automotive field is the technical implementation of a personalised functionality: data driven are collected and used to model the driver, thus adapting the given functionality to the driver's behaviour (see Fig. 5.5 for a conceptual view of personalised ADAS).

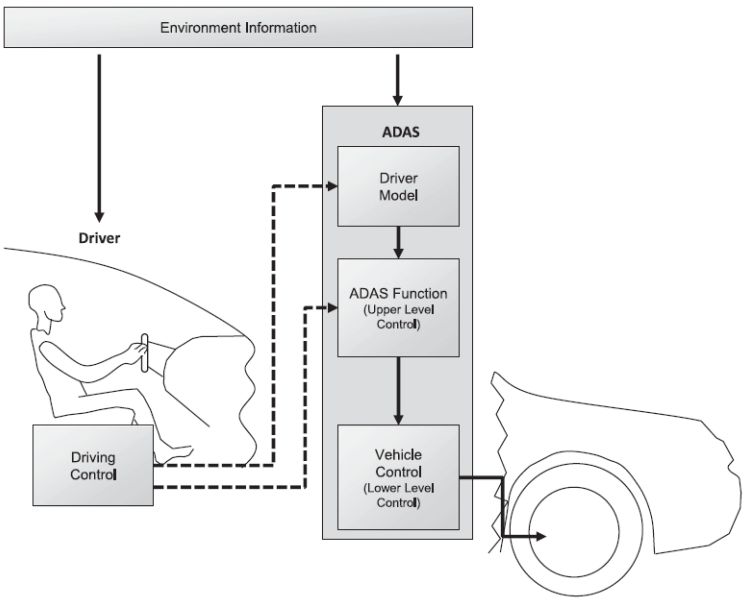

Fig. 5.5. Next generation personalised AI-based ADAS via an adaptation of the parameters of the driver model to the observed individual driving behaviour [123]

5.3.1. ADAS Levels

Depending on their degree of automation, ADAS are classified in different levels, according to the scale provided by The Society of Automotive Engineers (SAE). In particular, 5 levels have been identified, and are described below [124] (see fig. 5.6):

- Level 0: ADAS can provide information to the driver, but they are not capable of controlling the car. Some example of level 0 ADAS are traffic sign recognition, surround-view, parking sensors, lane departure warning, night vision, rear-cross traffic alert, and so on.
- Level 1-2: In both Level 1 and 2, the driver does most of the decision making. However, while Level 1 ADAS can only take control over one functionality, Level 2 ADAS can take control over multiple functionalities ho help the driver. Examples if Level 1 ADAS are ACC, automatic emergency brake assist, lane-keeping, and lane centering; highway assist, autonomous obstacle avoidance, and autonomous parking are instead considered level 2 ADAS.
- Level 3-5: From Level 3 to Level 5, the amount of control the vehicle increases, Level 5 ensuring a fully autonomous vehicle. However, some of these systems are not in commercial use yet. For instance, highway chauffeur is a Level 3 system, while automatic valet parking is a Level 4 system: both of them have not been completely embedded in commercial vehicles yet.

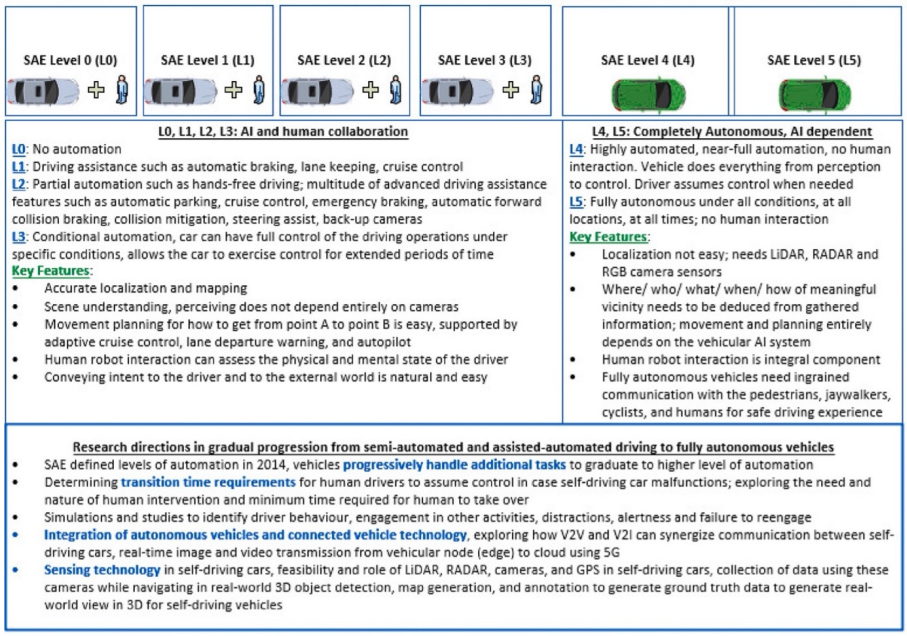

Fig. 5.6. SAE Levels of automation [125]

5.3.2. Driving Style Optimisation and Recognition for Intelligent Driving

Driving Style (DS) recognition has several applications, such as DS feedback and correction, ADAS performance enhancement and energy management in Hybrid Electric Vehicle (HEV), Plug-in Hybrid Electric Vehicle (PHEV) and Battery Electric Vehicle (BEV) [126]. All of these applications can be grouped in two categories: safety and fuel efficiency aware. In some cases, these can be correlated, as usually aggressive driving is related to inefficiency.

However, this is not always true: calm drivers, for instance, do not necessarily drive in an efficient way.

5.3.2.1. Driver Advisory Feedback

One of the main tasks of DS is represented by the driver style correction through some feedback, which can be online or offline, passive, active or a combination of both [126]. These applications can be directly installed in the vehicle or included in smartphones, in order to exploit the device sensors and processing capability [81, 82, 84]. A smartphone application for DS recognition and correction has been designed to display visual feedback to improve DS for both fuel consumption and safety [84]. Also, audio feedback to encourage DS correction has been developed in [127], and used in [82]. Moreover, an algorithm with three alternative levels of visual information has been developed and tested against the no-feedback scenario. All approaches showed improvement in the vehicle consumption up to 20-30%, although the scenario with the clearest and most readable provided information has ensured the best results [81]. A major step has been that of analysing the reaction of drivers to the feedback in order to adapt the information according to the individual characteristics of the driver [79].

Among DS, passive feedback strategies are easy to implement and can guarantee good results; however, they could be ignored by the driver, thus becoming useless. On the contrary, active feedback systems are able to directly affect the vehicle activity, thus being more efficient. For instance, through a visual and haptic feedback (the latter gained through the throttle pedal), up to 3.5% improvement in fuel economy has been obtained, without affecting the vehicle performance [128, 129]. However, haptic guidance is not always easily accepted by drivers, who can decide for system manual deactivation. To address this problem, in [129, 130], the drivers response acceptance to the feedback was studied with the aim of adapting the feedback in order for the less receptive users to accept it more easily. A similar solution consists in a gradual increasing of the resistance over the throttle pedal when the vehicle operation diverges from optimal use, due to an arbitrary response of the driver to the feedback [131]. Other studies are mainly focused on safety and efficiency in larger vehicles, such as busses and fleet management [72, 76] or passengers comfort in public transport [77].

In the next future, driver feedback will probably leverage a personalised assistance, where the system will be able to detect the driver preferences and generate appropriate feedback to both encourage style correction and minimise driver neglecting. These feedback should be able to combine both haptic and passive procedures and to process the right type and amount of information to become more and more compliant with the driver capacity and skills.

5.3.2.2. Enhance of ADAS Performance

ADAS would leverage DS to predict the drivers' reactions and adapt themselves to individual users. This adaptation to drivers may lead to safety systems of better performances [79,132]. For instance, in situations of collision avoidance that include driver-in-the-loop, ADAS would be able to do the best action depending on drivers' predicted reactions [133, 134]. However, the development of driver-adaptive ADAS requires further studies regarding, for instance, the research of the best way of exploiting DS information in intelligent vehicles [135]. In the view of this, a method to classify and use DS to improve the vehicle handling has been proposed [136]. It is based on an online/offline algorithm which leverages historical data.

In the safety field, further applications have been found in cooperative driving frameworks, such as tandem and platoon. This application, based on the assumption that the drivers are going to cooperate, provides feedback to improve both safety and the overall fleet efficiency [137]. Furthermore, [138] proposed an algorithm able to learn from drivers during manual operation and reproduce human-like manoeuvres autonomously within pre-established safety constraints. Hence, safe autonomous driving could be a further application of DS based on increasing levels of automation.

5.3.2.3. Control of HEV, PHEV and BEV

Hybrid and battery electric vehicles, differently from conventional vehicles, are less affected by DS, because of the higher efficiency of the electric components. [139] addressed the influence of interaction between DS and road type combinations on the consumption and CO2 emissions in four different powertrains: petrol, diesel, hybrid and liquefied petroleum gas. The results showed that the hybrid powertrain is able to provide lower consumption even under urban aggressive drive, especially thanks to start-stop and regeneration during braking. Furthermore, it was demonstrated that, for conventional powertrains, an aggressive DS requires up to 68% and 47% more fuel in urban and rural roads, respectively; on the other hand, liquid petroleum and most important hybrid powertrains are less affected by the different DS [74]. In [140], the effects of DS on a conventional vehicle, HEV, PHEV and BEV have been studied. The results showed how DS can differently affect the different vehicle platforms. Namely, HEVs present optimal response at low speed, while conventional vehicles improve the overall efficiency at higher speed values. Moreover, HEVs turn out to be particularly vulnerable to high acceleration; at the same time, they are also the less affected by braking, due to the regenerative capability. Hybrid modes selection in HEV and PHEV are strongly related with the driver torque request and, of course, to DS. Consequently, slight changes in DS can trigger unnecessary modes switching, thus causing suboptimal performances. [130].
In this framework, energy consumption can be optimised by leveraging a prior knowledge of DS in HEV and PHEV. For instance, an optimal control strategy can be reached by leveraging the knowledge of the entire driving cycle, environment and driver behaviour. This information can potentially lead to important fuel savings [132]. DS information have been also used to optimise the energy consumption of a hybrid truck [141], while [142] used information about driving pattern and style recognition to better estimate the remaining autonomy in PHEV. Similarly, [143] proposed an adaptive control strategy for PHEV using driving pattern recognition. DS recognition can also provide useful information to make an accurate estimation of the remaining range, improve range management and even extend it [144]. [145], too, developed a strategy able to estimate the remaining range of BEV leveraging route information, such as speed, gradient profile, traffic conditions, and DS. The results showed an accurate estimation of the battery range which could reduce the so-called range anxiety (typical of BEV drivers), which is perhaps the main obstacle for the spreading of electric vehicles.

5.3.3. Driver Monitoring Systems

DL plays a key role in the field of image processing. In fact, the possibility of representing images by means of multiple hidden-layer neural networks allows a focused analysis of the key parts of a given image. It follows that driving vigilance monitoring system are often based on DP techniques, leveraging cameras pointing to the driver's face. Some supervised algorithms are often exploited to predict the driver's distractions and to detect the driving

context. [146], for instance, leveraged input coming from sensors embedded in the mobile phone, such as accelerometer and GPS. These data have been at first processed through a mobile application, and then sent to the learning algorithms.
ML methods are also exploited to get classification models capable of identifying the behaviour of vehicles, with a particular attention on fuel consumption. In particular, in [147], the input data set has been obtained thanks to 11 drivers driving VOLVO trucks equipped with controlled area networks (CAN). All the data collected through embedded sensors, like speedometer, GPS, throttle and brake pedal percentage of pressure sensor, have been exploited by two learning algorithms: decision tree and linear logic regression classifier.

5.3.4. Longitudinal Control

ACC is a well-known ADAS able to maintain a given velocity and a safe longitudinal distance to the vehicle ahead. To do this, it automatically brakes or accelerates depending on the distance between the two vehicles. Moreover, ACC with stop and go functions can achieve complete stop and then accelerate to reach the chosen speed again. This ADAS system still requires a driver watching the enclosing environment, as it only controls speed and the distance to the car ahead. An AI-ACC has been proposed in [148], which deals with the importance of continuous on-line learning from the driver. In particular, the idea is a personalised ACC system capable of adapting to driver strategies in dynamic traffic environments. This is obtained through the combination of a RL approach, Neural Q-Learning to obtain the high level driving strategy, and a PID controller to manage the low level control of brake and throttle commands. The system has been tested in simulation: the results showed that it is able to keep different expected distances in different cases in a comfortable way when learning from an experienced human driver. Ongoing research in the ML community has yielded promising theoretical and practical results for the resolution of control problems in uncertain and partially observable environments, so this framework has been recently exploited for the Cooperative Adaptive Cruise Control (CACC) design. An example of RL-based CACC can be found in [149].

5.3.5. Collision Warning/Brake Assistance

Forward Collision Warning (FCW) deals with the speed monitoring of a vehicle and the cars around it (usually exploiting on-board cameras, radar or LiDAR). In particular, if the vehicle is getting too close to another vehicle, the system alerts the driver of a possible collision. In the field of AI, a real-time Collision Warning based on a Multi-Layer Perceptron Neural Network (MLPNN), named MLPNN-based rear-end collision Warning Algorithm (MCWA) has been proposed [150]. In [151], through a supervised ML approach, a personalised brake reaction time estimation has been addressed, with the aim of optimising the time of FCW systems.

5.3.6. Lateral Control and Lane Changing

AI is often exploited to solve the problem of the assistance systems for mandatory lane changes at drop lanes. For instance, a combination of two classifiers, namely decision-tree and Bayes, has been proposed [152]. The proposed classifier is based on a majority voting principal: to be considered, both Bayes and decision tree classifiers must predict the same event. Algorithms have been tested through artificial data collected by co-simulation platiforms (e.g. Next Generation Simulation (NGSIM)).
In this framework, in order to predict the driver's intention to change lane, Relevance Vector Machine (RVM), a Bayesian extension to Support Vector Machine (SVM), has been used [153]. In particular, different categories of sensors have been leveraged to capture the driv-

ing context including that of the vehicle, the driver's state and the environment. Namely, radars have been exploited to detect the different obstacles ahead, Side Warning Assist (SWA) to have a rear view, and cameras for driver head tracking and lane detection. Lateral dynamics, such as the automatic overtaking in different driving scenarios, have also been processed via reinforcement techniques, as Q-learning [154, 155].
[156] used RL to implement the cooperative lane change approach for connected vehicles. The study considered two factors in order to set up the reward function: the delay caused by an individual vehicle and traffic efficiency of the road segment. The simulation-based results showed that traffic efficiency is enhanced in congested scenarios. Moreover, exploiting DL approaches, [157] implemented a hierarchical Deep Q-Network RL-based decision-making framework for lane changing manoeuvre, while [158] integrated DRL and data analysis algorithms in order to predict the trajectory recommendations for connected vehilces.
Mixing supervised learning and RL have been also proposed to generates lane-selection strategies through trial-and-error interactions with the traffic environment [159].

5.3.7. Intersection Advanced Driver Assistance Systems

Recently, researchers have focused attention on Intersection Advanced Driver Assistance Systems (I-ADAS) approaches, as they are active safety systems able to prevent or at least mitigate crashes and injuries in intersections.
Along this line, [160] proposed a decentralised coordination graph algorithm based on MARL and a coordination graph, with the aim of making traffic control policies by exploiting the current traffic states, the history of observations, and other useful information. The I-ADAS problem has been also tackled in [161] via a DQN-based cooperative traffic signal control in the case of multi-intersection.

5.4. Autonomous Driving Systems

The evolution of autonomous vehicles through different automation levels is currently in progress. Actually, few attempts are going to industrialise the Level 4 Autonomous Driving Systems (ADSs) that do not require human interaction in most circumstances. The level 5 (full self-driving automation) is aim of research activity.
In this context, AI-tools, and more specifically DL, are mostly used in autonomous vehicles (AVs) at levels 4 and 5 to accomplish different perception tasks and real-time decisions making. In general, an AI-based ADS for AVs is composed of three functional layers, including a sensing layer, a perception layer and a decision layer, as well as an additional cloud service layer [126] as shown in Fig. 5.7. The role of AI in autonomous driving is to make AVs intelligent, in order to allow them to take safe and efficient autonomous decisions in every possible scenario [163].

5.4.1. Sensing Layer

The sensing layer is composed of heterogeneous sensors able to detect environmental information in the surrounding area of a given autonomous vehicle [164]. Among the different types of sensors which could be used by the sensing layer, the most deployed by the leading autonomous driving vehicle companies are GPS, IMU, cameras, LiDAR, Radar, and ultrasonic sensors. In more detail, the role of GPS is to provide information on the absolute position through the use of geostationary satellites, while IMU collects orientation, velocity and acceleration data. Moreover, cameras allow to capture visual information in the area of an autonomous vehicle. This information is analysed by the perception layer, in order for the

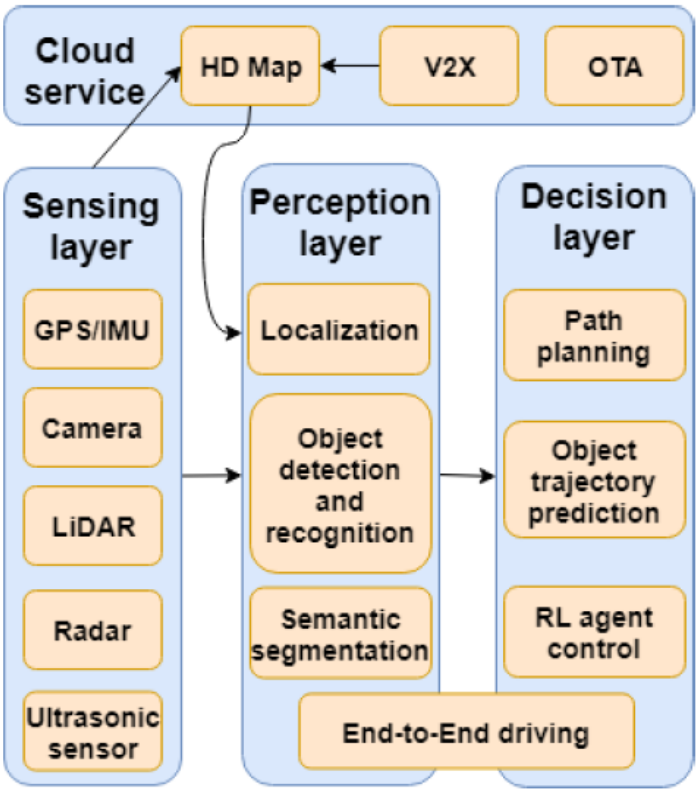

Fig. 5.7. ADS architecture [162]

vehicle to detect traffic signs and obstacles. LiDAR also allows the detection of objects and obstacles: based on the reflection of light, it is able to measure the distances between the objects and the vehicle. It is also able to provide real-time localisation and detection. Again, radar and ultrasonic sensors use electromagnetic pulses and ultrasonic pulse waves for the objects detection.

5.4.2. Perception Layer

localisation plays a key role in the route planning in an ADS for an AV. Usually, an AV driving system, in order to recognise objects on roads, is composed of two parts [162]:

- a module that provides detection and tracking information about the surroundings environment, such as vehicles, pedestrians, and traffic signs. This is made by leveraging inputs gained from different types of sensors such as radar, LiDAR, or cameras;
- a localisation and mapping module that refers to the relative states of AVs to others: the position of the AV in the map, its distance to other vehicles, its relative speed.

5.4.2.1. localisation and Mapping

Thanks to localisation technologies, the AV is capable to detect its accurate location on the map and understand the surrounding environment in real-time. Currently, localisation is mostly obtained through the fused data from GPS, IMU, LiDAR point clouds, and HD map. In particular, the fused data are used for the reconstruction of the surrounding environment of an AV and for the estimation of its current location. localisation and mapping have indeed evolved from stationary and indoor mapping to the SLAM: an outdoor, dynamic and high-

speed localisation and mapping for AVs. Many prototype vehicles, such as the Google and Uber, have used priori mapping methods, which consist at first of a prior collection of detailed sensor data, such as 3D images and highly accurate GPS information, used by large databases which store the created detailed maps. localisation is then achieved by observing similarities between priori maps and the current sensor data, while obstacle detection is gained through the detection of differences between the a priori map and the current sensor data [165]. For instance, in [166], data from GPS, inertial odometry and cameras have been used as the input of the SLAM in order to estimate the AV trajectory. To do this, image pairs have been compared and their differences used to identify potential street-view changes. Furthermore, [167] estimated car distances with camera and LiDAR signals from the KITTI dataset, exploiting two Convolutional Neural Network (CNN) systems, one for close-range (2–25 m) and another for far-range (15–55m) object detection, assuming a low resolution of input images. Then, the outputs of the two CNN systems have been merged to make an estimation of the final distance. Eventually, in [168], both CNN and Recurrent Neural Networks (RNN) have been exploited to estimate the movement and poses of an AV, using continuous images coming from a camera.

5.4.2.2. Road Object Detection and Recognition

Sensors represent fundamental tools for AVs to continuously scan and monitor the surrounding environment. Namely, they aim at reproducing human vision and other senses and thus mostly exploit computer vision models [169–172]. Perception algorithms can be classified in two groups [165]:

- mediated perception, which obtains detailed maps of the AV surroundings by leveraging distances to vehicles, pedestrians, trees, road markings, and so on;
- direct perception, which ensure an integrated scene understanding and decision making.

Specifically, mediated perception leverages AI tools, such as CNN, to detect single or multiple objects. Indeed, the accuracy of AI approaches, such as Deep Neural Network (DNN), has reached the value of 99.46% and, in some cases, overcome human recognition [173]. In the field of lanes and traffic lights detection, CNN achieved similar results. For instance, [174] addressed the problem of detection of roads for the vision navigation of AVs, proposing a combination of road knowledge and fuzzy logic rules. Moreover, another CNN system [175] has been proposed, able to detect more than 9 000 objects in real-time at 40–70 frames per second (fps) with a mean accuracy of about 80%. These methods leverage information on edge detection and saliency analysis to identify objects. Also [176] achieved a recognition performance of 99.54% on the benchmark data of the German traffic signs by introducing a CNN method to classify deep perceptual features.

Multi-task object perception helps improving the performance of a part or even all the tasks. To do this, it needs knowledge sharing in order to solve multiple correlated tasks. For instance, [177] proposed a CNN approach based on multi-task object detection, introducing the region-of-interest voting. This method has been validated through KITTI and PASCAL2007 vehicle datasets. Furthermore, [178] proposed the Cartesian product based multi-task combination to optimise at the same time both object detection and object distance prediction, leveraging the dependency among the two tasks.

As to direct perception, it is unable to create a complete local map or any detailed trajectory plans. However, it completes the mapping detection, determining, for instance, the current

angle on the road of an AV and the distance to surrounding vehicles and lane markings. Thus, direct perception does not address localisation and mapping stage, but directly controls the output of the steering angle and vehicle speed. Namely, in [179], TORCS image data have been exploited by a DNN method to detect an AV steering angle and velocity. The perception system has been validated using videos and images from the KITTI database. Moreover, a CNN framework has been proposed in [180,181]. It is composed of one normalisation layer, five convolutional layers, and three fully connected layers. The aim is to allow AVs to steer on the road leveraging camera images as the input and steering parameters as the output.
Faster Region-based CNN (R-CNN) have also been used to detect object using images [182]. For instance, You Only Look Once (YOLO) [183] is a famous object detection algorithm that treats the detection task as a regression problem. LiDAR-based object detection DL models are currently studied by both researchers and industry specialists: VoxelNet [184] is the first E2E model that directly predicts objects based on LiDAR, while PointRCNN [185] adapts the architecture of RCNN to take 3D point cloud as input for object detection, reaching better results in terms of efficiency.

5.4.2.3. Semantic Segmentation

SS in autonomous driving is a method for localisation of the vehicle through the detection of objects, marking lanes and the reconstruction of the map. It semantically classify different parts of an image into specific classes, such as vehicles, pedestrians and ground [162]. To this aim, DL models are usually exploited to achieve good performances, as FCN, which is able to modify the fully connected layer in a normal CNN to convolutional layer [186]. Another SS network is represented by PSPNet. It applies a Pyramid pooling architecture to achieve a good extraction of information from images [187].

5.4.3. Decision Layer

A fundamental part of the actual research focuses on different layers of motion planning with the aim of taking strategic decisions for trajectory and motion planning, and control. In what follows, a brief review of the most diffused AI tools used in this context is proposed.

5.4.3.1. Reinforcement Learning Agent Control

RL addresses the problem of a learning agent located in a given environment to achieve a goal. Differently from supervised learning, where the learner structure gets examples of good and bad behaviour, the RL agent has to understand by trial and error what is the best behaviour which guarantees the maximum reward. To do this, the agent has to detect information on a given state of the surrounding environment and, based on this information, makes a decision which leads to a new state. On the basis of the quality of his action, the agent gets a reward which will affect his future decisions. In order to model the environment state transitions based on the agent's actions, usually Partially Observable Markov Decision Process (POMDP) is leveraged [188]. The agent may be modelled through any inference model whose parameters can be modified depending of the agent's learning. Namely, the current actions affect the future states, and thus the future rewards. This means that the agent needs to have information on the future consequences of his actions in order to optimise the reward throughout the whole period. This task may be achieved through two main RL approaches: a value-based and a policy-based method. The concept of the first approach is well described in [189]. Namely, a DQN has been exploited. It allows the agent to predict a so-called Q value for each state-action pair, and to formulate the expected current

and future reward. From this information, the agent can either select the action with the highest expected reward as an optimal policy or choose exploration during the learning process. The final aim is to learn the optimal Q function, represented by a neural network in this case. This can be achieved through experiments, calculating the rewards of the future states for each action, and updating the network by exploiting the Bellman equation as a target. However, using the same network both for value evaluation and action selection may lead to unstable behaviour and slow learning, especially in noisy environments [188]. To overcome this issue, metaheuristics, such as experience replay, can be exploited, while other variants of the original DQN, such as Double DQN [190] or Dueling DQN [191], separates the action and the value prediction streams, allowing a faster and more stable learning process.
As to policy-based methods, they aim at directly selecting the optimal behaviour. Usually a neural network is used, through which the agent is able to calculate the normalised probability of the expected reward of the actions. This complements the exploration property of the RL process. Some variants contemplate a critic agent, who evaluates different kinds of prediction of the actions [192]. At a first time, finite action spaces for RL have been used. However, they turned out to be unsuitable for many control problems. Hence, a Deep Deterministic Policy Gradients (DDPG) agent has been proposed [193], in which the agent is able to directly map states to continuous actions.
Simplified rule-based algorithms cannot cover all the required complex driving scenarios for an extensive vehicle control, see Fig. 5.8. Indeed, the lower layers, such as trajectory fol-

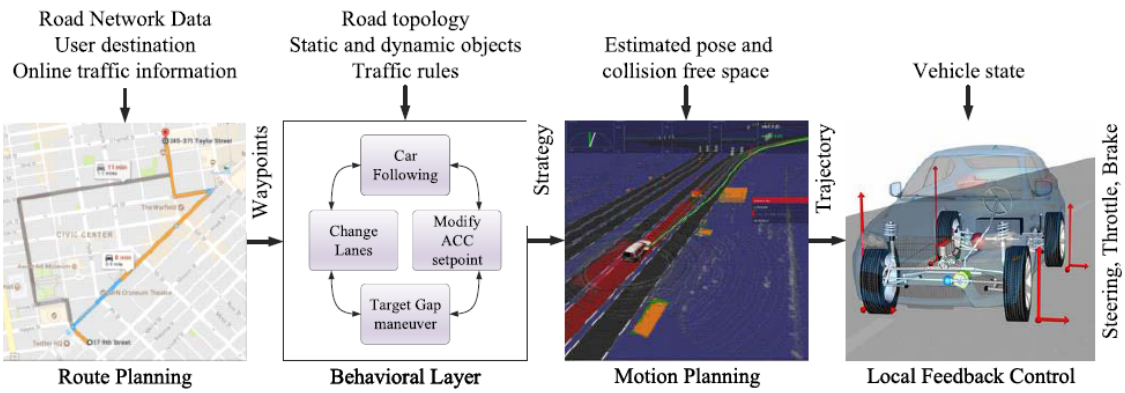

Fig. 5.8. Layers of motion planning [188]

lowing or simple control tasks, do not need interactions with other agents. However, on the higher levels, where the vehicle is involved in complex situations of interaction with other vehicles, like racing, passing intersections, merging, or driving in traffic, the other agents' reactions strongly influence the available choices. To overcome this problem, Multi-Agent Systems (MAS) [194] have been leveraged. If combined with RL techniques, they are called MARL [195]. A particular MARL approach may be seen as an extension of the original POMDP (see Fig. 5.10): it includes different actions and observation sets for each agent, or even different rewards if agents have various tasks. This method is known as decentralised partially observable Markov decision process (DEC-POMDP) [196, 197].

5.4.3.2. End-To-End Driving

An E2E model is a particular DL model which merges both the perception and decision processes. This model predicts the steering angle and driving speed on the basis of the environmental sensing information. In this field, the use of deep convolutional and temporal

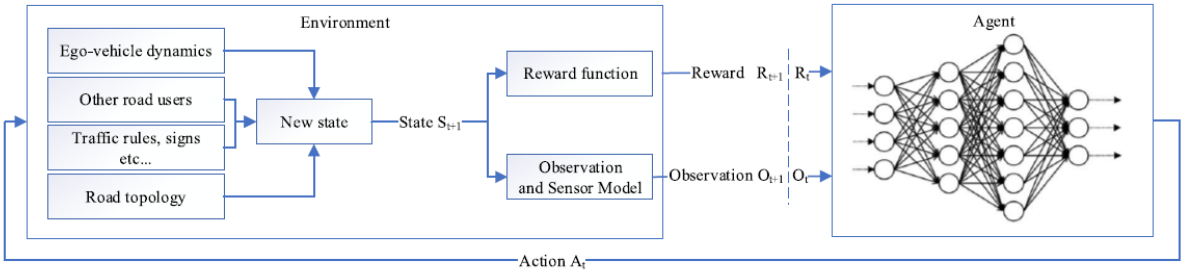

Fig. 5.9. The POMDP model for DRL-based autonomous driving [188]

networks for automated driving tasks is spreading. Namely, deep CNN have been leveraged with image from camera sensors as input and steering as output [198]. Additionally, spatio-temporal networks, as the so called FCNLSTM architecture, have been used for predicting ego-vehicle motion [199].
As to DRL models, DQN, that combines RL with DL [200], allows to choose a set of actions that maximise cumulative future rewards. Some variant of inverse RL can be also used to tackle the learning issue. [201] assumed that the agent follows an optimal policy with respect to an unknown reward function. Once the reward function has been recovered, RL has been exploited to select a policy that imitates the expert. In this context, a crucial issue is represented by the importance of DS for user approval [201, 202]. To overcome this problem, the goal is the ability to model individual DSs to reach personalisation. Hence, the DS have to be modelled through a cost function which is a linear combination of features, such as acceleration, following distance, desired speed, jerk. This cost function should be the result of inverse RL based on observed data.
An alternative to DQN and direct supervised learning could be represented by E2E driving with neuroevolution, in which evolutionary algorithms are used to train ANNs [203]. For instance, a ALVINN and a RNN trained with neuroevolution have obtained better results than direct supervised learning version [199, 204]. The major advantage of neuroevolution is the lack of back-propagation in favour of direct supervision.
The main drawbacks of E2E driving are represented by the lack of hard coded safety measures and interpretability [205]. Furthermore, DQN and neuroevolution require the real-time interaction with the environment, with the risk of failure in learning the desired behaviour. On the contrary, direct supervised networks can be trained off-line with human driving data; thus, the system is robust during operation.

5.4.3.3. Path Planning and Object Trajectory Prediction

Path planning is considered a basic task for AV. It consists in the definition of a route connecting a start location and the desired destination. The object trajectory prediction task requires AV able to predict trajectories of perceived obstacles leveraging sensors and perception layer. Recently, inverse RL has been used to achieve a superior results in path planning. Namely, by learning reward functions from human drivers, the vehicle is trained to select a route in a human-like way [206].
As to trajectory prediction, some variations of RNN and LSTM have been addressed to reach high prediction accuracy and efficiency [207]. Furthermore, 3D spatial-temporal data and single CNN have also been used to predict car trajectories [208].
The main difference between E2E driving and DL based local planners is represented by

the output: while the first provides direct vehicle control signals (i.e. steering and pedal operation), the second outputs a trajectory. DL and RL based local planners are going to represent a valid alternative. Fully convolutional 3D neural networks allow to obtain future paths from sensory input, such as LiDAR [209]. Another approach consists in the segmentation of image data with path proposals using a deep segmentation network [62]. RL has been instead proposed in [210], where a safe path planning in occluded intersections has been performed in a simulation environment.
Although DL based planners seem to be promising, they are not widely exploited in real-world systems yet. In fact, some issues are still open, such as the lack of hardcoded safety measures, generalisation, and the need for labelled data [211].

5.4.4. The Cloud Service

The cloud server is generally exploited as a service provider in autonomous driving. Namely, a prior HD Map containing important information, such as road lanes, signs and obstacles, is constructed by autonomous driving companies using LiDAR as well as other sensors. This map could be deployed on the cloud and used by the vehicle to make a first route planning, improving the knowledge of the environment. At the same time, real-time data and perception data of other AVs could be uploaded to the cloud by V2X service, in order to update the map adding important real-time information, such as surrounding vehicles.
DL models in AVs are indeed first trained on the cloud in a simulation environment. Once these models have been verified, the cloud provides Over-the-Air (OTA) update to remotely upgrade their software and DL models in AVs [162].

5.5. Cooperative Driving Systems

The exploitation of V2X, aiming to share on-board sensor information with the neighbouring, allows connected automated vehicles (CAVs) not only to autonomously drive, but also to make optimal joint decisions in real time [212]. More specifically, leveraging connectivity between vehicles (V2V), between vehicles and infrastructure (V2I), between vehicles and pedestrians (V2P) and between other road-users, autonomous vehicles can navigate safely and socially from their start location to the desired goal location in complex environments which involve multiple, intelligent actors whose intentions are not known by other actors. Vehicles driving in a cooperative environment usually execute the follow, merge, split, and change lane manoeuvres to maintain the safety and efficiency of road traffic.
It is worth highlighting here that the notion of collaborative or cooperative driving may correspond to different decision-making instances and mechanisms in different use cases of autonomous driving; hence, the decision of collaboration is followed by other decision instances, e.g., in platooning.
Cooperative problems can be approached using homogeneous, communicating multi-agent driving simulation environments for research and development of learning based solutions. Indeed, while in single-agent learning frameworks, the interaction between other agents in the environment or even the existence of other agents in the environment is often ignored, in the Multi-Agent learning frameworks the interaction between other agents can be explicitly modelled. In so doing, the driving problems can be approached using homogeneous, communicating multi-agent driving simulation environments for research and development of learning based solutions. Since cooperative driving involves complex interaction between multiple, intelligent (artificial or human) agents in a highly non-stationary environment, [213]

proposed the use of Partially Observable Markov Games (POMG) for formulating the connected autonomous driving problems with realistic assumptions. Furthermore, the study provided MACAD-Gym, a Multi-Agent Connected, Autonomous Driving agent learning platform, in order to exploit an extensible set of Connected Autonomous Driving (CAD) simulation environments that enable the research and development of DRL-based integrated sensing, perception, planning and control algorithms for CAD systems with unlimited operational design domain under realistic, multi-agent settings. Furthermore, MARL could very useful in high-level decision making and coordination between groups of autonomous vehicles, such as overtaking in highway scenarios [214], or negotiating intersections without signalised control. Again, MARL approaches could be exploited in the development of adversarial agents for testing autonomous driving policies before deployment [215], i.e. agents controlling other vehicles in a simulation that learn to expose weaknesses in the behaviour of autonomous driving policies by acting erratically or against the rules of the road. It is worth to note that MARL approaches could potentially have an important role to play in developing safe policies for Connected and Autonomous Vehicles (CAVs) [216].

5.5.1. Platooning

As already mentioned, cooperative environments help in developing algorithms that can learn near-globally optimal policies for all the driving vehicles that act as a cooperative unit. Such environments help in developing agents that learn to communicate [217] and benefit from learning to cooperate [218]. This type of environments will enable development of efficient fleet of vehicles that cooperate and communicate with each other to reduce congestion, eliminate collisions and optimise traffic flows.

A typical example is Vehicle Platooning, also known as convoy driving, is the practice of driving a group of two or more consecutive vehicles nose-to-tail on the same lane with small inter-vehicle spacing at the same speed. In platooning, the vehicles are virtually linked (by Camera/Radar/LiDAR and wireless communication technologies, V2X).

Vehicle platooning has been the focus of multiple stakeholders: academia and the transportation industry. Within this framework, few RL algorithms have been applied in vehicle platoon control, which has large-scale action and state spaces. Indeed, if we need to tackle RL multi-agent problems, the parameters space grows exponentially with the increasing number of involved agents. A recent attempt can be found in [219], where the specific aim has been to reduce energy consumption in Traffic Oscillations with guaranteed traffic safety and driving efficiency (see fig. 5.10). Moreover, a parameter-sharing RL structure has been adopted to reduce computational complexity and control agents with a variable agents' number. An optimal space-gap controller based on RL, which is demonstrated by an actorcritic policy with a deep deterministic policy gradient algorithm, has instead been proposed in [220], where results showed that there exists a trade-off between accuracy and learning time.

[221] addressed the management of multiple autonomous platoons leveraging C-V2X communication technology to disseminate the Cooperative Awareness Messages (CAMs) to their followers, while ensuring timely delivery of safety-critical messages to the Road-Side Unit (RSU). Here the problem of Age of Information (AoI) aware radio resource management is tackled and solved via a distributed resource allocation framework based on MARL, where each Platoon Leader (PL) acts as an agent and interacts with the environment to learn its optimal policy. Moreover, the MARL framework trains two critics with the following goals: a global critic which estimates the global expected reward and motivates the agents

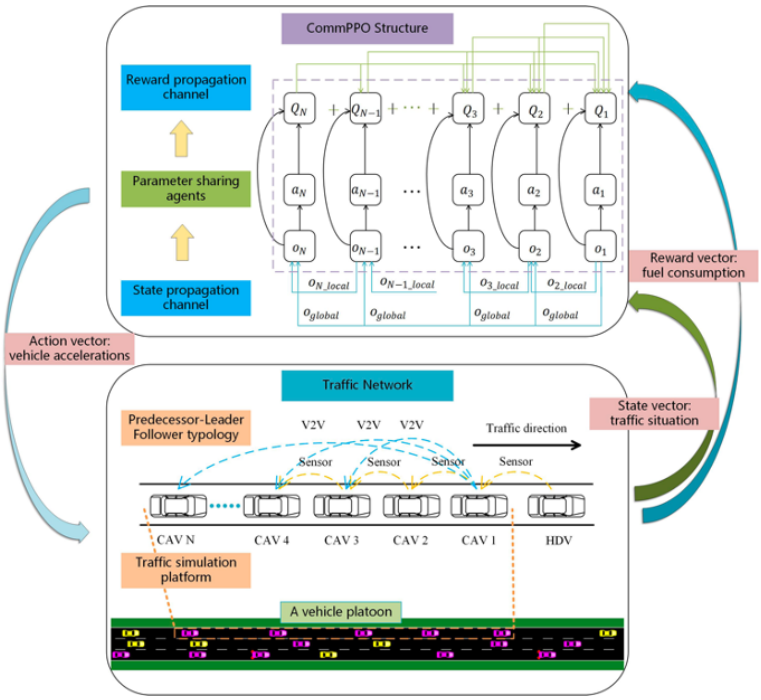

Fig. 5.10. Framework of RL multi-agent vehicle platoon strategy [219]

toward a cooperating behaviour, and an exclusive local critic for each agent that estimates the local individual reward. Furthermore, based on the tasks each agent has to accomplish, the individual reward of each agent is decomposed into multiple sub-reward functions where task-wise value functions are learned separately.
DRL has also been proposed for resource allocation for vehicle platooning supported by 5G New Radio V2X (NR-V2X) [222], where unicast, groupcast and broadcast communications coexist, and all of the vehicular communications operate without the assistance of Base Station (BS). In this context, the PL can learn from interactions with the communication environment and figure out a clever policy of collaborating with PMs to improve the communication reliability based on the received feedback.

5.5.2. Vehicular Cybersecurity

One of the most evolving research areas in cooperative driving is represented by communication technologies. Because of the adoption of several wireless communication-technologies, such as cellular, Wi-Fi, DSRC, and so on, and the interconnection of electronic controller units (ECUs), sensors, and actuators, the number of security vulnerabilities is growing rapidly. That's why the detection of potential vulnerabilities is a key issue of V2X communication. Although several conventional and innovative approaches have been addressed for cybersecurity of CAVs (see [223] for a comprehensive review), current research is mainly focused on AI innovative approaches that can be exploited in the field of ITS security strategies. Namely, big data handling in real-time processes is a significant problem in the age of connected cars. In this field, AI is increasingly used in Intrusion Detection Systems (IDS), due to the increased risk to security and the complexity of tasks.
AI-based algorithms for vehicular cybersecurity are basically related to sequence context anomaly detection with LSTM, support vector machine (SVM) based intrusion detection, distributed anomaly detection with hierarchical temporal memory (see [224] for an overview

of the novel AI methods addressed for vehicular cybersecurity). Among the proposed approaches, [225] exploited LSTM to detect anomalies in CAN bus data. The method is able to identify abnormal messages that were injected, modified, or even dropped, ensuring low false-alarm rates. [226] proposed an IDS based on a DCNN to protect the CAN bus. The study compared different ML algorithms (LSTM, ANN, support vector machine, etc.) using four different types of attacks. [227] addressed a novel hybrid DL and Dendritic Cell Algorithm (DeepDCA) in the field of IDS. Experimental results show that DeepDCA ensures over 98.73% of accuracy and a low false-alarm rate.
One of the main issues in the field of vehicular cybersecurity is represented by the necessity of a comprehensive standard. Namely, the interoperability among the various standards related to CAVs and the interaction with the surrounding world (Smart Cities, IoT) needs to be well considered and tested. This is strictly related to the QoS over the network, which should be ensured through an efficient resource allocation and sufficient infrastructure. In this context, cybersecurity strategies should always consider an efficient use of the resources, as all the entities involved in V2X communication have different capabilities and features. For instance, current security models do not consider the power consumption as a challenge because they are implemented on vehicles with a long life battery [228]. However, in V2X, some devices such as mobile phones have a limited battery. Thus, designing lightweight security strategies is recommended for V2X.
The efficient use of the bandwidth for V2X communications is essential for cybersecurity. Critical applications such as safety-related applications in vehicular networks, indeed, require a minimum delay for delivering warning messages in order to guarantee a high safety level.
Eventually, as to the AI approaches, although their advantages and potential are well known, the security implications of their integration in CAVs cybersecurity are not fully investigated yet. Extensive experimental results could be useful to test the adoption of these technologies in ITS security systems [223].
In table 5.1, we summarise the main existing works on AI-based applications in the field of autonomous vehicles.

Ref.	**Objective**	**Application**	**AI Technique**
		ADAS	
[142]	EV Range Estimation	Driving pattern identification	ML
[149]	Cooperative driving	CACC	RL
[150]	Collision avoidance	Rear-end collision warning	MLPNN
[151]	Collision avoidance	FCW	ML
[154]	Automatic Overtaking	Lateral control and lane changing	RL
[155]	Automatic Overtaking	Lateral control and lane changing	RL (Q-learning)
[156]	Cooperative driving	Cooperative lane changing	RL
[157]	Driving decision and control	Lateral control and lane changing	DRL
[158]	Cooperative driving	Lane merge coordination	DRL
[161]	Cooperative traffic signal control	Traffic flow prediction in multi-intersection	DQN

ADSs			
[166]	Environmental perception	Visual SLAM	DN
[167]	ADS validation	Virtual test	ML & DNN
[168]	E2E driving	Visual odometry	RCNNS
[176]	E2E driving	Traffic sign recognition	KELM
[177]	Obstacle avoidance	Vehicle detection	CNN & RoI voting
[178]	Obstacle detection and avoidance	Object detection and distance prediction	MTL
[179]	Environmental perception	Vision-based ADS	CNN
[180]	E2E Driving	Lane Detection and lateral control	CNN
[181]	E2E Driving	Longitudinal and lateral control	DNN
[182]	Detection	Object detection and segmentation	Mask RCNN
[183]	E2E driving	Object detection	YOLO
[184]	Environmental perception	3D detection	RPN
[185]	Environmental perception	3D detection	PointRCCN
[186]	Environmental perception	SS	FCN
[189]	E2E driving	Automatic learning of successful control policies	DRL
[190]	E2E driving	Automatic learning of successful control policies	DQN
[191]	E2E driving	Automatic learning of successful control policies	DDQN
[192]	E2E driving	Automatic learning of successful control policies	DPGA
[193]	E2E driving	Continuous control	DRL
[198]	E2E driving	Vision-based ADS	FCN-LSTM
[200]	E2E driving	Artificial agent	DQN
[201]	E2E driving	Artificial agent	Inverse RL
[204]	Environmental perception	Vision-based ADS	RL
[205]	E2E driving	Deep Steering	Convolutional LSTM
[206]	Motion planner	Automatic learning of successful control policies	Inverse RL

[208]	Tracking and motion forecasting	3D detection	SCN
[209]	E2E driving	Path generation	CNN
[210]	Motion planning and trajectory tracking	Unsignaled intersection crossing	DRL
Cooperative Driving Systems			
[213]	Connected autonomous driving	Multi-agent control	MARL & POSG
[215]	Cooperative driving systems testing	Failure scenarios identification	MADDPG
[216]	Trajectory planning and tracking	Comfort and safety of driving	Option graph
[217]	Environmental perception	Vision-based ADS	Dataset for autonomous driving
[220]	Platooning	Multi-agent control	DRL
[221]	Platooning	C-V2X distributed resources allocation	MARL
[222]	Platooning	5G NR-V2X distributed resources allocation	DRL
[225]	Vehicular Cybersecurity	Anomaly Detection	LSTM
[226]	Vehicular Cybersecurity	Intrusion Detection	DCNN
[227]	Vehicular Cybersecurity	Intrusion Detection	DeepDCA

Table 5.1: Summary of the existing literature on the main AI-based applications in automotive

5.6. Major Challenges for AI-Driven Applications

5.6.1. Sensor Issues in AI Approaches

In order for AI methods to be successful in AV applications, a key role is played by the quality of the sensor data used as input. Sensors in AV applications may be classified in three categories [165]:

- self-sensing, which leverage proprioceptive sensors, such as odometers or IMU, to detect the current state of AV (velocity, acceleration, and steering angle);
- localisation, which exploit external sensors, such as GPS or dead reckoning by IMU readings, to find out the AV's global and local positions;
- surrounding-sensing, which use exteroceptive sensors to detect road markings and slope, weather conditions, traffic signs, and the state (position, velocity, acceleration) of obstacles, such as the surrounding vehicles.

Proprioceptive and exteroceptive sensors can be further divided into active and passive sensors: while the first emit energy in form of electromagnetic waves, such as radar and LiDAR, the latter perceive electromagnetic waves in the environment, such as light-based and in-

frared cameras.
The most exploited sensors in AV applications are camera vision, LiDAR, radar, and sonar sensors. As to cameras, their spatial resolution in AVs is generally included between 0.3 and 2 megapixels. They are capable of generating video stream at 10–30 fps, so capturing important objects in real-time, such as traffic light, traffic sign, and obstacles [229]. LiDAR sensors periodically scan the surrounding environment, collecting multiple measurement points. This "cloud" of points are then processed to determine a 3D map of the environment. Moreover, radar and ultrasonic sensors may be characterised by different kinds of detection areas, such as short-range or wide-angle, midrange and wide-angle, and long-range and narrow-angle [230]. In general, AVs exploit information from different sources in order to improve the estimation accuracy, the robustness and reliability of the system. For instance, a LiDAR system is able to detect the regions of interest, and a camera system can make an accurate detection of objects, allowing to add fundamental details to these regions. Indeed, a fusion of data from both cameras and LiDAR sensors has led to better results under poor light conditions [231].
Another important issue which can be addressed by the fusion of different sensor data concerns precision and accuracy problems on sensor outputs caused by unusual situations, such as extreme weather conditions (snow, heavy rain, fog, etc.). Namely, these scenarios are often a problem even for human drivers. That's why this field represents an important AV research topic. It has been found that, in snowy conditions, both vision-based and LIDAR-based systems have extreme difficulties, as the density of the snow affects the LiDAR beams, causing reflections that generate inexistent obstacles [232]. To overcome the perception problem, different approaches, such as sensor fusion of camera, LiDAR, and radar sensors [232] and taillight recognition [233] have been addressed.
In addition to weather conditions, another obstacle for perception is represented by particular environment conditions, such as complex urban areas or unknown regions. In this framework, a rough set theory to deal with some possible noise and outliers has been proposed [234]. However, in order to select the priority of specific sensors, several key questions should be answered. In other words, different AV objectives may be chosen, such as efficiency of sensors under extreme weather conditions, trade off between cost and accuracy, and so on. That's why the sensors chosen by different stakeholders are noticeably different. For instance, the AVs in the DARPA Urban Challenge were generally equipped by multiple, expensive LiDAR and radar sensors, but lacked sonar sensors, low-speed and automated parking. That's why their prior challenges rule out low-speed and precise automated parking. Conversely, many commercial vehicles include ultrasonic sensors for automated parking, as well as infrared cameras to detect pedestrians and other obstacles at night [235], but not LiDAR to minimise cost.
Summing up, when designing an AI approach, a deep analysis on the set objectives and the subsequent choice of sensors inputs should be carried out. Namely, sensor data features should be investigated, such as availability and quality, as multiple combinations of sensors lead to heterogeneous datasets for specific AI approaches.

5.6.2. Complexity and Uncertainty

The uncertainty related to AI approaches in AV driven can be identified into two groups [165]:

- uncertainty induced data issues: almost all data gained by sensors are affected by noise. As these data are used as input for AI models, this can lead to unpredictable errors;

- uncertainty due to the implemented models [236].

As explained before, data collected by sensors may be unreliable under particular weather or environment conditions, and this may increase the uncertainty perception.
To solve the uncertainty problem, false detection and isolation methods have been proposed. [237], for instance, applied analytical redundancy and nonlinear transformation methods in order to identify faulty or deviant sensor measurements, whereas [238] leveraged RL to detect abnormal input due to missing data, environmental changes, and so on.
On the other hand, uncertainty related to AI models strictly depend on their functional requirements and assumptions. Namely, AI approaches assume that data gained from sensors are always compliant with the algorithms, as well as that the operational environment is constantly detectable. Actually, these assumptions are often not compliant with the AVs' environment, being the latter unpredictable and dynamically changing [238]. Furthermore, complexity and uncertainty can be increased on connected AVs due to malicious attacks, as the latter do not require a physical access to AVs. Therefore, malicious attack and intrusion detection is a crucial issue in connected AVs.
AI approaches such as neural networks or fuzzy logic have been explored in external communication systems [239]: they seem to guarantee more efficient methods able to deal with complex scenarios if many AVs were connected.

5.6.3. AI for Risk and Uncertainty Assessment

Quantifying the uncertainties and the risk level of the driving scene seems a promising methodology that can increase the safety of ADSs [240]. To do this, Bayesian methods have been proposed in order to detect and measure uncertainties of DNN [241], as the Bayesian DL architecture addressed in [240] with the aim of propagating uncertainty throughout an ADS pipeline: compared with conventional methods in a hypothetical scenario, it has achieved better results.

5.7. Necessary Tools for Design

A crucial issue of the training process of RL for AVs is represented by the modelling of the ego-vehicle, as it is affected by the trade-off problem between model accuracy and computational resources. Namely, RL techniques deal with a huge number of episodes for identifying the optimal policy; therefore, the training time is strongly influenced by the step time of the environment, which highly depends on the evaluation time of the vehicle dynamics model. Hence, during the environment design, the model's choice may range from the simplest ones with a low number of degree of freedom to the more sophisticated dynamics models with a high number of parameters. Furthermore, the modelling of traffic and surrounding vehicles so to use a unique co-simulation platform is required [188]. Some designers created indeed self-made environments to achieve full control over the model, the communication and sensing features and the road environment, also leveraging some Open-source tools that can provide this feature [242]. A brief description of some of them dealing with RL approaches follows.
In the field of environment modelling, Simulation of Urban MObility (SUMO) is widely exploited. It is a microscopic, inter- and multi-modal, space-continuous and time-discrete traffic flow simulation platform [243], and is able to convert networks from other traffic simulators, such as VISUM, Vissim, or MATSim. Moreover, it also reads other standard digital road-network formats, such as OpenStreetMap or OpenDRIVE, and allows the interfacing with

several environments, such as python, Matlab, C++, etc. All these features make this tool an excellent choice for training agents to handle traffics, even though the abstraction level is microscopic, and the vehicle behaviour is limited. VISSIM is considered another valid microscopic simulator [244, 245].
Focusing on the vehicle dynamics, The Open Racing Car Simulator (TORCS) represents a popular choice. It is indeed a modern, modular, highly portable multi-player, multi-agent car simulator [246], even though it requires an interface with Python or Matlab for the implementation of the AI algorithms. Alternative choices may be Airsim or Udacity [247, 248]. The second one, exploiting various sensors, such as high quality rendered camera image, LiDAR and infrared information, is also able to model other traffic participants. Moreover, CARLA has been developed to support the training and validation of autonomous urban driving systems. It is an open-source platform which provides open digital assets, such as urban layouts, buildings, and vehicles, created for this purpose. It also supports different specification of sensor suites and environmental conditions [249, 250].

5.8. Verification and Validation of Autonomous Vehicles

An important issue to be considered when addressing Autonomous Vehicles is Verification and Validation ($V\&V$) of AI-based software for safety assessment. Indeed, due to the possibly unpredictable nature of AI approaches, and in particular of ML systems, their use create concerns that need to be faced using appropriate $V\&V$ processes to guarantee trustworthy AI and safe autonomy.

A specific study on the state of the art of $V\&V$ for autonomous cars has been conducted in the framework of RAILS [251]; this review covers several aspects including certification issues against reference standards, challenges in assessing ML, general $V\&V$ methodologies and approaches. Here we summarise the findings that can be of interest not only to transferability, but also to further discuss the challenges risen by the usage of AI to achieve (full) autonomy.

Safety Assessment and Certification. ISO 26262 provides guidelines and best practices for the safety assessment of road vehicles according to the well-known V-model, but Autonomous Vehicles pose new challenges. According to [252], *the main issue in checking that a system complies with ISO 26262, is to statistically demonstrate that the system will remain in agreement with the safety goals while operating*, but even a low statistical failure rate for a single vehicle becomes unacceptable when millions of vehicles are considered. The ISO 26262 standard requires that if the system operates for 10^9 hours then the number of faults observed should not exceed 10 (i.e., 10 FIT - Failures in Time) [253], therefore a serious obstacle to the adoption of the new AI-based technology is the extensive test suit needed to statistically demonstrate that the requirement is met.

Challenges in assessing Machine Learning. Several problems must be faced in assessing ML, some of them are general issues and have been already pointed out in WP1. Here we mention few research works discussing such challenges for autonomous cars or proposing directions to explore for validation of safe self-driving vehicles.

- **V-model and over-fitting.** ML systems in industry mainly use an inductive approach: they rely on training data to create models, some data from the training set can be kept to be later used to test the system. The process can be mapped to the V-model if training data is associated with the left side of the model at requirements specification

level; consequently, on the corresponding right side of the model, requirements can be validated by using the subset of initial training data that was kept out to validate the system. There should be no coincidental correlation between the training set and the expected result to avoid over-fitting. Likewise, the selected validation set should be diverse and should not correlate with the training set while conforming to the requirements in order to detect over-fitting. There is no common way to prove that the resulting ML model for the system is not over-fitted as a safety requirement [254].

- **Data labelling.** Labelling is either done by someone or some other unsupervised learning algorithm, both having their own complications. ML systems are sensitive to change: doing a minor change leads to a necessity to re-validate the whole system. When a problem in the training set is identified, it also adds the extra work of collecting more data to validate the system. Autonomous Vehicles are likely to encounter many extremely *rare cases* that were not considered in the initial training set. Every time a new case is detected, the system should be updated and re-validated accordingly [255].
- **Explainability.** Making ML easy to understand for humans has not currently been achieved. Being unable to predict the behaviour of ML, makes it harder to assess its decision-making process and leaves us to use costly brute force techniques. Even if a brute force can be applied given sufficient resources, it only validates the result within the training set and does not show the coverage or accuracy of the training data and how it complies with the safety standards [256].
- **Corner cases, adversarial attacks and testing tools.** Behaviour and decisions of DL algorithms are sometimes unpredictable, or even wrong. Corner cases might exist due to issues in the model or training data. Additionally, DL systems can be vulnerable to adversarial attacks that make minimal changes in the input: perturbations that may be invisible for humans and need to be discovered during testing [257]. *DeepXplore* is the first white box testing framework for the industry, aiming to achieve systematic testing of real world DL applications [258]. Following DeepXplore, another testing framework called *DLFuzz*, has been proposed in [259] to find corner cases in DL systems.
- **Validation.** An alternative way to validate systems that rely on inductive learning is discussed in [255]. The objective is to make the high-ASIL monitor a deductive component, while the low-ASIL actuator remains an inductive component. Here, the main validation process would be shifted to a component that does not rely on inductive learning, thus making the solution of the validation problem easier. The monitor can observe and catch faults in the functionality of the actuator within a safety envelope to achieve fail-safe operation. Consequently, the safety issue is changed to an availability issue, as the system becomes unavailable but remains safe. An efficient approach to validate an object detection system that uses ML algorithms is described in [260]. For an image recognition algorithm to function properly in safety-critical automotive a failure rate as small as 10^{12} should be achieved. Emulators can be used to generate synthetic data, rather than collecting real-life data through test drives, in order to speed up testing. The problem is that the physical implementation of the system does not yet exist to rely on when validating a system at the design level. In this case, simulation approaches should be used, which in turn generates high costs if the model of the system is required to be accurate. To reduce validation cost in such a system, the study in [260] proposes an approach of subset sampling in which the objective is to estimate the

failure rate of an ML algorithm in an autonomous vehicle in terms of different probabilities. Finally, a novel approach is introduced in [261] that suggests an iterative process in order to solve the AV validation challenges and achieve SAE Level 5 autonomy. The proposed methodology aims to limit AV decisions to those which are validated and can be guaranteed to be safe, i.e. the vehicle can execute actions only inside a validated safe space. The paper demonstrates a control architecture that can be applied to vehicles in any level of autonomy starting from Level 1. An AV with Level 2, which requires full situation awareness from the human driver, can initially be released and using the proposed approach to assess itself while operating. The deployment starts with Level 2 as it initially does not cover the validation space completely. However, by time as the vehicle learns, it can increase the coverage of the validation space by assessing itself in an iterative manner with, the goal of achieving Level 5, i.e., full autonomy.

AI for Testing An interesting application of AI that emerges from this study is its use to enhance the testing process. The work described in [262] proposes a new approach utilising ML and DNN for assessing ADASs and AVs both in lab environments and in the real world. According to [262], the primary challenge of using the V-model is the lack of efficient information exchange between different phases and between real-world and lab tests. The methodology proposed in that work aims to categorise and group the real-world test data according to functionalities using ML and DNN algorithms. Data can be reused to recreate real-world test cases inside a simulation. Data is also generalised and stored in a common database to be accessible in all phases of the V-model and therefore to be suitable for different original equipment manufacturers (OEM). The paper also illustrates the use of AI-core (ML system) for test case and scenario generation for both laboratory and real-world environments. The authors suggest that AI-core can be used to validate high levels of safe autonomy with minimal human interference.

6. Tranferability Directions

In this chapter, we leverage the knowledge gained from WP1 and from the review activity performed in Task 2.1 to delineate some transferability directions that seem promising according to the criteria we provided in section 3.1. At first, a review of high-speed railway communication systems is proposed, in order to analyse the maturity of Train-to-everything (T2X) communication in the new paradigm of Internet of Trains, that have to be addressed when dealing with autonomy. Then, we consider the relevant railway problems, the main challenges and areas for the application of AI in the domain of railway safety and automation, according to the analysis reported in D1.1, D1.2, and D1.3. A synthesis of the previous Chapters from a transferability perspective follows. Finally, possible research directions for transferability are derived by crossing the available information.

6.1. T2X Communication: State of the Art and Future Challenges

The rapid development of High-Speed Railways (HSRs) brings significant challenges in terms of industry, technology and environment. In order to satisfy the ever increasing high-data-rate requirements, new technologies for T2X communication systems, such as Long-Term Evolution for Railway (LTE-R), Fifth Generation (5G) on HSR, and 5G for Railway (5G-R), and the corresponding transmission technologies, e.g., mobile relay, coordinated multi-point, massive multiple-input multiple-output (MIMO), and millimeter-wave (mmWave), have recently attracted much attention. Since 2014, indeed, the International Union of Railways (UIC) has considered replacing the global system for mobile communications for railway (GSM-R) with LTE-R, in order to support future railway services and requirements. Furthermore, 5G-R is expected to cover a variety of high mobility scenarios, such as HSR, subway, and highway, since, thanks to the larger bandwidth, it will allow to simultaneously provide both the high-data-rate services for train operation and passenger experience.
To support the advances of communication systems for next generation railways, The S2R MISTRAL Project [263], which falls within the scope of X2RAIL-1, developed a Validated Techno-Economic Specification of the future communication systems for railways in light of the migration from the current obsolete GSM-R. The conditions for the implementation in railways of the new communication technologies already exploited in public communications, such as the 4G-LTE and 5G candidates, are analysed in terms of technical and economic feasibility. The new communication technologies will exploit the broadband capacity of IP-based wireless communication to enhance signalling; moreover, innovative services for both users and train automation/control will be available. However, the trade-off between the speed of technological innovation and the time of acceptance of new solutions in railways should be taken into account, since, differently from the telecommunication market, the railway sector is resilient to changes.
To avoid a complicated validation process with costly on-site testing for the new T2X communication systems, the S2R EMULRADIO4RAIL Project [264] (a complementary project of X2RAIL-3) developed an innovative hardware and software emulation platform for the test of new communication system prototypes. The main objective of the project is to answer "zero on site testing" challenge for the testing and validation of various RATs, such as Wi-Fi, GSM-R, LTE, LTE-Advanced (LTE-A), 5G and satellite communications.

Furthermore, The S2R AB4RAIL Project [265], belonging to X2RAIL-5, is focused on the study and the assessment of the Adaptable Communication System (ACS) in terms of alternative bearers and communication protocols for railways applications. The project aims at identifying, assessing, and analyse alternative communication bearers for the rail environment, from a technology perspective, in addition and beyond RATs technologies such as UMTS/HSPA, LTE, LTE-A, geostationary satellites. The main purposes of the project are therefore to manage multi communication bearers and heterogeneous connection link to ensure the best performance of specific rail applications, as well as to guarantee appropriate QoS and Quality of Experience (QoE) levels.
In the following, the main features of the current and upcoming communication technologies in railways are detailed.

6.1.1. GSM-R

GSM-R is an international wireless communication adopted by European rail companies to replace the conventional railway communication systems in order to ensure train safety when travelling to different countries and to avoid any communication issue [266]. The GSM-R mobile technology is a radio network which allows T2X communication, as the coverage of the rail network is always ensured, even in cuttings and tunnels [267]. GSM-R and GSM system are basically the same but GSM-R has railway-specific functions based on European standards and specifications.
GSM-R system architecture is shown in Fig. 6.1. In particular, it is composed by dedicated base stations (BSs) close to the rail track. The distance between neighbouring BSs may be different from a country to another and depends on the environment [268]. A Base Station Controller (BSC) controls groups of BSs and allows the connection among BSs and the Mobile Switching Centre (MSC). The latter is responsible of the connection between the users and allows the connection between the GSM-R network and public networks [269].
GSM-R offers different services exploited for T2X communication. One of these is Voice

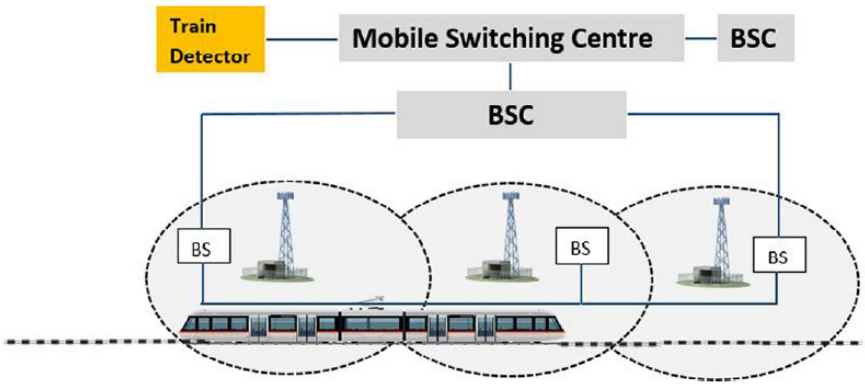

Fig. 6.1. GSM-R system architecture [270]

Group Call Service (VGCS), which conducts group calls between trains and BSs or among trackside workers, station staff, and so on. The BS can also broadcast messages to certain groups of trains, or trains broadcast messages to BSs and other trains in a defined area through the Voice Broadcast Service (VBS). Compared to VGCS, only the caller can speak in VBS, while the other users who join the call can only listen. This service is mostly used to

send recorded messages or to make announcements in HSR operations. Enhanced multi-level precedence and preemption (eMLPP) defines the user's priority and is used to achieve high performance for emergency group calls, while the Shunting Mode ensure an efficient communication among a group of personnel involved in shunting operations.
For its mature technology, GSM-R is the unified communication technology supporting European Train Control System (ETCS), which is the signalling system used for railway control [271]. The ETCS has three levels of operation and uses the GSM-R radio network to send and receive information from trains in order to guarantee a real-time supervision of train position and speed.
However, GSM-R is characterised by some significant limitations. First of all, the transmission of the signal in the GSM-R system suffers from shadowing and multi-path effect, and is affected by the Doppler shift. Furthermore, the increasing interference from public networks hinders the use of GSM-R, while the assigned radio frequencies limit its capacity [268]. For these reasons, even though the use of GSM-R is ensured for the next years, the need of another technology able to overcome the above-mentioned limitations seems necessary.

6.1.2. LTE-R

The increasing high-data-rate requirements in T2X communication has led to the development of LTE-R, a new digital signal processing and modulations techniques able to improve the speed and capacity of wireless networks compared with the limited capability of GSM-R. LTE-R, which is based on LTE standards, is characterised by a simpler architecture consisting of a IP-based network which can ensure a lower transfer latency [272]. Some considerations have been made by the UIC on the feasibility of replacing the current railway communication systems with LTE-R [272], and the first LTE-R networks are going to be developed in some countries [268].
LTE-R system guarantees a high data rate up to 50 and 10 Mbps for down-link and up-link, respectively. The handover process is one of the main differences between GSM-R and LTE-R. The first one uses a hard handover, in which the connection of the mobile station (the train) is entirely broken with the current BS before switching to the next BS. This can cause a short break in the connection which is emphasised by the high speed movement of the train. LTE-R system, instead, exploits the soft handover between the BSs, in which the mobile station is always connected to at least one channel. When the train is in the overlapping area covered by neighbouring BSs, the signals that are received from these BSs are combined at the receiver. This process significantly improve the QoS as it both reduces the probability of call drop and removes the interference [273].
The system is designed to support high-speed trains up to 500 km/h. Indeed, to deal with the high speed of trains and the small area covered by each BS, the number of handovers between the cells in LTE-R network has been increased [274], in order to ensure a reliable and efficient communication system for HRS.
Even though the availability of bandwidths is higher at high frequencies, lower frequency bands from 450 to 470 MHz have been considered for T2X communication, since this choice allows countries to reuse the existing GSM-R mast sites [268]. Furthermore, it is well known that high frequencies cause propagation loss and fading.
The main challenge of LTE-R is to fulfill the railway requirements in terms of safety, QoS, reliability, availability, and maintenance. Several studies based on simulation results and technical analysis highlighted that the LTE-R system is the preferred candidate for the future of T2X communication [275–278].

However, there are some criticisms related to the development and adoption of LTE-R. One of these is represented by the coexistence between LTE-R and the LTE public safety network (e.g., police, firefighters and ambulance), as they use the same frequency bands. This causes radio interference between networks, since both of them are more concerned about reliability and safety [279]. Furthermore, high train speeds leads to the undesired Doppler shift with a consequent phase shift of the signal, even though tracking and compensation are possible, as train speed and position are well-known and monitored in real-time [268]. Eventually, propagation loss in the HSR environments, characterised by tunnels, bridges, train stations, etc., can significantly affect the performance of the LTE-R system [280].

6.1.3. 5G-R

The data-rate that T2X communication will require in the next future is not compliant with the capacity of the current communication systems. All of the existing technologies, indeed, support data-rates up to 100 Mbps only, as they work with frequencies lower than 6 GHz. Therefore, the interest towards a technology that exploits higher bandwidth and capable to handle both the critical and non-critical T2X communications has increased [281]. In this regard, 5G technology is expected to play a fundamental role in IoT applications that require more reliable and low-latency communication. Transmission technologies such as MIMO, mmWave, small BSs, and so on, play a fundamental role in the advancement of 5G.
In order to exploit the preexisting infrastructures, 5G could adapt the architecture of the current communication systems, such as 4G [282]. Indeed, existing networks capabilities could be enhanced in order to allow 5G-R to fulfill T2X communication requirements.
Latency is one of the feature improved by 5G. The aim is to reduce the latency up to 1ms compared to 70ms of the current 4G technology. This could allow the use of real-time functions or applications which require a quick response. Furthermore, mmWave exploited by the 5G guarantees a higher bandwidth which could improve data-rate transmission for T2X communications. Indeed, while the available bandwidth of 5G is 9 GHz, only 100 MHz is used in 4G-LTE networks. Moreover, the targeted date-rate 5G is 20 Gbps, which could be reached thanks to the implementation of massive MIMO. This features could allow the 5G-R technology to be more efficient for railway communication than the current communication systems [282].
However, even though 5G technology seems to be the best upgrade in T2X communications, these are some issues to be considered. First of all, self-interference cancellation could have a significant impact on 5G networks [283]. Then, due to larger bandwidth, power consumption is higher compared to the existing technologies [284]. Eventually, different propagation factors can that affect the performance of the 5G mmWave, such as reflection, diffraction, and scattering [285].

6.2. Indications from WP1

Fig. 6.2 shows the subset of the railway problems falling in the context of enhanced safety and railway automation.

It is worth noting that some problems belong to both safety and automation areas or are beyond the scope of WP2, such as anomaly detection. Moreover, some of them could be included in a wider class (for example, block occupancy and train localisation may be considered in smart signalling). Nonetheless, we prefer to keep the set as it was, thus highlighting specific problems that were considered especially relevant.

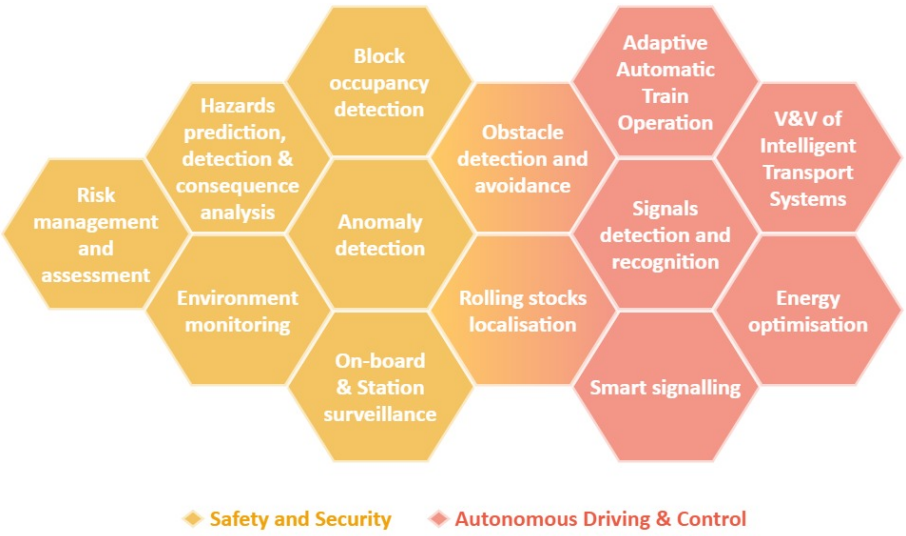

Fig. 6.2. Railway problems for AI application in WP2 (excerpt from D1.3)

In addressing this problems with AI-based approaches, the following major obstacles must be faced, according to the Survey on Challenges and State-of-Practice (SoP) of Artificial Intelligence in railways, conducted involving the railway stakeholders:

- safety, dependability and trustworthiness concerns;
- lack of proper datasets for training the AI models;
- lack of specific standards and regulations.

In the view of these indications and of the review work conducted in the first phase of the project, the application areas in the safety and automation domain as they have been identified in deliverable D1.3 include AI for:

- Data-driven risk assessment;
- Smart Verification & Validation;
- Hazardous events prediction and consequence analysis;
- Safety of workers;
- Passenger safety at stations;
- Smart signalling and adaptive Autonomous Train Operation (ATO), including train localisation, energy optimisation, automatic wayside signals recognition/detection, obstacle detection and their trajectory prediction;
- Self-organising systems to improve flexibility, capacity, and resilience of the railway system as a mobility backbone.

Crossing such information with the specific objectives of WP2, in this deliverable we mainly focus on:

- adaptive train operation and obstacle detection in the field of autonomous driving and control.
- risk assessment and hazards analysis from a safety perspective.

6.3. AI Applications to Intelligent Vehicles

In this section the main *applications* are reported from Chapters 4 and 5 for which artificial intelligence techniques and approaches have been investigated or adopted. The section summarises applications in the sectors of aerial vehicles, ground vehicles and cars to point to the more relevant topics discussed in the previous part of the document and identify the most used AI techniques or approaches that could be considered for transferability to the rail sector, according to the objective of this study. Therefore, this section also provides indication on the most suited AI techniques to consider for the target domain to move towards autonomous trains and cooperative driving, as they emerge from the review reported in Chapters 4 and 5. The main research lines are then discussed in Sections 6.5 and 6.6. As RAILS does not explicitly deal with (cyber)security, in the following we do not address security issues.

For a description and discussion of the reported applications and techniques in the context from which they are taken, the reader can refer to the previous chapters. AI applications from other sectors are all worth of investigation for transferability, as they potentially may be generalised/modified to some extent to be applied to railways problems. Nonetheless, as explained at the beginning of this document, we do not develop here detailed transferability analyses for specific purposes, but we suggest some directions within which such analyses can be performed.

6.3.1. Autonomous movements/navigation

This class of applications includes:

- Obstacle detection and avoidance;
- Intelligent path planning;
- Coordination and Collision avoidance.

The objective of an AI application is to cope with a specific problem. Problem like obstacle detection and avoidance, or path planning, are relevant for both a *single vehicle* and a *fleet of vehicles*. In the second case coordination and collision avoidance are necessary. In some cases a vehicle may take its own decision based on the computation on its local side (e.g., by a local neural network).

6.3.1.0.1 Promising AI techniques and approaches for transferability. The most used *AI techniques* for object detection are based on Fast Region-based Convolutional Neural Networks (R-CNN), Faster R-CNN, Region-based Fully Convolutional Network (R-FCN), Spatial Pyramid Pooling (SPP-net), Single Shot Detector (SSD), Histogram of Oriented Gradients (HOG). Frequently exploited techniques for Intelligent path planning are RL and DRL. Further interesting AI techniques used in case of fleets of vehicles are Swarm Intelligence and Genetic Algorithms.

Among the *Methodological approaches* adopted, those based on the actor-critic method ([18], [31], [32]) seem interesting regardless of their specific application for unmanned vehicles and self-driving cars.

6.3.2. Intelligent localisation and distance estimation

Although distance estimation is an important issue when dealing with autonomous movements, we consider here a specific class of AI application as it is also associated to *vehicle localisation*. Vehicle localisation is mainly obtained through data fusion techniques and algorithms (i.e., through fused data from GPS, IMU, LiDAR point clouds, and HD map), distance estimation/prediction between vehicles and other surrounding objects also makes use of AI techniques. Specifically, the fused data are used for the reconstruction of the surrounding environment of an AV and for the estimation of its current location exploiting ML.

6.3.2.0.1 Promising AI techniques and approaches for transferability. The main *AI techniques* for distance estimation are CNNs and RNNs (in conjunction with CNNs and using continuous images coming from a camera).
A further method for vehicle localisation is *SS*. The method works by classifying parts of an image into specific classes according to the types of the objects detected in the image.In particular, PSPNet (Pyramid Scene Parsing Network) is a sophisticated SS model that uses a pre-trained CNN.

6.3.3. Intelligent communication in *fleets*

Two main classes of applications are:

a) intra-communication (V2V communication) through vehicles networks;
b) inter-communication (V2I communication, e.g., ground base stations).

The objective is to maintain efficient and reliable communication. A more specific objective can be to preserve communication between leaders and followers, for example in cooperative driving.

6.3.3.0.1 Promising AI techniques and approaches for transferability. The more frequently *AI techniques* exploited by the above mentioned applications are: RL, MARL, Deep Q-Networks, Q-Learning, Markov decision process.

6.3.4. Intelligent Agent Control: Cooperative Driving and Platooning

Intelligent Agent Control addresses the problem to achieve a goal by a learning agent located in a given environment. The agent makes a decision on the basis of the available information (e.g., the state of its surrounding environment) and it learns by trials and errors while trying to understand what is the best behaviour to take in order to maximise a reward.

6.3.4.0.1 Promising AI techniques and approaches for transferability. The main *AI technique* for this type of application is RL together with Deep Q-Learning, combined into a number of *methodological approaches* to overcome the problems raised by unstable behaviour and slow learning, especially in noisy environments. Multi-agent Systems have been leveraged combined with RL techniques to cope with complex situations of interaction with other vehicles (MARL).
Specific characteristic of such applications is that the vehicles have to cooperate and take decisions in a coordinated manner. Cooperative problems are addressed by using proper

simulation environments for research and development of learning based solutions. Again, multi-agent approaches, such as MARL, are promising in high-level decision making and coordination between groups of autonomous vehicles.

6.4. Directions for Transferability

From the review conducted in Task 2.1, it emerges that a large set of studies and applications exist which use AI in the selected sectors. Therefore, we choose some directions for transferability studies in extended safety and rail automation by taking the following steps:

1. definition of diverse types of transferability intervention;
2. application of the **congruence** and **significance** criteria introduced in section 3.1;
3. evaluation on the basis of the remaining criteria, where possible.

These steps may change according to the railway domain to address. In particular, as explained in 3.1, the weight of the criteria adopted may change for different domains.

As for the first point, we have identified three transferability types, which correspond to three different abstraction levels to be considered in the transferability analysis: 1) Paradigm, 2) Approach, and 3) Technology. These concepts are explained herein:

Paradigm Transferability (Conceptual Level) means that the set of assumptions, concepts, values and practices in place in the source domain can be moved and adapted to the target domain. This may require the transferability of approaches and technologies.

Approach Transferability (Methodological Level) means that a methodology or a method successfully applied in the source domain can also work in the target domain, even pursuing different objectives.

Technology Transferability (Application Level) means that the application of scientific knowledge and techniques for practical purposes in the source domain can be transferred in the target domain to the same or similar purpose.

The second step takes into account results and considerations from the state-of-the-art of AI application in railways reported in deliverables D1.1, D1.2 and D1.3. This is the basis to apply the criteria for transferability, in particular congruence and significance, and to make a preliminary evaluation.

The third step shows a concrete limit of the analysis (not surprisingly): most of the available information about the specific AI solution adopted for practical purposes comes from the scientific research, and just few information are available about solutions implemented for commercial products developed by industry. Therefore, we also exploit the (partial) experience and the knowledge of the research group.

6.5. Paradigm Transferability: From Automatic to Intelligent Train Operation

Of all the possible transferability directions emerging from the current state-of-the-art in relevant sectors, the one relating to Autonomous Driving is both interesting and challenging. Autonomous Driving of Trains requires a Paradigm Transfer, as it can be accomplished only by transferring concepts, approaches, architectures and technologies. Therefore, it is not easy to envisage a proper *roadmap* to be realised.

The *target* of this transferability is Intelligent Train Operation, that is one step further smart/adaptive Autonomous Train Operation (ATO), and the *source* is ADSs.

In automotive, ADSs have several characteristics that make them an attractive source domain for transferability to railways. ADSs share several concepts, approaches and technologies that are also used for autonomous movements of UAVs.

The goal of such transferability is to leverage the AI techniques currently investigated for ADSs in order to bring ATO beyond its current capabilities.

As pointed out in chapter 5, *autonomous* can be different from *automatic*, although it does not necessarily mean that sophisticated AI techniques are used. Autonomy is related to the capability to make decisions independently and self-sufficiently. In such a context, we address autonomy based on AI techniques. Therefore, the transferability direction would drive a paradigm shift from automatic to autonomous and intelligent train operations. A paradigm shift requires a huge long-term effort that must be justified by the congruence and significance that it has in the railway domain. Namely, it should be taken into account that there is a lack of standardisation for AI, although committees dedicated to Artificial Intelligence have been established by standardisation bodies (e.g., ISO-IEC SC42, CEN-CENELEC JTC 21) as well as specific working group for related topics (e.g., CEN-CENELEC SG 34 ”Digitalization for railways” within the CLC/TC 9X committee).

6.5.1. Congruence and Significance

Congruence is related to the aims and scope of the source and target AI applications and also includes ethical principles.

As for the scope, the role of AI for ADSs in the railway domain could be the same played in the automotive sector: to make Autonomous Trains (ATs) more intelligent, in order to allow them to take safe and efficient autonomous decisions in many different scenarios with several uncertainties.

As for ethical principles related to trustworthiness, both target and source applications are in a context where safety standards have to be met. Automotive Safety Integrity Levels (ASILs) are defined by the ISO 26262 and the V-model for system development is similar for automotive and railway industry. This means that AI must be trustworthy when applied to autonomous systems in both domains, and that the approaches taken in the automotive sector have to guarantee similar safety features when transferred to the railway sector.

As for *previous experience*, some work is being made in this direction in railways. In particular, the ongoing Shift2Rail project TAURO (Technologies for the Autonomous Rail Operation) has the objective to identify, analyse and propose suitable founding technologies for the future European automated and autonomous rail transport.

In summary, the congruence of the proposed transferability direction is very high: mission, aims and scope are the same, i.e, safe and autonomous transportation (on the ground) of passengers and freight; trustworthiness issues are also the same, including transparency, explainability and accountability; the research project TAURO in Shift2Rail [286] testifies the interest of the railway industry towards autonomous train operations and guarantees that foundations exist for taking this direction.

Significance says that the benefits of the intervention should be proportional to the effort and cost needed to implement it.

It is out of the scope of our work to make a cost-benefit analysis, therefore we recall some motivations that may drive the decision to undertake this direction in transferability.

Smart signalling and smart/adaptive Autonomous Train Operation (ATO) has been identified

as one of the relevant application area for AI by railway stakeholders, according to the WP1 outcomes. It will improve:

- the overall system safety;
- the energy efficiency;
- the service reliability and availability;
- the capacity and utilisation of rail lines;
- the operational costs saving.

In most railway passenger and freight lines, ATP (Automatic Train Protection) includes SIL4 functions in charge of providing absolute train control, for these systems the implementation of Intelligent Train Operation would also bring the advantages listed above.

But on the other hand, some railway lines - especially in developing countries - do not implement ATP systems. For example, very recently Indian Railways has *approved* an indigenous Train Collision Avoidance System [287]. In these cases, the development of an Intelligent Train Operation with enhanced ADAS-like capabilities supported by AI (e.g., obstacle detection and signal recognition) have the potential to bring enormous advantages in terms of improving system safety with a limited investment, thus representing a sort of ”cheap ATP” for low-speed traditional railways that could even lead to GoA3/4.

Furthermore, Intelligent Train Operation technologies based on signal recognition and obstacle detection could act as a fall-down system in case of control degradation, e.g., in partial supervision modes (such as on-sight, staff-responsible, shunting manoeuvre, etc.), when the ATC is not fully available due to failures to track circuits, switch points, communication interfaces, etc.

This vision leads to a notion of Intelligent Train Control, as described in Fig.6.3, in which both scenarios delineated so far are included.

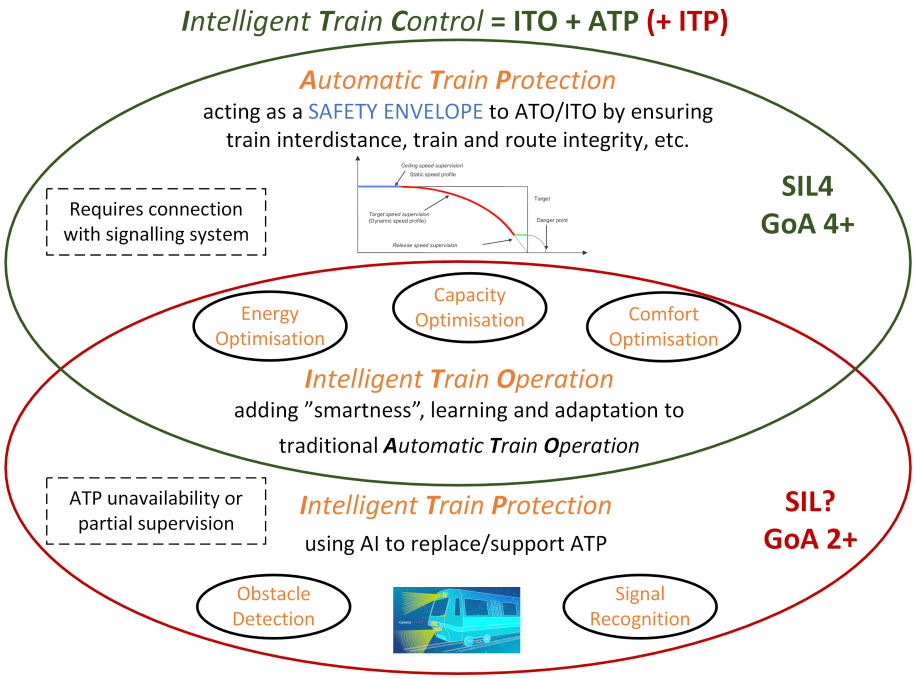

Fig. 6.3. A vision of Intelligent Train Control

The first scenario (the top ellipse in the figure) leverages on the concept of *safety envelope* introduced by Philip Koopman for highly automated vehicles [256]. In its simplest form, a *safety envelope* can be realised, for example, by using a safety margin, so that the behaviour of the system can be limited to a safe set of states. This scenario envisages an ITO system with learning and adaptation capabilities, and safety is guaranteed by ATP that acts as a safety envelope over ITO.

The second scenario (the bottom ellipse in the figure) envisages the development of an ITO that could provide enhanced safety in absence of ATP or in case of degraded control, by using obstacle detection and signal recognition algorithms.

Such new paradigm also enables a vision of future railways, by opening possibilities that are now very difficult if not impossible to achieve such as AI-aided cooperative driving.

6.5.2. Transferability Hints

According to the International Association of Public Transport (UITP), there are five Grades of Automation (GoA) of trains, from GoA0 to GoA4, as shown in Fig. 6.4:

Grade of Automation	Train Operation	Description
GoA0	Driver	No automation
GoA1	ATP + Driver	Manual operation with Automatic Train Protection
GoA2	ATP + ATO + Driver	Semi-automatic train operation with driver
GoA3	Driverless	Driverless train operation with on-board staff
GoA4	Unattended	Unattended train operation without staff

Fig. 6.4. GoAs: Grades of Automation

The degree of automation in automotive is currently measured according to the scale provided by SAE. This scale has 6 levels, from Level 0 to Level 5. They have been discussed in section 5.3.1. For convenience of discussion, SAE Levels are reported again, here below.

Both automation processes started not so many years ago, and both are not finished yet. GoAs are based on the concept of *automatic* operation, whereas SAE Levels immediately introduced the concept of *Driving Assistance* and led to a *progression* towards autonomy.

The difference in the evolution of these systems is also due to the different characteristics of railway transportation compared to other transportation systems, the most evident of them being the fact that trains have constrained longitudinal-only movements compared to ground or areal vehicles; furthermore, in modern railways, trains are supervised by the signalling and control infrastructure, i.e. the so called trackside subsystem. This suggests that the **similarity** between the source and target application domains is low due to different supervision paradigms (i.e., vehicle centered vs infrastructure controlled); on the other hand, the transfer of ADAS capabilities seems less challenging due to a less degrees of freedom in train movements (e.g., no lane keeping is required).

the first challenge is to map GoAs to increasing levels of intelligence, by progressively introducing AI-aided functions with the objective to provide ATO with learning and adaptation capabilities.

Nonetheless, it is important to clarify that ADAS Levels can be implemented without exploiting the full AI potential, and that the safe usage of AI for higher levels is currently under

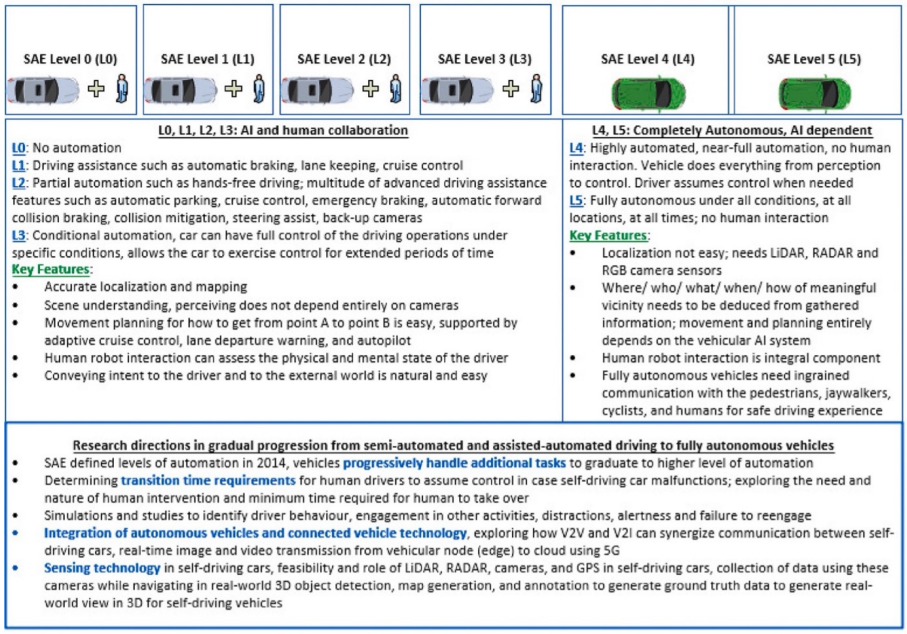

Fig. 6.5. SAE Levels of automation [125]

investigation. Therefore, even if a number of pilot applications exist, they have not reached a full **maturity** yet. Similarly, GoA4 relates to fully automatic train operation that is not necessarily intelligent, e.g., in terms of advanced learning and adaptation capabilities such as real-time hazard forecasting based on historical data.

The second stage addresses the realisation of an ADS, i.e., an Intelligent Train Operation system. To achieve this goal, a proper supporting architecture is needed. From automotive, we can transfer the conceptual layers in Fig. 5.7. We recall that the following layers are proposed in [162] for exploiting all the possibility of AI-based functions:

- Sensing Layer;
- Perception Layer;
- Decision Layer;
- Cloud Layer.

From the description made in Section 5.4, it is clear that ADS needs to be supported by methods and technologies that have to be transferred as well, if they are not already used or in place in the target domain, i.e., railways. Not all those supporting tools or enabling technologies are AI-based or AI-related. The *maturity* of specific technologies adopted at each layer can be high, as witnessed by the availability of pilot implementations on commercial cars and other vehicles, but fully autonomous self-driving is still being investigated.

Ongoing research activities in the railway domain aim at developing solutions for indoor and outdoor environment perception (e.g., in TAURO [286]). Therefore, some steps are being taken, at least at the perception level, but **an integrated, architectural approach** has yet to be defined.

The TTable in Fig. 6.6 summarises the above discussion with the objective of exemplifying the application of the transferability framework proposed in Section 3.

		Very High	High	Medium	Low	Very Low
Dimension	Criterium					
Congruence	mission/aim/scope	X				
	trustworthiness (expected)		X			
	previous experience			X		
Significance	potential	X				
	impact	X				
Preservation	safety		X			
Similarity	objective/goal		X			
	domain characteristics				X	
Maturity	AI technique		X			
	AI application			X		
Implementability	technology		X			
	sustainability (in terms of effort)				X	

Fig. 6.6. TTable for Paradigm Transferability from ADS to ITO

6.6. Technology Transferability: AI-aided Cooperative Driving

Cooperative driving is a technology supporting safe and efficient operation of fleets of UAV (Unmanned Aerial Vehicle), UGV (Unmanned Ground Vehicle), and self-driving cars. The European Commission in 2016 has adopted a common strategy on Cooperative Intelligent Transport Systems (C-ITS), with the objective to support the deployment of mature C-ITS services in the next years [288]. In particular, cooperative driving on roads brings several well-known *benefits*, among them: improved safety, reduction of casualties, reduction of traffic congestion, increased efficiency, and reduced harmful emissions. The basic assumptions underlying cooperative driving is that vehicles are connected through wireless communication systems. Therefore the implementation of cooperative driving leverages V2V and V2I communication. The combination with *adaptive* cruise control allows to automatically adjusting the speed of the vehicle by maintaining a nearly constant distance with the following vehicle. One of the most studied form of cooperative driving is known as platooning, where vehicles move nose-to-tail at the same speed on the same lane with minimum inter-vehicle spacing. The role played by AI in UGV cooperative driving and platooning is discussed in section 5.5.

In view of an accurate transferability analysis of the above mentioned methods to the railway sector, it would be beneficial to consider both the well established cooperative and adaptive applications already exploited in the field of automotive, and the new AI techniques currently spreading in this field. Indeed, although the latter are still prototypical, they seem to be very promising, as pointed out in Chapter 5. One promising perspective, for instance, is the transferability of platooning to railways for the realisation of train convoys, an approach known as Virtual Coupling (VC).

6.6.1. Congruence and Significance

Congruence

The transferability of cooperative driving from UGV to trains has some peculiarities. First, VC is a somehow visionary innovation for which no detailed specifications or hazard analyses is available. Second, we have to distinguish between cooperative driving itself and the appli-

cation of the AI technologies supporting its implementation. Cooperative driving requires a set of innovative technologies that are being investigated for road vehicles with no commercial implementation available at the time of writing. Therefore, a promising direction should investigate the transferability of AI technologies currently experimented for UGV cooperative driving to railway convoys. Although the *aim* is the same, i.e., to allow vehicles to move in a coordinated fashion to achieve a common goal, the level of *previous experience* is very low. As for the trustworthiness, similar considerations made for the transferability of autonomous driving apply, although in this case there are not enough data from real implementations in the source domain, to state which level of trustworthiness can be achieved. Therefore, trustworthiness is considered to be very low at the current state of research.

Significance

Several study have been conducted to investigate the impact of VC (e.g., see the Shift2Rail project MOVINGRAIL [289],[290]). It is already recognised that VC could provide several benefits and ongoing work is devoted to its definition (e.g., in the Shift2Rail project X2Rail3 [291]). In its document on "Rail 2030 Research & Innovation Priorities" [292], ERRAC has indicated automation and artificial intelligence among the key innovation areas, and VC as a concept supporting the increase of flexibility, capacity and resiliency in connection with autonomous trains and automated freight operation. Therefore the overall significance level of the interventions aiming at investigating and realising VC is high due to both *potential* and *impact*.

6.6.2. Transferability Hints

AI-aided cooperative driving is currently an open challenge in the automotive sector. Hence, its transferability cannot rely on mature AI applications, but the research direction taken in the target domain can be considered as a results itself and proposed to carry out a feasibility study in railways. As reported in Section 6.3, cooperative problems in autonomous driving environments are addressed by Multi-Agent learning using proper multi-agent simulation environments, and in particular exploiting MARL. MARL approaches are also investigated for testing autonomous driving policies. Therefore, the hypothesis is that V2V communication and Autonomous Driving are in place, and DRL integrated sensing, perception, planning and control algorithms can be researched and developed. Although the specific characteristics of railways can make some aspects of the problem less difficult to treat, as discussed in previous section, such transferability direction opens onto a visionary horizon. TTable in Fig. 6.7 summarises the discussion with the aim of showing that the application of the transferability framework proposed in Section 3 catches the differences between the two trasferability directions considered in Sections 6.5 and 6.6.

		Very High	High	Medium	Low	Very Low
Dimension	Criterium					
Congruence	mission/aim/scope	X				
	trustworthiness (expected)				X	
	previous experience					X
Significance	potential	X				
	impact	X				
Preservation	safety				X	
Similarity	objective/goal		X			
	domain characteristics				X	
Maturity	AI technique			X		
	AI application				X	
Implementability	technology		X			
	sustainability (in terms of effort)					X

Fig. 6.7. TTable for Transferability of AI-aided Cooperative Driving

6.7. Approach Transferability: Machine Learning for Risk Assessment

Risk Assessment of critical systems is a well assessed and mature discipline. Nonetheless, the ever increasing computational capabilities and data availability are supporting emerging research and development directions. Deliverable D1.3 identified this trend and posed the application of AI to risk assessment as one of the urgent issues to be faced in railways. The urgency is motivated by the great potential that AI has in coping with existing and future sources of hazards threatening cyber-physical systems. These hazard sources come from climate change, extreme weather conditions, terrorism, and other threats that can be difficult to describe and model quantitatively due to their uncertainty. This section provides an overview of how ML is currently exploited for engineering risk assessment, therefore no TTable is proposed. We selected some works from other sectors that seem to indicate concrete directions. In the following, they are proposed in descending order with respect to their scope.

6.7.1. Risk Assessment

ML for risk assessment is researched in many sectors, including railways. The automotive industry seems to be leading the adoption of ML for risk assessment, followed by the construction industry. This is witnessed not only by the number of available studies, but also by the fact that: a) the automotive and construction industry frequently validate the models through real-world implementations, and b) simulator-based implementation is only used by research works focusing on the automotive industry. The results presented in the following are mainly based on the recent review paper by Hegde and Rokseth [293]. Such results may help to understand the research *trends*. According to the findings presented in the above mentioned review, if we consider the main phases of risk assessment, the works addressing ML are distributed as follows with respect to the total of the revised papers:

- hazard identification: 0.88%
- risk analysis: 0.61%
- risk evaluation: 0.29%

Many of those papers address all phases or at least two of them. If we consider the number

of papers specifically focused on one phase, the trend shows a greatly uneven distribution in favour of hazard identification. This brings us to think that ML techniques well (or more easily) suit hazard identification. A list of the most frequently used ML techniques in risk assessment is reported in [293]. The top two techniques in this list are **ANNs** and **SVM**. It is worth to notice that ANN is a broad family, e.g., it also includes CNNs, GANs, and so on.

As discussed in the paper, the choice of the ML technique can be driven not only by the problem to cope with, but also by the type and quality of available data. Most studies (71.8%) use historical data, and the type of input data can be industry specific (e.g., sensors data, time to failure time-series, textual accident description, daily rainfall, and the like). In addition, the reviewed papers mainly focus on learning from *textual* or *numerical* data.

The following observations are generally valid when addressing ML transferability:

- The 'opaque' nature of Artificial Neural Networks, and in particular of Deep Neural Networks, raises ethical and judicial concerns that make them not suitable in high SIL applications.

- ML models proposed in other sectors may be limited by the availability of data sources in the target domain. If data sources are limited in quantity or quality, reusing the same techniques may not be feasible, hence preventing repetition and benchmarking of the methods used in the source domain.

These issues have to be taken into account also dealing with Risk Assessment procedures. In particular, the standard processes of hazard analysis and risk evaluation currently applied in the rail settings, require the involvement of all relevant stakeholders to define and clearly explain scenarios and agree on the risk estimation. The introduction of AI techniques to carry out this activities by leveraging on the available data and ML techniques could be feasible in two cases: a) it is possible to "explain" the "reasoning flow" bringing to the results; b) not "explainable" results are just used to support the stakeholders' work, for example by suggesting scenarios that should be considered or analysed more in depth.

6.7.2. Incident Analysis

A large number of papers address Incident Analysis. Some of them are also surveyed in [293]. AI can enhance safety management by recognising patterns across big datasets in real-time, i.e., determining the most effective leading indicators and how they may relate to rare but high-impact events. In the past, AI models have already been applied for similar purposes, for example to bow-ties [294, 295] and hazard and operability studies (HAZOPs) [296]. The work in [297] uses **ML and keyword analysis** to analyse incidents and reduce risk. The paper proposes two case studies based on incident data provided by an oil company to demonstrate the proposed methodology. The main objectives are applicable to other industries including railways [297]:

- Strengthen the current incident reporting system by creating a customised library using artificial intelligence, ML and statistics.
- Support the design of more sensitive risk prevention and mitigation strategies, as well as leading factors.
- Enhance organisations learning from incidents and create opportunities to reduce losses.

The paper introduces a methodology (based on **supervised ML algorithms** used to classify incident reports), and discusses the two case studies. The approach can produce risk ma-

trices, trend reports, prevention/mitigation strategies, leading indicators that can be further used as inputs for other risk analysis methods, e.g. bow-ties, root cause analysis, fault tree analysis or HAZOP studies.

Hence, it could be considered for integration with the ongoing work in railways, as it emerges from RAILS deliverables D1.2 and D1.3.

6.8. Explainable AI and safety

Explainability is a key attribute for ML to be applied to safety critical functions. It is widely recognised that the black-box nature of ANN, in particular of Deep Neural Networks, raises ethical and judicial concerns that lead to a lack of confidence in their use especially in high SIL applications. For this reason, there is a growing interest in eXplainable Artificial Intelligence (XAI), as discussed in RAILS deliverable D1.2, where a number of approaches and tools have been mentioned. XAI is expected to generate interpretable models and explanations comprehensible to humans for ML decisions, in order to improve AI trustworthiness. Some considerations should be made when planning XAI approaches for safety-critical applications:

- Recent studies have been published that point to the limitations of XAI and aim at increasing the awareness of the risks associated with the use of XAI. Generally speaking, explanations provided by XAI may not be as transparent or truthful as expected [298, 299]. In particular, Adversarial Perturbations (APs) are techniques intended to mislead a target CNN model, by means of an almost imperceptible noise, e.g., by injecting a hardly perceptible perturbation into an image. Results have been published showing that APs can strongly affect the XAI outcomes especially in situations where APs are easy to perform [300].
- XAI cannot be achieved by adding a specific component to the system, rather it must be part of system design. This means adding further complexity to systems that need to be certified. Furthermore, XAI has to comply with requirements and common practices. How can we certify XAI? At least one project for developing XAI standards is currently ongoing, led by the eXplainable AI Working Group of the IEEE Computational Intelligence Society Standards Committee (CIS/SC), and the Expected Date of submission of draft to the IEEE SA for Initial Standards Association Ballot is January 2024 [301].

In summary, while the benefits of AI explainability are recognised, with succesful applications for example in fault prediction [302], in other fields XAI can be better used to provide support for other purposes, like *the verification and validation of ML systems*. Therefore, the usability of XAI techniques should be investigated from different perspectives in order to enhance railway system dependability.

6.9. Coping with Limited Data

The lack of suitable datasets for training ML models is a general issue to be coped with to adopt data-driven AI approaches in railways, as emerged from WP1. Very large datasets are needed when coming to Deep Neural Networks: the higher the complexity of the problem, the greater the number of parameters, the larger the amount of data required. In addition, very limited number of high quality training data is one of the root cause of *overfitting*. In many case, it is impossible to gather or obtain the amount of data needed to build such

models. Therefore, the problem is so relevant that it is necessary to point out the techniques that can help to face the limited availability of data. Two main techniques can be used when dealing with limited data:

- Transfer Learning [303, 304];
- Data augmentation [305, 306].

These are two completely different but possibly complementary ways to face the problem.

The term ”Transfer Learning” is used to name a well-known topic in machine learning and its related approaches. Therefore, the word ”transfer” in this context refers to the ML domain. Indeed, Transfer Learning encompasses techniques to *transfer knowledge* gained from learned tasks to different tasks and solve a new problem; for example if we want to address an ML task (e.g, classification) in our domain (e.g., railways), but we only have sufficient training data in another domain (e.g., automotive). Therefore, Transfer Learning approaches can be used to obtain competitive results even with a limited amount of data.

Data Augmentation encompasses techniques that *enhance the size and quality* of available training datasets in the domain of interest.

It is of great importance to investigate the applicability of both Transfer Learning and Data Augmentation to railway applications, leveraging on existing publicly available and open datasets in different domains of the railway sector.

A review of AI-oriented railway data published under Creative Commons (CC) or any other copyright type that entails public availability and freedom of use has been conducted within the RAILS project and published in [307]. This work focuses on the railways sub-domains addressed in RAILS (i.e., safety, maintenance and inspection, traffic planning and management) and on many types of data, including numerical, string, image and other. The datasets reviewed cover the last three decades, from 1990 to 2021. The resulting collection is a first step towards a shared basis for developing research on the integration of AI in the railway sector.

7. Case Studies

One of the main recommendation provided in D1.3 when closing the DISCOVER phase of the project was to define pilot case studies/demonstrators to investigate the effects of AI solutions on safety-related applications.

In this Chapter, *two pilot case studies* are proposed as indications for future research. They are broad case study that are not intended to be completely developed within this project. but to lead to *proof of concepts and benchmarks* within the RAILS project.

The selection will be made taking into account that a pilot case study has to meet at least two among the following requirements, in order to guarantee its adherence to the objectives of the project:

- It falls into one or more application areas identified in D1.3;
- It allows to perform one or more transferability studies along at least one of the directions identified in Chapter 6;
- It has been suggested and/or supported by the project Advisory Board.

The proposed case studies need to be further discussed with the railway stakeholders and the Advisory Board. Therefore a more detailed definition, on which it will be possible to conduct the proof of concepts, is part of task T2.2.

7.1. Case Studies Identification

As a result of the previously conducted search (Chapter 4 and Chapter 5), dealing with AVs and CAVs (Connected Autonomous Vehicles) technologies, it follows that these technologies could be potentially transferred, along the line detailed in Chapter 6, to next future Autonomous Trains (ATs) and their operations. The growth of autonomous vehicles using state-of-the-art connected vehicle technologies has paved the way for the development of passenger and freight ATs, also known as Driverless Trains [308, 309].
The deployment of ATs is expected to offer the following advantages to railroad companies [310]:

- safety improvement, such as reduction in accidents due to human errors;
- decrease in operational costs;
- reduction in emissions produced;
- increased capacity for passenger and freight transport;
- improved reliability of rail services;
- effective communication with connected vehicles (CVs) and AVs.

To this aim, we assume that some CAVs technologies can be effectively applied to ATs, and specifically that hardware on-board facility and infrastructures are effectively available on train and along the railway system, so that trains can be controlled using advanced communication and internet technologies, such as high-speed internet technologies (e.g., 5G), Internet of Things, Dedicated Short Range communications (for exchanging data with moving vehicles, and infrastructure), proprioceptive and exteroceptive sensors, train control via navigation systems (based on GPS and IMU technologies). See Fig. 7.1 for a review of

trends and emerging technologies for ATs in railways.

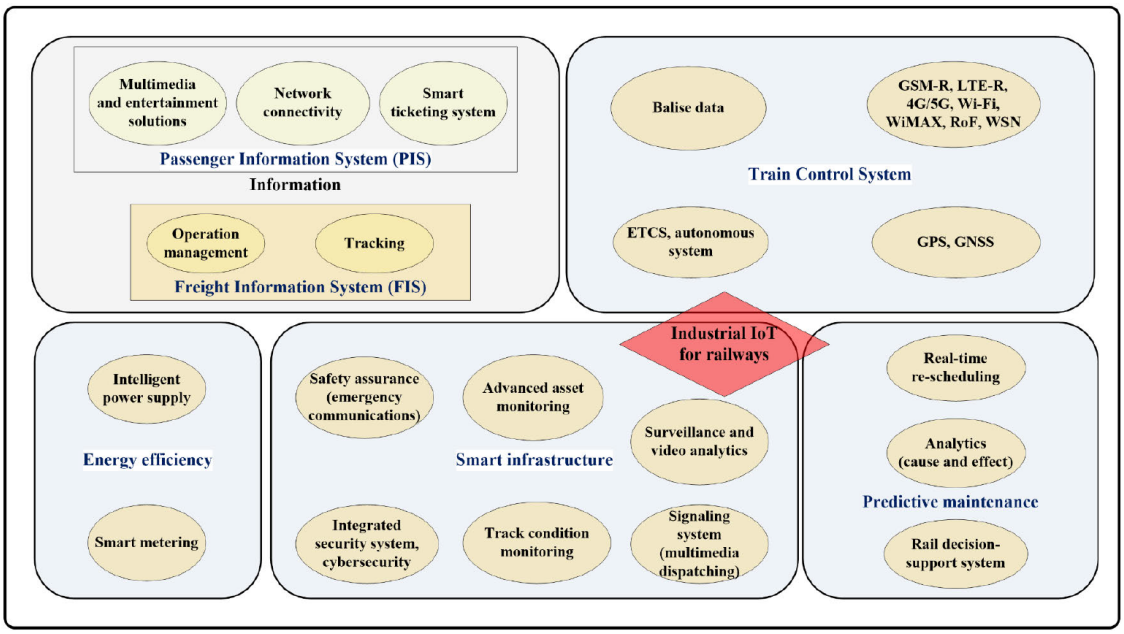

Fig. 7.1. Services enabled by IIoT [311]

Within this wide technological scenario, in what follows we identify two representative case studies suitable to investigate the effectiveness of artificial intelligence-based methods for the deployment of next future ATs. Namely:

- Railway Obstacle Detection;
- Cooperative driving for VC of ATs.

These two case studies are meant to be representative of one of the main challenges arising when dealing with AI, i.e. the ability to tackle safety-critical real-time decisions exploiting limited data.

The high impact of the above-mentioned case studies can be further appreciated when considering a general framework of the autonomous driving system architecture at the GAo4 Level, that can be abstracted from the automotive field [312, 313]. Here, the ability in performing Obstacle Detection and Avoidance is one of the fundamental pillars of the Perception Layer, while VC is a critical issue to be solved at both Planning and Control layers. Moreover, in the next future, the railroad industry could benefit from exploiting various opportunities that are offered by the Industrial Internet of Things (IIoT), which is an important component of the paradigm called “Internet of Trains” [314].

To achieve the great benefits arising from the Internet of Trains, still face a large variety of issues (e.g., interoperability, standardisation, scalability, and cybersecurity, and AI-based control, and so on) that have to be effectively addressed by researchers and practitioners in the following years.

It follows that, within the context of Train Control Systems based on IIoT, VC represents one of the most promising and challenging paradigms, since Cooperative Driving strategies for ATs have to be designed at GAo4 (at this level, train runs fully autonomous with no on board driver/attendant), and, hence, the advantages of deploying the latest AI methods leveraging

broadband communication technologies (e.g., 5G technologies, Long-Term Evolution [LTE] technologies) could be really appreciated.

7.2. Case study N.1: Railway Obstacle Detection and Collision Avoidance

Railway accidents, in which trains collide with obstacles, often occur because of human error or fatigue. In addition, security problems can also arise by the intrusion of foreign objects, or illegal entry of pedestrians along the line. It is therefore necessary to detect traffic objects in front of the trains in order to automatically react or inform the driver to take timely action (in the case of human-driven trains).
Within this context, Obstacle Detection and Collision Avoidance is a safety-critical function of the Perception Layer (see Fig. 7.2) that refers to the ability of an Autonomous Vehicle (AV) to collect information and extract relevant knowledge from its surrounding using data from sensors (e.g., on-board smart-cameras installed on front of the train) and V2X messages. It can be mainly decomposed into Environmental perception and Localisation. While the Localisation (commonly leveraging GPS and IMU or a combination of these sensors) aims to build and update a map of the actual environment while simultaneously tracking the AV's position and orientation within it, the efficient Environmental perception for detection requires to accurately detect and classify the different surrounding objects including moving and static obstacles (vehicles, pedestrians) position and velocity, and signalling information. The proper accomplishment of the task requires to tackle numerous challenges such as multiple types of objects and the complexity of train running environment. Their solution requires effective ability in real-time multi-object classification and tracking on the basis of current information provided by LiDARs [315], cameras [316, 317], radars [318], or a fusion between LiDARs and cameras [319–322]. Another category of sensors which could be exploited is represented by the vibration sensors, which are generally installed on the rails, or accelerometers which could allow for the detection of different scenarios. In particular, leveraging AI techniques, each scenario could be associated to a specific vibration pattern. This could support the managing of different danger situations that could happen on the railway lines.

Note that, since V2X enables trains exploiting information that exists beyond perceptual sensory, the overall decision-making process of the AT can be also augmented with information from the infrastructure or other trains.
The main idea is to use multiple sensors [323], possibly acting as intelligent event detectors, to collect information about the line in front of the train, such as track status, light signals, and obstacles. The control and processing system consists of processor, interface, switch unit, storage unit and so on, which is used to process the sensor signal input by the data collection system. When detecting the presence of obstacles in front of the train, according with the software architecture designed for automatically running the train, which can be transferred from the automotive field as in Fig 7.3), the Perception Layer has to send out the information to the Path Planning/Control Modules (according to the vision of Intelligent Train Control and depending on the GoA Level, see Section 6.5), that are responsible for imposing the train motion, including safe and emergency braking for collision avoidance. Indeed, in contrast to road vehicles, which can change direction to avoid an obstacle, the only way for a train to avoid collision is to slow down or stop before colliding with an obstacle. This is only possible if the detection distance exceeds the stopping distance of the vehicle. It follows that, part of the activity will be devoted to the identification of use cases (UCs) with respect to the

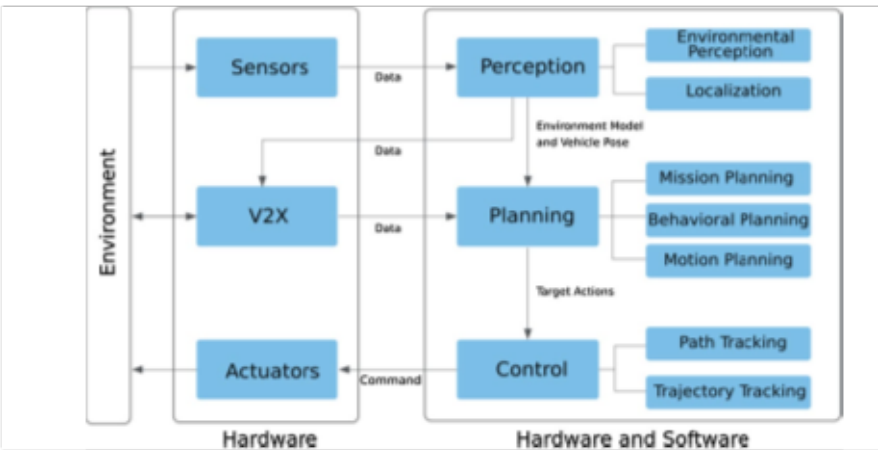

Fig. 7.2. A general framework of an autonomous driving system architecture [312]

mode of operation, the grade of automation (GoA), and the different operating conditions, including general UCs for mainline railway and UCs specific to freight.

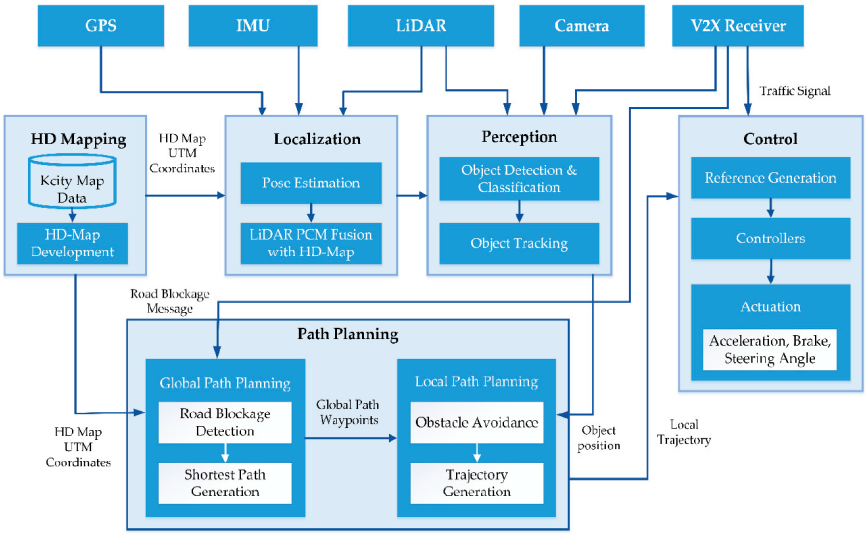

Fig. 7.3. An exemplar software architecture for autonomous driving in the automotive field [324]

The final aim of the case study is hence to provide the context to research/transfer a set of AI-based on-board approaches that could be potentially used in real-time for detection in a moving environment and their applicability to the different UCs. The different AI approaches, for example deep learning-based object detection or neural network-based distance estimation techniques, could be tested and compared in terms of accuracy, false negative and false positive detection rates, easy deployment, as well as their ability to meet real-time detection performance and obstacle recognition capabilities. LSTM-based tools could be also exploited for the tracking of moving targets and prediction of their dynamic behaviour. For design and testing the different AI-tools, proper datasets, which also contains railway obstacles and related distance annotation, as well as various driving situations in complex envi-

ronments and targets from several classes, will be also identified, transfer learning methodologies or GAN techniques could be investigated to cope with limited availability of data.

7.3. Case Study N.2 : Cooperative Driving for Virtual Coupling of Autonomous Trains

Recently the Shift2rail program [325] proposed a novel paradigm in train control systems based on the concept called VC. Following the very recent developments in the field of safe platooning of CAVs, the VC is based on the idea of convoys, or fleets, of ATs. One of the main advantages of this driving paradigm is the increasing in the capacity of the existing railway lines [326]. The paradigm overcomes the moving block system, where trains automatically and continuously adjust their motion by continuously calculating and communicating their exact position and speed to wayside equipment distributed along the line. Within the moving block paradigm, it is assumed that consecutive trains on the same track must be separated by a sufficient margin, i.e. able to ensure that every train is capable of braking and stopping before reaching the last known position of the train in front at any time. However, this conservative behaviour causes a large gap between trains. In reality, on the basis of the braking features of consecutive trains, the safety margin could be reduced. Furthermore, as happens in platooning, even smaller distance between consecutive ATs could be achieved, leveraging advanced technologies (e.g., accurate train positioning, V2V communication, predictive braking, cooperative driving). Indeed, these allow the ATs moving on a line to be virtually coupled via V2V communication and hence to move as a convoy with a safe distance much lower than the braking distance needed for a full stop [327].
VC is one of the most challenging functionalities of cooperative driving since it strongly is based on the ability to share information with neighbours (V2V) and receiving the reference signals coming from the infrastructure (I2V). Indeed, on the basis of the information received from its neighbours within the convoy, each AT autonomously regulates its motion. So, the on-board controller is responsible for the safe tracking of speed profiles while respecting the inter-train spacing policy, allowing the followers to track a dynamic behaviour imposed by a leader (that can be the infrastructure acting as a virtual leader or the first train in the convoy) in a safe way, while also guaranteeing good transient dynamics (e.g., see [326, 328]).
The VC transfers the automotive Platooning concept to the railway domain. Note that Platooning implies the use of self-driving cars at SAE Level 4/5, and commonly exploits a hierarchical command-and-control architecture, e.g. see Fig. 7.4. Here, the High-Level decision layer is a behavioural layer that provides a decision-making process regarding the choice of manoeuvres and actions to execute depending on the environment. The High-Level decision layer is also responsible for reading and sending messages, evaluating requests, etc. The Platooning Manoeuvres layer performs safe cooperative manoeuvres depending on any incoming platooning messages and reacting accordingly. The trajectory planner generates trajectories, or paths to a new target position when required. So it is still a control level responsible for generating suitable reference trajectories and their effective tracking. Indeed, trajectories are translated to a set of commands (e.g. acceleration, braking, lane change right/left) that are input to the Low-level control layer, which is in charge of physically applying these commands.
The aim of this case study is to explore the feasibility of VC through AI techniques. The main challenges will be to understand how and if it is possible to cope with the complex interaction between multiple, intelligent agents, e.g., via MARL techniques in a highly non-stationary

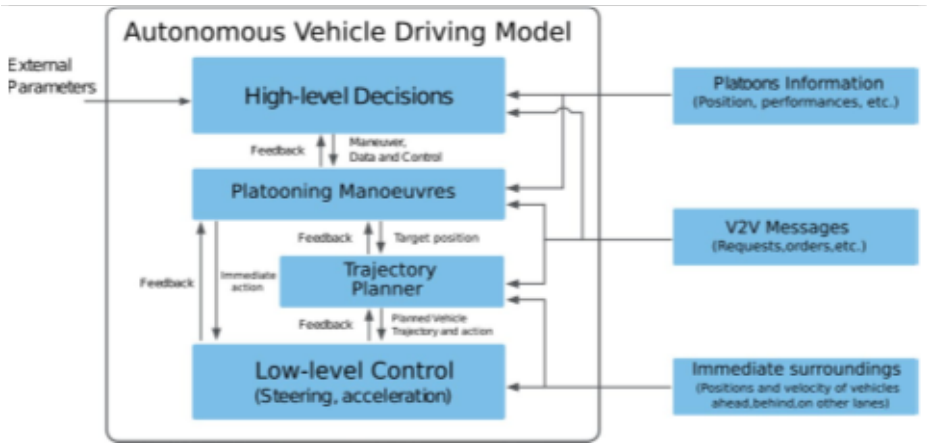

Fig. 7.4. Hierarchical command-and-control structure for autonomous vehicles platooning [312]

environment leveraging Partially Observable Markov Games (POMG) for formulating the driving problem of connected ATs under realistic assumptions in the railway field. The different AI approaches will be compared from an operational point of view, i.e. analysing trip times, time delays, the distance between trains, as well as versus the previous moving block concept. The study will also investigate the ability of AI-based methods in performing cooperative train manoeuvres within the VC Movement Authority. So, the different techniques will be also compared with respect to multiple the operational states and corresponding transition phases that an AT needs to go through when coupling/uncoupling to/from another train under VC signalling (e.g., see Fig. 7.5 and the definitions in [326]).

The analysis will also try to cope with the complexity and uncertainty due to the implemented models. Indeed, as mentioned in Chapter 5, the AI techniques applied to fully autonomous driving are affected by the trade-off problem between model accuracy and the computational resources needed during the training phase for identifying the optimal policy. So, particular care will be devoted to analysing the model's choice effects (ranging from very simple approaches to more sophisticated dynamics with a high number of parameters). A fundamental part of the study will be also devoted to the individuation of a microscopic emulation environment for detailed time-driven railway traffic simulations that could be suitable for embedding multi-state train-following models needed to perform the assessment of the AI-based VC.

Finally, hybrid approaches, merging the learning and adaptation capabilities of the AI techniques with more classical control schemes, will be also investigated in order to enable a progressive introduction of AI-aided functionalities.

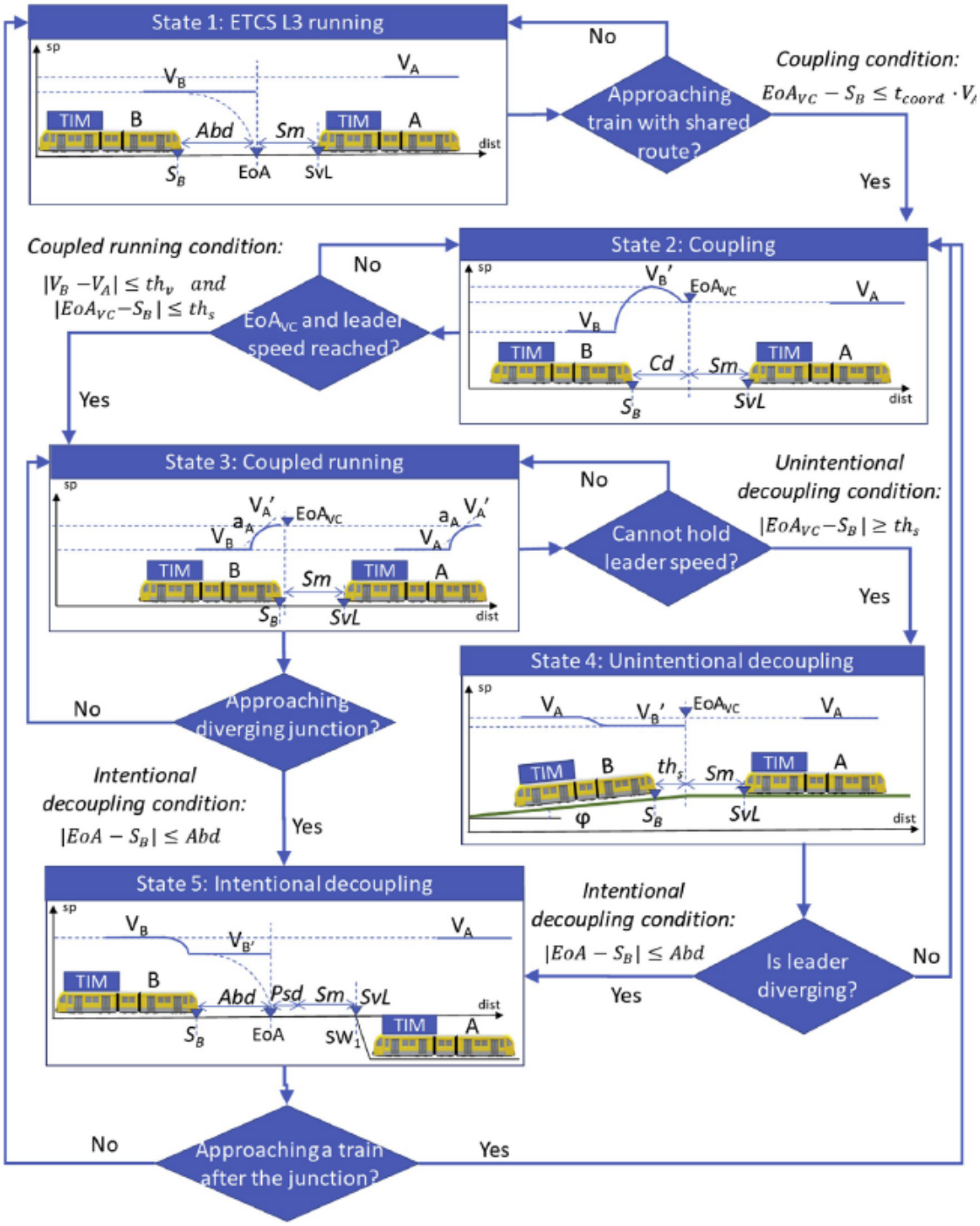

Fig. 7.5. Illustrative example of Virtual Coupling operational states and transitions [326]

8. Conclusions

The overall objective of this document, which represents the Deliverable D2.1 of WP2, has been that of investigating which AI methods already used in other transportation sectors could be exploited in the rail sector in order to enhance rail safety and automation. The analysis has been carried out starting from the findings and application areas identified in WP1.

At first, a transferability framework has been defined through the identification of some transferability criteria, useful to make a qualitative evaluation of the AI applications' degree of transferability to railway.

Then, an overview of the main current and emerging AI-based technologies in other transportation sectors has been addressed. In particular, UXVs and automotive sectors have been investigated. As to unmanned vehicles, AI applications in both UAVs and UGVs have been reviewed; in the field of automotive, a particular focus has been dedicated to the major AI techniques exploited for ADAS, ADSs and Cooperative Driving Systems. Regarding autonomous vehicles, further considerations on some crucial issues related to the adoption of AI techniques have also been discussed, such as the quality of sensor data used as input, the risk and uncertainty related to both data and implemented models, and the verification and validation of AI-based software for safety assessment.

By leveraging the analysis reported in D1.1, D1.2, and D1.3, and through a synthesis of the over mentioned overview from a transferability perspective, possible research directions have been identified. In particular, a set of pilot case studies have been selected, such as railway obstacle detection and collision avoidance, and cooperative driving for virtual coupling of autonomous trains, with the aim of identifying some roadmaps which will be further investigated within the RAILS project. The proposed analysis is indeed a first evaluation of the possible AI techniques that could be potentially transferred to the railway sector; specific proof of concepts will be addressed to identify the advantages and benefits that AI could provide to rail safety and automation.

Bibliography

[1] H. E. D. Burchett, S. H. Mayhew, J. N. Lavis, and M. J. Dobrow, "When can research from one setting be useful in another? Understanding perceptions of the applicability and transferability of research," *Health Promotion International*, vol. 28, no. 3, pp. 418–430, 07 2012. [Online]. Available: https://doi.org/10.1093/heapro/das026

[2] H. Munthe-Kaas, H. Nøkleby, and L. Nguyen, "Systematic mapping of checklists for assessing transferability," *Systematic Reviews*, vol. 8, 01 2019.

[3] M. Goodrich, B. Morse, D. Gerhardt, J. Cooper, M. Quigley, J. Adams, and C. Humphrey, "Supporting wilderness search and rescue using a camera-equipped mini uav," *Journal of Field Robotics*, vol. 25, no. 1-2, pp. 89–110, 2008.

[4] D. Orfanus, E. De Freitas, and F. Eliassen, "Self-organization as a supporting paradigm for military uav relay networks," *IEEE Communications Letters*, vol. 20, no. 4, pp. 804–807, 2016.

[5] N. Motlagh, M. Bagaa, and T. Taleb, "Uav-based iot platform: A crowd surveillance use case," *IEEE Communications Magazine*, vol. 55, no. 2, pp. 128–134, 2017.

[6] N. Thakur, P. Nagrath, R. Jain, D. Saini, N. Sharma, and D. J. Hemanth, "Artificial intelligence techniques in smart cities surveillance using uavs: A survey," *Machine Intelligence and Data Analytics for Sustainable Future Smart Cities*, pp. 329–353, 2021.

[7] D. Kang and Y.-J. Cha, "Autonomous uavs for structural health monitoring using deep learning and an ultrasonic beacon system with geo-tagging," *Computer-Aided Civil and Infrastructure Engineering*, vol. 33, no. 10, pp. 885–902, 2018.

[8] I.-H. Kim, H. Jeon, S.-C. Baek, W.-H. Hong, and H.-J. Jung, "Application of crack identification techniques for an aging concrete bridge inspection using an unmanned aerial vehicle," *Sensors*, vol. 18, no. 6, p. 1881, 2018.

[9] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, "A tutorial on uavs for wireless networks: Applications, challenges, and open problems," *IEEE communications surveys & tutorials*, vol. 21, no. 3, pp. 2334–2360, 2019.

[10] P. S. Bithas, E. T. Michailidis, N. Nomikos, D. Vouyioukas, and A. G. Kanatas, "A survey on machine-learning techniques for uav-based communications," *Sensors*, vol. 19, no. 23, p. 5170, 2019.

[11] N. C. Luong, D. T. Hoang, S. Gong, D. Niyato, P. Wang, Y.-C. Liang, and D. I. Kim, "Applications of deep reinforcement learning in communications and networking: A survey," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3133–3174, 2019.

[12] A. Sharma, P. Vanjani, N. Paliwal, C. M. W. Basnayaka, D. N. K. Jayakody, H.-C. Wang, and P. Muthuchidambaranathan, "Communication and networking technologies for uavs: A survey," *Journal of Network and Computer Applications*, p. 102739, 2020.

[13] S. H. Alsamhi, O. Ma, and M. S. Ansari, "Survey on artificial intelligence based techniques for emerging robotic communication," *Telecommunication Systems*, vol. 72, no. 3, pp. 483–503, 2019.

[14] W. Huang, Y. Wang, and X. Yi, "Deep q-learning to preserve connectivity in multi-robot

systems," in *Proceedings of the 9th International Conference on Signal Processing Systems*, 2017, pp. 45–50.

[15] ——, "A deep reinforcement learning approach to preserve connectivity for multi-robot systems," in *2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*. IEEE, 2017, pp. 1–7.

[16] N. R. Zema, D. Quadri, S. Martin, and O. Shrit, "Formation control of a mono-operated uav fleet through ad-hoc communications: a q-learning approach," in *2019 16th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON)*, 2019, pp. 1–6.

[17] Y. Zhao, J. Guo, C. Bai, and H. Zheng, "Reinforcement learning-based collision avoidance guidance algorithm for fixed-wing uavs," *Complexity*, vol. 2021, 2021.

[18] V. R. Konda and J. N. Tsitsiklis, "Actor-critic algorithms," in *Advances in neural information processing systems*, 2000, pp. 1008–1014.

[19] D. M. P. F. Silva, L. F. F. de Oliveira, M. G. M. Macedo, and C. J. A. B. Filho, "On the analysis of a swarm intelligence based coordination model for multiple unmanned aerial vehicles," in *2012 Brazilian Robotics Symposium and Latin American Robotics Symposium*, 2012, pp. 208–213.

[20] L. Weng, Q. Liu, M. Xia, and Y. Song, "Immune network-based swarm intelligence and its application to unmanned aerial vehicle (uav) swarm coordination," *Neurocomputing*, vol. 125, pp. 134–141, 2014.

[21] O. Anicho, P. B. Charlesworth, G. S. Baicher, A. Nagar, and N. Buckley, "Comparative study for coordinating multiple unmanned haps for communications area coverage," in *2019 International Conference on Unmanned Aircraft Systems (ICUAS)*. IEEE, 2019, pp. 467–474.

[22] U. Challita, W. Saad, and C. Bettstetter, "Cellular-connected uavs over 5g: Deep reinforcement learning for interference management," *arXiv preprint arXiv:1801.05500*, 2018.

[23] Y. Zhao, Z. Zheng, and Y. Liu, "Survey on computational-intelligence-based uav path planning," *Knowledge-Based Systems*, vol. 158, pp. 54–64, 2018.

[24] I. K. Nikolos, K. P. Valavanis, N. C. Tsourveloudis, and A. N. Kostaras, "Evolutionary algorithm based offline/online path planner for uav navigation," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 33, no. 6, pp. 898–912, 2003.

[25] Y. Zhou, B. Rao, and W. Wang, "Uav swarm intelligence: Recent advances and future trends," *IEEE Access*, vol. 8, pp. 183 856–183 878, 2020.

[26] R. K. Dewangan, A. Shukla, and W. W. Godfrey, "Three dimensional path planning using grey wolf optimizer for uavs," *Applied Intelligence*, vol. 49, no. 6, pp. 2201–2217, 2019.

[27] F. Ge, K. Li, Y. Han, W. Xu *et al.*, "Path planning of uav for oilfield inspections in a three-dimensional dynamic environment with moving obstacles based on an improved pigeon-inspired optimization algorithm," *Applied Intelligence*, pp. 1–18, 2020.

[28] X. Zhen, Z. Enze, and C. Qingwei, "Rotary unmanned aerial vehicles path planning in rough terrain based on multi-objective particle swarm optimization," *Journal of Systems Engineering and Electronics*, vol. 31, no. 1, pp. 130–141, 2020.

[29] W. He, X. Qi, and L. Liu, "A novel hybrid particle swarm optimization for multi-uav cooperate path planning," *Applied Intelligence*, pp. 1–15, 2021.

[30] C. Qu, W. Gai, M. Zhong, and J. Zhang, "A novel reinforcement learning based grey wolf optimizer algorithm for unmanned aerial vehicles (uavs) path planning," *Applied soft computing*, vol. 89, p. 106099, 2020.

[31] G. Stampa, M. Arias, D. Sánchez-Charles, V. Muntés-Mulero, and A. Cabellos, "A deep-reinforcement learning approach for software-defined networking routing optimization," *arXiv preprint arXiv:1709.07080*, 2017.

[32] C. Wang, J. Wang, X. Zhang, and X. Zhang, "Autonomous navigation of uav in large-scale unknown complex environment with deep reinforcement learning," in *2017 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*. Ieee, 2017, pp. 858–862.

[33] Y. Gao, L. Xiao, F. Wu, D. Yang, and Z. Sun, "Cellular-connected uav trajectory design with connectivity constraint: A deep reinforcement learning approach," *IEEE Transactions on Green Communications and Networking*, 2021.

[34] P. Susarla, Y. Deng, G. Destino, J. Saloranta, T. Mahmoodi, M. Juntti, and O. Sílven, "Learning-based trajectory optimization for 5g mmwave uplink uavs," in *2020 IEEE International Conference on Communications Workshops (ICC Workshops)*. IEEE, 2020, pp. 1–7.

[35] M. Theile, H. Bayerlein, R. Nai, D. Gesbert, and M. Caccamo, "Uav coverage path planning under varying power constraints using deep reinforcement learning," in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2020, pp. 1444–1449.

[36] B. Li and Y. Wu, "Path planning for uav ground target tracking via deep reinforcement learning," *IEEE Access*, vol. 8, pp. 29 064–29 074, 2020.

[37] C. Yan, X. Xiang, and C. Wang, "Towards real-time path planning through deep reinforcement learning for a uav in dynamic environments," *Journal of Intelligent & Robotic Systems*, vol. 98, no. 2, pp. 297–309, 2020.

[38] Q. Liu, L. Shi, L. Sun, J. Li, M. Ding, and F. Shu, "Path planning for uav-mounted mobile edge computing with deep reinforcement learning," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 5, pp. 5723–5728, 2020.

[39] L. Zhu, Y. He, F. R. Yu, B. Ning, T. Tang, and N. Zhao, "Communication-based train control system performance optimization using deep reinforcement learning," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 12, pp. 10 705–10 717, 2017.

[40] N. O'Mahony, S. Campbell, L. Krpalkova, D. Riordan, J. Walsh, A. Murphy, and C. Ryan, "Deep learning for visual navigation of unmanned ground vehicles: A review," in *2018 29th Irish Signals and Systems Conference (ISSC)*. IEEE, 2018, pp. 1–6.

[41] U. Muller, J. Ben, E. Cosatto, B. Flepp, and Y. L. Cun, "Off-road obstacle avoidance through end-to-end learning," in *Advances in neural information processing systems*. Citeseer, 2006, pp. 739–746.

[42] C. J. Ostafew, A. P. Schoellig, and T. D. Barfoot, "Visual teach and repeat, repeat, repeat: Iterative learning control to improve mobile robot path tracking in challeng-

ing outdoor environments," in *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2013, pp. 176–181.

[43] K. Zhang, F. Niroui, M. Ficocelli, and G. Nejat, "Robot navigation of environments with unknown rough terrain using deep reinforcement learning," in *2018 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*. IEEE, 2018, pp. 1–7.

[44] M. Bakken, R. J. Moore, and P. From, "End-to-end learning for autonomous crop row-following," *IFAC-PapersOnLine*, vol. 52, no. 30, pp. 102–107, 2019.

[45] Y. Pan, C.-A. Cheng, K. Saigol, K. Lee, X. Yan, E. A. Theodorou, and B. Boots, "Imitation learning for agile autonomous driving," *The International Journal of Robotics Research*, vol. 39, no. 2-3, pp. 286–302, 2020.

[46] A. Nguyen, N. Nguyen, K. Tran, E. Tjiputra, and Q. D. Tran, "Autonomous navigation in complex environments with deep multimodal fusion network," in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2020, pp. 5824–5830.

[47] G. Kahn, P. Abbeel, and S. Levine, "Badgr: An autonomous self-supervised learning-based navigation system," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 1312–1319, 2021.

[48] G. Kahn, A. Villaflor, B. Ding, P. Abbeel, and S. Levine, "Self-supervised deep reinforcement learning with generalized computation graphs for robot navigation," in *2018 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2018, pp. 5129–5136.

[49] G. Kahn, A. Villaflor, P. Abbeel, and S. Levine, "Composable action-conditioned predictors: Flexible off-policy learning for robot navigation," in *Conference on Robot Learning*. PMLR, 2018, pp. 806–816.

[50] S. Josef and A. Degani, "Deep reinforcement learning for safe local planning of a ground vehicle in unknown rough terrain," *IEEE Robotics and Automation Letters*, vol. 5, no. 4, pp. 6748–6755, 2020.

[51] T. Manderson, S. Wapnick, D. Meger, and G. Dudek, "Learning to drive off road on smooth terrain in unstructured environments using an on-board camera and sparse aerial images," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 1263–1269.

[52] D. Ribeiro, A. Mateus, P. Miraldo, and J. C. Nascimento, "A real-time deep learning pedestrian detector for robot navigation," in *2017 IEEE international conference on autonomous robot systems and competitions (ICARSC)*. IEEE, 2017, pp. 165–171.

[53] A. Garcia-Garcia, S. Orts-Escolano, S. Oprea, V. Villena-Martinez, and J. Garcia-Rodriguez, "A review on deep learning techniques applied to semantic segmentation," *arXiv preprint arXiv:1704.06857*, 2017.

[54] X. Chen, K. Kundu, Y. Zhu, H. Ma, S. Fidler, and R. Urtasun, "3d object proposals using stereo imagery for accurate object class detection," *IEEE transactions on pattern analysis and machine intelligence*, vol. 40, no. 5, pp. 1259–1272, 2017.

[55] J. Thörnberg, "Combining rgb and depth images for robust object detection using convolutional neural networks," 2015.

[56] B. Li, T. Zhang, and T. Xia, "Vehicle detection from 3d lidar using fully convolutional network," *arXiv preprint arXiv:1608.07916*, 2016.

[57] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, "Mobilenets: Efficient convolutional neural networks for mobile vision applications," *arXiv preprint arXiv:1704.04861*, 2017.

[58] M. J. Islam, J. Hong, and J. Sattar, "Person-following by autonomous robots: A categorical overview," *The International Journal of Robotics Research*, vol. 38, no. 14, pp. 1581–1618, 2019.

[59] S. Patra, P. Maheshwari, S. Yadav, S. Banerjee, and C. Arora, "A joint 3d-2d based method for free space detection on roads," in *2018 IEEE Winter Conference on Applications of Computer Vision (WACV)*. IEEE, 2018, pp. 643–652.

[60] A. Dai and M. Nießner, "3dmv: Joint 3d-multi-view prediction for 3d semantic scene segmentation," in *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 452–468.

[61] N. Dabhi *et al.*, "A review on outdoor scene image segmentation," 2012.

[62] D. Barnes, W. Maddern, and I. Posner, "Find your own way: Weakly-supervised segmentation of path proposals for urban autonomy," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2017, pp. 203–210.

[63] M. Siam, S. Elkerdawy, M. Jagersand, and S. Yogamani, "Deep semantic segmentation for automated driving: Taxonomy, roadmap and challenges," in *2017 IEEE 20th international conference on intelligent transportation systems (ITSC)*. IEEE, 2017, pp. 1–8.

[64] V. Murali, H.-P. Chiu, S. Samarasekera, and R. T. Kumar, "Utilizing semantic visual landmarks for precise vehicle navigation," in *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2017, pp. 1–8.

[65] L. B. Marinho, P. P. Rebouças Filho, J. S. Almeida, J. W. M. Souza, A. H. S. Junior, and V. H. C. de Albuquerque, "A novel mobile robot localization approach based on classification with rejection option using computer vision," *Computers & Electrical Engineering*, vol. 68, pp. 26–43, 2018.

[66] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs," *IEEE transactions on pattern analysis and machine intelligence*, vol. 40, no. 4, pp. 834–848, 2017.

[67] G. Lin, A. Milan, C. Shen, and I. Reid, "Refinenet: Multi-path refinement networks for high-resolution semantic segmentation," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 1925–1934.

[68] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask r-cnn," in *Proceedings of the IEEE international conference on computer vision*, 2017, pp. 2961–2969.

[69] D. Lin, J. Dai, J. Jia, K. He, and J. Sun, "Scribblesup: Scribble-supervised convolutional networks for semantic segmentation," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 3159–3167.

[70] K.-K. Maninis, S. Caelles, J. Pont-Tuset, and L. Van Gool, "Deep extreme cut: From extreme points to object segmentation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 616–625.

[71] Y. L. Murphey, R. Milton, and L. Kiliaris, "Driver's style classification using jerk analy-

sis," in *2009 IEEE Workshop on Computational Intelligence in Vehicles and Vehicular Systems*. IEEE, 2009, pp. 23–28.

[72] V. Manzoni, A. Corti, P. De Luca, and S. M. Savaresi, "Driving style estimation via inertial measurements," in *13th International IEEE Conference on Intelligent Transportation Systems*. IEEE, 2010, pp. 777–782.

[73] D. Filev, J. Lu, K. Prakah-Asante, and F. Tseng, "Real-time driving behavior identification based on driver-in-the-loop vehicle dynamics and control," in *2009 IEEE International Conference on Systems, Man and Cybernetics*. IEEE, 2009, pp. 2020–2025.

[74] D. Dörr, D. Grabengiesser, and F. Gauterin, "Online driving style recognition using fuzzy logic," in *17th international IEEE conference on intelligent transportation systems (ITSC)*. IEEE, 2014, pp. 1021–1026.

[75] M. Van Ly, S. Martin, and M. M. Trivedi, "Driver classification and driving style recognition using inertial sensors," in *2013 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2013, pp. 1040–1045.

[76] V. Vaitkus, P. Lengvenis, and G. Žylius, "Driving style classification using long-term accelerometer information," in *2014 19th International Conference on Methods and Models in Automation and Robotics (MMAR)*. IEEE, 2014, pp. 641–644.

[77] Z. Constantinescu, C. Marinoiu, and M. Vladoiu, "Driving style analysis using data mining techniques," *International Journal of Computers Communications & Control*, vol. 5, no. 5, pp. 654–663, 2010.

[78] A. Mudgal, S. Hallmark, A. Carriquiry, and K. Gkritza, "Driving behavior at a roundabout: A hierarchical bayesian regression analysis," *Transportation research part D: transport and environment*, vol. 26, pp. 20–26, 2014.

[79] A. Doshi and M. M. Trivedi, "Examining the impact of driving style on the predictability and responsiveness of the driver: Real-world and simulator analysis," in *2010 IEEE Intelligent Vehicles Symposium*. IEEE, 2010, pp. 232–237.

[80] H. Xiong and L. N. Boyle, "Drivers' adaptation to adaptive cruise control: Examination of automatic and manual braking," *IEEE transactions on intelligent transportation systems*, vol. 13, no. 3, pp. 1468–1473, 2012.

[81] A. Corti, C. Ongini, M. Tanelli, and S. M. Savaresi, "Quantitative driving style estimation for energy-oriented applications in road vehicles," in *2013 IEEE International Conference on Systems, Man, and Cybernetics*. IEEE, 2013, pp. 3710–3715.

[82] D. A. Johnson and M. M. Trivedi, "Driving style recognition using a smartphone as a sensor platform," in *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2011, pp. 1609–1615.

[83] M. Fazeen, B. Gozick, R. Dantu, M. Bhukhiya, and M. C. González, "Safe driving using mobile phones," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 3, pp. 1462–1468, 2012.

[84] R. Stoichkov, "Android smartphone application for driving style recognition," *Department of Electrical Engineering and Information Technology Institute for Media Technology, July*, vol. 20, 2013.

[85] J. Sussman, *Introduction to transportation systems*, 2000.

[86] N.-E. El Faouzi, H. Leung, and A. Kurian, "Data fusion in intelligent transportation

systems: Progress and challenges–a survey," *Information Fusion*, vol. 12, no. 1, pp. 4–10, 2011.

[87] H. D. Whyte, "Simultaneous localisation and mapping (slam): Part i the essential algorithms," *Robotics and Automation Magazine*, 2006.

[88] Z. Hu, H. Leung, and M. Blanchette, "Evaluation of data association techniques in a real multitarget radar tracking environment," in *Signal and Data Processing of Small Targets 1995*, vol. 2561. International Society for Optics and Photonics, 1995, pp. 509–518.

[89] C.-C. Wang, C. Thorpe, and A. Suppe, "Ladar-based detection and tracking of moving objects from a ground vehicle at high speeds," in *IEEE IV2003 Intelligent Vehicles Symposium. Proceedings (Cat. No. 03TH8683)*. IEEE, 2003, pp. 416–421.

[90] H.-S. Tsao, R. W. Hall, and S. E. Shladover, "Design options for operating automated highway systems," in *Proceedings of VNIS'93-Vehicle Navigation and Information Systems Conference*. IEEE, 1993, pp. 494–500.

[91] S. K. Kenue, "Lanelok: Detection of lane boundaries and vehicle tracking using image-processing techniques-part ii: Template matching algorithms," in *Mobile Robots IV*, vol. 1195. International Society for Optics and Photonics, 1990, pp. 234–245.

[92] K. Kluge, "Yarf: An open-ended framework for robot road following," CARNEGIE-MELLON UNIV PITTSBURGH PA SCHOOL OF COMPUTER SCIENCE, Tech. Rep., 1993.

[93] ——, "Extracting road curvature and orientation from image edge points without perceptual grouping into features," in *Proceedings of the Intelligent Vehicles' 94 Symposium*. IEEE, 1994, pp. 109–114.

[94] C. Kreucher and S. Lakshmanan, "Lana: a lane extraction algorithm that uses frequency domain features," *IEEE Transactions on Robotics and automation*, vol. 15, no. 2, pp. 343–350, 1999.

[95] D. L. Hall and S. A. McMullen, *Mathematical techniques in multisensor data fusion*. Artech House, 2004.

[96] Y. Bar-Shalom, X. R. Li, and T. Kirubarajan, *Estimation with applications to tracking and navigation: theory algorithms and software*. John Wiley & Sons, 2004.

[97] W. Li and H. Leung, "Constrained unscented kalman filter based fusion of gps/ins/digital map for vehicle localization," in *Proceedings of the 2003 IEEE International Conference on Intelligent Transportation Systems*, vol. 2. IEEE, 2003, pp. 1362–1367.

[98] R. R. Murphy, "Sensor and information fusion improved vision-based vehicle guidance," *IEEE Intelligent Systems and their Applications*, vol. 13, no. 6, pp. 49–56, 1998.

[99] J. Langheim, A. Buchanan, V. Willhoeft, U. Lages, and G. Gyory, "Carsense-sensor fusion for das," in *9th World Congress on Intelligent Transport SystemsITS America, ITS Japan, ERTICO (Intelligent Transport Systems and Services-Europe)*, 2002.

[100] C. Stiller, J. Hipp, C. Rössig, and A. Ewald, "Multisensor obstacle detection and tracking," *Image and vision Computing*, vol. 18, no. 5, pp. 389–396, 2000.

[101] M. Wei and K. Schwarz, "Testing a decentralized filter for gps/ins integration," in *IEEE Symposium on Position Location and Navigation. A Decade of Excellence in the Navigation Sciences*. IEEE, 1990, pp. 429–435.

[102] N. El-Sheimy, K.-W. Chiang, and A. Noureldin, “The utilization of artificial neural networks for multisensor system integration in navigation and positioning instruments,” *IEEE Transactions on instrumentation and measurement*, vol. 55, no. 5, pp. 1606–1615, 2006.

[103] A. Hiliuta, R. Landry, and F. Gagnon, “Fuzzy corrections in a gps/ins hybrid navigation system,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 40, no. 2, pp. 591–600, 2004.

[104] G. Naik, B. Choudhury, and J.-M. Park, “Ieee 802.11 bd & 5g nr v2x: Evolution of radio access technologies for v2x communications,” *IEEE Access*, vol. 7, pp. 70 169–70 184, 2019.

[105] X. Wang, S. Mao, and M. X. Gong, “An overview of 3gpp cellular vehicle-to-everything standards,” *GetMobile: Mobile Computing and Communications*, vol. 21, no. 3, pp. 19–25, 2017.

[106] “Study on lte-based v2x services (v14.0.0 release 14),” 2016.

[107] “5gaa. v2x technology benchmark testing,” 2018. [Online]. Available: https://www.fcc.gov/ecfs/filing/109271050222769

[108] R. Molina-Masegosa and J. Gozalvez, “Lte-v for sidelink 5g v2x vehicular communications: A new 5g technology for short-range vehicle-to-everything communications,” *IEEE Vehicular Technology Magazine*, vol. 12, no. 4, pp. 30–39, 2017.

[109] “Study on enhancement of 3gpp support for 5g v2x services (v16.2.0 release 16),” 2018.

[110] “Ieee p802.11—next generation v2x study group,” 2019. [Online]. Available: http://www.ieee802.org/11/Reports/tgbd_update.htm

[111] M. I. Hassan, H. L. Vu, and T. Sakurai, “Performance analysis of the ieee 802.11 mac protocol for dsrc safety applications,” *IEEE Transactions on vehicular technology*, vol. 60, no. 8, pp. 3882–3896, 2011.

[112] “Evolved universal terrestrial radio access (e-utra),” *Physical Layer Procedures (v14.3.0 Release 14)*, 2017.

[113] A. Filippi, K. Moerman, V. Martinez, A. Turley, O. Haran, and R. Toledano, “Ieee802.11p ahead of lte-v2v for safety applications,” *Autotalks NXP*, pp. 1–19, 2017.

[114] “Sae j2945/1: On-board system requirements for v2v safety communications,” 2016, warrendale, PA, USA.

[115] A. Bazzi, B. M. Masini, A. Zanella, and I. Thibault, “On the performance of ieee 802.11 p and lte-v2v for the cooperative awareness of connected vehicles,” *IEEE Transactions on Vehicular Technology*, vol. 66, no. 11, pp. 10 419–10 432, 2017.

[116] K. A. Hafeez, L. Zhao, B. Ma, and J. W. Mark, “Performance analysis and enhancement of the dsrc for vanet’s safety applications,” *IEEE Transactions on Vehicular Technology*, vol. 62, no. 7, pp. 3069–3083, 2013.

[117] S. Antipolis, “Intelligent transport systems (its); vehicular communications; basic set of applications; definitions,” 2009, france.

[118] H. Z. B. Sun, “Ieee 802.11-18/0861r9: 802.11 ngv proposed par,” *IEEE 802.11 NGV Meeting*, 2019.

[119] "Rp-181480: New sid: Study on nr v2x," *Proc. 3GPP Planery Meeting*, vol. 80, pp. 1–10, 2018.

[120] D. Butler, "How 'talking'and 'listening'vehicles could make roads safer, cities better," *Online: https://medium. com/@ ford/how-talking-andlistening-vehicles-could-make-roads-safer-cities-better-f215c68f376f*, 2019.

[121] U. Z. A. Hamid, F. R. A. Zakuan, K. A. Zulkepli, M. Z. Azmi, H. Zamzuri, M. A. A. Rahman, and M. A. Zakaria, "Autonomous emergency braking system with potential field risk assessment for frontal collision mitigation," in *2017 ieee conference on systems, process and control (icspc)*. IEEE, 2017, pp. 71–76.

[122] S. R. Garzon, "Situation-aware personalization of automotive user interfaces," in *Adjunct Proceedings of 4th Int. Conf. on Automotive User Interfaces and Interactive Vehicular Applications*, 2012, pp. 15–16.

[123] M. Hasenjäger, M. Heckmann, and H. Wersing, "A survey of personalization for advanced driver assistance systems," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 2, pp. 335–344, 2019.

[124] M. Galvani, "History and future of driver assistance," *IEEE Instrumentation & Measurement Magazine*, vol. 22, no. 1, pp. 11–16, 2019.

[125] A. Gupta, A. Anpalagan, L. Guan, and A. S. Khwaja, "Deep learning for object detection and scene perception in self-driving cars: Survey, challenges, and open issues," *Array*, p. 100057, 2021.

[126] C. M. Martinez, M. Heucke, F.-Y. Wang, B. Gao, and D. Cao, "Driving style recognition for intelligent vehicle control and advanced driver assistance: A survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 3, pp. 666–676, 2017.

[127] T. Lee and J. Son, "Relationships between driving style and fuel consumption in highway driving," SAE Technical Paper, Tech. Rep., 2011.

[128] L. Xu, J. Hu, H. Jiang, and W. Meng, "Establishing style-oriented driver models by imitating human driving behaviors," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 5, pp. 2522–2530, 2015.

[129] F. U. Syed, D. Filev, and H. Ying, "Real time advisory system for fuel economy improvement in a hybrid electric vehicle," in *NAFIPS 2008-2008 Annual Meeting of the North American Fuzzy Information Processing Society*. IEEE, 2008, pp. 1–6.

[130] F. Syed, S. Nallapa, A. Dobryden, C. Grand, R. McGee, and D. Filev, "Design and analysis of an adaptive real-time advisory system for improving real world fuel economy in a hybrid electric vehicle," SAE Technical Paper, Tech. Rep., 2010.

[131] G. Reichart, S. Friedmann, C. Dorrer, H. Rieker, E. Drechsel, G. Wermuth *et al.*, "Potentials of bmw driver assistance to improve fuel economy," in *FISITA World Automotive Congress, Paris*, vol. 27, 1998, pp. 1–16.

[132] R. Wang and S. M. Lukic, "Review of driving conditions prediction and driving style recognition based control algorithms for hybrid electric vehicles," in *2011 IEEE Vehicle Power and Propulsion Conference*. IEEE, 2011, pp. 1–7.

[133] F.-Y. Wang, "Scanning the issue and beyond: Parallel driving with software vehicular robots for safety and smartness," *IEEE Transactions on Intelligent Transportation Systems*, vol. 4, no. 15, pp. 1381–1387, 2014.

[134] J. C. McCall and M. M. Trivedi, “Driver behavior and situation aware brake assistance for intelligent vehicles,” *Proceedings of the IEEE*, vol. 95, no. 2, pp. 374–387, 2007.

[135] A. Bolovinou, A. Amditis, F. Bellotti, and M. Tarkiainen, “Driving style recognition for co-operative driving: A survey,” in *The Sixth International Conference on Adaptive and Self-Adaptive Systems and Applications*. Citeseer, 2014, pp. 73–78.

[136] G. Kurz, A. Müller, T. Röhrig-Gericke, R. Schöb, H. Tröster, and A. Yap, “Method and device for classifying the driving style of a driver in a motor vehicle,” Sep. 10 2002, uS Patent 6,449,572.

[137] S. Rass, S. Fuchs, and K. Kyamakya, “A game-theoretic approach to co-operative context-aware driving with partially random behavior,” in *European Conference on Smart Sensing and Context*. Springer, 2008, pp. 154–167.

[138] C. P. Urmson, D. A. Dolgov, and P. Nemec, “Driving pattern recognition and safety control,” Jan. 21 2014, uS Patent 8,634,980.

[139] G. Lenaers, “Real life co 2 emission and consumption of four car powertrain technologies related to driving behaviour and road type,” SAE Technical Paper, Tech. Rep., 2009.

[140] J. Neubauer and E. Wood, “Accounting for the variation of driver aggression in the simulation of conventional and advanced vehicles,” National Renewable Energy Lab.(NREL), Golden, CO (United States), Tech. Rep., 2013.

[141] C.-C. Lin, S. Jeon, H. Peng, and J. Moo Lee, “Driving pattern recognition for control of hybrid electric trucks,” *Vehicle System Dynamics*, vol. 42, no. 1-2, pp. 41–58, 2004.

[142] H. Yu, F. Tseng, and R. McGee, “Driving pattern identification for ev range estimation,” in *2012 IEEE International Electric Vehicle Conference*. IEEE, 2012, pp. 1–7.

[143] S. Zhang and R. Xiong, “Adaptive energy management of a plug-in hybrid electric vehicle based on driving pattern recognition and dynamic programming,” *Applied Energy*, vol. 155, pp. 68–78, 2015.

[144] J. Neubauer and E. Wood, “Thru-life impacts of driver aggression, climate, cabin thermal management, and battery thermal management on battery electric vehicle utility,” *Journal of Power Sources*, vol. 259, pp. 262–275, 2014.

[145] A. Bolovinou, I. Bakas, A. Amditis, F. Mastrandrea, and W. Vinciotti, “Online prediction of an electric vehicle remaining range based on regression analysis,” in *2014 IEEE International Electric Vehicle Conference (IEVC)*. IEEE, 2014, pp. 1–8.

[146] P. Tchankue, J. Wesson, and D. Vogts, “Using machine learning to predict the driving context whilst driving,” in *Proceedings of the South African Institute for Computer Scientists and Information Technologists Conference*, 2013, pp. 47–55.

[147] C. d’Agostino, A. Saidi, G. Scouarnec, and L. Chen, “Learning-based driving events recognition and its application to digital roads,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 4, pp. 2155–2166, 2015.

[148] X. Chen, Y. Zhai, C. Lu, J. Gong, and G. Wang, “A learning model for personalized adaptive cruise control,” in *2017 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2017, pp. 379–384.

[149] C. Desjardins and B. Chaib-Draa, “Cooperative adaptive cruise control: A reinforcement learning approach,” *IEEE Transactions on intelligent transportation systems*, vol. 12, no. 4, pp. 1248–1260, 2011.

[150] D. Lee and H. Yeo, “Real-time rear-end collision-warning system using a multilayer perceptron neural network,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 11, pp. 3087–3097, 2016.

[151] V. Govindarajan, K. Driggs-Campbell, and R. Bajcsy, “Affective driver state monitoring for personalized, adaptive adas,” in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2018, pp. 1017–1022.

[152] Y. Hou, P. Edara, and C. Sun, “Modeling mandatory lane changing using bayes classifier and decision trees,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 2, pp. 647–655, 2013.

[153] B. Morris, A. Doshi, and M. Trivedi, “Lane change intent prediction for driver assistance: On-road design and evaluation,” in *2011 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2011, pp. 895–901.

[154] R. Zheng, C. Liu, and Q. Guo, “A decision-making method for autonomous vehicles based on simulation and reinforcement learning,” in *2013 International Conference on Machine Learning and Cybernetics*, vol. 1. IEEE, 2013, pp. 362–369.

[155] X. Li, X. Xu, and L. Zuo, “Reinforcement learning based overtaking decision-making for highway autonomous driving,” in *2015 Sixth International Conference on Intelligent Control and Information Processing (ICICIP)*. IEEE, 2015, pp. 336–342.

[156] G. Wang, J. Hu, Z. Li, and L. Li, “Cooperative lane changing via deep reinforcement learning,” *arXiv preprint arXiv:1906.08662*, 2019.

[157] T. Shi, P. Wang, X. Cheng, C.-Y. Chan, and D. Huang, “Driving decision and control for automated lane change behavior based on deep reinforcement learning,” in *2019 IEEE intelligent transportation systems conference (ITSC)*. IEEE, 2019, pp. 2895–2900.

[158] O. Nassef, L. Sequeira, E. Salam, and T. Mahmoodi, “Deep reinforcement learning in lane merge coordination for connected vehicles,” in *2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications*. IEEE, 2020, pp. 1–7.

[159] D. E. Moriarty and P. Langley, “Distributed learning of lane-selection strategies for traffic management,” *Daimler-Benz Res. Technol. Center, Palo Alto, CA, Tech. Rep*, pp. 98–2, 1998.

[160] S. Yang, B. Yang, H.-S. Wong, and Z. Kang, “Cooperative traffic signal control using multi-step return and off-policy asynchronous advantage actor-critic graph algorithm,” *Knowledge-Based Systems*, vol. 183, p. 104855, 2019.

[161] D. Kim and O. Jeong, “Cooperative traffic signal control with traffic flow prediction in multi-intersection,” *Sensors*, vol. 20, no. 1, p. 137, 2020.

[162] Y. Deng, T. Zhang, G. Lou, X. Zheng, J. Jin, and Q.-L. Han, “Deep learning-based autonomous driving systems: A survey of attacks and defenses,” *IEEE Transactions on Industrial Informatics*, 2021.

[163] H. Saleem, R. Khatoon, F. Riaz, and M. A. Butt, “Evaluating the role of neural networks and cyber security for the development of next generation autonomous vehicles: a survey,” in *Proceedings of the 4th International Electrical Engineering Conference*, 2019.

[164] C. M. Martinez, M. Heucke, F.-Y. Wang, B. Gao, and D. Cao, “Driving style recog-

nition for intelligent vehicle control and advanced driver assistance: A survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 3, pp. 666–676, 2017.

[165] Y. Ma, Z. Wang, H. Yang, and L. Yang, "Artificial intelligence applications in the development of autonomous vehicles: a survey," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 2, pp. 315–329, 2020.

[166] P. F. Alcantarilla, S. Stent, G. Ros, R. Arroyo, and R. Gherardi, "Street-view change detection with deconvolutional networks," *Autonomous Robots*, vol. 42, no. 7, pp. 1301–1322, 2018.

[167] H. J. Vishnukumar, B. Butting, C. Müller, and E. Sax, "Machine learning and deep neural network—artificial intelligence core for lab and real-world test and validation for adas and autonomous vehicles: Ai for efficient and quality test and validation," in *2017 Intelligent Systems Conference (IntelliSys)*. IEEE, 2017, pp. 714–721.

[168] S. Wang, R. Clark, H. Wen, and N. Trigoni, "Deepvo: Towards end-to-end visual odometry with deep recurrent convolutional neural networks," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2017, pp. 2043–2050.

[169] J. Chen, W. Jiang, P. Zhao, and J. Hu, "A path planning method of anti-jamming ability improvement for autonomous vehicle navigating in off-road environments," *Industrial Robot: An International Journal*, 2017.

[170] D. O. Sales, D. O. Correa, L. C. Fernandes, D. F. Wolf, and F. S. Osório, "Adaptive finite state machine based visual autonomous navigation system," *Engineering Applications of Artificial Intelligence*, vol. 29, pp. 152–162, 2014.

[171] K. Akermi, S. Chouraqui, and B. Boudaa, "Novel smc control design for path following of autonomous vehicles with uncertainties and mismatched disturbances," *International Journal of Dynamics and Control*, vol. 8, no. 1, pp. 254–268, 2020.

[172] X. Dai, C.-K. Li, and A. B. Rad, "An approach to tune fuzzy controllers based on reinforcement learning for autonomous vehicle control," *IEEE Transactions on Intelligent Transportation Systems*, vol. 6, no. 3, pp. 285–293, 2005.

[173] D. CireAan, U. Meier, J. Masci, and J. Schmidhuber, "Multi-column deep neural network for traffic sign classification," *Neural networks*, vol. 32, pp. 333–338, 2012.

[174] W. Li, X. Jiang, and Y. Wang, "Road recognition for vision navigation of an autonomous vehicle by fuzzy reasoning," *Fuzzy Sets and Systems*, vol. 93, no. 3, pp. 275–280, 1998.

[175] D. J. Fagnant and K. Kockelman, "Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations," *Transportation Research Part A: Policy and Practice*, vol. 77, pp. 167–181, 2015.

[176] Y. Zeng, X. Xu, D. Shen, Y. Fang, and Z. Xiao, "Traffic sign recognition using kernel extreme learning machines with deep perceptual features," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 6, pp. 1647–1653, 2016.

[177] W. Chu, Y. Liu, C. Shen, D. Cai, and X.-S. Hua, "Multi-task vehicle detection with region-of-interest voting," *IEEE Transactions on Image Processing*, vol. 27, no. 1, pp. 432–441, 2017.

[178] Y. Chen, D. Zhao, L. Lv, and Q. Zhang, "Multi-task learning for dangerous object detection in autonomous driving," *Information Sciences*, vol. 432, pp. 559–571, 2018.

[179] C. Chen, A. Seff, A. Kornhauser, and J. Xiao, "Deepdriving: Learning affordance for

direct perception in autonomous driving," in *Proceedings of the IEEE international conference on computer vision*, 2015, pp. 2722–2730.

[180] M. Bojarski, D. Del Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L. D. Jackel, M. Monfort, U. Muller, J. Zhang *et al.*, "End to end learning for self-driving cars," *arXiv preprint arXiv:1604.07316*, 2016.

[181] M. Bojarski, P. Yeres, A. Choromanska, K. Choromanski, B. Firner, L. Jackel, and U. Muller, "Explaining how a deep neural network trained with end-to-end learning steers a car," *arXiv preprint arXiv:1704.07911*, 2017.

[182] X. Nie, M. Duan, H. Ding, B. Hu, and E. K. Wong, "Attention mask r-cnn for ship detection and segmentation from remote sensing images," *IEEE Access*, vol. 8, pp. 9325–9334, 2020.

[183] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 779–788.

[184] Y. Zhou and O. Tuzel, "Voxelnet: End-to-end learning for point cloud based 3d object detection," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 4490–4499.

[185] S. Shi, X. Wang, and H. Li, "Pointrcnn: 3d object proposal generation and detection from point cloud," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019, pp. 770–779.

[186] J. Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 3431–3440.

[187] A. Agarwal, S. Gupta, and D. K. Singh, "Review of optical flow technique for moving object detection," in *2016 2nd International Conference on Contemporary Computing and Informatics (IC3I)*. IEEE, 2016, pp. 409–413.

[188] S. Aradi, "Survey of deep reinforcement learning for motion planning of autonomous vehicles," *IEEE Transactions on Intelligent Transportation Systems*, 2020.

[189] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller, "Playing atari with deep reinforcement learning," *arXiv preprint arXiv:1312.5602*, 2013.

[190] H. Van Hasselt, A. Guez, and D. Silver, "Deep reinforcement learning with double q-learning," in *Proceedings of the AAAI conference on artificial intelligence*, vol. 30, no. 1, 2016.

[191] Z. Wang, T. Schaul, M. Hessel, H. Hasselt, M. Lanctot, and N. Freitas, "Dueling network architectures for deep reinforcement learning," in *International conference on machine learning*. PMLR, 2016, pp. 1995–2003.

[192] D. Silver, G. Lever, N. Heess, T. Degris, D. Wierstra, and M. Riedmiller, "Deterministic policy gradient algorithms," in *International conference on machine learning*. PMLR, 2014, pp. 387–395.

[193] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra, "Continuous control with deep reinforcement learning," *arXiv preprint arXiv:1509.02971*, 2015.

[194] P. Stone and M. Veloso, “Multiagent systems: A survey from a machine learning perspective,” *Autonomous Robots*, vol. 8, no. 3, pp. 345–383, 2000.

[195] P. Hernandez-Leal, B. Kartal, and M. E. Taylor, “A survey and critique of multiagent deep reinforcement learning,” *Autonomous Agents and Multi-Agent Systems*, vol. 33, no. 6, pp. 750–797, 2019.

[196] D. S. Bernstein, R. Givan, N. Immerman, and S. Zilberstein, “The complexity of decentralized control of markov decision processes,” *Mathematics of operations research*, vol. 27, no. 4, pp. 819–840, 2002.

[197] F. A. Oliehoek and C. Amato, *A concise introduction to decentralized POMDPs*. Springer, 2016.

[198] H. Xu, Y. Gao, F. Yu, and T. Darrell, “End-to-end learning of driving models from large-scale video datasets,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 2174–2182.

[199] S. Baluja, “Evolution of an artificial neural network based autonomous land vehicle controller,” *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 26, no. 3, pp. 450–463, 1996.

[200] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski *et al.*, “Human-level control through deep reinforcement learning,” *nature*, vol. 518, no. 7540, pp. 529–533, 2015.

[201] P. Abbeel and A. Y. Ng, “Apprenticeship learning via inverse reinforcement learning,” in *Proceedings of the twenty-first international conference on Machine learning*, 2004, p. 1.

[202] M. Kuderer, S. Gulati, and W. Burgard, “Learning driving styles for autonomous vehicles from demonstration,” in *2015 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2015, pp. 2641–2646.

[203] D. Floreano, P. Dürr, and C. Mattiussi, “Neuroevolution: from architectures to learning,” *Evolutionary intelligence*, vol. 1, no. 1, pp. 47–62, 2008.

[204] J. Koutník, G. Cuccu, J. Schmidhuber, and F. Gomez, “Evolving large-scale neural networks for vision-based reinforcement learning,” in *Proceedings of the 15th annual conference on Genetic and evolutionary computation*, 2013, pp. 1061–1068.

[205] L. Chi and Y. Mu, “Deep steering: Learning end-to-end driving model from spatial and temporal visual cues,” *arXiv preprint arXiv:1708.03798*, 2017.

[206] T. Gu, J. M. Dolan, and J.-W. Lee, “Human-like planning of swerve maneuvers for autonomous vehicles,” in *2016 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2016, pp. 716–721.

[207] A. Gupta, J. Johnson, L. Fei-Fei, S. Savarese, and A. Alahi, “Social gan: Socially acceptable trajectories with generative adversarial networks,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 2255–2264.

[208] W. Luo, B. Yang, and R. Urtasun, “Fast and furious: Real time end-to-end 3d detection, tracking and motion forecasting with a single convolutional net,” in *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, 2018, pp. 3569–3577.

[209] L. Caltagirone, M. Bellone, L. Svensson, and M. Wahde, “Lidar-based driving path generation using fully convolutional neural networks,” in *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2017, pp. 1–6.

[210] D. Isele, R. Rahimi, A. Cosgun, K. Subramanian, and K. Fujimura, "Navigating occluded intersections with autonomous vehicles using deep reinforcement learning," in *2018 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2018, pp. 2034–2039.

[211] E. Yurtsever, J. Lambert, A. Carballo, and K. Takeda, "A survey of autonomous driving: Common practices and emerging technologies," *IEEE access*, vol. 8, pp. 58 443–58 469, 2020.

[212] A. L. Bazzan and F. Klügl, *Multi-agent systems for traffic and transportation engineering*. IGI Global, 2009.

[213] P. Palanisamy, "Multi-agent connected autonomous driving using deep reinforcement learning," in *2020 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2020, pp. 1–7.

[214] C. Yu, X. Wang, X. Xu, M. Zhang, H. Ge, J. Ren, L. Sun, B. Chen, and G. Tan, "Distributed multiagent coordinated learning for autonomous driving in highways based on dynamic coordination graphs," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 2, pp. 735–748, 2019.

[215] A. Wachi, "Failure-scenario maker for rule-based agent using multi-agent adversarial reinforcement learning and its application to autonomous driving," *arXiv preprint arXiv:1903.10654*, 2019.

[216] S. Shalev-Shwartz, S. Shammah, and A. Shashua, "Safe, multi-agent, reinforcement learning for autonomous driving," *arXiv preprint arXiv:1610.03295*, 2016.

[217] S. Yogamani, C. Hughes, J. Horgan, G. Sistu, P. Varley, D. O'Dea, M. Uricár, S. Milz, M. Simon, K. Amende *et al.*, "Woodscape: A multi-task, multi-camera fisheye dataset for autonomous driving," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2019, pp. 9308–9318.

[218] C. J. C. H. Watkins, "Learning from delayed rewards," 1989.

[219] M. Li, Z. Cao, and Z. Li, "A reinforcement learning-based vehicle platoon control strategy for reducing energy consumption in traffic oscillations," *IEEE Transactions on Neural Networks and Learning Systems*, 2021.

[220] A. Farag, O. M. AbdelAziz, A. Hussein, and O. M. Shehata, "Reinforcement learning based approach for multi-vehicle platooning problem with nonlinear dynamic behavior."

[221] M. Parvini, M. R. Javan, N. Mokari, B. Abbasi, and E. A. Jorswieck, "Aoi-aware resource allocation for platoon-based c-v2x networks via multi-agent multi-task reinforcement learning," *arXiv preprint arXiv:2105.04196*, 2021.

[222] L. Cao and H. Yin, "Resource allocation for vehicle platooning in 5g nr-v2x via deep reinforcement learning," *arXiv preprint arXiv:2101.10424*, 2021.

[223] T. Mecheva and N. Kakanakov, "Cybersecurity in intelligent transportation systems," *Computers*, vol. 9, no. 4, p. 83, 2020.

[224] K. Kim, J. S. Kim, S. Jeong, J.-H. Park, and H. K. Kim, "Cybersecurity for autonomous vehicles: Review of attacks and defense," *Computers & Security*, p. 102150, 2021.

[225] A. Taylor, S. Leblanc, and N. Japkowicz, "Anomaly detection in automobile control network data with long short-term memory networks," in *2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE, 2016, pp. 130–139.

[226] H. M. Song, J. Woo, and H. K. Kim, "In-vehicle network intrusion detection using deep convolutional neural network," *Vehicular Communications*, vol. 21, p. 100198, 2020.

[227] P. Vähäkainu and M. Lehto, "Artificial intelligence in the cyber security environment," in *ICCWS 2019 14th International Conference on Cyber Warfare and Security: ICCWS 2019*. Academic Conferences and publishing limited, 2019, p. 431.

[228] A. Alnasser, H. Sun, and J. Jiang, "Cyber security challenges and solutions for v2x communications: A survey," *Computer Networks*, vol. 151, pp. 52–67, 2019.

[229] W. Shi, M. B. Alawieh, X. Li, and H. Yu, "Algorithm and hardware implementation for visual perception system in autonomous vehicle: A survey," *Integration*, vol. 59, pp. 148–156, 2017.

[230] M. Aki, T. Rojanaarpa, K. Nakano, Y. Suda, N. Takasuka, T. Isogai, and T. Kawai, "Road surface recognition using laser radar for automatic platooning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 10, pp. 2800–2810, 2016.

[231] J. Jo, Y. Tsunoda, B. Stantic, and A. W.-C. Liew, "A likelihood-based data fusion model for the integration of multiple sensor data: A case study with vision and lidar sensors," in *Robot Intelligence Technology and Applications 4*. Springer, 2017, pp. 489–500.

[232] P. Radecki, M. Campbell, and K. Matzen, "All weather perception: Joint data association, tracking, and classification for autonomous ground vehicles," *arXiv preprint arXiv:1605.02196*, 2016.

[233] Z. Cui, S.-W. Yang, and H.-M. Tsai, "A vision-based hierarchical framework for autonomous front-vehicle taillights detection and signal recognition," in *2015 IEEE 18th International Conference on Intelligent Transportation Systems*. IEEE, 2015, pp. 931–937.

[234] X.-m. Chen, M. Jin, Y.-s. Miao, and Q. Zhang, "Driving decision-making analysis of car-following for autonomous vehicle under complex urban environment," *Journal of central south university*, vol. 24, no. 6, pp. 1476–1482, 2017.

[235] J. Van Brummelen, M. O'Brien, D. Gruyer, and H. Najjaran, "Autonomous vehicle perception: The technology of today and tomorrow," *Transportation research part C: emerging technologies*, vol. 89, pp. 384–406, 2018.

[236] M. S. Ramanagopal, C. Anderson, R. Vasudevan, and M. Johnson-Roberson, "Failing to learn: Autonomously identifying perception failures for self-driving cars," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 3860–3867, 2018.

[237] N. Pous, D. Gingras, and D. Gruyer, "Intelligent vehicle embedded sensors fault detection and isolation using analytical redundancy and nonlinear transformations," *Journal of Control Science and Engineering*, vol. 2017, 2017.

[238] S. Shafaei, S. Kugele, M. H. Osman, and A. Knoll, "Uncertainty in machine learning: A safety perspective on autonomous driving," in *International Conference on Computer Safety, Reliability, and Security*. Springer, 2018, pp. 458–464.

[239] K. M. Ali Alheeti and K. McDonald-Maier, "Intelligent intrusion detection in external communication systems for autonomous vehicles," *Systems Science & Control Engineering*, vol. 6, no. 1, pp. 48–56, 2018.

[240] R. McAllister, Y. Gal, A. Kendall, M. Van Der Wilk, A. Shah, R. Cipolla, and A. Weller, "Concrete problems for autonomous vehicle safety: Advantages of bayesian deep learning." International Joint Conferences on Artificial Intelligence, Inc., 2017.

[241] Y. Gal, “Uncertainty in deep learning,” *University of Cambridge*, vol. 1, no. 3, p. 4, 2016.

[242] S. Santini, A. Salvi, A. S. Valente, A. Pescapé, M. Segata, and R. Lo Cigno, “A consensus-based approach for platooning with intervehicular communications and its validation in realistic scenarios,” *IEEE Transactions on Vehicular Technology*, vol. 66, no. 3, pp. 1985–1999, 2017.

[243] D. Krajzewicz, J. Erdmann, M. Behrisch, and L. Bieker, “Recent development and applications of sumo-simulation of urban mobility,” *International journal on advances in systems and measurements*, vol. 5, no. 3&4, 2012.

[244] M. Fellendorf and P. Vortisch, “Microscopic traffic flow simulator vissim,” in *Fundamentals of traffic simulation*. Springer, 2010, pp. 63–93.

[245] Y. Ye, X. Zhang, and J. Sun, “Automated vehicle’s behavior decision making using deep reinforcement learning and high-fidelity simulation environment,” *Transportation Research Part C: Emerging Technologies*, vol. 107, pp. 155–170, 2019.

[246] B. Wymann, E. Espié, C. Guionneau, C. Dimitrakakis, R. Coulom, and A. Sumner, “Torcs, the open racing car simulator,” *Software available at http://torcs. sourceforge. net*, vol. 4, no. 6, p. 2, 2000.

[247] H. An and J.-i. Jung, “Decision-making system for lane change using deep reinforcement learning in connected and automated driving,” *Electronics*, vol. 8, no. 5, p. 543, 2019.

[248] J. Wang, Q. Zhang, D. Zhao, and Y. Chen, “Lane change decision-making through deep reinforcement learning with rule-based constraints,” in *2019 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2019, pp. 1–6.

[249] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, “Carla: An open urban driving simulator,” in *Conference on robot learning*. PMLR, 2017, pp. 1–16.

[250] F. Rosique, P. J. Navarro, C. Fernández, and A. Padilla, “A systematic review of perception system and simulators for autonomous vehicles research,” *Sensors*, vol. 19, no. 3, p. 648, 2019.

[251] N. Rajabli, F. Flammini, R. Nardone, and V. Vittorini, “Software verification and validation of safe autonomous cars: A systematic literature review,” *IEEE Access*, vol. 9, pp. 4797–4819, 2021.

[252] R. Rana, M. Staron, C. Berger, J. Hansson, M. Nilsson, and F. Törner, “Early verification and validation according to iso 26262 by combining fault injection and mutation testing,” *Communications in Computer and Information Science*, vol. 457, pp. 164–179, 2014.

[253] Z. Chen, G. Li, K. Pattabiraman, and N. Debardeleben, “Binfi: an efficient fault injector for safety-critical machine learning systems,” in *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*, 2019, pp. 1–23.

[254] P. Koopman and M. Wagner, “Autonomous vehicle safety: An interdisciplinary challenge,” *IEEE Intelligent Transportation Systems Magazine*, vol. 9, no. 1, pp. 90–96, 2017.

[255] P. Koopman and M. Wagner, “Challenges in autonomous vehicle testing and valida-

tion," *SAE International Journal of Transportation Safety*, vol. 4, no. 1, pp. 15–24, 2016.

[256] ——, "Toward a framework for highly automated vehicle safety validation," *SAE Technical Papers*, vol. 2018-April, 2018.

[257] R. Mekala, G. Magnusson, A. Porter, M. Lindvall, and M. Diep, "Metamorphic detection of adversarial examples in deep learning models with affine transformations." Institute of Electrical and Electronics Engineers Inc., 2019, pp. 55–62.

[258] K. Pei, Y. Cao, J. Yang, and S. Jana, "Deepxplore: Automated whitebox testing of deep learning systems." Association for Computing Machinery, Inc, 2017, pp. 1–18.

[259] J. Guo, Y. Jiang, Y. Zhao, Q. Chen, and J. Sun, "Dlfuzz: Differential fuzzing testing of deep learning systems," L. G. Garci A., Pasareanu C.S., Ed. Association for Computing Machinery, Inc, 2018, pp. 739–743.

[260] W. Shi, M. Alawieh, X. Li, H. Yu, N. Arechiga, and N. Tomatsu, "Efficient statistical validation of machine learning systems for autonomous driving," vol. 07-10-November-2016. Institute of Electrical and Electronics Engineers Inc., 2016.

[261] E. Rocklage, "Teaching self-driving cars to dream: A deeply integrated, innovative approach for solving the autonomous vehicle validation problem," vol. 2018-March. Institute of Electrical and Electronics Engineers Inc., 2018, pp. 1–7.

[262] H. Vishnukumar, B. Butting, C. Muller, and E. Sax, "Machine learning and deep neural network - artificial intelligence core for lab and real-world test and validation for adas and autonomous vehicles: Ai for efficient and quality test and validation," vol. 2018-January. Institute of Electrical and Electronics Engineers Inc., 2018, pp. 714–721.

[263] "Mistral - communication systems for next-generation railways." [Online]. Available: http://www.mistral-s2r-project.eu/

[264] "Emulradio4rail - emulation of radio access technologies for railway communications." [Online]. Available: http://www.emulradio4rail.eu

[265] "Ab4rail - alternative bearers for rail." [Online]. Available: https://www.ab4rail.eu/

[266] Q. Shan and Y. Wen, "Research on the ber of the gsm-r communications provided by the em transient interferences in high-powered catenary system environment," in *2010 International Conference on Electromagnetics in Advanced Applications*. IEEE, 2010, pp. 757–760.

[267] Y. Cao, B. Cai, T. Tang, and J. Mu, "Reliability analysis of ctcs based on two gsm-r double layers networks structures," in *2009 WRI International Conference on Communications and Mobile Computing*, vol. 3. IEEE, 2009, pp. 242–246.

[268] R. He, B. Ai, G. Wang, K. Guan, Z. Zhong, A. F. Molisch, C. Briso-Rodriguez, and C. P. Oestges, "High-speed railway communications: From gsm-r to lte-r," *Ieee vehlcular technology magazlne*, vol. 11, no. 3, pp. 49–58, 2016.

[269] Z.-D. Zhong, B. Ai, G. Zhu, H. Wu, L. Xiong, F.-G. Wang, L. Lei, J.-W. Ding, K. Guan, and R.-S. He, *Dedicated mobile communications for high-speed railway*. Springer, 2018, vol. 22.

[270] W. Gheth, K. M. Rabie, B. Adebisi, M. Ijaz, and G. Harris, "Communication systems of high-speed railway: A survey," *Transactions on Emerging Telecommunications Technologies*, vol. 32, no. 4, p. e4189, 2021.

[271] A. Sniady and J. Soler, "An overview of gsm-r technology and its shortcomings," in

2012 12th International Conference on ITS Telecommunications. IEEE, 2012, pp. 626–629.

[272] A. D. Zayas, C. A. G. Perez, and P. M. Gomez, "Third-generation partnership project standards: For delivery of critical communications for railways," *IEEE Vehicular Technology Magazine*, vol. 9, no. 2, pp. 58–68, 2014.

[273] E. A. Ibrahim, M. Rizk, and E. F. Badran, "Study of lte-r x2 handover based on a3 event algorithm using matlab," in *2015 International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE, 2015, pp. 1155–1159.

[274] M. Cheng, X. Fang, and W. Luo, "Beamforming and positioning-assisted handover scheme for long-term evolution system in high-speed railway," *Iet Communications*, vol. 6, no. 15, pp. 2335–2340, 2012.

[275] A. D. Zayas, C. A. G. Perez, and P. M. Gomez, "Third-generation partnership project standards: For delivery of critical communications for railways," *IEEE Vehicular Technology Magazine*, vol. 9, no. 2, pp. 58–68, 2014.

[276] A. Sniady and J. Soler, "Capacity gain with an alternative lte railway communication network," in *2014 7th International Workshop on Communication Technologies for Vehicles (Nets4Cars-Fall)*. IEEE, 2014, pp. 54–58.

[277] J. Calle-Sánchez, M. Molina-García, J. I. Alonso, and A. Fernández-Durán, "Long term evolution in high speed railway environments: Feasibility and challenges," *Bell Labs Technical Journal*, vol. 18, no. 2, pp. 237–253, 2013.

[278] A. Vinel, "3gpp lte versus ieee 802.11 p/wave: Which technology is able to support cooperative vehicular safety applications?" *IEEE Wireless Communications Letters*, vol. 1, no. 2, pp. 125–128, 2012.

[279] J.-K. Choi, H. Cho, H.-S. Oh, K.-H. Kim, M.-J. Bhang, I.-S. Yu, and H.-G. Ryu, "Challenges of lte high-speed railway network to coexist with lte public safety network," in *2015 17th International Conference on Advanced Communication Technology (ICACT)*. IEEE, 2015, pp. 543–547.

[280] B. Ai, X. Cheng, T. Kürner, Z.-D. Zhong, K. Guan, R.-S. He, L. Xiong, D. W. Matolak, D. G. Michelson, and C. Briso-Rodriguez, "Challenges toward wireless communications for high-speed railway," *IEEE transactions on intelligent transportation systems*, vol. 15, no. 5, pp. 2143–2158, 2014.

[281] F. Mazzenga, R. Giuliano, A. Neri, and F. Rispoli, "Integrated public mobile radio networks/satellite for future railway communications," *IEEE Wireless Communications*, vol. 24, no. 2, pp. 90–97, 2016.

[282] S. A. A. Shah, E. Ahmed, M. Imran, and S. Zeadally, "5g for vehicular communications," *IEEE Communications Magazine*, vol. 56, no. 1, pp. 111–117, 2018.

[283] S. Hong, J. Brand, J. I. Choi, M. Jain, J. Mehlman, S. Katti, and P. Levis, "Applications of self-interference cancellation in 5g and beyond," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 114–121, 2014.

[284] I. A. Hemadeh, K. Satyanarayana, M. El-Hajjar, and L. Hanzo, "Millimeter-wave communications: Physical channel models, design considerations, antenna constructions, and link-budget," *IEEE Communications Surveys & Tutorials*, vol. 20, no. 2, pp. 870–913, 2017.

[285] M. M. Ahamed and S. Faruque, "Propagation factors affecting the performance of

5g millimeter wave radio channel," in *2016 IEEE International Conference on Electro Information Technology (EIT)*. IEEE, 2016, pp. 0728–0733.

[286] Technologies for the AUtonomous Rail Operation (TAURO). [Online]. Available: https://projects.shift2rail.org/s2r_ipx_n.aspx?p=tauro

[287] Railways eyes export of indigenous train collision avoidance system. [Online]. Available: https://timesofindia.indiatimes.com/india/railways-eyes-export-of-indigenous-train-collision-avoidance-system/articleshow/84804099.cms

[288] A European strategy on Cooperative Intelligent Transport Systems, a milestone towards cooperative, connected and automated mobility. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52016DC0766&from=EN

[289] MOving block and VIrtual coupling New Generations of RAIL signalling (MOVINGRAIL). [Online]. Available: https://movingrail.eu/

[290] MOving block and VIrtual coupling New Generations of RAIL signalling (MOVINGRAIL). [Online]. Available: https://projects.shift2rail.org/s2r_ip2_n.aspx?p=MOVINGRAIL

[291] Advanced Signalling, Automation and Communication System (IP2 and IP5) – Prototyping the future by means of capacity increase, autonomy and flexible communication (X2RAIL3). [Online]. Available: https://projects.shift2rail.org/s2r_ip2_n.aspx?p=X2RAIL-3

[292] ERRAC. Rail 2030 Research & Innovation Priorities. [Online]. Available: https://errac.org/publications/rail-2030-research-and-innovation-priorities-2/

[293] J. Hegde and B. Rokseth, "Applications of machine learning methods for engineering risk assessment – a review," *Safety Science*, vol. 122, p. 104492, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0925753519308835

[294] N. Khakzad, F. Khan, and P. Amyotte, "Dynamic safety analysis of process systems by mapping bow-tie into bayesian network," *Process Safety and Environmental Protection*, vol. 91, no. 1, pp. 46–53, 2013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957582012000067

[295] H. Parkinson and G. Bamford, "The development of an enhanced bowtie railway safety assessment tool using a big data analytics approach," in *International Conference on Railway Engineering (ICRE 2016)*, 2016.

[296] J. Zhao, L. Cui, L. Zhao, T. Qiu, and B. Chen, "Learning hazop expert system by case-based reasoning and ontology," *Computers Chemical Engineering*, vol. 33, no. 1, pp. 371–378, 2009. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0098135408002111

[297] D. Kurian, F. Sattari, L. Lefsrud, and Y. Ma, "Using machine learning and keyword analysis to analyze incidents and reduce risk in oil sands operations," *Safety Science*, vol. 130, p. 104873, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0925753520302708

[298] E. Le Merrer and G. Trédan, "Remote explainability faces the bouncer problem," *Nature Machine Intelligence*, vol. 2, no. 9, pp. 529–539, 2020. [Online]. Available: https://hal.laas.fr/hal-03048809

[299] N. Bansal, C. Agarwal, and A. Nguyen, "Sam: The sensitivity of attribution methods to

hyperparameters," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.

[300] A. Galli, S. Marrone, V. Moscato, and C. Sansone, "Reliability of explainable artificial intelligence in adversarial perturbation scenarios," in *Pattern Recognition. ICPR International Workshops and Challenges*, A. Del Bimbo, R. Cucchiara, S. Sclaroff, G. M. Farinella, T. Mei, M. Bertini, H. J. Escalante, and R. Vezzani, Eds. Cham: Springer International Publishing, 2021, pp. 243–256.

[301] Standard for XAI – eXplainable Artificial Intelligence - for Achieving Clarity and Interoperability of AI Systems Design. [Online]. Available: https://development.standards.ieee.org/myproject-web/public/view.html#pardetail/8923

[302] A. Galli, V. Moscato, G. Sperlí, and A. D. Santo, "An explainable artificial intelligence methodology for hard disk fault prediction," in *Database and Expert Systems Applications*, S. Hartmann, J. Küng, G. Kotsis, A. M. Tjoa, and I. Khalil, Eds. Cham: Springer International Publishing, 2020, pp. 403–413.

[303] S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Transactions on knowledge and data engineering*, vol. 22, no. 10, pp. 1345–1359, 2009.

[304] K. R. Weiss, T. M. Khoshgoftaar, and D. Wang, "A survey of transfer learning," *J. Big Data*, vol. 3, p. 9, 2016. [Online]. Available: https://doi.org/10.1186/s40537-016-0043-6

[305] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *J. Big Data*, vol. 6, p. 60, 2019. [Online]. Available: https://doi.org/10.1186/s40537-019-0197-0

[306] C. Shorten, T. M. Khoshgoftaar, and B. Furht, "Text data augmentation for deep learning," *J. Big Data*, vol. 8, no. 1, p. 101, 2021. [Online]. Available: https://doi.org/10.1186/s40537-021-00492-0

[307] M. J. Pappaterra, F. Flammini, V. Vittorini, and N. Bešinović, "A systematic review of artificial intelligence public datasets for railway applications," *Infrastructures*, vol. 6, no. 10, 2021. [Online]. Available: https://www.mdpi.com/2412-3811/6/10/136

[308] M. Cairns, "A future with autonomous vehicles: Issues, the potential for research topics, and a personal perspective," in *Canadian Transportation Research Forum 52nd Annual Conference-Canadian Transportation: 150 Years of Progress//Les transports au Canada: 150 ans de progrès-Winnipeg, Manitoba, May 28-31, 2017*, 2017.

[309] P. Bucsky, "Autonomous vehicles and freight traffic: Towards better efficiency of road, rail or urban logistics?" *Problemy Rozwoju Miast*, vol. 58, pp. 41–51, 2018.

[310] "Autonomous train technology market outlook," 2020. [Online]. Available: https://www.alliedmarketresearch.com/autonomous-train-technology-market

[311] P. Singh, M. A. Dulebenets, J. Pasha, E. D. S. Gonzalez, Y.-Y. Lau, and R. Kampmann, "Deployment of autonomous trains in rail transportation: Current trends and existing challenges," *IEEE Access*, vol. 9, pp. 91 427–91 461, 2021.

[312] T. Braud, J. Ivanchev, C. Deboeser, A. Knoll, D. Eckhoff, and A. Sangiovanni-Vincentelli, "Avdm: A hierarchical command-and-control system architecture for cooperative autonomous vehicles in highways scenario using microscopic simulations," *Autonomous Agents and Multi-Agent Systems*, vol. 35, no. 1, pp. 1–30, 2021.

[313] S. D. Pendleton, H. Andersen, X. Du, X. Shen, M. Meghjani, Y. H. Eng, D. Rus, and

M. H. Ang, “Perception, planning, control, and coordination for autonomous vehicles,” *Machines*, vol. 5, no. 1, p. 6, 2017.

[314] P. Fraga-Lamas, T. M. Fernández-Caramés, and L. Castedo, “Towards the internet of smart trains: A review on industrial iot-connected railways,” *Sensors*, vol. 17, no. 6, p. 1457, 2017.

[315] Z. Chen, J. Zhang, and D. Tao, “Progressive lidar adaptation for road detection,” *IEEE/CAA Journal of Automatica Sinica*, vol. 6, no. 3, pp. 693–702, 2019.

[316] H. Karunasekera, H. Wang, and H. Zhang, “Multiple object tracking with attention to appearance, structure, motion and size,” *IEEE Access*, vol. 7, pp. 104 423–104 434, 2019.

[317] D. Ristić-Durrant, M. Franke, and K. Michels, “A review of vision-based on-board obstacle detection and distance estimation in railways,” *Sensors*, vol. 21, no. 10, 2021. [Online]. Available: https://www.mdpi.com/1424-8220/21/10/3452

[318] C. Ilas, “Electronic sensing technologies for autonomous ground vehicles: A review,” in *2013 8th International Symposium on Advanced Topics in Electrical Engineering (ATEE)*. IEEE, 2013, pp. 1–6.

[319] Z. Wang, “Application research of rail transit safety protection based on laser detection,” in *Advanced Laser Manufacturing Technology*, vol. 10153. International Society for Optics and Photonics, 2016, p. 101530E.

[320] L. Caltagirone, M. Bellone, L. Svensson, and M. Wahde, “Lidar–camera fusion for road detection using fully convolutional neural networks,” *Robotics and Autonomous Systems*, vol. 111, pp. 125–131, 2019.

[321] J. R. Schoenberg, A. Nathan, and M. Campbell, “Segmentation of dense range information in complex urban scenes,” in *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2010, pp. 2033–2038.

[322] M. van Veen, D. J. Hutchinson, R. Kromer, M. Lato, and T. Edwards, “Effects of sampling interval on the frequency-magnitude relationship of rockfalls detected from terrestrial laser scanning using semi-automated methods,” *Landslides*, vol. 14, no. 5, pp. 1579–1592, 2017.

[323] F. Flammini, S. Marrone, R. Nardone, M. Caporuscio, and M. D’Angelo, “Safety integrity through self-adaptation for multi-sensor event detection: Methodology and case-study,” *Future Generation Computer Systems*, vol. 112, pp. 965–981, 2020.

[324] S. Arshad, M. Sualeh, D. Kim, D. V. Nam, and G.-W. Kim, “Clothoid: an integrated hierarchical framework for autonomous driving in a dynamic urban environment,” *Sensors*, vol. 20, no. 18, p. 5053, 2020.

[325] Shift2Rail. [Online]. Available: https://shift2rail.org/

[326] E. Quaglietta, M. Wang, and R. M. Goverde, “A multi-state train-following model for the analysis of virtual coupling railway operations,” *Journal of Rail Transport Planning & Management*, vol. 15, p. 100195, 2020.

[327] F. Flammini, S. Marrone, R. Nardone, A. Petrillo, S. Santini, and V. Vittorini, “Towards railway virtual coupling,” in *2018 IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC)*. IEEE, 2018, pp. 1–6.

[328] C. Di Meo, M. Di Vaio, F. Flammini, R. Nardone, S. Santini, and V. Vittorini, “Ertms/etcs

virtual coupling: Proof of concept and numerical analysis," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 6, pp. 2545–2556, 2019.