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Intelligent Environment Enabling Autonomous Driving

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ABSTRACT Automated driving is expected to enormously evolve the transportation industry and ecosystems. Advancement in communications and sensor technologies have further accelerated the realization process of the autonomous driving goals. There are a number of autonomous driving initiatives around the world with varying objectives and scope, e.g. vehicle perception in a controlled environment or highway settings. Autonomous driving in a more complex environment with mixed traffic poses major challenges. The solutions for such environments is the focus of this paper. We start with a quick overview of current autonomous driving development activities worldwide. We then discuss the solution concept for autonomous driving in urban environments and its enabling components, e.g. road digitization and flexible communication infrastructure, to realize an urban autonomous driving testbed. We highlight the major challenges hindering the realization use-cases of Level 5 autonomous driving. Solution sketches to address these or similar changes are briefly discussed. We also implement some elements of the solution approaches on the real test-road. We demonstrate an artificial intelligence based approach for the analysis of real traffic data measured on the testbed. We implement approaches for predicting the network resource demands and allocation, which are crucial for realizing the use-cases of autonomous driving in complex environments. For the experiments, real data from the test-road is used. Results show that traffic patterns and resource demands are predicted accurately. These experiments are expected to instrumental for realizing other use-cases of autonomous driving.

INDEX TERMS Autonomous systems, intelligent vehicles, network function virtualization.

I. INTRODUCTION

The advancement of sensor and communication technologies has accelerated the pace of realizing autonomous driving (AD). Although autonomous driving has gained more attention in the recent past, the concept was implemented decades back and the farther past has witnessed a number of activities in this regard. Autonomous Vehicles (AV) date back to 70s, when the first autonomous car was presented by Tsugawa at Japan's Tsukuba mechanical engineering laboratory [1], which was then followed by various other activities around the world. Ernst Dickmann's vision guided Mercedes Benz in 1980 could reach 39mph in a controlled environment [2]. The two Daimler-Benz vehicles VaMP and Vita-2 drove for over 620 miles in Paris in 1994. The DARPA urban challenge in 2007 focused on a 60 mile urban environment [3]. High-Tech companies like Google have also become active in the domain by initiating their autonomous driving activities. The journey of building AVs has made its way through the initial levels of automation and we will soon be witnessing Level 4 autonomous vehicles on public roads. Automobile makers have already produced vehicles with features of level 3 automation, though some of the automobile makers have recently withdrawn from the race e.g. Audi's A8 Sedan [4].

The Society of Automotive Engineers (SAE [5]) provides a clear understanding of the SAE international J3016 standard describing the role of driver, system, and level of vehicle automation. For each level, the Dynamic Driving Task (DDT) procedure and fallback policy are defined. DDT is described: as the real-time loopback procedure required to maintain the operational and tactical functions intact while driving a vehicle. DDT fallback defines the course of action taken to

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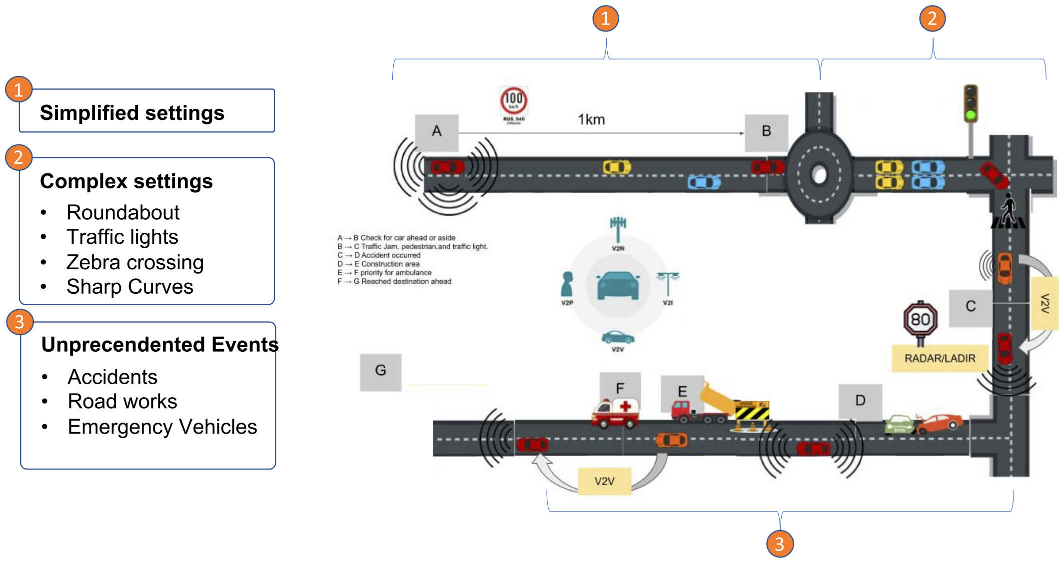


FIGURE 1. Figure capturing the complex environmental dynamics for autonomous driving.

achieve required DDT performance or achieve minimal risk condition (MRC), in case of any vehicle failure, or Automated Driving System (ADS) failure or approaching exit from Operational Design Domain (ODD). ODD is the operating condition in which the system is intended; to perform the automation. At levels 1, 2, and 3 the DDT fallback is performed by the driver, and at Level 4 and Level 5, the procedure is performed by the system, conditions applied. In Level 4 automation, the automated driving system is responsible for any lateral or longitudinal vehicle motion, the ADS is responsible for sensing, monitoring, and responding to events. ADS is responsible for achieving the MRC in the response of any vehicle failure, ADS failure, or approaching an ODD exit. However, ADS may request the passengers to intervene and perform the DDT but would not reply if the passenger does not reply. In the case of Level 5 automation, the scope of ODD is unlimited. Meaning thereby, in any condition, the ADS is responsible for DDT performance and undertakes the DDT fallout procedure if required.

The race towards achieving the goals of fully autonomous vehicles (i.e., Level 5) is continuing and the stakeholders, including car makers and technology leaders, are consistently evolving their solutions to achieve the required level of automation for their vehicles. A further step towards the autonomous driving reality was achieved with the establishment of testing facilities and demonstrators around the world. These testing environments are of vital importance for evaluating the capabilities of the autonomous vehicles under different environmental dynamics. One of the major objectives of testing facilities is to create a realistic environment that best represents the real environment autonomous vehicles are going to operate in.

Dynamic traffic situations on public roads require coordination between the AV, conventional vehicles and road infrastructure. This is still a great challenge for autonomous driving as evident from recent incidents involving AVs on public roads. Cooperative driving relying purely on sensors is prone to sensor errors, processing delays, and line-of-sight restrictions [6].

The idea of autonomous driving rests on the capabilities of vehicles to understand their environment and to react to the dynamic events of the environment, which we term as the vehicle's perception or situational awareness. With the information and sensory data from on-vehicle sensors, the vehicles are able to create a perception of their environment. Vehicles' perception together with the capability of interacting with other vehicles does allow some level of automation but relies on the vehicle's visibility. It is unclear as to how capable the AV can cope with different situations and environments. Autonomous driving does pledge an increase in road safety. The fact that a vehicle's sensors are a limiting factor on the quality and extent of the vehicles perception is however detrimental to that pledge of increased safety.

The challenging question is: Will autonomous vehicles be able to cope with unprecedented and complex situations? Roads with unregulated traffic, temporary or dynamic obstacles, vulnerable road users, sharp turns, etc., Figure 1 capture these dynamics, by defining different road segments e.g., segment 1 is with simplified setting i.e., a straight road with clear road marking. Autonomous vehicles operate on knowledge from past experiences, either built-in by engineers or trained using machine learning. However, not all variables and situations for decision-making are known in advance. Relying on the information from on-vehicle sensors alone or implementing pre-trained reactions to events may not suffice to achieve the goals of level 5 autonomous driving [5].

To improve the situational awareness and environment understanding of vehicles in complex urban environments, an improved version of Cooperative, Connected and Automated Mobility (CCAM) is provisioned, which is expected to push the automated driving to the next level of vehicle automation (i.e., SAE Level 4 and Level 5). This asks for the upgrade of existing street furniture and key assets e.g., network infrastructure, roadside and cloud infrastructure and vehicles to realise improved performance of autonomous driving in complex urban environment.

These requirements drive a project of Germany (author was the technical lead of the project) [7] to follow the philosophy of *"Intelligent vehicle is good but intelligent environment is better"*. The project focused on providing an end-to-end solution with a distributed and autonomous decision-making framework that is envisioned as a promising step towards achieving human-like perception within the vehicle and ensures road safety with fully autonomous vehicles.

In this work, we discuss the necessary ingredients and solutions that help achieve the objectives of higher automation levels. We provide details of road infrastructure and communication infrastructure for cooperative, connected and automated mobility (CCAM) use cases and demonstrate their implementations. The paper is structured as follows: In Section II, we present efforts around the world to create testing facilities for autonomous driving. Section III details how a testing facility for autonomous driving in an urban environment is realized. Sections IV and V present this testing facility's distributed architecture of the compute and storage infrastructure and the communication infrastructure respectively. Section VI highlights major challenges hindering the realization of fully autonomous driving. Some examples of implemented use cases are presented in Section VII. Potential solution sketches are discussed in Section VIII. This article also focuses on realizing the flexible communication infrastructure employing 5G enabling technologies and end-to-end autonomous management enabled by artificial intelligence (AI) i.e., demand attentive infrastructure adaptation based on learned traffic patterns. We demonstrate the fundamental step, which is the analysis of real traffic data collected by various traffic sensors in the urban autonomous driving testbed. Knowing future traffic demands provides valuable inputs for efficient, low delay management of various autonomous driving infrastructure operations, e.g. communication, MEC, or vertical services, this is discussed in section IX-A. Section X concludes the paper.

II. RELATED PROJECTS AND ENABLING TECHNOLOGIES

Realistic testing tracks are crucial to probing the capabilities of autonomous vehicles. Various autonomous driving labs aim at providing realistic traffic situations for training intelligent vehicles, e.g. obstacles detection, self-braking and steering, and collision avoidance. *Mcity* [8] is a testing facility at the North Campus of Michigan University in Ann Arbor, which aims at evaluating the potential of automated and connected vehicles by simulating the urban environment. The simulation includes urban roads, roundabouts, crossings, buildings, sidewalks, obstacles, and footpaths. AV functionalities for different use cases are evaluated by simulating scenario specific environments. Similarly, there are initiatives with closed and controlled testing facilities to evaluate the performance of AV solutions. Shanghai International Automobile City in China, K-City autonomous driving facility in Korea [9], or Gunma University's Aramaki campus in Japan [10] are some of the examples for controlled test facilities that are developed through public private partnerships. Automobile makers have also been involved in creating such testing facilities, e.g. Toyota Research Institute's oval track in the USA. Readers are also encouraged to refer to the following list of autonomous driving testing facilities around the world: e.g., C-ITS test corridor [11], [12], Colorado testroad [13], Columbus connected corridor [14], Forth Road Bridge Corridor in Edinburgh [15], [16] featuring full sized autonomous buses operating at AV Level 4 autonomy, DTU Lyngby Campus corridor [17], On-demand self-driving car service to Frisco, Texas [18], and iMove, Autonomous parking service for VW, Audi, and Porsche vehicles at Hamburg Airport [19]. There are large number of test-roads focusing on investigating different aspects of autonomous driving. Readers are encouraged to refer to [20] for an updated list of the test-roads around the globe and their scope.

Most of the facilities are in controlled or closed environment, which do provide more realistic environmental dynamics but pose the challenge to properly replicate the dynamics of public roads in the controlled testing facility. It goes without saying that no matter how detailed the environmental dynamics are modeled for validating AV solutions in simulation or controlled environments, the real environment (urban/rural) presents with unprecedented dynamics that cannot easily be captured. This strengthens the need for open and urban test facilities.

Consequently, recent clarifications of legal frameworks for autonomous vehicles testing and operation have paved the way for testing facilities to be extended or built on public highways and even in urban areas, especially in the US, Sweden, Germany, and China. These real environments allow probing AVs in a wider breadth of autonomous operations, for example cooperative driving and mixed traffic. End-to-end intelligent transport services, e.g. parking management, route planning, traffic control, infotainment can also be developed and tested there. For this purpose, public roads are upgraded with sensor and communication infrastructures supporting AVs. Germany's "Digital Motorway Testbed" on A9 autobahn [21] is the first public road that allows testing AVs, which recognizes the importance of the environment perception. The digitization of the A9 segments includes, among others, communication infrastructure allowing V2X communication and the use of 700 Mhz bands for V2V communication. Additional public testbeds are being deployed in several German cities, e.g. Karlsruhe, Düsseldorf, Berlin. In the city of Karlsruhe, the test site include different road types, from reduced-speed areas and parking lots up to interstate and highway roads. Urban test beds worldwide also aim at providing complex public environments for testing innovations of autonomous driving, e.g. London (UK), Brainport (NL), Tampere (FI), Vigo (SP), or Daejeon (KR). In the mentioned public test beds, communication infrastructure is identified as an important enabler for autonomous driving, which explains the participation of network operators and providers of vertical services in corridor use-cases i.e., A2-M2 corridor [22] in the UK connecting London urban and link roads in Kent or 5G network coverage for the Thessaloniki - Sofia - Belgrade corridor, which will allow tests to be conducted with AVs over hundreds of kilometers of motorways.

Achieving the evolved CCAM for higher levels of autonomous driving is expected to be heavily complemented by the communication infrastructure that meets the service requirements (e.g., bandwidth, delay, supported speed for handover management, connection density, etc.) of communication amongst CCAM infrastructure, autonomous vehicles, and backends of the automobile makers. Recognizing the importance of communication infrastructure for cooperative driving, recent development of future communication network technologies aims at identifying the requirements, the architecture and the approaches with focus on autonomous driving applications. Standardization groups like the Next Generation Mobile Networks Alliance (NGMN) V2X task force, 5G Automotive Association (5GAA), and TD-LTE, are cooperating with the automotive industry to promote LTE and New Radio (NR) based V2X solutions known as cellular V2X (C-V2X) technology. Multi-Access edge computing (MEC) extends cloud computing capabilities closer to devices and services to the network edge and is standardized by ETSI MEC group [23]. It is increasingly recognized as an important enabler for future mobile networks to support autonomous driving. MEC infrastructure has been designed to realize vehicle to everything (V2X) communication in various autonomous driving test beds, forexample in C-V2X (China), CAV (UK), or Concorda (NL). An extensive review of MEC architectures is provided in [24].

Beside the various digitization and communication technologies for enabling constant data flows, a cooperative and distributed decision making framework also plays a crucial role in enabling a stable autonomous driving system. In [25], the benefit of cloud-based, central vehicles control making use of collective sensing data from multiple vehicles is realized. The authors demonstrate flexible coordination of data processing between data center and MEC infrastructure to eliminate the former's delay constraint and the latter's resource constraint in order to realize stability of AV fleets. The authors of [26] propose an integrated urban traffic management architecture with 5G and MEC. The work demonstrates the benefit of an efficient communication system in supporting vehicle localization, data pre-fetching, traffic light control, and traffic prediction during an accident rescue operation in urban settings.

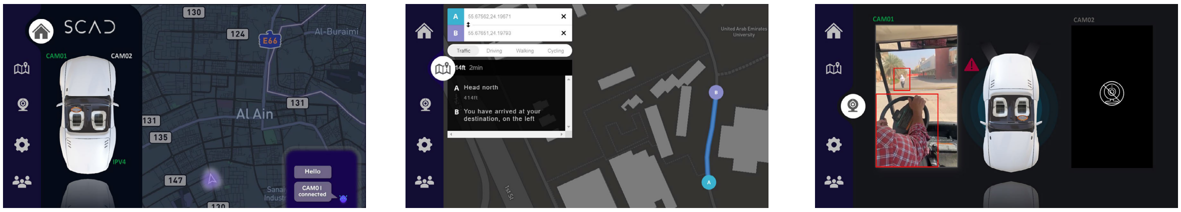
III. THE INGREDIENTS FOR AUTONOMOUS DRIVING IN URBAN AND OPEN ENVIRONMENT

The challenges of urban and open environments are a lot different than those of controlled, rural, and highway environments. This work is in parts inspired by the Diginetps and Smart City Berlin projects, an autonomous driving test-road and digitized roundabout in Berlin. To understand the challenges, let us have a brief overview of the ground truths of urban test-road for autonomous driving at the center of Berlin, Germany. There are two roundabouts with 5 ins and 5 outs, the road itself has three lanes in each direction. Co-existence of an autonomous vehicle with conventional vehicles in these complex roundabouts require efficient control and extensive knowledge of the roundabouts and their vicinity. We believe that relying on vehicle research alone will not suffice to reach the goals of Level 5 autonomous driving, which is why we suggest a three-level solution architecture i.e., vehicle level, roadside level, and central data-center level. The proposed big picture is depicted in Figure 3. At each level, the sensory data is collected by the IoT middleware that further makes the data available to a smart decision engine that encamps various AI mechanisms for different decision making instances. The middleware APIs are exposed for developer of different applications including traffic, parking, impact of traffic intensity on environment, traffic data flow management, security, filtering, and others. Let us now discuss the three levels and their operations, which we depict in Figure 3.

A. INTELLIGENCE AT THE VEHICLE LEVEL

The Level 5 autonomous vehicles are required to have the competencies of a human driver, specifically the ability to make safe and rule-conforming decisions based on their environment perception. An autonomous vehicle builds its perception of the environment based on the sensory data it captures through on-board sensors. It corresponds to the capability of the vehicle to know its environment including obstacles, road markings, traffic lights, other vehicles, pedestrians, cyclists, or objects. The autonomous vehicle is a combination of sensors, actuators, sophisticated algorithms, and powerful processors to execute software. There are hundreds of such sensors and actuators in an AV, which are situated in various parts of the vehicle. All these sensors feed into what we know as Local Dynamic Map (LDM), which holds all the vehicles knowledge. The LDM plays a key role when it comes to the decision making at the vehicle level. In Figure 4, we depict the well known four hierarchical layer structure of the LDM [27], ranging from very static environmental information to transient static to transient dynamic to very dynamic information.

The standardized four layered architecture of LDM may not cope with the requirements of Level 5 autonomous driving i.e., capturing the real-time and external information (e.g., perception created through on-road deployed sensors, information from backends of automobile makers, city authorities, prediction of environmental variables from edge, etc.). Hence, evolution of the classical LDM is imperative.



(a) Screenshot developed GUI (b) Experiment of Navigation (c) Drive test in University Campus

FIGURE 2. Different options/views of the developed AV GUI.

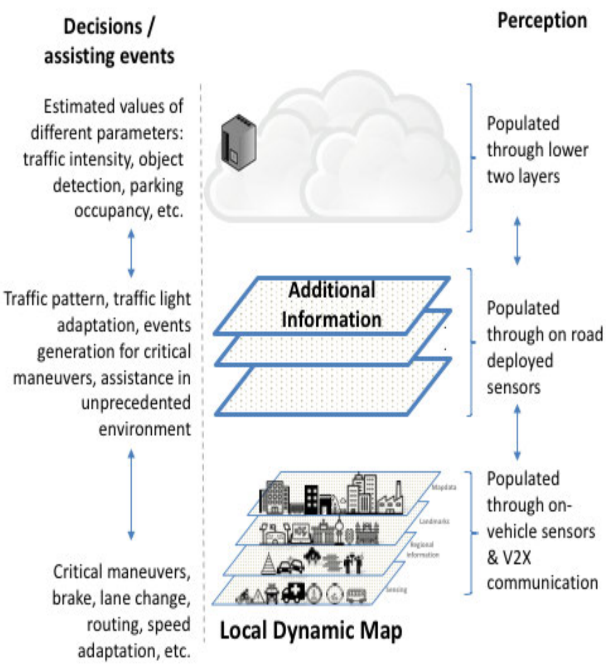


FIGURE 3. 3-layer architecture of perception creation and decision making.

FIGURE 4. The traditional LDM layers of information.

We propose the extension of the LDM by introducing additional information layers that are fed with information from external sources and other stakeholders. A version of the evoled LDM is developed by the author and his research group. The evolved LDM is capable of capturing and translating the external information. We have also designed and developed coalitional learning approaches for improving the perception and by training the machine learning models with the local data of on-vehicles and on-road deployed sensors (Similar to federated learning approaches). We were able create a predicted environment layer in the evolved LDM that assists in decision instances like trajectory planning, lane change, or speed adaption. We skip the details of implemented algorithms, as they are out of the scope of this paper and will be published in a separate article. However, readers are encouraged to refer to our earlier publications using similar approaches [28], [29]. In Figure 2, we show the screenshots of the GUI while carrying out some experiments to study the performance of extended perception i.e., through fusing the data from external sources (e.g., from the on-road deployed sensors).

B. INTELLIGENCE AT THE ROADSIDE LEVEL

With the view to extending the vision of autonomous vehicles, the environment is digitized and the distant information is made available to the vehicles. The purpose of digitizing the environment is to enable the environment to communicate with the autonomous vehicles and other relevant stakeholders (e.g., city authorities, communication service providers, etc.). Digitization helps to describe the dynamic features of roads, e.g. i) road condition sensors notify the vehicles if the road segment is icy or muddy, ii) car parking sensors update the autonomous vehicles of available parking spaces in the vicinity, iii) traffic analysis sensors keep updating the autonomous vehicles on the traffic situation in different road segments that are even miles away, iv) environment sensors assist the autonomous vehicles to reduce their impact on emissions and other environmental variables. In Table 1, we provide the high level technical description and the technologies of the required sensors. The last column of table lists the parameters measured by sensors.

Roadside level is the intermediate level in the architecture. It corresponds to an enhanced roadside unit (eRSU), which hosts computer hardware and communication interfaces. It does not only allow Vehicle to Infrastructure/Vehicle (V2X) communication but also provides a platform to host local services. It allows the connectivity to the near edge of the mobile operator. This level creates upstream link to connect with central data centre and creates downstream link to connect with on-road deployed sensors and vehicles. The eRSU on the downstream connects with various on-road deployed sensors over Wi-Fi and to vehicles over DSRC (802.11p) links. Being capable of collecting the data from environment (via on-road deployed sensors) and from vehicles, we implement approaches for sensory data fusion and

TABLE 1. Types and description of sensors.

Sensor Type	Description	Parameters measured
Car Parking	These sensors help drivers to find a parking space according to their preferences. It also identifies parking violations, expired tickets, or wrong parking. One sensor can cover up to 300 spaces and has a range of up to 400m. For enhanced privacy, raw video streams are not forwarded upstream, rather video is processed on-board.	Total parking spots, occupied spots, free sports
Traffic Analysis	These sensors capture traffic density in different segments of the roads and can cover up to four lanes per camera. The frequency of data capture may be adjusted as per need, e.g. per minute, hour, day, week and month. The evaluation can be viewed by the user through a display on the camera image, delivered as export in a CSV file or as regular reports via email through a reporting engine.	Automatic counting of vehicles with classification into two-wheel, passenger car and bus/truck
Activity Analysis	These sensors identify the activity at a specific geographical location. The evaluation of sensory data provides information about motion traces as well as the most popular dwelling spots. The information collected from these sensors may also help in proactive decision-making, i.e., knowing the pattern of activities (pedestrian walking, cyclists, etc.), different decisions may be proactively made for autonomous driving, e.g. LDM trajectory planning, or traffic light control scheduling.	Visualization of motion and dwelling time, objective measurement of hot spots, compilation of statistical evaluations with adjustable duration and intervals of evaluation.
Environmental	These sensors help analyze the impact of autonomous driving on the environment. The sensory data fused together with weather and traffic analysis sensors enable us to study the relationships between different parameters	NO2, NO, O3, particulate matter (PM1, PM2.5, PM10), Air quality index
Road condition	These are non-invasive road condition sensors and are mounted several meters above the surface at bridges or masts (e.g. street lamps). The sensors make use of optical principle and pyrometers as measurement technologies.	Road surface temperature, water film height, road status (dry, damp, wet, ice, snow, chemically wet), snow height
Traffic Light	Integration of components (based on dedicated short range communication standard) for communication in the already deployed traffic lights on the test road, which enables us to communicate with the traffic control system.	Status of lights (red, yellow, green)

filtering to create patterns for different use cases. For this purpose, we deploy an IoT middleware, an optimization and machine learning toolbox, and a decision toolbox in the eRSU (cf. Figure 3). The eRSU creates a map based on the information collected from connected road sensors and vehicles. We term the knowledge gained based on external environment information *Perception at Edge* (PAE). It is shared with the vehicles for more informed decision making. For ready reference the components of the proposed architecture at this layer is pictorially shown in Figure 5.

C. INTELLIGENCE AT THE DATA-CENTER LEVEL

This level has the global view, as it communicates with all the eRSUs and the vehicles. It hosts the backend of all the on-road deployed sensors, the communication network core, the network operation controllers, the service orchestrator, computation infrastructure and the optimization and machine learning toolboxes. The real-time and delay sensitive decisions taken by the vehicle and edge levels. However, at the central data-center level, the patterns are created based on the sensory data collected from vehicles and all on-road sensors. This global knowledge is contained in the Global Information Module (GIM), which is shared with the lower level decision making entities for a coordinated and consistent operation of the overall infrastructure. In section IX-A, we demonstrate the extraction of traffic demand patterns from sensor data and prediction of future demand with machine learning approach. The predicted results allow different network and service orchestrators to make informed decisions for the managed infrastructures. For example, a proactive mobility management approach based on user's mobility patterns was proposed in our previous work [30]. We rely on our previous

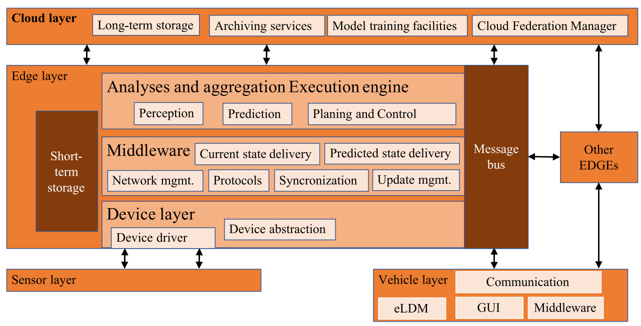


FIGURE 5. An overview of the edge architecture.

(e.g., [28], [31]) for modeling the decision mechanisms in different scenarios.

In the next sections, we further provide the detailed specifications of the infrastructure that support the operation and shared perception among the three intelligent layers discussed in this section.

IV. MULTI-ACCESS EDGE AND CLOUD INFRASTRUCTURE

The autonomous driving infrastructure plays an important role in enabling CCAM operations, e.g., by enabling extended perception. A detailed architecture of the system components and connectivity of such infrastructure is depicted in Figure 6. In this section, we provide a detailed specification of the road infrastructure including the application protocols and message, and essential software and hardware components.

A. V2X INTERFACES SPECIFICATION

For different use case scenarios, the AVs rely on V2I and V2V communication to exchange perception and

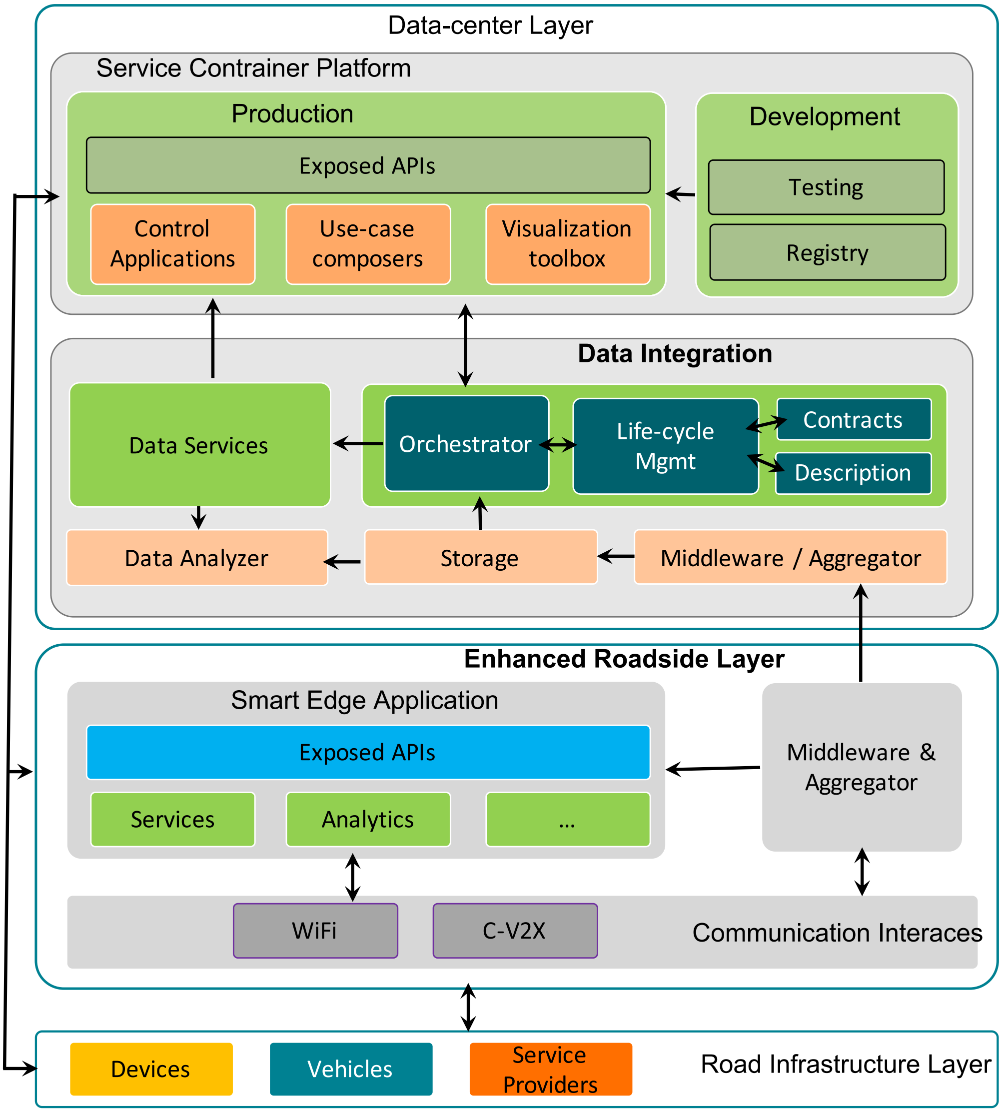


FIGURE 6. **End-to-end infrastructure components and interfaces for CCAM application.**

control information. The LDM component in the AV constantly updates its environment perception and shares this information with the PAE instances hosted on the eRSUs using available Wi-Fi, C-V2X (PC5 sidelink) interfaces. This allows additional information for the PAE and GIM to construct a virtual map of a broader area. The global map is also shared with all vehicles in the area through PAE applications. Based on the environment perceptions, the AVs coordinate their driving decision through V2V interfaces. The vehicle interfaces are specified as follows:

- V2V: Interfaces include both short-range low delay communication for autonomous driving operations and high bandwidth communication for CCAM application and vehicle perception. The short-range interface is based on DSRC (802.11p) wireless technology. On DSRC interface, cooperative driving and traffic control application protocols and messages are implemented, e.g. Decentralised Environmental Notification Messages (DENM), Cooperative Awareness Messages (CAM) or Basic Safety Message (BSM). Other roadside infrastructure related messages are also transmitted over the DSRC interface: Signal Phase and Timing Message (SPAT), In Vehicle Information Message (IVI), and Service Request Message (SRM).
- V2I: Communication for CCAM applications relies on high bandwidth technologies with less stringent delay requirements in contrast to the short-range communication technology. These interfaces are based on C-V2X (LTE-V2X, 5G-V2X) and Wi-Fi technologies for the transfer of media data, messages of the ITS V2X reference architecture protocols [32], or other IP-based protocols.

B. E-RSU INTERFACES SPECIFICATION

CCAM infrastructure operations involve the real-time update of the GIM and PAE maps, their interactions with other ITS and road management applications, and the management of network and edge computing resources for those applications. CCAM applications have a global instance deployed in data center while location specific instances deployed on-demand on eRSUs. PAE instances on eRSUs are constantly fed with data from nearby road sensors through Wi-Fi and wired interfaces. They synchronize the analyzed sensor information with the global instance using application specific protocols through cellular and wired interfaces. The RSU interfaces are specified as follows:

- eRSU-2-eRSU: communication is based on high bandwidth and low latency direct Wi-Fi connection. These links serve as reliable transport and back-haul network for road side infrastructure. The interfaces between eRSUs is used by the Software Defined Network (SDN) data and control plane, which provides a virtualized network for the distributed MEC platform hosted on the eRSUs.
- eRSU-2-MEC/Cloud: communication is provided by 4G/5G. The use of Mobile Network Operator's MEC infrastructure in the core network (CN) for CCAM applications enables their low delay communication from eRSU. Autonomous vehicles with broadband access can make use of this interface to access services hosted in the road infrastructure.

C. E-RSU AND MEC SPECIFICATION

Based on the eRSU interface specification above, the eRSUs include network interfaces and computing capability. For the access network, the roadside unit provides DSRC and Wi-Fi interfaces. The transport network has two interfaces: Cellular network and a redundant P2P wireless link. In some cases, neighbouring eRSUs are connected through another P2P wireless link. To provide edge computing resources, a machine may be connected to the router in the roadside unit. Depending on the deployment, roadside sensors are connected through either wired or wireless connections. Given that the transport network is created by wireless links, only a 230V power supply is required to provide power to the devices (230V, Power-over-Ethernet (PoE), PoE+).

Given the high mobility nature of autonomous vehicle applications, the mobile broadband network has been the baseline infrastructure for the design of their MEC enabled architecture. The ETSI MEC reference architecture [23] components are required to be flexibly placed in cellular infrastructure. eRSUs coverage extend the mobile network with small cell (SC) segments, which plays a significant role in future autonomous driving scenarios. The Mobile Edge Host (MEH) in the MEC architecture corresponds to the eRSU component that provides computing, storage, and network capacity for edge applications. Depending on how close the applications are required to be placed towards UEs and AVs, they must be dynamically deployed on MEH available in different mobile network segments.

Intuitively, SC segment will produce and consume most application data. It goes without saying that applications for autonomous driving are mainly data sensitive e.g., applications for generating collision warnings, applications for identifying the vulnerable road users, etc. The data locally generated by AV sensors and roadside components are combined with downstream data from cloud services to provide AV agents context for autonomous decision-making. With their inherent computing capacity, AVs can be seen as moving MEHs. This raises the challenges for the management of mobile edge platforms (MEP) and the orchestration of edge applications. Due to the wider coverage of Radio Access Network (RAN) components (eNB/gNB), mobile edge applications (MEA) are expected to aggregate situational data from AVs and road sensors and provide AVs with a broader context for more strategical decision-making. Samples of such applications are traffic information and route planning services. Where eNBs provide wireless backhaul to the eRSUs, additional network management functions, e.g. mobility management or resource management, could employ the associated MEHs to increase network control efficiency by timely reconfiguration of network components. Towards CN and service segment, critical MEAs are increasingly concerned with the management and orchestration of mobile network provisioning, and MEC infrastructure in lower network segment. Disappearing network and computing constraints of centralized computing infrastructures allows CN and service applications to be deployed in in data center or on a dedicated server. Nevertheless, they may take advantage of management and orchestration functions for MEP i.e., sharing of user context, dynamic migration, load balancing, or high availability. The application services must be designed and implemented with the support for cloud-based provisioning paradigms, e.g. XaaS, container, and micro-service-based architectures.

In proportion with the high degree of distribution of MEHs, management and orchestration (MANO) of both MEPs and application services has to deal with increasingly complex network operations, service provisioning and compositions. While distributed MANO functions themselves can be deployed on MEHs closer to the network segments to be managed, centralized MANO in system layer is an inevitable part of the architecture. With the global view and aggregated intelligence, it deals with the business objectives of multiple stakeholders i.e., service providers, operators, and users. These objectives are translated to lower level operational objectives and configurations to be carried out by the respective network, VIM and MEP control elements. As a result, the control interfaces (reference points) between MANO elements constitutes a MEC control plane, which utilizes non-negligible mobile network data plane resources. The delay and reserved bandwidth for the MEC control plane must be guaranteed to provide consistence and stable operation of the MEC platform depending on the selected application and virtualization technologies.

D. DATA-CENTER INFRASTRUCTURE INTERFACES SPECIFICATION

Beside the centralized CCAM service instances, the cloud infrastructure also hosts network management and orchestration (MANO) applications. The network slice management and orchestration service deployed in the central cloud platform may coordinate difference network functions deployed on eRSUs and AVs. Mobility and application aware network management protocols are developed to meet e2e QoS requirements of CCAM applications. The cloud interfaces are specified as follows:

- eRSU (MEC)-2-Cloud: To meet the high availability and QoS requirements of CCAM scenarios, MEC infrastructure with central and distributed mobile edge hosts is the main platform for microservice based CCAM applications. Mobile edge CCAM services are developed as web services and composed by REST based protocols.
- Multi-Cloud: Platforms with large computing and network capacities host various backend components of CCAM services, e.g. data analytics, data fusion processes, data bases, or service implementations. Depending on application scenario and service providers, CCAM services can be deployed on cloud, near edge, and far edge platforms. This raises the challenges for service composition and interactions. The solutions for such a highly flexible deployment is based on network virtualization technologies, e.g. SD-WAN, tunnelling, and hybrid cloud management and orchestration.

E. CLOUD INFRASTRUCTURE SPECIFICATION

The cloud infrastructure consists of a data center and a far edge. The cloud infrastructure provides different QoS for CCAM services allowing them to be flexibly deployed to meet the use cases' requirements. It is connected to the Internet and external network through the data center network. Additionally, a SDN based transport network allows a direct high bandwidth and low latency connectivity between the data centre and other (eRSU) infrastructure in the test-road. The far edge infrastructure provides universal access to deployed CCAM services through mobile broad band network. In contrast to the access to public cloud infrastructure through the Internet, the direct connection between the far edge infrastructure and cellular CN allows very low delay connectivity to the deployed services.

Depending on the QoS requirements, autonomous driving and network infrastructure management services may be deployed on far edge or data centre. These services provide the solution approaches at the data-centre level to support autonomous driving use cases:

- Autonomous Driving Services at the Global Level: Coordinate the distributed CCAM service instances and provide global context for autonomous driving application (i.e., GIM). Examples for such services are the control center, data collection and storage, data analytics, machine learning components, etc.
- IoT middleware, data fusion, analytics, etc.
- Autonomous Network and Service Management Framework: it is based on a meta-machine learning approach that enables the autonomic management of network entities and dynamically orchestrates the services in different segments of the network.
- Software Defined Network (SDN) enabled core and transport network: is designed and developed as customized virtualized lite-core network (L-EPC) that implements specialized network functions.

V. FLEXIBLE COMMUNICATION INFRASTRUCTURE

The communication infrastructure enables vehicle to vehicle (V2V), vehicle to sensors, vehicle to data-center, and sensors to data-center communication. Figure 7 presents an overview of the communication infrastructure of the testbed. In this section, the two constituting parts of the communication network are described: roadside access and transport network, and mobile broadband network.

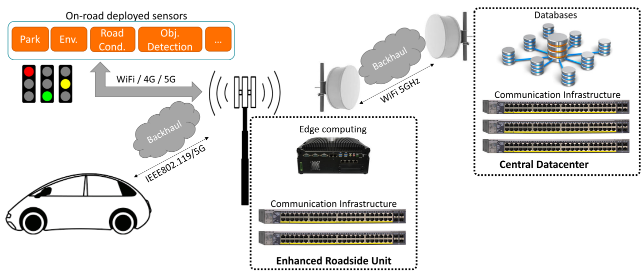


FIGURE 7. An overview of communication infrastructure architecture.

A. SOFTWARE DEFINED ACCESS AND TRANSPORT NETWORK

Figure 8 depicts the solution approaches at the roadside level, which includes the software defined eRSU access and transport network connecting them. Each eRSU has an SDN switch with multiple radio interfaces, e.g., Wi-Fi, DSRC, etc. A logically centralized controller is able to control the data flows in the access network. The centralized control plane is implemented as multiple controllers, which coordinate the control of multiple access network segments.

To enable SDN control of wireless interfaces, multiple extensions and customization are made to the OpenFlow protocol implementation and wireless network stack. A virtual interface managed by Open vSwitch is created for each wireless interface. The wireless stack converts wireless network events and measurements to Open vSwitch data and update the flow tables for the managed interfaces, as shown in the left of Figure 8. To overcome the lack of features and restrictions current OpenFlow version (v1.5), various extension are proposed and implemented as customized SDN switch for the eRSU. This includes new OpenFlow header,

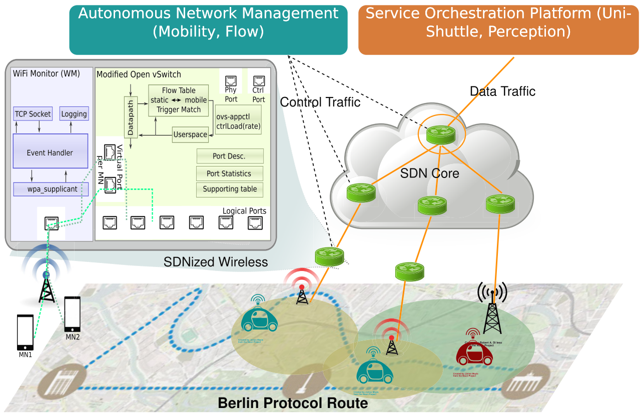


FIGURE 8. SDNized wireless network.

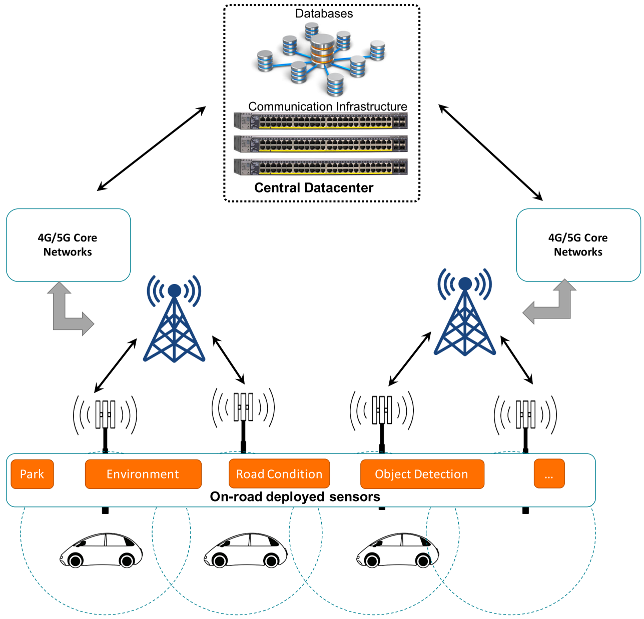


FIGURE 9. Flexible communication infrastructure for CCAM application.

instructions, and actions. Further extensions are made to Open vSwitch data path (kernel forwarding path) by applying protocol oblivious forwarding (POF [33]) paradigm. Packet processing rules are implemented as eBPF programs and installed to the SDN switches using OpenFlow protocol by the central controller. The controller implements an autonomous network and service management framework. It incorporates meta-machine learning approaches on global network information that enables the autonomic management network entities and dynamically orchestrates the services in different segments of the network. As a result, proactive flow control rules are calculated to dynamically adapt the network to application requirements and network states. The proactive rules allows the low delay processing of packet in data plane, increase control plane efficiency, and support novel delegated mobility management. More details of the mentioned techniques are provided in [30], [34]–[36].

B. BEYOND 5G NETWORK TECHNOLOGIES FOR CCAM

While the SDNized eRSU network can efficiently manage the flows of large amount of data generated by the roadside sensor and processed by roadside MEC infrastructure, the mobile broadband access provides a reliable coverage for the communication with the global CCAM services in central data-center platform. The lite-EPC core is an in-house developed LTE core with focus on mobility management, session continuity to support high mobility operation of AVs. The testbed may also provide emulate the multi-operator and mobility management scenarios, which allow the investigation of handover delays and service switchover delays when the communication bit-pipes are provided by different providers. Additional interfaces may be implemented to allow the interactions with other LTE/5G CN and the end-to-end services and network orchestration platforms as shown in Figure 9. The two core networks may implement all the autonomous network management services, for this we rely on author's earlier publications. We next provide details of the core network features specific to the AD operations of connected infrastructure and vehicles.

1) AD SERVICE HANDOVER

To ensure the seamless mobility of the vehicles and availability of the AD services throughout the road segments, mechanisms should be in place not only on the intra-operator (i.e., support for both horizontal and vertical handovers) but also at the inter-operator levels. This asks for agreement on the inter-core interactions and accordingly the development of fitting interfaces/protocols. The situation gets more complex when the AD services are provided by the third parties and where the authorities are actively involved. One potential direction to address this or similar issues is dynamic network slicing. This is to say that an operator may compose a service specific network slice, which the technologies of the target operator may replicate by implementing proactive mobility management and dynamic Service Level Agreement (SLAs) approaches. In this connection, core network's APIs may be exposed to the other operator and stakeholders. Amongst others, this will also allow flexible routing of user data plane and accessing user context for 3rd party MEC infrastructure. We implement an architecture for the interconnection of the virtualized lite-EPC and 5G core network, inspired by the architecture depicted in Figure 10, which is based on the local breakout architecture specified by 3GPP [37].

In a typical scenario, CCAM services hosted on the MEC are accessible to AVs and users through 5G core network (i.e., P-GW). The functionalities of the 5G network are stored in the Network Resource Function (NRF), whereas the services produced by the MEC are registered in the service registry of the MEC platform. Hence, to use the 5G services, MEC communicates with the Network Expose Function (NEF), which allows 3rd party application to access the APIs of 5G CN functions. NEF will act as a centralized point to expose the services, and it will also check if all the requests coming from outside the system are authorized to access the

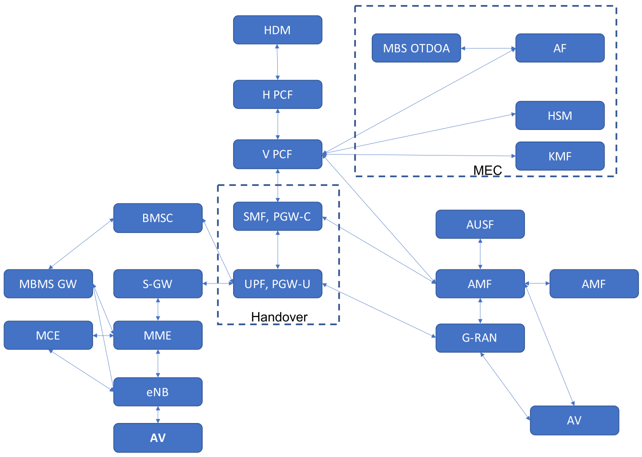


FIGURE 10. Multi-core-network functions chaining for network services and common network functions for roaming support.

services. Far edge MEC may directly be connected with the 5G core. From the MEC perspective the User-Plane UPF is a configurable distributed data plane. The control of that data plane, i.e. the traffic rules configuration, now follows the NEF-PCF-SMF route.

2) NETWORK SLICING

A 5G network slice instance is defined by 3GPP in [37], which includes the CN Control Plane, User Plane Network Functions and the next-generation Radio Access Network described in [38].

To achieve the network slices for autonomous driving use-cases, the core network is virtualized and multiple instances are created. The virtualized platform are capable of computing and network hardware virtualization technologies and managed by a cloud management components. This allows the flexible deployment of network slices, which consist of various virtual network functions and services for the infrastructure components' communication demands. The deployed system only supports a subset of autonomous driving use case related procedures, information and configurations specified for network slice instance selection support and network slicing for roaming support, which are described in [37].

Multiple network slices may be deployed, which deliver exactly the same features but for different groups of CCAM infrastructure components. The slicing of 5G CN supports all standard slicing and service types defined in [37]: eMBB, URLLC, MIoT. The network may serve a single UE (e.g., AV) with one or more network slice instances simultaneously via a 5G-AN. The AMF instance serving the UE logically belongs to each of the network slice instances serving the UE i.e., this AMF instance is common to the network slice instances serving a single UE. The selection of the set of network slice instances for a UE is triggered by the first contacted AMF in a registration procedure normally by interacting with the NSSF, and can lead to a change of AMF. A PDU session belongs to one and only one specific Network Slice instance per PLMN. Different Network Slice instances do not share a PDU Session; though different Network Slice instances may have slice-specific PDU sessions using the same data network name. During the Handover procedure the source AMF selects a target AMF by interacting with the NRF. Further description of the related procedures is provided in [37], [38].

One important component of the network slicing infrastructure deployed in the testbed is the management and orchestration (MANO) platform with slice management functions as part of the service chain as shown in Figure 11. These functions are managed by the global MANO platform and expose a subset of management functions to slice consumers. The MANO platform realizes a service delivery paradigm with highly integrated networks, computing infrastructures, and application services. The boundary between software applications and physical infrastructure has been removed by the advancements of virtualization technologies. The virtual 5G CN and application services are implemented as dynamic compositions of micro services realizing application and network functions. However, the complexity brought about by the resulting increased interactions between the application services and network functions, new business models, new stakeholders, and their relationships requires more efficient and intelligent management and orchestration framework. The application of AI in MEC platforms makes traffic optimization and network resource management more efficient. Dynamic network slicing, for instance, includes real-time selection of optimal data rate or choosing the best 5G slice configuration for CCAM services. Using AI in dynamic network slicing enables differentiated qualities of service (QoSs) for autonomous driving infrastructure components. More details of the end-to-end virtual network function MANO framework and implementation is provided in [39].

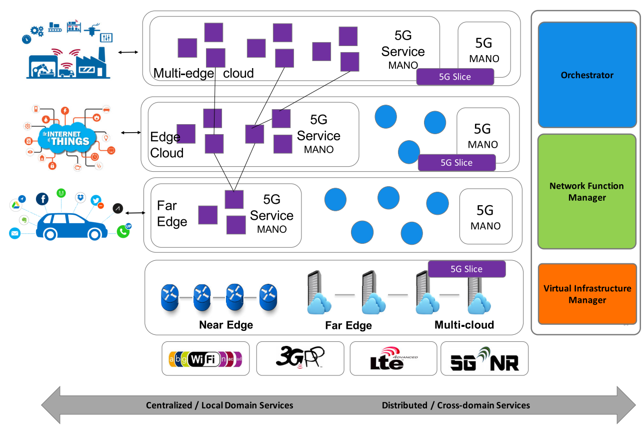


FIGURE 11. Network slice management and orchestration architecture with slice management function as a service.

VI. MAJOR CHALLENGES

Availability of information from different stakeholders (e.g, street furniture, city authorities, service providers, neighbouring vehicles, etc.) to the autonomous vehicle in any scenario plays very crucial role. This positions the communication bit-pipes as a major solution component to achieve the objectives of Level 5 autonomous driving. Hence, in this section, we list major communication related challenges.

- **Ch 1: Delay in Switching between 5G Standalone Networks -** Vehicles relying on external information and C-V2X communication for creation of their environment understanding will need near real-time availability of information. However, a vehicle moving with the speed of 50kmph or more will go through coverage of many small cells and likely to carryout frequent handovers between standalone networks of 5G, which may incur latency.
- **Ch 2: Delay in Switching between 4G eNodeB and 5G gNodeB -** On the similar lines as in Ch2, if the coverage footprint constitutes of heterogeneous mobile networks. Handing over the between these mobile network technologies incur higher handover delays, specifically if one of the technologies if pre-5G. Reducing the handover delays in such settings is a major challenge.
- **Ch 3: Delay in Switching between 5G Standalone and Non-standalone networks -** 5G network capacity planning is expected to following the deployment of NSA followed by SA. Hence, the coverage footprint of the network will be a mix of these network technologies over the stretch of a trajectory. On the similar lines as above, in complex scenarios of L-5 autonomous driving, the handover latency between these technologies should be as low as possible.
- **Ch 4: Under-covered and Low Capacity Coverage Footprint -** It goes without saying that not all the road segments and city areas have enough network capacity. Even if the installed capacity is enough for a region, it may choke during busy hours of the day. To realize all the use-cases of level 5 autonomous driving, the network resources with required service quality should be ensured under all circumstances.
- **Ch 5: Improper Handover -** In a complex urban environment, the coverage footprint of mobile network is usually irregular and creates improper overlapping/ handover regions. Hence, to facilitate the required communication of autonomously driven vehicles, the execution of handovers in the irregular coverage regions should be smooth.
- **Ch 6: Impact on Efficiency of Protocol(s) -** As we know that the change of point of attachment results in: change of IP address, flow tables in the network devices, and other services over the backhaul, core, and radio segments of the network. Considering that a large number of vehicles will frequently change the point of attachments (switching eNodeBs, gNodeBs, etc.), it should ensured that the required operations for the aforementioned switching are executed within the acceptable time (i.e., seamless handover).
- **Ch 7: Unprecedented Network Load -** The recent transit from Internet-of-People (IoP) to Internet-of-Things (IoT) consequences in dynamically varying network resource demands. Availability of required resources (specifically in terms of throughput) should be ensured.
- **Ch 8: Different Network Functions -** Device isolation provisions different network functions so that it can provide access to external traffice (i.e., from other vendors, sources, etc.)
- **Ch 9: Cloud Imparted Latency -** It is expected that MEC deployment will be a new normal when it comes to infrastructure deployment of mobile networks. It is expected to reduced the latency. However, when the vehicle moves to a different cell the latency will increase e.g., due to data exchange with neighbouring MECs via cloud node, etc.
- **Ch 10: APIs for 3rd Party Services -** Autonomous driving is looking into adapting the eco-system by introducing new stakeholders and creating the relationships amongst them. For instance, the road infrastructure provider will be a key player in sharing the on-road created perception with vehicles, city authorities will be actively involved in policy implementation, network providers will ensure the exchange of information amongst the relevant stakeholders, vehicles, and infrastructure. Hence, right interfaces, protocols, and APIs should be developed, which are then exposed to the stakeholders to implement the defined operations of the inter-stakeholders relationships.
- **Ch 11: Support for Multi-interface Communication -** Owing to the fact that operator has deployment of heterogeneous technologies covering different areas and road segments, the need for optimal use of the available network resources is imperative. Hence, operators may opt for the simultaneous use of the multiple network interfaces for enabling communication amongst the entities of autonomous driving. This however, is challenging to achieve specially if most of the operations are to be executed in real-time.

VII. USE-CASE SCENARIOS FOR LEVEL-5 AUTONOMOUS DRIVING

Having discussed the intelligent environment concepts at the edge and cloud levels and their realization by different infrastructure components to support AD, this section discusses a few use cases of complex scenarios that are representative of level 5 autonomous driving. The use-case scenarios are inspired by the ones detailed in 3GPP TS 22.186 [40] and the documents mentioned therein. Readers are further encouraged to refer to communication relevant requirements for different use-case scenes in this 3GPP document. It should be noted that use-case scenarios are carefully selected to highlight the communication relevant challenges owing to the fact that efficient communication is expected to be the crucial component for realizing level 5 autonomous driving. Although a few selected use-case scenarios are detailed in this paper, we discuss the realization of the crucial scenes of the scenarios due to limited paper length.

A. AUTONOMOUS DRIVING IN COMPLEX SETTINGS

The standard document [40] refers to such driving as enabling the semi-automated or fully automated driving. Consider Figure 1, where a number of dynamics of the complex urban environments are visualized. Some of the crucial scenes of this scenario are: i) Lane merge - analysing the traffic flow of the target lane e.g., system is capable of detecting existing vehicles with their lane position, acceleration, speed, size, etc. Such information should be made available for any road segment of the urban areas. Having received this information, the automated vehicle determines the best merge manoeuvre. ii) Overtaking - analyzing the traffic and intention of vehicles in front in the same and neighbouring lanes. iii) 360 perception - detects the events and objects on the road segments around the autonomous vehicles, which are then used to create the 360 degrees understanding of the environment. This scene covers all the major critical maneuvers of the vehicle of driving in urban environment.

For lane merging scene, automated vehicle may share their sensory data directly or over the infrastructure with each other to determine the best merge manoeuvre. For this the Vehicles will rely on capabilities of C-V2X and other enabling technologies like: MEC node, roadside infrastructure, roadside radars and object detection sensors, etc. Presence of the other vehicle or object (information about its size, exact position, direction, speed, etc.) in the merging area should be notified in real-time to the autonomous vehicle intending to lane merge. Such information is exchanged by exploiting the communication bit-pipes (either direct, PC-5 or indirect 5G/LTE-V/DSRC). Most of the aforementioned challenges (i.e., Ch 1 - Ch 10) may be potential challenges for this scene of the use-case scenario.

In the overtaking scene, there may be complexities as: hampering of vision because of large trucks, faster moving vehicle coming out a side street, sharp turn in front of the preceding vehicle, vulnerable road user/pedestrian passage in front of preceding vehicle, etc. Furthermore, the overtake may take place on 2 lanes, 3 lanes, or more, where the situations of multiple simultaneous overtakes may occur. Hence, relying on the communication and on-board sensors may not suffice to meet the above or similar challenges. Relying on the on-road deployed sensors and sensory information from other vehicles is the way to go. This obviously requires reliable connectivity, adequate bandwidth (e.g., for streaming the video sensory data of preceding vehicle temporarily), timely handover (e.g., for ensuring seamless availability external information and 3rd party perception application, etc.), extended vision of autonomous vehicles so that vehicles may create perception of more than a few kilometers rather than a few hundred meters. Similar to the lane changing maneuver, this scene also highlights most of the challenges (i.e., Ch 1 - Ch 10).

The 360 perception scene is an important scene and crucial in enabling the use-cases of level 5 autonomous driving. The idea is that autonomous vehicle is provided with information about its surroundings i.e., creating a perception of the full surrounding of the autonomous vehicle. For creating such a perception, the information from on-board sensors, on-road sensors, that received from other vehicles and stakeholders is fused. The information may represent: exact position, speed, dimensions, trajectories, intention of maneuvers, etc. of other vehicles/objects. Assuming that environmental variables are very dynamically changing, the information about these variables have to be made available in real-time for processing and decision making of autonomous vehicles. The challenges (Ch 1 - Ch 10) are more relevant to this scene.

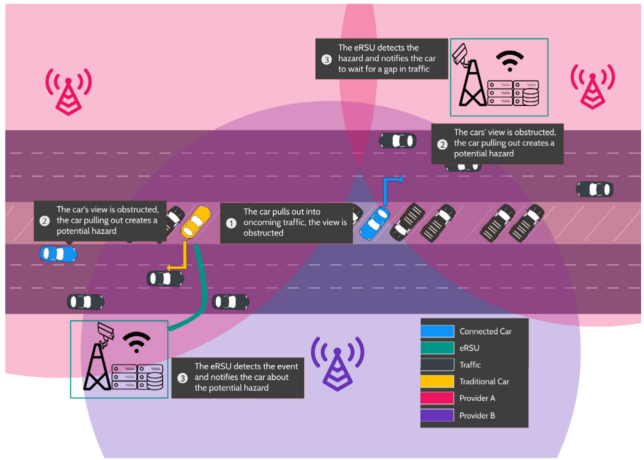


FIGURE 12. In the smart parking use case, intelligent infrastructure assists connected vehicles to find free parking spaces and to navigate in parking maneuvers.

B. SMART PARKING

This use case showcases how roadside infrastructure and traditional, connected, and autonomous cars interact with each other and with parking areas that are monitored by sensors. On the test-road, different parking areas can be observed. Parking lots next to the road to on-street parking (both parallel on the side of the road and slanted parking in the middle of the road) allow for the evaluation of infrastructure and driving functions in different settings.

Three scenarios are evaluated in the test-road:

- Parking Management: Parking sensors monitor the state of parking spaces in the testbed and communicate the state to roadside and cloud infrastructure. The service allows operators to guide connected vehicles to free parking and long term data collection enables predicting if parking will be available when a vehicle reaches its destination in the area
- Sensor Fusion: Sensor data from vehicles and roadside infrastructure (e.g. traffic cameras) is combined to detect potentially hazardous situations, for example when a vehicle pulls out of a roadside parking spot into oncoming traffic
- Maneuver Sharing: Connected and automated vehicles communicate their planned parking maneuver to other

vehicles and roadside infrastructure, for example when braking to pull into a parking spot.

C. GREEN DRIVING

A vehicles' environmental impact is caused by the use of its engine, tires and brakes in the form of emissions (e.g. Carbon monoxide, NOx) and fine dust. These emissions and particles are caused by any moving vehicle and cannot be entirely eliminated. However, intelligent and anticipatory driving as well as smart traffic management can reduce the amount of emissions and fine dust significantly. While the emissions of a combustion engine are directly linked to the fuel consumption and the efficiency of the exhaust filtration system, fine dust created by abrasion of brakes and tires are linked to the driving behavior. For example, a shorter route reduces tire abrasions while a green wave reduces brake abrasions.

The Green Driving use case explores the efficacy of the testbed, its systems and its autonomous vehicles in reducing vehicles' emission of exhaust gases and fine dust. Measuring the levels of fine dust and emissions harmful for humans' health, traffic control and intelligent transport systems can steer traffic in a way to mitigate the vehicle traffic's impact on these levels in certain areas.

By integrating with ITS services (i.e., traffic analysis), environment reading can be linked with the traffic volumes at different times of the day. The impact of the traffic can also be accessed relatively with the sensing of visitors in the area by activity analysis sensors (visualizing motion and dwelling time, objective measurement of hot spots, statistical evaluation). Based on the assessment, traffic regulation can be dynamically adapted to the perceived load of emission. Traffic control and management services deployed at the edge can regulate traffic lights and average speed of AVs based on both statistical and real-time data to minimize environmental impacts. Such dynamic regulation immediately results in "green-line" driving experience and avoids forming queues and stop-and-go traffic, which greatly increase emission and fuel consumption.

VIII. POTENTIAL SOLUTION DIRECTIONS

In this section, we sketch the solution directions to address the aforementioned challenges and realize the use-cases.

A. DYNAMIC DEMAND ESTIMATION

Challenges Ch 1 - Ch 9 may be addressed if the system is provided with an estimated network resource demand in advance so that relevant operations required for resource reservation and allocation are carried out beforehand. For instance, if the traffic intensity at different road segments is known then the operator may do the proper capacity planning proactively. Ch 1 - Ch 3 may be addressed by preempting the mobility pattern the vehicles on the road segments and proactively managing the handover/mobility operations. Ch 4, Ch 5, and Ch 7 may be addressed by implementing proper resource reservation and allocation, which can be made very efficient if the algorithm is provided with estimated resource demands. In a later section of this paper, we discuss the details of our experiments for demand estimation, traffic patterns investigation and resource allocation.

B. EVOLVING THE LOCAL DYNAMIC MAP

The IETF standardized four layered architecture of Local Dynamic Map (LDM) may be evolved with additional layers of information, which are populated with perception created from on-road deployed sensors and learning mechanism in the edge and cloud. These layers may also be populated AI enabled approaches for predicting events, objects, variables of the environment.

C. INTELLIGENT ROAD INFRASTRUCTURE

Traditional roadside units should be evolved to intelligent edge that do not only support V2X communication but also serve as the perception creator, network manager, and service orchestrator. In this connection, contributions may include: IoT middleware integrating all the on-road deployed sensors by developing the right drivers and protocols for the type of sensors; communication solutions for downstream and upstream for implemented network slicing to meet the autonomous driving service requirements for the use-cases. Traffic engineering approaches by developing the SDN native applications, smart management and dynamic knitting of VNFs, exploiting the service based architectural features of 5G-C for efficient service crafting and network slicing, etc. are some of the potential communication solution areas.

D. ACTIVE LEARNING FOR PLANNING, BEHAVIOR, AND CONTROL LAYERS

Since the objects and environment is to be detected in real-time and best maneuver should be executed for realizing level-5 autonomous driving scenarios, it is imperative to achieve real-time learning framework federating different learning instances (e.g., on vehicle, intelligent edge, and clouds) to meet the requirements of complex environmental dynamics. Multi-layer coalitional learning with speedup framework is one potential research direction in this regard. It should be noted that this approach advances and exploits the deep learning approaches. The interplay of game-theory and deep learning for autonomous driving may be investigated. Approaches for speeding up for both deep learning and gradient-based algorithm in the L-5 autonomous driving use-cases may be investigated, as we expect deep learning algorithms will have larger depth. Our earlier approaches like Bregman based algorithms for speedup, meta-learning for self-x network management, strategic deep learning algorithms for robust games may be evolved. A coalition framework to federate the learning mechanisms at the vehicle, edge, and cloud levels. Furthermore, coalitional framework may also be implanted with features for inter-vehicles coordination (specifically in platooning use-case). For instance, platoon formation may be based on coalition game-theoretic approach. The utilities of vehicles will be modelled and intra/inter-platoons coordination will be complemented by the information captured from on-road deployed sensors, on-board sensors, and federated clouds [28], [29].

IX. IMPLEMENTATION OF BASIC SOLUTION APPROACHES

Although a number of use-cases are crafted to be tested on the testroad, in this section, we discuss initial set of experiments. These experiments focus on dynamic demand estimation and study of traffic pattern on the testroad, which are crucial when it comes to realizing use-cases of autonomous driving (refer to Section VII).

A. TRAFFIC PATTERN GENERATION

In this section, we demonstrate the analysis of traffic data using a neural network regressor. The learned patterns enable the prediction of future traffic demands, which are valuable inputs for other network and vertical service orchestration functions deployed in our data-center. For this study, we rely on the traffic analysis sensors deployed around the Ernst-Reuter-Platz, a major traffic junction of Berlin, and image data has been automatically analyzed for a few years. The data gathered (also available at https://flow.dai-labor.de/datasets/ and https://daten.berlin.de, the outcome of Smart City Berlin Project) includes vehicle counts for most road segments, counts of pedestrians entering or leaving two selected buildings as well as other metrics (e.g., number of connected mobile devices) that correlate with activity on and around the Ernst-Reuter-Platz.

Although various sensors are detailed in previous section, for traffic pattern analysis, we focus here on a few types of (visual) traffic, pedestrian and parking space observation sensor, which are deployed around the Ernst-Reuter-Platz and analyses of the image data captured since January 2018. The data includes vehicle counts, counts of pedestrians entering or leaving two selected buildings, number of connected mobile devices, parameters that correlate with activity on the road segments.

1) AN OVERVIEW OF DEPLOYMENT SENSORS

For the traffic generation around the considered roundabout, 13 camera based sensors are deployed at the locations depicted in Fig. 13.

- Location 1: multiple traffic analysis sensors, parking sensor, and people counter.
- Location 2: multiple traffic analysis sensors.
- Location 3: traffic analysis sensor, people counter, and multiple access points.
- Location 4: multiple traffic analysis sensors and multiple access points.
- Location 5: multiple traffic analysis sensors and APs.

Although the deployment was so carried out that the sensor capture all the dynamics of the round about, there were still some discrepancies at different times e.g., some dynamics were hidden behind the trucks or busses. Obviously, this affects the accuracy. But the experiments show that such instances did not occur too often.

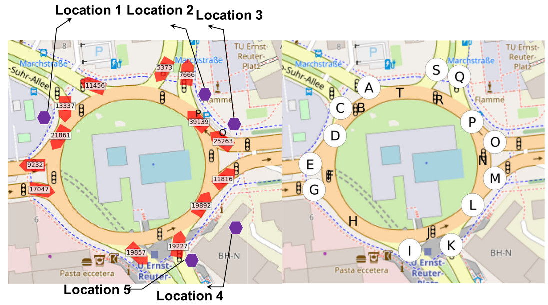


FIGURE 13. Observed road segments (indicated by letters within white circles, right) throughout the intersection including aggregated vehicle counts (left, numbers on arrows) of 24 hours on 2018-01-24 for the driving direction (indicated by the arrows' directions).

The sensors and equipment are configured to capture the count of vehicles in the roundabout. In this connection the following are is carried out: i) the traffic flow analyzers are configured for the inflows and outflows at all the incoming and outgoing segments of the roundabout; ii) the segments nearer the incoming and outgoing roads are also covered by the activity analysis sensors; iii) people count are configured on the pedestrian areas and zebra crossings; iv) communication infrastructure is configured to enable near real-time communication with the data-center. This configuration ensures that the vehicles entered in the roundabout will remain in the roundabout and may be tracked. Counts are aggregated in one minute intervals and vehicle are classified by their types.

2) RESULTS OF TRAFFIC ANALYSIS

The experiments were initiated by carrying out the sanity checks i.e., by visually conforming the traffic intensity patters at different times of the day and evaluating against the expected patterns. We also carried out consistency checks and an assessment of the system's accuracy by:

- Properties Analyses: to analyze the properties and nature of the recorded data, aggregation type, and time resolution.
- Aggregation: to aggregate the statistics and compare those with reference values (i.e., please refer to [41]).
- Time Relationship Analysis: to analyze time relationships and constraints in the observed data based on the spatial relation of the point of measurement (i.e., causal and spatio-temporal correlations).

Vehicle counts are extracted from the image streams and the numbers are recorded. The vehicles and types are classified with visual object detection. At specific times in the data the typical distribution of vehicle types changes drastically. Consequently, we decide to only use the aggregated (total) counts of vehicles in this work and include the vehicle type classification in future works.

For the traffic analysis, the data is accumulated in minute intervals, our expectations include:

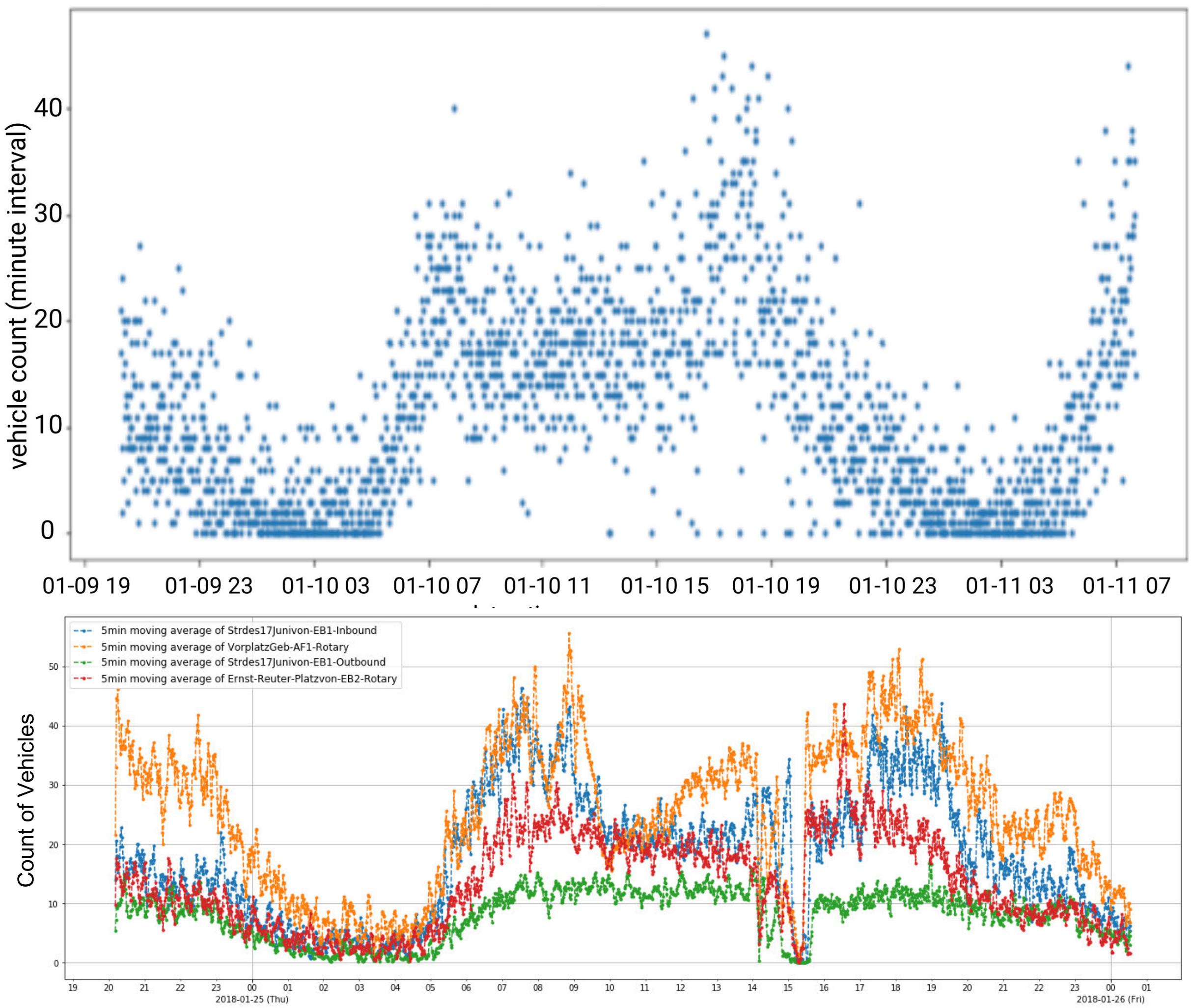


FIGURE 14. Example for raw traffic volume (number of vehicles per minute) data as provided by the system over a period of 1.5 days around Wednesday 2018-01-10 (top) and 5 minute averages of four selected locations highlighting a traffic interruption on 2018-01-25 (bottom).

- Matching: In this, we match the data with data from other sources e.g., distribution over day and peaks, daily averages, and other general trends for working days and holidays etc.
- Temporal Closure: It is validated that the temporal closures may easily be detectable.
- Correlation: There should be simple and obvious correlations observable between sensor stations, refer to Figure 15.
- Detectability: Depending on time resolution, the phase of traffic lights may be detectable, at least as statistical artifact.

We explore the dataset by visualizing it using interactive plots with freely selectable time ranges, freely selectable subsets of sensor locations, and smoothing options. For a spatial understanding the cumulative counts for a time-interval of all the stations can be visualized on a map (cf. Fig 13).

It was observed that there are some common patterns in daily traffic with simple explanations that match well with other sources. The peaks (commonly referred to as 'rush hour', usually present in the morning and evening) are expected (see e.g. [41]) and easily spotted (cf. figures 14 & 15). They are attributed to people going *to* their daily business (8h-11h) and back home *from* work (16h-19h). Weekends, holidays and bridge-days differ in this regard, so that the first peak is reduced or absent and that there is overall slightly less total activity. The data collected at Ernst-Reuter-Platz differs only slightly in its characteristics from those published in the 2014 report. One example being that the 2nd daily peak is not reduced as much.

The data is valuable for creating valid models for the traffic occurring on the Ernst-Reuter-Platz intersection to optimize the routing of vehicles, by adapting traffic signal phases or individual navigation decisions or can be used as input to predict the state at intersections for the communication network.

For traffic volume predictions we trained a simple Neural Network regressor on the first 20 days of the test set

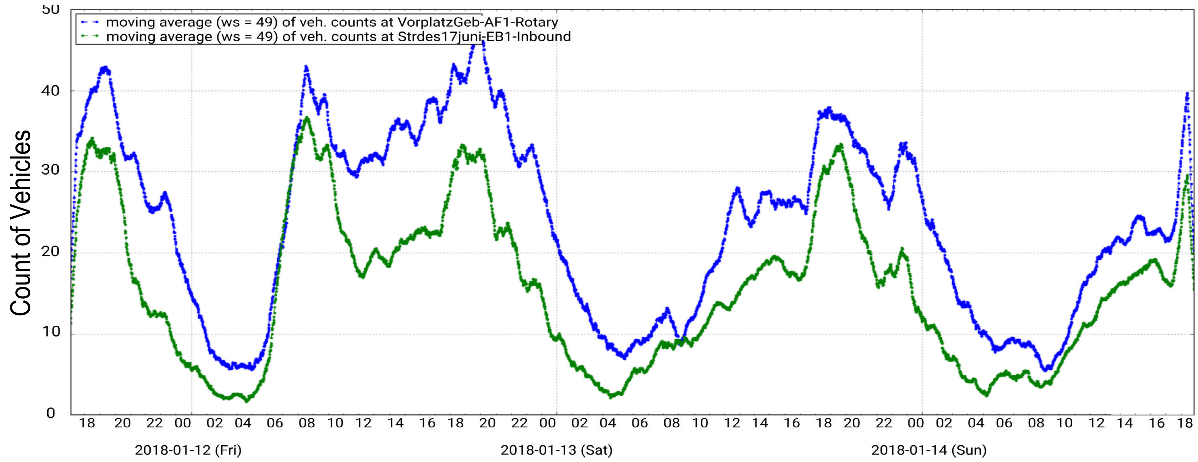


FIGURE 15. **Exemplary causal relations between sensor readings (here: inclusion): Because of the spatial arrangement all vehicles passing sensor location 'O' (cmp. fig. 13) (the lower, green plot) should also pass sensor location P (the higher, blue plot) with some delay; the plots show data of roughly three days around Sat./Sun., 13/14th of Jan. 2018.**

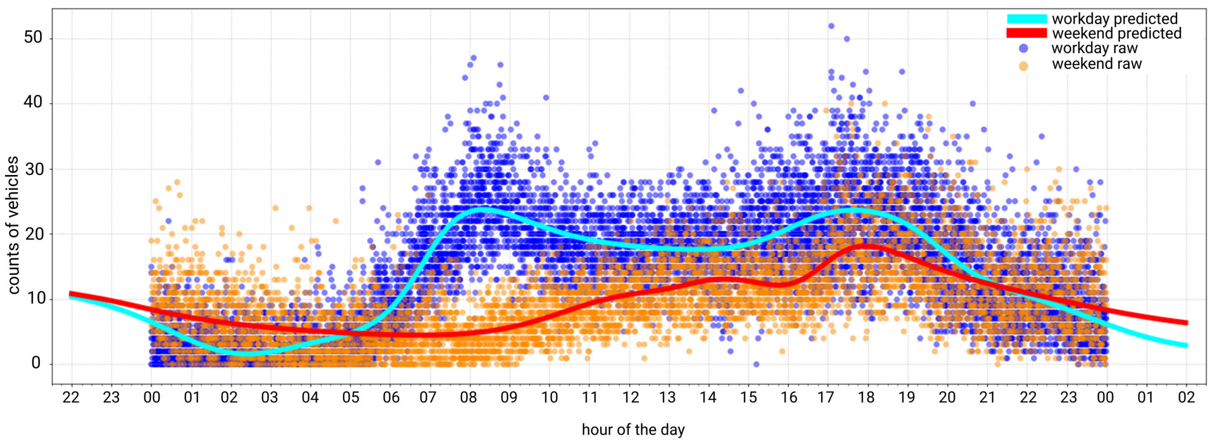


FIGURE 16. **Response of neural network regressor trained on 2 weeks of data. Predicting the traffic volume given the minute of day. The two curves are predictions for workday (Mon.-Tue. in cyan) and weekend (Sat./Sun. in red) with correspondingly colored training instances in the background.**

from a total of an equivalent of 38 days of available data. We experimented with different input formatting, the number of layers and neurons trying to find a comparatively simple and small network, that produces acceptable predictions, as shown in Figure 16. Of course, this depends on the accuracy required for the application intended. We finally settled on a network with 100 neurons in a single hidden layer, L-BFGS [42] as solver and tanh as activation function, using the following features:

- Minute of the day (0..1439),
- Day of week (0..6 Mon.-Sun.),
- Is a holiday (true, false),
- Vehicle count of that minute (number) - the class label/output.

Additional promising features, which we think to have a high potential to improve prediction accuracy, are: Seasonal vacations (school) or weather information. However these are not yet included because of the limited amount of available data (less than a year) at this point.

B. AI ENABLED NETWORK DEMAND ESTIMATION AND NETWORK RESOURCE ALLOCATION

This experiment focuses on estimating the network resource demands and allocation for autonomous vehicles on the test-road. As mentioned earlier that the road segment shown in Figure 17 is driven by the fact that it is most complex segment with 5 ins and 5 outs, where each in and out are 3 lanes. It also has cuts and walkways for pedestrians. Hence, meeting the requirements for communication services is of utmost importance to enable the exchange of right information for execution of the right critical maneuvers.

Figure 17 depicts our understanding of the traffic flow on the considered road segment. There are 5 paths defined (as can be seen in the figure), which are represented by different colors i.e., blue, grey, black, green, and red. These paths are

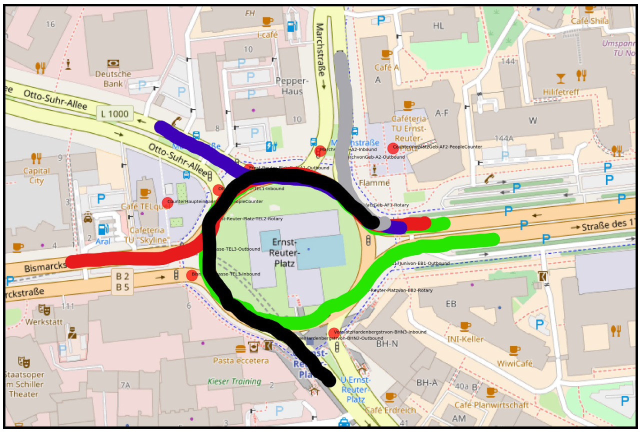


FIGURE 17. Figure highlighting the trajectories on the Ernst-Reuter-Platz. Different colors correspond to traffic flow with specific entry and exit points.

covered by different network cells. The paths are decomposed into multiple trajectories to highlight the entry and departure areas with respect to network cells, which are summarized in Table 2.

TABLE 2. Trajectories (Represented by T).

		Outbound				
		Cell_1	Cell_2	Cell_3	Cell_4	Cell_5
Inbound	Cell_1	$\mathbf{T}_1$	$\mathbf{T}_2$	$\mathbf{T}_3$	$\mathbf{T}_4$	$\mathbf{T}_5$
	Cell_2	$\mathbf{T}_6$	$\mathbf{T}_7$	$\mathbf{T}_8$	$\mathbf{T}_9$	$\mathbf{T}_{10}$
	Cell_3	$\mathbf{T}_{11}$	$\mathbf{T}_{12}$	$\mathbf{T}_{13}$	$\mathbf{T}_{14}$	$\mathbf{T}_{15}$
	Cell_4	$\mathbf{T}_{16}$	$\mathbf{T}_{17}$	$\mathbf{T}_{18}$	$\mathbf{T}_{19}$	$\mathbf{T}_{20}$
	Cell_5	$\mathbf{T}_{21}$	$\mathbf{T}_{22}$	$\mathbf{T}_{23}$	$\mathbf{T}_{24}$	$\mathbf{T}_{25}$

The data is capture through IoT middleware from on-road deployed sensors is forwarded to the central database after being anonymized at the sensors. So far, 8 months of data have been collected on the considered round-about through the on-road deployed sensors and communication infrastructure. The sensors capture the data of different road users including: motorcycles, cars, trucks, pedestrian, etc. Obviously, these road users have varying communication bit-pipe requirements for C-V2X communication and infotainment based on their position, on-vehicle deployed sensors, and inter-vehicle-infrastructure-pedestrian communication, etc.

Analyses of such datasets enable us to predict the traffic intensity on, and occupancy of the roads. Hence, smartly chosen assumptions for communication bit-pipe requirements for different applications (e.g., ITS services, infotainment, etc.), we are able to predict the communication requirements and consequently assist in capacity planning on different road segments.

1) SOLUTIONS IMPLEMENTATION STAGES

To achieve the basic objective of identifying and tracking the road users so that fitting communication C-V2X bit-pipes are made available at all locations on the road segment, we worked out a basic design. The design is pictorially depicted in Figure 18. As can be seen that the data server contains regularized dataset to perform supervised and unsupervised learning techniques. We process the real dataset (captured through on-road deployed sensors) with different machine learning algorithms to trace mobility and activity of the road users.

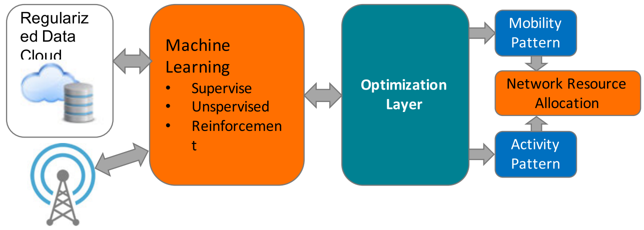


FIGURE 18. Figure depicting the conceptual view of the implemented approach for demand estimation by explicitly highlighting different stages.

We implemented a data pre-processing stage, which further implements data regularization and data personalization stages. In the data presonalization stage, necessary adjustments to the data is made for different scenes of the scenarios. To separate features of the datasets, we carried out the data representation activity. In this connection, operations such as k-field validation were performed. When it comes to improving the results, standardization. These stages are followed by choosing and applying algorithm to predicts traffic intensity and resource demands with highest accuracy.

2) GROUND TRUTH AND DATA QUALITY VALIDATION

Having acquired the right dataset, we needed to verify the ground truth of the dataset. Figure 20 shows the first two Monday's dataset and pattern in this graph correlate with each other means data is in the right shape. We have carried out a complete exploratory data analysis to understand traffic density patterns in Ernst-Reuter-Platz roundabout. One of the major objectives of data analyses was to assess the data for its quality to be used for modeling the demands examination. During the analyses, it was observed that sensory data of some of the sensors is missing for a few hours. This consequences in dataset, where not everyday has the same number of rows. However, we assume that a day fully captured, if 54,000 sensory readings from sensor is available. We believe that the assumption is realistic, as it captures the environmental dynamics on small enough time quanta. In our experimental settings, as soon as road user is detected, we define two boxes, source and destination. If the object passes through the source and then through the destination box, it counts as +1. So the number in the data indicates the total number of detected vehicles that passed through the defined boxes. The former definition implies that it will count only moving vehicles.

3) RESOURCE ALLOCATION AND DEMANDS PREDICTION

Based on the discussion in previous subsections, it is evident that we are now capable of estimating the communication,

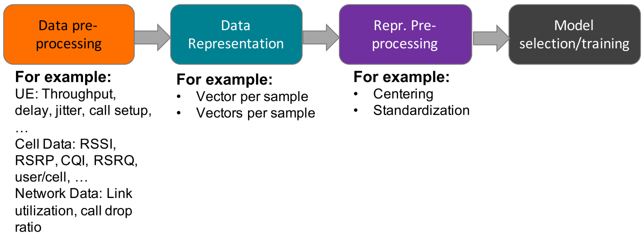


FIGURE 19. Figure depicting the processing stages of data analysis and machine learning implementation.

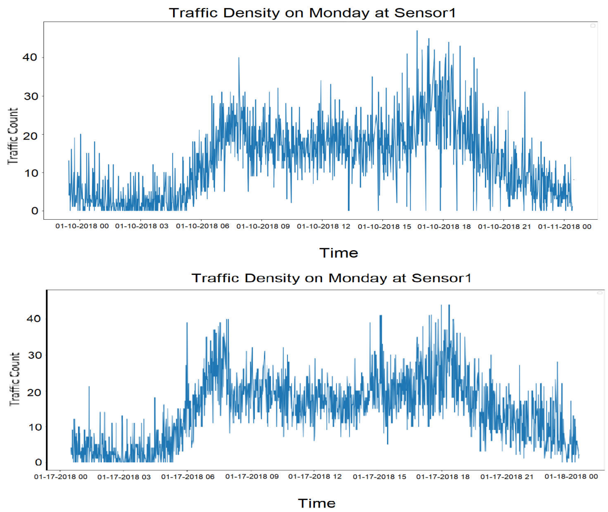


FIGURE 20. Curves showing the traffic count on 2 Mondays.

bit-pipes in dynamic setting. This allows us to implement various algorithms for resource allocation against the predicted demands. The performance of the implemented algorithms was measured e.g., through Root Mean Square Error (RMSE). We capable of predicting the next location and signal strength of a moving vehicle in the road segment. Hence, accordingly we can allocate the right amount of communication resources following the estimated demands. since the considered settings are specific to a complex road segment, time series dataset results proved to be very attractive together with classification algorithms and k-fold validation. The results are summarized in Table 3

An important fact to highlight here is that inspired by the user-centric paradigm, we have taken great care of satisfying device layer demands and at the same time maximizing the profit function of operators i.e., by modeling the profit function of the operator as a function of users'/ vehicles' satisfaction. The details are avoided here due to space limitations, however, the readers are encouraged to refer to a variant of our approach in [28], [43], and [44].

C. RESOURCE ALLOCATION MODELS

We implemented different variant of the resource allocation approaches based on the estimated network demands. The details of resource allocation models may be found in [44],

TABLE 3. Population setting results.

No#	Approach	Algorithm	RMSE
1	Classification	Ada Boost	7.41
2		Decision Tree	0.0
3		GaussianNB	1.92
4		KNN	10.74
5		Random Forest	9.21
6		SVM	9.07
7	Clustering	Affinity Propagation	7.03
8		Agglomerative	18.08
9		K Mean	27.67
10		Mean Shift	14.85
11	Regression	SVR	9.09
12		KNR	9.81

TABLE 4. Proportional resource allocation.

	Available Bandwidth		Demand	
Total	150	100%	200	100%
	Bandwidth	%	Bandwidth	%
$Cell_1$	60	40%	80	40%
$Cell_2$	45	30%	60	30%
$Cell_3$	15	10%	20	10%
$Cell_4$	7.5	5%	10	5%
$Cell_5$	22.5	15%	30	15%

which include: over-provisioning, proportional priority, uniform, and manual resource allocations. However, for ready reference in what follows next, we provide the details of a few selected models.

1) PROPORTIONAL RESOURCE ALLOCATION

In this method of resource allocation, we focus on achieving the fairness. This is to say if the available bandwidth is more than or equal to demand then the cell is provided with required bandwidth. Otherwise, the available bandwidth is allocated proportional to the bandwidth demands by each cell. Table summarizes the resource allocation for the available cells. Experimental results are shown in Figure 21, where the resource allocation is carried out as expected i.e., the bandwidth is allocated proportional to the bandwidth demands.

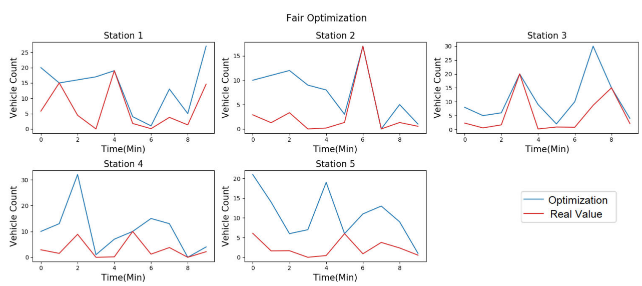


FIGURE 21. Proportional resource allocation.

2) PRIORITY BASED RESOURCE ALLOCATION

In this settings, the implemented algorithm allocates the resources by taking into account the priority assigned to cells e.g., the cells covering path in red color of Figure 17 is given higher priority. This is to say in situations of higher demands than the capacity, the system will allow the reservation of resources following the defined priority values, which could be in terms of percentage.

This turns out to be an effective way to provide the bandwidth where traffic congestion becomes a normal phenomenon. This algorithm gives priority to the max traffic either two-node or one node.

3) MANUAL RESOURCE ALLOCATION

In this method, operators can manually select the bandwidth for a specific cell for certain periods of time. There are two options in this algorithm: one operator can assign the bandwidth by percentage, the second operator can give the quantity of bandwidth each cell manually. Figure 22 expresses the manual technique that we did, bandwidth value is not changing because this value is to remain the same for certain time window.

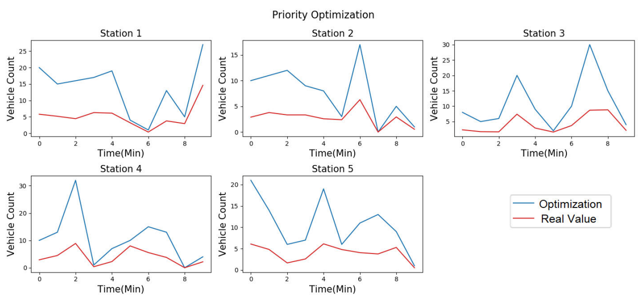


FIGURE 22. **Priority based resource allocation.**

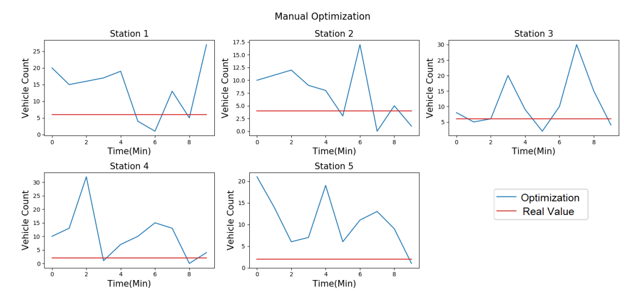


FIGURE 23. **Manual resource allocation.**

X. CONCLUSION

In this paper, we briefly reviewed current activities related to autonomous driving, especially the deployment of test beds in controlled environments and on public roads worldwide. We have discussed the concepts, e.g. road digitalization or flexible communication infrastructure, for reaching the ambitious goals of fully autonomous driving vehicles. We have highlighted the challenges hindering the realization of autonomous driving. The potential solution approaches are discussed directing the readers towards potential research areas. We discussed the solutions designed for the large-scale autonomous driving project of Berlin. We also demonstrated the use of machine leaning approach for traffic demand prediction.

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