Machine Learning for Optimizing Autonomous Vehicle Communication Protocols

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1. Introduction

Effective dissemination of accurate data is crucial to enhance driving efficiency and safety in intelligent transportation systems. Connected vehicles communicate with the transportation network and the vicinity of nearby vehicles to enhance road safety and improve mobility. Current advancements in the automotive industry have seen the development of highly advanced systems that rely on wireless communication, predictive modeling, and 3D mapping. The key to successful cooperation of vehicle-to-everything, vehicle-to-vehicle, vehicle-to-pedestrian, and vehicle-to-infrastructure communication lies in part on the radio protocols used and their efficiency. Cooperative intelligent transportation protocols such as Dedicated Short Range Communication and cellular long-term evolution are used to relay packets, but often result in unwanted collisions and congestion with the potential to be detrimental.

One mode of improvement of these standard radio protocols is formulated through machine learning. This paper focuses on performing reinforcement learning approaches, deep Q-learning, and Q-learning to optimize an operation regarding service data unit distances, maximum contention window, and retransmission limit. The paper also suggests a recurrent neural network that can be used as an enhancement to the already proposed deep Q-learning framework presented throughout the research. Additionally, we suggest that parameter metrics can also be varied, such as vehicle-to-vehicle distance, traffic conditions, or antenna gain, to analyze the relative efficiency of these new machine learning approaches over the classic model.

1.1. Background and Motivation

The growing penetration of autonomous vehicles and the demand for their continuous operation have set high expectations for reliable vehicular communication systems. Semi-

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automated and fully automated vehicles can exhibit a set of different mobility and operational scenarios. The existing communication protocols for vehicular environments are generally designed based on a specific operating condition, and they assume that vehicles continue to operate in the same static environment. Thus, a fixed set of parameters and protocol configurations that are not able to adapt to any sort of environmental changes may lead to reduced vehicular communication performance.

In order to overcome these limitations of vehicle communication systems, it is envisioned that, as vehicle environments are dynamic and, hence, communication requirements can change, developing machine learning-based communication protocols can significantly impact the operation of autonomous vehicular operations. Consequently, the next evolution in vehicular communication can benefit from machine learning-driven communication protocols that can adapt and reconfigure the vehicular communication protocols based on the requirements and dynamics of the vehicular scenario. The successful integration of advancements in artificial intelligence and autonomous vehicles has the potential to lead to the development of autonomous vehicles capable of executing vehicular operations more safely and efficiently.

With the growing demands of communication services between autonomous vehicles, a scalable and efficient vehicular communication system is necessary. To date, vehicle communication systems have significant vulnerabilities, such as limited bandwidth and a significant volume of data. Meeting the ever-growing communication needs between autonomous vehicles is a significant challenge. The widespread use and proliferation of autonomous vehicles will necessitate dense vehicular environments with an associated transmission delay or latency. In several autonomous vehicles, fresh data packets with various requirements from throughputs to different priorities need to be sent over the network within a limited timeframe.

1.2. Research Objectives

In this research, we aim to investigate the application of machine learning for enhancing vehicle-to-vehicle and vehicle-to-infrastructure communication protocols in the autonomous vehicle domain. To this end, the ultimate goal of this project is to use reinforcement learning for efficient and effective communication for autonomous vehicles in either urban or motorway environments. Optimal strategies for communication can lead to strategies to

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change one vehicle's velocity and/or the timing of sending a message in order to increase the chance of message reception. This smart message timing can benefit autonomous vehicles by increasing coordination of their velocity changes. Consequently, communication to exchange data needs to be designed efficiently to avoid increasing vehicle energy use.

The research conducted in this project will have the following objectives: (1) Developing a basic methodology for modeling the communication process and vehicle dynamics in motorway traffic. (2) Investigating how learning environments can be developed to use reinforcement learning for motorway communication at any traffic density and creating experiments to evaluate the performance of different techniques. (3) Conducting a performance evaluation of different learning methods with motorway experiment data. Performance will be measured in terms of message exchange rates and vehicle miles traveled. (4) Enhancement of safety by introducing ML-processed node local view in messages. The outcomes of this research will contribute to academic research through the development of an efficient, coordination-oriented, and adaptive strategy for distributed communication among autonomous vehicles.

2. Fundamentals of Autonomous Vehicle Communication Protocols

The proliferation of automobiles equipped with sensors, processors, and communications has resulted in the deployment of connected vehicle networks. This transformation has contributed to a significant improvement in the performance of transportation systems by fostering vehicle-to-vehicle and vehicle-to-infrastructure communications. These networks serve to exchange information regarding roadway conditions, driving behaviors, signal phase and timing, platoon formation, and other essential characteristics. As a result, the adoption and deployment of connected networks have been viewed as critical due to their potential increases in transportation system safety, capacity, and operational efficiency.

To build a reliable vehicle-to-vehicle and vehicle-to-infrastructure communications infrastructure, a strong communication platform is necessary. Several communication protocols have been proposed to operate communication platforms in both commercial and research environments. Some of these protocols include Dedicated Short Range Communication and Cellular Vehicle-to-Everything. All communication protocols carry unique advantages and disadvantages with respect to their applicability in autonomous

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vehicles. The IEEE 802.11p, for example, enjoys low latency and may be employed in environments where there is no cellular infrastructure or connectivity. However, each of these protocols can still coexist and be used together. Overall, the salient goal of these communication protocols is to facilitate communication among autonomous vehicles in order to support the increasing amount of vehicle population experiencing high network traffic at any given time. Distributing massive amounts of information inside and outside an autonomous vehicle is designed to boost safety and reduce congestion.

2.1. Overview of Connected Vehicle Networks

Connected vehicle networks for intelligent transportation systems (ITS) allow vehicles to communicate with each other and with sensor-enabled infrastructure, as well as to receive information from and send information to clouds for further processing. Vehicles can communicate with local infrastructure via short-range communication, with various sensors, actuators, and controllers embedded in the infrastructure. These can relay processed data directly to other vehicles, or they can communicate with local or remote cloud services. These cloud services can collect data from multiple systems for further processing or further dissemination to vehicles. The modular architecture and the interplay among components make connected vehicle networks a systems-wide solution rather than a stand-alone infrastructure. Unlike the traditional sensor-Internet-server model, ITS infrastructure presents a continuous chain of sensor-actuator communication systems capable of either short-range or cloud-based long-range communication.

Connected vehicle systems use different technologies to support communication among themselves, infrastructure, and cloud services. One technology, Wi-Fi, is part of the 802.11 technology known as DSRC, which operates in the 5.9 GHz frequency. Another V2X technology is dedicated short-range communication, based on the 5.9 GHz spectrum. Some systems may or may not use a subscription-supported wireless cellular network connection in addition to V2V, V2I, or C-V2X communications. With 5G, vehicles may be equipped with a wireless communication device that broadcasts basic safety information to other vehicles, including details such as the vehicle's speed, the three geographical coordinates of the vehicle, the time, and lateral spacing between the front tires. Real-time data sharing can increase traffic efficiency, improve safety, enable vehicle-to-infrastructure applications, and provide valuable

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data for the future of autonomous vehicle operation. Thus, the traffic demands for connected vehicle systems that support real-time data exchange will be significantly greater than the traffic demands for basic vehicle systems.

2.2. Key Communication Protocols

Vehicles. Section 2.2 outlines key communication protocols that enable vehicle interactions, also known as Vehicular Ad-hoc Networks operations.

2.2 Key Communication Protocols

Dedicated Short Range Communications: DSRC is a standard for vehicle-to-everything wireless communications. DSRC operates at 5.9 GHz. It is based on IEEE 802.11p for MAC to physical layer functions. DSRC focuses primarily on safety message exchange for V2V and infrastructure-to-vehicle operations. Further, it is a 30-year-old technology with a proven track record. Cellular Vehicle-to-Everything: Cellular V2X operates in 4G LTE and 5G as specified by the 3rd Generation Partnership Project Release 14 onwards. In C-V2X, direct short-range communication between vehicles or sensors does not exist, which restricts it from direct vehicle-to-vehicle message exchange until 5G medium access control mode 4 cellular sidelink was introduced. As a result, C-V2X is unsuitable for latency-constrained and safety-critical automotive applications. However, both are widely used in vehicle platooning, traffic management, and infotainment services. These VANET communication protocols can enable vehicle-to-vehicle, vehicle-to-infrastructure, and vehicle-to-network operations.

Vehicle interactions are fundamental for autonomous vehicles, as they allow vehicles to coordinate in their decisions and support traffic managers in managing traffic flows in congested urban areas. The V2V, V2I, and V2N operations in VANET can support numerous typical real-world applications. The Vehicle Dynamics and Control research community has heavily used the IEEE 802.11p communication stack for all their connected autonomous vehicle testing. Two well-known real-world connected and automated vehicle testing and evaluation platforms in the U.S. are connected vehicle research test beds located in Ann Arbor and Wyoming. These test beds are a mile long with fully equipped field-side and vehicle-based infrastructure to collect data on V2V and V2I performance. The need for communication protocols that can support latency-constrained and safety-critical control and communication

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applications in automated vehicle networks is increasing. The synchronization between sensors and controllers in such time-sensitive applications can benefit from low communication latencies. Therefore, 5G MAC mode 3 cellular sidelink direct vehicle-to-vehicle short-range communication is not new. The two initial design paradigms use dedicated spectrum and infrastructure-based direct vehicle-to-vehicle network technologies - DSRC and C-V2X. Both paradigms have been compared infrequently due to the lack of extensive real-world field tests, until recently. In quality of service support, modern VANET applications were captured post extensive field tests based on a distance-based metric.

3. Machine Learning Techniques in Autonomous Vehicles

Machine learning is a field of computational science that focuses on teaching computer systems to conduct tasks and learn patterns with no explicit programming. Research in machine learning is carried out in attempts to come up with ways for collecting, transferring, and analyzing as well as interpreting big data in the industry. Learning from the past activities of machine learning models, such as enhancing protocols for communication among vehicles, can boost real-world use value. Communication vehicle issues like secure information, routing, safety, footprints, and decision speeds among others have a risk of causing accidents. A few studies have proposed using machine learning paradigms for enhancing communication for vehicles, but the effect of using various machine learning paradigms has been extensively examined. We provide distinct benefits from previous reviews, examining for each paradigm the study prototype, the input features, the total number of features, the performance improvement results, the metric employed to equate the set of functions, and the benefits as well as weak points. Particularly, we are exceeding the study direction that centers exclusively on supervised machine learning strategies like convolutional neural networks and backpropagation, and we extend this to unsupervised machine learning methodologies that can help identify crucial communication signals and may help improve communication efficacy. This study showed that excellent applications for enhancing communication for autonomous vehicles exist in supervised machine learning, like minimizing computer vision data size and prediction with long short-term memory. Consequently, the advantages and weaknesses of employing system interaction and deep learning prospects, which generally exist in combination, and typically for the purpose of surveillance and control areas, should

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be considered. The potential also involves machine learning, based on deep learning, to minimize the use of such resources.

3.1. Supervised Learning for Communication Optimization

In the domain of smart autonomous systems, communication may be greatly enhanced by employing supervised learning algorithms. These algorithms use statistical techniques to analyze historical data and extract relevant information that can assist a decision-making system in optimizing its performance. Given a properly selected input feature that characterizes the system and an output feature of interest, one can model the relationship between the input and the output. Predictions on future outcomes based on the input parameter values can be derived from this model. Supervised regression models predict a continuous-valued output, whereas supervised classifiers predict a finite set of labels. These predictive models provide the foundation that can be leveraged to improve the optimization of a communication protocol. Some of the supervised learning algorithms include artificial neural networks, support vector machines, linear regression, logistic regression, decision trees, and random forests, among others.

The predictive models derived from supervised learning can have immediate utility in autonomously placing agents to optimize communication without the need for expert-designed formulas or heuristics. Experimentation in supervised learning models for localization has been explored in energy-based multi-hop time of arrival models for ad hoc network localization and successfully implemented using real experimental data. The potential of applying supervised learning techniques to communication is shown in the ability to alter protocols and decision-making events that are inextricably linked evolutions in co-optimization. This section explores the application of supervised learning algorithms for communication protocols. There is a critical requirement for a significant dataset that sufficiently spans the configuration space to train an accurate supervised model. Model accuracy is a critical feature needed for the validity of prediction results derived from training data. Challenges from this approach include overfitting, where a model performs worse than by chance on new data, and data bias. Mitigating strategies proposed here include extensive sampling of configurations in training data, partitioning of data to enhance training validation, and model validation using disconnected experimental configurations. Careful

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attention is required to the configuration space in the sample set to minimize potential effects of overfitting or data bias. Employing extensive sampling of numerous configurations of interest can produce a reliable model. The potential to predict communication outcomes, such as consensus formation between autonomous systems, can be improved using machine learning. The introduction of supervised regimes of analysis can potentially predict whether or not a consensus state has been reached based on input configurations. This approach has applicability for many different domains, including autonomous systems, ad hoc networks, and data fusion. The potential to introduce supervised protocols is shown to improve the performance of bipartite consensus formation.

3.2. Unsupervised Learning for Data Exchange Enhancement

Possible research directions also regard the application of unsupervised learning techniques. These techniques help in finding structure in unstructured data without a preconception of their outcome. To name a few, clustering methods group unlabeled data according to its degree of similarity, producing sorted data that can be more easily managed, while anomaly detection methods focus on identifying unusual patterns that do not conform to the majority of points, thus allowing for the addressing of zero-day events and mitigating their impact. In this scenario, centroid migration of a streaming clustering method and isolation forest for anomaly detection could be exploited, for instance, in order to pave an efficient way to share the most needed information or to mitigate the negative effect produced by an uncooperative or even faulty AV. Unsupervised learning could support adaptive message aggregation from and to different AVs, also for the development of distributed blockchain-based solutions ensuring the redundancy of data even in case of the appearance of an anomalous AV altering chains of elements or in the case of network disconnections.

Although relevant progress has been made in the last years, unsupervised learning to guide intelligent data dissemination in the network of smart vehicles is still in its early infancy phase. It is quite challenging, especially for counteracting "intelligent" adversaries, when less-than-widespread real data is available for training the system. Some efforts have also tried to make unsupervised learning interpretable. However, large labeled datasets are necessary for unsupervised learning, too. Many research initiatives in this context thus largely focus on the

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identification of the need for unsupervised learning to guide AVs in efficiently devising an effective communication protocol enabling opportunistic interactions among AVs.

4. AI Applications in Connected Vehicle Networks

AI applications in active connected vehicle networks are myriad. Machine learning can help in a number of applications and methods for reconfiguring communication protocols. In fact, the transmission range and link quality should be adaptable to the network environment and outperform all the non-AI techniques. Traffic management systems rely on machine learning algorithms for collecting and processing data for real-time monitoring and decision-making, like rerouting to less congested arterial roads. Additionally, proactive AI-based optimization in traffic management is also performed using machine learning for prediction and characterization of non-uniform traffic flow over time. Finally, collision avoidance systems consist of a short-range controller for comfort and a prevention mechanism based on vehicle-to-vehicle communication, which also calls for real-time adaptability of the medium access protocol to the environment. Interestingly, external considerations of the performance of the collaborative two-trick are also performed.

AI technology can be embraced to address significant challenges arising from autonomous vehicle communications. A plethora of AI-driven applications can enhance AV network functionality and the safety of the involved cars. From a communication protocol perspective, AI can be harnessed, at a fine-grained level, to dynamically create reconfigurable mediums that enable vehicles to intentionally collide for softly resolving inter-vehicle conflicts. Within autonomous and cooperative driving research, a handful of studies apply automated learning methodologies for tackling protocol-related aspects. The main role of AI is in enhancing preventive policies, determining the causality of accidents and deriving valuable safety measures that can be communicated among vehicles in proximity. Numerous AI-based applications can significantly contribute toward fostering trustworthy and intelligent vehicles via state-of-the-art communication protocols.

4.1. Traffic Management Systems

Increased investments in connected vehicle technologies promise to enable high-volume data-driven collaboration, where vehicles can sense and communicate among themselves, the

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infrastructure, and infrastructure-connected devices. This allows the processing of real-time operational data from vehicles and other data sources, making numerous decision-making steps for optimal traffic flow, mitigating congestion and the amount of pollutant emissions by vehicles, reducing commercial shipment costs, making the trip more comfortable, and reducing the probability of car accidents. At the core of commercial traffic management systems are a variety of AI algorithms capable of processing vast amounts of data from different sources in a short time, including sensors embedded in vehicles on the road, other IoT devices, video streams transmitted by traffic cameras, and point data collected from toll areas. These systems combine predictive analytical functions with AI-driven decision support features to optimize traffic signals at intersections and route assignment.

Implementing solutions that would optimize communication between autonomous vehicles and, in the current urban traffic scenarios, between autonomous vehicles and conventional ones comes with challenges as the technologies are integrated. We have to consider that in the upcoming future, the infrastructure of urban and inter-urban areas will be equipped with different communication hubs designed to enable seamless connectivity for these different autonomous vehicle categories. After all, traffic management processes should ensure that vehicles on the road operate in a safe environment. Automated key traffic functionality will use AI to facilitate communication with autonomous vehicles and other road actors by increasing their awareness through the information surfaces delivered. Even without the autonomous vehicle traffic control manual, these automated systems can remove bottlenecks in the hub leg of big cities by guiding vehicle flows in distinct but continuous lanes. This gives drivers an opportunity to have a smoother ride and reduces the risk of accidents.

4.2. Collision Avoidance Systems

Artificial intelligence (AI) algorithms are frequently used in collision avoidance systems. They continuously process input data from a vehicle's sensors to detect surrounding objects and forecast the possible future movements of both controlled and uncontrolled objects. Common methods used to synthesize autonomous vehicle decision-making AI include classical rules-based programming as well as probabilistic and rule-based driving models. While input data from these sensors are sometimes fused, AI mostly processes data independently of one another and on their own timeline. Ultrasonic, LIDAR, and radar sensors can typically detect

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objects at distances of up to 100 meters. Cameras, another common sensor in autonomous vehicles, can detect objects at distances of up to 200 meters or more. Researchers have recently presented new techniques and frameworks for integrating sensor inputs from these various distance ranges into a unified object detection task.

Several use cases exist within the automotive and collision avoidance literature to showcase AI's ability to detect imminent collisions. Such use cases in developing machine learning-powered AI, like support vector machines or neural networks, have been demonstrated to be effective in improving the system's performance at detecting possible collisions. The ISM algorithm combines vehicle-to-vehicle and vehicle-to-infrastructure communication to avoid accidents in different scenarios through combined global path planning and local trajectory adjustments. Internal controller limitations and vehicle specifications are used to simulate vehicle trajectories in a physics-based simulation, accounting for limitations such as traction, wheel angle disturbance, and latency. Trajectories that intersect with the driver's planned trajectory within a 2-second horizon are discarded. Lastly, AI-driven fault prediction can be used on an autonomous vehicle to predict when needed repairs or replacements may be necessary.

5. Challenges and Future Directions

There are several challenges to the deployment of machine learning techniques in the context of autonomous vehicle communications. Data privacy is an area of contention, as privacy issues are paramount within the context of a network with a high percentage of end users acting as individuals. Additionally, security concerns are also an area for potential concern. Relevant to these is the issue of potential opportunities regarding data integrity. This opportunity for the exploitation of machine learning techniques in collaboration with communications is an area interesting for modeling. Finally, it is also a potential issue to develop a machine learning technique specifically to exploit vulnerabilities within a system. Specifically, there are risks if model updates must be carried out across large, widely distributed systems, especially during runtime, which could render a system vulnerable as well as expensive and inconvenient.

A further issue is in the rapid movement of Software Defined Networking work into integration with cloud technologies and emerging networking concepts to deploy machine

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learning techniques. Opportunities in the development of SOAI-enabled software for 5G networks that can be implemented as a communications protocol are similarly tempered with challenges, such as the complexity of deploying a dual stack IP service format as the road towards fully DOAI networks containing 5G interconnected autonomous vehicles that are predominantly IPv6-based. At this point, ease of use must be balanced against performance considerations in areas such as dual-stack networking data marshalling, where low-latency performance is of the essence. Work in this area then focuses on both potential benefits and the means to optimize performance within this context. Finally, regarding integration, interoperability issues must be addressed across a range of connected vehicle communication systems. Such work lends itself particularly to the formation of collaborative transport domain semantic blockchains. Several key challenges exist related to the regulatory and policy oversight of the deployment of machine learning techniques into autonomous vehicles, with a potential spectrum of regulatory and standardization challenges from vehicles to infrastructure across networks as well as operational landscapes. Research thrusts in these areas will be ongoing in our work going forward.

5.1. Data Privacy and Security Concerns

The growing demand for autonomous vehicle communication protocols reflects the new applications that become available in AV networks, from traffic light monitoring to car-platoon coordination. Indeed, a connected vehicle might generate from tens of gigabytes to 1.3 petabytes of data per hour, and this amount will increase as technology advances. Human comfort and convenience are another major driver for information exchange. In a vehicle-to-everything communication network, drivers become the direct recipients of alerts and advisories that improve driving efficiency and safety. Intelligent Transport Systems could work to optimize road traffic conditions in urban areas. At the same time, the unrestrained collection of data from AV-side controllers opens up potential privacy and security vulnerabilities. Personal data could be leaked from an accident. Also, data that has been published by drivers could be stolen or mishandled due to erroneous versioning. Users expect high-security communications between all external parties involved. The security and privacy of dynamic on-board generated data points become the focus in this application.

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The pervasiveness of connected vehicle data may lead to a privacy breach if data is shared without user consent. A closer look at recent incidents in the automotive sector reveals the privacy and security phenomena. A modern vehicle generates—as a rough estimate—around 25 gigabytes of data per hour and is in need of encryption. This volume of personal information elevates the risk involved in potential data breaches as collectors fail to anonymize data. Data exchanged ethically must prioritize the world's citizens. Moreover, in line with data collection standards, to retrieve and specify consent prior to data transfer from the user's part, an application will also verify user consent and user authentication. Secure and encrypted exchange to avoid an attacker having a position is desired to transmit that authorization.

5.2. Integration with 5G and Beyond

5G technology and beyond have the capability to provide massive connectivity, ultra-reliable communication, low latency, and high-speed mobility between various devices. For instance, 5G technology can support a microsecond level of latency and a connection speed of 1 ms. Further, the data speed will be improved to 50 Mbps to 1 Gbps based on various scenarios. These peak data speeds can also be improved based on technical advancements. Indeed, various improvements such as dynamic ultrasonic machine learning can provide several advantages such as higher data speed, less latency, network slicing, and so on. Due to these distinguished features, one autonomous vehicle can transmit or measure at least hundreds of packets, which may reach several gigabits, and a few of which may increase the packet size up to several terabits. Thus, this data cannot be processed by traditional machine learning algorithms in real-time.

One way to process these humongous datasets is through machine learning algorithms. However, the existing machine learning algorithms can only analyze the datasets at a predefined speed. Meanwhile, convolutional neural networks and deep learning can process the data with high packet rates in less time. However, in order to achieve this in real-time, it is necessary to consider the implementation details. In spite of all the advancements, the static communication pattern cannot be altered dynamically. In a rural area, deploying an enormous 5G network is a big challenge, and the above scenario with 5G technology fits well for urban

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areas. Therefore, enhancing the static machine learning models with 6G can make autonomous vehicles more intelligent and powerful.

6. Conclusion

In this study, we reviewed the related literatures and conducted technical reports to discuss how machine learning can be used in designing and optimizing communication protocols for the future intelligent and autonomous vehicles. It is worth mentioning that this is the first paper talking about using deep reinforcement learning for designing communication protocols for advanced intelligent vehicles. We have critically discussed the role of communication in the safety, efficiency, and even the durability of the vehicles. The evolution of the V2X and communication protocols, and the challenges of the communication in the software-based systems and services are discussed. The offered services, segmentation, framing, and the end to end performance of the systems for safety applications will be impacted by the communications. In this report, we investigated the current and future usage, as well as the potential of machine learning and deep reinforcement learning in optimizing and designing communication protocols for Safety Applications, Communication Intensive Applications, and Autonomous Vehicles.

This report lists and discusses the related challenges of using and optimizing machine learning for future vehicle-to-everything-based and autonomous vehicles. The challenges range from privacy to the security of the data, human behavior, technology readiness, technological dependencies, equipment and hardware independence. Integrating data-driven communication systems and protocols may impact fundamental challenges of the Autonomous Vehicle – thus, it is essential to conduct multidisciplinary research. In conclusion, the recent advances in machine learning can accelerate the optimization and the design of communication systems for autonomous vehicles, and closing the open challenges raised in this report, including the open potential future research as presented. The design of communication systems for autonomous vehicles has begun to receive an enormous amount of interest, especially with the advent of communication systems that piggyback on connected devices. The experts of this field are working in two consistent methodologies or requirements, what level of performance existing communication paradigms are capable of, an instance, comparison to Wired LANs, security and reliability, and the potential

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performance improvements provided by the new technology requirements and characteristics. Thus far there had been less interest in account settings if vehicle systems could be operational without the advanced infrastructure, they typically test emulation of network conditions, rather than assessment of a system designed to operate without them. The motivation behind this study is different and is related to interoperability of systems, due to concerns with the current divergence between the behavioural aspects communicated in the perception-action loop established by industrial designs and safety assurance. As illustrated throughout this report, the mobile cellular industry need to create a behaviour which can cater for the internet applications and network layer protocols at a high reliability in a truly end-to-end manner when delivering the data through the hops of the internet. The project does not need to bear the same operational concerns as the industry but it also does not have the capacity or time to address every and any operational concern.

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