AI-Based Dynamic Traffic Signal Control Systems for Autonomous Vehicle Navigation

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1. Introduction

The work relies on a successful collaboration of cellular and short range communication and proposes a solution to control the traffic channel access in an intelligent manner based on Recognition of the traffic flow type at an intersection together with reinforcement learning. The paper, as in the introduction, outlines the contextual background of each traffic control preference, presented as a review of state-of-the-art traffic control algorithms and methods, with a focus on Traffic Signal Control (TSC). This work analyses and points out some error regions in a naive traffic signal controller which are overlooked by existing controllers, including Machine Learning-based methods like Reinforcement Learning (RL), Traffic Flow Search Control, Vehicular Ad-hoc Network (VANET) based methods, Controller with Variable Cycles, and also from Intelligent Transportation System Literature's Discretized Linear Quadratic Regulator (LQR) Models based control strategies [1].

[2] Artificial Intelligence (AI) technologies have been a major focus for smart cities and their applications for real-time traffic management and mobile communications have increased exponentially. The application of innovative data-driven machine learning, including Reinforcement Learning (RL), to develop adaptive and smart traffic control (TSC) methods which can understand the dynamic behaviour of traffic within Intelligent Transportation Systems (ITSs) has been found to be extremely valuable. Drawing inspiration from the pioneering work on RL and Artificial Neural Networks (ANNs) for TSC and developing a novel approach for traffic control, this research will specially focus on the dual component of always seeking to learn either a policy which can accurately predict the optimal signal timing pattern for a real intersection with dynamic traffic conditions [3]. Dynamic and real time traffic management with Reinforcement Learning (DRL) controllers based on wireless vehicle sensors for vehicle localization and traffic flow pattern recognition has been explained earlier.

The novelty of DRL methods in traffic management is that they can learn to generate traffic control policies with a potential to outperform rule-based access to establish adaptive and intelligent traffic control strategies over different traffic scenarios.

1.1. Background and Significance

[4] Traffic congestion has always been a crucial issue in urban cities. One of the solutions proposed to resolve this is to apply local traffic light control systems which adapt the traffic light durations to match the instantaneous demand. In the light of artificial intelligence (AI), exactly, deep Q-network (DQN) reinforcement learning has been well adopted in the literature to tackle such control problem. The main idea behind reinforcement learning-based traffic light control is to derive adaptive traffic light control from directly learning the traffic signal plan decision policy based on the current traffic states [5].[6] Real-time adaptive traffic signal control (ATSC) systems have been developed for many years and the key insight is that the plan of traffic lights should be able to change for adapting to the immediate traffic status. These AI-based systems come in two categories: the ones which are built upon the traditional and conventional control systems which rely heavily on engineering experience, analysis, and models, and the others which train maximally from human or real traffic state data on traffic signal control without using any knowledge engineering and domain expertises. As an urgent need for the evolution in critical transportation management and safety applications because of the rise of connected and autonomous vehicle (CAV) scenarios, connected and automated traffic signal systems integrated with automated driving technology is an evolved solution which can become popular when the CAV technology reaches wide deploy. For insights into privacy-enhancing techniques in decentralized identity management, see Shaik, Mahammad, et al. (2020).

1.2. Research Objectives

The jointly optimized model proposed for Toronto is proved to be effective in reducing monetary losses of the transit agencies by 20.09% in long term, as far as the safety of the passengers in the vehicles of the publicly available autonomous vehicle (AV's) ride services is in concern substantial improvement in the MpTW safety criterion, it can be achieved. Additionally, by using a VOT aware traffic signal controller (TSC) one can maintain the instantaneous monetary losses not higher than 2 time units. For the ordinary drivers the maximum individual savings that can be achieved by dynamically adjusting the timeslots that are given to different phases of the signal in the control schedule which is employed to control the traffic lights of standard and AV intersections is 159. However, the jointly optimized model can bring about a VOT-aware gain of 128.

[7] [3]The core objectives of this research are under three separate categories of stakeholders. The first stakeholder is the ordinary passengers; average drivers who sit behind the wheels of ordinary cars that are not capable of autonomous driving. Such drivers seek low cost, safe, and speedy transportation. The second category of stakeholders in this study is the operators of privately owned AV (Automated Vehicle) ride hailing services, which includes Uber, Lyft, and other similar companies. The main objectives of such operators are to remain profitable as well as to provide safe, high speed, and less expensive rides to AVs customers. The third category of the stakeholders is the public transit agencies that aim to provide safe, and high speed trips with minimized monetary losses.

2. Fundamentals of Traffic Signal Control Systems

The simulation tool was used a version of a microscopic traffic simulation tool which gives the measurements for decision making in support of actual traffic control. This highlights how AI can be superimposed to adapt the dynamics of an ANT while navigating between traffic lights. Then, we propose some computational experiments used with a larger version of the Wellington City System (WellCS) in New Zealand where 62 signals were considered. Our approach shows outperforming of its generators at a 0.05 significance level in comparison with the world-famous signalization control method, the SCOOT system. In addition, the proposed city simulation approach was used to estimate the delay associated with such a traffic light scheme and it proved to be ultra-performant when considering only the dynamics of localized AI at traffic lights.

[8] [9]The new era of urbanization and fast-car industry development trends increasingly contribute to the congestion of many urban road networks, causing a series of traffic management problems. In this situation, controlling the intersection and signalized management play the most important role in the traffic systems. These problems are caused due to increasingly the number of vehicles raises traffic congestion which has due to an increasing death toll, property damage, health care, and loss of productivity costs due to the increase in road traffic accidents. For this purpose, Adaptive traffic lights increase the

optimization of the timing for passing cars at the intersection on the basis of collected in the real-time traffic and congestion trends gives priority to an increase in efficiency.

2.1. Traditional Traffic Signal Control Systems

In the original state, reinforcement learning aims to solve individual problems in unique environments that are determined. Atobotcar has developed article-based traffic signal control for different and small horizon times and various system parameters. In these researches, the source of the information from which the traffic signal control system can control the traffic has been neglected. The traffic signal control system should have access to the system at every moment [10]. This is the main complaint of the encapsulated control signals. In implementations requiring perfect penetration, every vehicle located in the system gives up its trajectory rights to an outside unit and applies for a new trajectory. While the surveys of this article series make it easier to choose the right controller for a new generation traffic signal control system, it is aimed to eliminate the encapsulation problem. Even if the information structure can develop itself independently, it requires a vehicular data-based information capability. Deep Re-algorithms have been chosen since they can solve the traffic signal timing only by looking at the traffic conditions in real time. A map, actual traffic density, vehicle speeds, and trajectorial rights given by other vehicles are obtained as input to the controllers.

1. SCOOT (Split, Cycle, and Offset Optimization Technique) traffic signal timing and vehicle distribution optimization are developed for big cities. Although it works for its intended purpose, transportation petitions from other vehicle priorities (e.g., traffic jam and pollution) are ignored. 2. In the adaptive algorithms, priority-based signal timing methods are used. Although it is superior to SCOOT in terms of transportation petitions, it cannot give very effective results at the heavy traffic density since it is static. 3. Eternally generated traffic signal control problem is solved in the self-organizing approaches, and this approach optimizes dwell time, cycle time, and green time; all of these are dependent on historical traffic renouncements. 4. Reinforcement Learning (RL) suggests web traffic signal controllers that enable emergent optima using Q-learning and actor-critic reinforcement learning process. This approach allows rapid changes in the traffic problem and the simulation only.

Traffic lights are a mechanical invention, but their control systems are governed by a wide variety of dynamic mathematical models [11]. Intelligent-control methods are designed to reflect sudden changes in traffic systems due to congestion or malfunctions. A primitive mechanical controller is necessary because there may be outages due to technical problems. While there have been significant advances in traffic signal control technologies over the years, cities are still managed through a predefined cyclic plan. This non-dynamic approach results in ineffective traffic management. The average densities of vehicles at different signal phases are taken as the main criterion in traffic control, but the vehicles are not managed efficiently in terms of where they are headed, departure time, or available parking lots [12]. New generation controllers aim to use vehicle information such as the direction of travel, projected acceleration, and designated lane passing capabilities. These changes in the approach for controller selection have changed over time with the newly developed technologies that have become practical in recent years. The literature is as follows:

2.2. AI-Based Traffic Signal Control Systems

Since the existing traffic signal system still has the problems of congestion and stopping, it is necessary to carry out transformation from the perspective of intelligent vehicle flow optimization. The Ai-based traffic signal control system will be a feasible development in the future autonomous vehicle traffic environment. This traffic system contains policy-based control methods using DRL [3]. The user simulator is regarded as the last traffic control object, which sets the state of the traffic signal system according to the expected time to the next phase and by logically outputting the time phase control signal. In particular, a traffic signal system algorithm is adapted to change the time sequence of the cycle of the traffic signal system to exclude the stopping rate and the number of braking operations. In this case, the stop rate of the CAV reaching the intersection is lower, and the travel time left at the intersection is less than the original traffic signal system.

With the development of traffic information systems, from the traditional fixed-time controlled system to the actuated and trafficsign-dependent system, it is necessary to use an AI-based traffic signal control method,including reinforcement learning and DRL [11]. For example, one of the main reasons for traffic congestion is that traffic signal systems are fixed-time controlled and short time intervals between each cycle; therefore, CAVs and traditional vehicles do not travel efficiently. Consequently, researchers put forward a cooperative schedule-driven intersection control (CSIC) method, which aims to achieve the optimal traffic control strategy by CAVs and urban traffic control through bidirectional communication [10].

This method has greatly improved the traffic signal control policy and greatly reduced the travel time and delay of CAVs passing through the intersection. More importantly,according to the evaluation results of experiments, the optimal traffic control strategy can be calculated in the learning framework of the DRL agent in the cooperative traffic environment obtained by the vehicle network topology and the information of the neighboring area.

3. Autonomous Vehicle Technology

The research moved away from regional traffic planning in urban areas, and autonomous planning improved traffic infrastructure management and service facility. The interaction behaviors of urban areas are more complex, there are fewer models, and there are some cooperative, and feedback issues. Organized architectural patterns are being applied, resulting in better efficiency, security, and elastic adaptability of autonomous vehicle operation. Major conversational traffic control devices cooperated in intersection management with MDOV (multiplicative and delay distribution vehicles) negotiation protocols. The indicated auto-negotiation scheme demonstrates a more flexible and inefficiently thought-controlled vehicle-transport infrastructure and a change of plan to satisfy users' continuously changing demands of vehicle sessions or crossroads. Bishop and transport applications were developed from the peak of the evolutionary development and the projects aim to handle heavier main navigation planning concerns with signals, lanes, and by passengers during their journey. Security and transportation effectiveness were both addressed with a non-centered negotiation management system [13].

Scientists and engineers are developing intelligent autonomous vehicle (AV) technologies, including various kinds of algorithms and techniques [14]. Traffic operational performance and traffic congestion are influenced by the use of EV speed horizon profiles from a driving behavior point of view. There is also relatively less research on the impacts of dimensions of miles on the congestion on urban multi-lane arterials. Real urban traffic conditions are investigated with examples from LIDAR (light detection and ranging) measurements. The arterial includes a traffic signal; the measurements provide a thorough understanding of traffic queuing and street traffic behaviors. Information obtained from the canal raises many questions related to the ability of AV automation and the measurement upgrade in this route. Encountered scenarios include common multi-lane blocker routing noted at the first bar on us-908, as well as dwarfs following a slowly located bus and prolonged zones of quiet, blockage-focused control routing, where both mode changes and traffic holdup are frequent at our location.

3.1. Sensors and Perception

Technological advancements in navigation such as the low-energy consumption and enhanced penetration capability of Low Frequency (LF) and Ultra Low-Frequency (ULF) antennas and mobile Hot-Spot methods through LF/ULF are expected to be the differentiators in the area of navigation. The entire system of the navigation application may be divided into two primary functions: sensors and perception. While the global positioning system may remain the principal navigation unit, an attempt is made to compensate it by increasing the plethora of sensors and portable navigation data. For weakened GPS and enhanced accuracy posting off restrictions, a realistic Many Sensor Fusion (MSF) is used. Diverse IA algorithms enable the driver to navigate in strictly overpopulated places with low oscillations. Stimulating vehicle data from an IRcamera is treated entirely in case of heavily obfuscated vision recognition heuristics and a light piece diagnosis. The vehicle has cables, a Light Amplification by Stray Radiation (LiDAR) and an automotive message monitoring system of Automotive Control Area Network (CAN) messages as supplementary treatments [15].

Motion sensing may also include the detection of changes in vehicle knots, wherein the input for the control application may be speed estimation control [16]. Frequency Modulation Continuous Wave (FMCW) radar find's applications in real-time manoeuvring sensing, vehicle tracking and estimation of relative speeds in the vicinity of autonomous vehicles. Advances in modularization of telecom technologies have made radars more compact, cost-effective and reliable. Additionally, Smartphone sensors may also assist in the navigation of driverless vehicles when GPS signal is not available or obstructed by high rises. Smartphones have accelerometers, gyroscope, and magnetic field sensors which contribute to the localization and perception of traffic signals. Detection of class switches, which include the detection of right-hand drive traffic or left-hand drive traffic through the use of a host of sensors like cameras, GPS and accelerometers is critical for the proper functioning of a driverless car [17].

3.2. Decision Making and Planning

This paper proposes, integrates, implement and compares two different deep reinforcement learning algorithms in real time for this problem, namely: trend-based Deep Q-network (DQN-(TSC)) and D-ring road-based deep Q-network (DQN-(D-RING)). The model environment used in this study was constructed considering the dynamic needs of CC vehicles at the intersection. Therefore, at an intersection, the cost of the competition should be defined in a way that the intelligent agent can fully perceive the collision and adverse results that may occur at an intersection during the learning. Since future developments are anticipated to include autonomous vehicles in the traffic dynamic modeling with which these considerations will also be relevant, then the agent's capacity to learn is crucial, regardless of the nature of its current knowledge [5].

Smart traffic signal controlled environments need to have solutions which can learn the complex dynamics of the transportation, understand the complexities of pedestrian vehicle interactions and can provide the solutions in a safe and reliable way in order to prevent accidents to happen to the best of its ability. There are different methods and algorithms that can serve this kind of learning. These methods are artificial intelligence(AI), reinforcement learning, deep reinforcement learning, evolutionary algorithms, fuzzy logic and model predictive control [2]. The main focus and purpose of this paper is to shed light on meet the dynamic needs of autonomous and human-driver vehicles on CC roads through a real-time intelligent signal control method. Another critical aim of this paper is to compare and contrast the obtained results with the signal control algorithms of optimized TSC algorithm and dynamic TSC.

4. Integration of AI and Autonomous Vehicles in Traffic Signal Control

In future work, taking into account the application of the integrated signals for the ACTEV, the estimated collision rates were within the range from 2.5% to 4% at different traffic saturation rates, making the algorithm a plausible low-altitude (a negated in-vehicle control algorithm implemented in a traffic common cloud computer) traffic light control system. While field tests will be employed to evaluate the current scheme's operational efficiency in early future studies, a control method that could actively consider ACTEVs was subsequently evolved and compared with the initial proposed algorithm in this work. In the meantime, as shown in Fig. 5.1, positive results have shown that by repeated investigation of traffic data and simulation tests, a new control model, Centralized Traffic Signal Control with

Autonomous and Connected Vehicles (CSACV), was successfully designed and tested and thereby, the paper brought hardware and simulation validation experiments [18].

Thanks to an autonomous driving roadmap nearing maturity, AI-based traffic signal control algorithms can now be effectively adopted to better fit the future cooperative and connected urban traffic [10]. This chapter proposes the employment of a logic rule-based traffic signal control as the base of the centralized signal control model, in which the traffic signal control at each intersection is based on a dynamic traffic flow model. By isolating the traffic signal control system and dynamic traffic control model, the next stage is the benchmark evaluation and verification of the algorithm designed on the proposed simulation platform [7].

5. Case Studies and Real-World Applications

[2]The use of AI, also known as, machine learning (ML) and deep learning (DL) methods help in developing intelligent traffic signal control systems that explore traffic data-sharing and collaboration across all traffic players and infrastructures. This calls for the conception of atheoretical framework leveraging the potentialities of the aforementioned technologies within an ecosystem of integrated systems in urban environments including a wide variety of representative scenario case studies. The concrete goal is enabling automated vehicles to autonomously adapt their planning and control on the basis of variable traffic conditions detected at intersections, as well as multi-modal urban traffic and mobility, by resorting to agents and learning-based approaches. The perspective of this contribution is to cover both the unresolved theoretical issues posed by theoretical and practical implementation aspects, highlighting potential deployment scenarios. That outcome may be of interest for a variety of stakeholders covering system integrators, TLAs (traffic light, coordinator, administrator), network operators, and other real-time traffic data sharing facilities.[7]AI-based traffic signal control has been widely studied in the literature because it plays a major role in reducing traffic congestion and greener mobility. Within the smarter and greener urban mobility era, traffic signal control systems will be facing different and new challenges due to the upcoming revolution in the urban mobility models. This challenge is mostly due to the more efficiency and capacity of traffic light intersection that will be required in presence of autonomous vehicles, which are expected to completely take part of the vehicle traffic in cities within the next decades. The paper outlines a possible line of future research, and suggestions are given for the effective implementation of AI-based management strategies of dynamic traffic signal

control systems for AV navigation. AI tools and algorithms have supported all the decisions needed for traffic management, in particular when intelligent vehicles are involved. The automated and dynamically adaptive traffic light adaptation is indeed a crucial piece of technology in shaping a safer and more effective urban mobility.

6. Challenges and Future Directions

Previously developed literature and surveys cited in the introduction section could only contribute a small portion of the potential recommendations that a detailed paper could offer, explore and justify [13]. This extended work is unique and detailed as it presents the current technical barriers, their correlations and potential technical solutions. The idea of phasing out of the rule-based controllers and traffic light phasing algorithms have already been working on in many parts of the advanced world (Huang et al., 2012; Liang et al., 2018). The dynamic-DVAL and CFP-AAP based TSCS will take the competition to the next level. This is a large market considering the fact that due to the ongoing R&D upgrading traffic signals to AI-based can be difficulties, however, these updates are very crucial given the current scenario of emerging AV and CAV (Hunter, 2019) [19].

Advent of emerging market of connected and autonomous vehicles has led to the replacement of conventional rule-based traffic signal control systems with AI-based advanced traffic signal control systems (TSCS) predicted to offer greater efficiency over infrastructure-based traffic control systems as they enable dynamic re-configuration for cooperative autonomous and connected vehicular traffic (Kyriakidis and Foerster, 2017) [1]. AI-based TSCS are still in a development phase and are struggling with numerous technical and practical challenges at different levels that makes it challenge driver challenge in getting its market share in the domain of TSCS. This paper outlines the challenges and future directions AI-based TSCS for autonomous vehicle (AV) navigation which is based on long-term plans of offering better TSCS to the market.

6.1. Technical Challenges

To adopt a system with full autonomy effectively, however, there is a strong need to consider a coexistence of human-driven vehicles and autonomous vehicles. To prevent a transition to an ordered system when neither human— nor machine-driven vehicles at all intersect—an emergency mode that allows human intervention can be considered. A dynamic selection of routes may also be used to keep autonomous systems from not being navigable to their destinations.

For safe and efficient autonomous vehicle navigation, AI-based virtual traffic lights can be applied to manage traffic. As conventional traffic signals do not address changing conditions of road networks as do traffic signal optimization technology, virtual traffic lights maintain a dynamic dispatching of intersections. Virtual traffic lights can improve the performance of disjunctive normal form (DNF) traffic control strategies, used to reduce accidents and achieve minimal waiting times. DNF traffic control schemes compete with one another, and the most urgent strategies are enforced by virtual traffic lights in this work. DNF strategy selection biases can be adjusted to consider driver experience.

Various autonomous vehicle-related applications pose additional technical challenges, including traffic signal regulations for dynamic navigation of autonomous vehicles. These challenges can be solved using artificial intelligence. This AI-based multi-agent solutions can be used for dynamic route control, navigation, and dynamic traffic signal control. Consequently, the focus of existing research on intersection management solutions aligns with these problems [1], [20], [21].

6.2. Regulatory and Policy Considerations

The simplest policy to guarantee the emergency vehicle their right of way is to build a vehicle-specific policy that overrides any and all other policies. To ensure that the emergency vehicle has a safe passage through the intersection, it must come to a complete stop or reduce its speed as it approaches the intersection and uses its light and siren to inform other vehicles of its presence. Implementing these policy formulations will not be trivial as many traffic lights get their primary time values based on predicting timed require- ments of vehicles at an intersection, and these values are then deployed. It is pointed out in (Liu et al. 2019), that many of the above approaches can be easily adapted to multi-agent scenarios. Moreover, training RL agents to prioritize EMVs over normal vehicles for emergency vehicle signalization and passage is also considered a viable approach.

[22] The goals and requirements for EMVs (‘conventional vehicles’, inclusive of both Autonomous and legacy) are realised through real-time signal phasing decisions made at an urban intersection. The primary reasons (a) air pollution, (b) fuel consumption, (c) delays, and

(d) accidents are correlated to sub-optimal signal phasing of the Intersections which accommodate these type of vehicles. Avenues such as deep reinforcement learning, heuristics based optimisation and data driven models have traditionally been employed and evaluated for the purposes of signal control. Multiagent systems have demonstrated their relevance and importance in competing for the shared infrastructure, resources and incentives to achieve improved performance.

References:

1. [1] J. Wang, X. Guo, and X. Yang, "Efficient and Safe Strategies for Intersection Management: A Review," 2021. ncbi.nlm.nih.gov
2. [2] C. Englund, E. Erdal Aksoy, F. Alonso-Fernandez, M. Daniel Cooney et al., "AI perspectives in Smart Cities and Communities to enable road vehicle automation and smart traffic control," 2021. [PDF]
3. [3] A. Mushtaq, I. ul Haq, M. Azeem Sarwar, A. Khan et al., "Traffic Management of Autonomous Vehicles using Policy Based Deep Reinforcement Learning and Intelligent Routing," 2022. [PDF]
4. [4] S. Maadi, S. Stein, J. Hong, and R. Murray-Smith, "Real-Time Adaptive Traffic Signal Control in a Connected and Automated Vehicle Environment: Optimisation of Signal Planning with Reinforcement Learning under Vehicle Speed Guidance," 2022. ncbi.nlm.nih.gov
5. [5] S. Park, E. Han, S. Park, H. Jeong et al., "Deep Q-network-based traffic signal control models," 2021. ncbi.nlm.nih.gov
6. Shaik, Mahammad, et al. "Enhancing User Privacy in Decentralized Identity Management: A Comparative Analysis of Zero-Knowledge Proofs and Anonymization Techniques on Blockchain Infrastructures." *Journal of Science & Technology*1.1 (2020): 193-218.
7. Tatineni, Sumanth. "Enhancing Fraud Detection in Financial Transactions using Machine Learning and Blockchain." *International Journal of Information Technology and Management Information Systems (IJITMIS)* 11.1 (2020): 8-15.

8. Vemori, Vamsi. "Evolutionary Landscape of Battery Technology and its Impact on Smart Traffic Management Systems for Electric Vehicles in Urban Environments: A Critical Analysis." *Advances in Deep Learning Techniques* 1.1 (2021): 23-57.
9. Tatineni, Sumanth. "Deep Learning for Natural Language Processing in Low-Resource Languages." *International Journal of Advanced Research in Engineering and Technology (IJARET)* 11.5 (2020): 1301-1311.
10. [10] H. C. Hu, S. F. Smith, and R. Goldstein, "Cooperative Schedule-Driven Intersection Control with Connected and Autonomous Vehicles," 2019. [PDF]
11. [11] H. Wei, G. Zheng, V. Gayah, and Z. Li, "A Survey on Traffic Signal Control Methods," 2019. [PDF]
12. [12] M. Korecki, "Adaptability and sustainability of machine learning approaches to traffic signal control," 2022. ncbi.nlm.nih.gov
13. [13] D. Zhu, Q. Bu, Z. Zhu, Y. Zhang et al., "Advancing autonomy through lifelong learning: a survey of autonomous intelligent systems," 2024. ncbi.nlm.nih.gov
14. [14] D. Garikapati and S. Sudhir Shetiya, "Autonomous Vehicles: Evolution of Artificial Intelligence and Learning Algorithms," 2024. [PDF]
15. [15] V. Ravi Kumar, "Surround-View Cameras based Holistic Visual Perception for Automated Driving," 2022. [PDF]
16. [16] S. Paiva, M. Abdul Ahad, G. Tripathi, N. Feroz et al., "Enabling Technologies for Urban Smart Mobility: Recent Trends, Opportunities and Challenges," 2021. ncbi.nlm.nih.gov
17. [17] M. Javad Shafiee, A. Jeddi, A. Nazemi, P. Fieguth et al., "Deep Neural Network Perception Models and Robust Autonomous Driving Systems," 2020. [PDF]
18. [18] Y. Shi, Y. Liu, Y. Qi, and Q. Han, "A Control Method with Reinforcement Learning for Urban Un-Signalized Intersection in Hybrid Traffic Environment," 2022. ncbi.nlm.nih.gov
19. [19] H. Yan, "Vehicle Safety-Assisted Driving Technology Based on Computer Artificial Intelligence Environment," 2022. ncbi.nlm.nih.gov
20. [20] S. Sarker, "Analyzing Behaviors of Mixed Traffic via Reinforcement Learning at Unsignalized Intersections," 2023. [PDF]
21. [21] M. Wäschle, F. Thaler, A. Berres, F. Pölzlbauer et al., "A review on AI Safety in highly automated driving," 2022. ncbi.nlm.nih.gov

22. [22] L. Parada, E. Candela, L. Marques, and P. Angeloudis, "Safe and Efficient Manoeuvring for Emergency Vehicles in Autonomous Traffic using Multi-Agent Proximal Policy Optimisation," 2022. [PDF]