AI-Driven Systems for Autonomous Vehicle Traffic Flow Optimization and Control

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1. Introduction

A key challenge is expected to be the management of road congestion and traffic control [1]. The introduction of cooperative automation in mobility calls for new solution concepts for traffic management in cities, for which we present an Artificial Intelligence (AI) concept with the collective decision-making and optimization paradigm based on mediated and autonomous intelligent traffic control (MAITC) for traffic system-of-systems (TSS). As mobility can no longer only be seen as a technical act but as a complex socio-technical act with long-term interactions, AI needs to be seen and implemented from multiple perspectives, mirroring the adaptivity of human driving and traffic approaches. The inherently non-centralized configuration, and the richness and heterogeneity of each participant's data set, allows the MAITC approach to assess the traffic system both from individual and collective system-of-systems perspectives. The concept has the potential to be incorporated into existing traffic systems and be linked to urban and city facilities.

Automotive vehicles and traffic management [2] have during the last few decades been developing systems which reduce the need for human driving assistance, and the automotive sector is approaching a serious move from traditional mechanistic automotive design to intelligence-embedded machine automation [3]. This development will potentially revolutionize the industry and world-wide interconnected road mobility in several different ways.

1.1. Background and Significance

The everyday use of human-driven vehicles is contributing to urban problems like traffic congestion, accidents, and higher emissions. Meanwhile, the increased vehicle penetration in developing nations like China, India, and Brazil is only making the matters worse. A realistic long-term vision to alleviate these problems in the future could be to integrate fully-autonomous (driverless) vehicles with new and upgraded road infrastructure. In the interim, however, vehicles with different levels of vehicle automation are likely to interact with humans in shared driving environments, almost ensuring part-automated vehicles to avoid slowness and rudeness. More likely, as the penetration rate of part-automated vehicles will increase gradually in coming years, so will the problem of mixed traffic flow in our roads. The issue of mixed-traffic flow control in the transitioning period when vehicles with different automation levels coexists is identified as significant research [4]. Transportation experts often consider intersections as 'hot spots' on road networks where many traffic system performance measures make it challenging to operate and control efficiently. This seems right because the congestion is mainly generated from the intersections. To address the inefficient intersection management problems in existing as well as future transportation systems, a new cooperative approach to intersection management is proposed. This new mechanism is based on the idea of creating virtual traffic lights for managing competing traffic flows approaching an intersection area. It is based on V2V and V2I connected vehicles management. The presented mechanism employs the concepts of queues and pre-signals for slowing down different flows for saving overall waiting time. The algorithm claims to improve the safety and efficiency of the intersection by adding communication, coordination, and autonomous decision-making to save the overall waiting time up to 87% [5]. A scheduling algorithm was designed for the cooperative approach and av replica, VPP (Virtual Pre-signal Point) was realized as the decision-making unit at the front of the intersection. Experiments were performed in three different intersection settings to validate system performance. The results illustrate that the shortage of the roads and the irregularity of traffic demand caused irregular updating if a certain standard value is reached. Lives were at risk if the degradation continued. Vehicles should be assembled into groups to give way to protect the intersection safety under such circumstances. The intersection system presented in this study could be used not only in the situation when the system could not release the next vehicle as regularly as usual, but also when crossing the intersection when their regular stops could not form a gap at the next intersection [6].

1.2. Research Objectives

This research aims to develop and implement AI-driven traffic flow optimization and control techniques to manage the traffic flow on the networks with a high percentage of AVs. The project will study the traffic flow in a mixed traffic environment, i.e., the presence of Automated Vehicles (AVs) and non-AVs, which are assumed to drive with humanlike behaviors. More specifically, two main scenarios can be considered in this project. In the first scenario, the project will investigate automated control systems that can be employed to advise a driver of a non-AV to drive optimally. That is, in this case it can be assumed that all the AVs in the network (and the infrastructure) communicate their behaviors to the traffic management system, which processes the data and sends accurate feedback to guide driver. In the second scenario, which will be considered in the second task, volunteers will drive controlled vehicles and the fleet management system will operate and monitor all the non AVs (this scenario can be named as the case of semi-automated traffic fleet). In each sub-task, control systems are implemented without human intervention and considering fully autonomous driving, corresponding to the two end-figures of the fleet management applications.[7] Specifically, this research investigates "wheel" traffic flow, the case of ACCE, and cooperative automated driver assistance systems to reduce traffic energy consumptions and travel times. Unlike existing works, the proposed work consider Stochastic Heterogeneous wHeel Traffic Energy Consumption, specially in the context of Conventional and HEVs driving under a cooperative automation policy, in which the latter is linked among all vehicular network using Dedicated Short Range Communication (DSRC) devices. By experiencing homogeneous and partially-heterogeneous traffic conditions in a variety of traffic scenarios under different aspects of control design such as attractor-basin protocols, Adaptive CRoSS state Averaging control, and Adaptive-Frequency-Admittance Tuning of Overtaking Links, this study can contribute to the Traffic Engineering domain by demonstrating the fact that equilibrium speed and energy are lower as compared to CERTS states in the presence of ACCES.

2. Fundamentals of Autonomous Vehicles

The system hardware and software of matrix transformation of the prototype platform car are developed according to the above-mentioned technology. This platform car is selected as the main experimental vehicle in the subsequent experiments. The prototype platform car environment perception system is embedded with a high-performance microprocessor of the Davinci series from Texas Instrument and new software architecture based on real-time operating systems. The G70 series multimedia processors provide strong support in satisfying the GBA and H.264 decoders, Virtual Machine Monitor (VMM) hyperlink, EarMark link optimization, and other features of car rear-view order-of-magnitude difficulty, solutions include scene capture optimization techniques, partition separated PCIe toolbox, and standard Linux technique-based drive reference. These improvements help to speed up the virtualization business and reduce the unavailable time. The high reliability of the B/S architecture network software service of the platform car is achieved. The condition improves to commercial accuracy. In the rubber-consuming test, the new Scene Framework, frame-by-frame detection and optimization techniques improve the object detection speed, reduce the 'sticking' phenomenon, and achieve better integrity during off-line and line scenarios [1].

[8] [9] This section introduces the fundamentals of Autonomous Vehicles (AVs). A general structure of the driverless vehicle framework consists of an environment perception system, a planning decision tree system, and a motion control system. The autonomous driving system fundamentally depends on car navigation and positioning technology which performs the function of locating the vehicle and planning its driving route. The accuracy and stability of these two core underlying technologies is critical for promoting the reliability of the driverless vehicle running in various complicated road environments. In recent years, some researchers on autonomous driving have used sensor fusion technology with Kalman filtering to integrate electromagnetic navigation and some simultaneous localization mapping (SLAM) algorithms for integrated navigation in the car navigation system.

2.1. Definition and Types of Autonomous Vehicles

Autonomous vehicles are considered from the perspective of their autonomy and the existence of communication infrastructure [10]. These vehicles can be divided into three categories of individual autonomous vehicles, Automated Vehicles (AVs), and Connected and Autonomous Vehicles (CAVs). These three differ in terms of information sharing and autonomy. Individual AVs control themselves and do not communicate with each other or the infrastructure, while CAVs use V2V, V2I, and V2X technologies to communicate with each other and the infrastructure, and at the same time rely on their capabilities for control. Connected vehicles share their position and speed information with other connected vehicles by using V2V, and they share this information with the infrastructure by using V2I. Though

Connected Vehicles (CVs) can exchange information with each other and the infrastructure, they are still mainly controlled by human drivers.

Autonomous vehicles, also known as self-driving cars, are transport vehicles driven by an automated system. They consist of several devices that provide information about the state of the vehicle, such as cameras and sensors, and can then control the vehicle with actuators. Full autonomous vehicles do not need human intervention, however, manual control of the vehicle is usually disabled in semi-autonomous vehicles, while higher automated vehicles can control the vehicle with the support of the driver. In more advanced cases, providing information from vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-X (V2X) is also possible [11]. SAE International defines six levels for automated vehicles starting with level 0 for conventional vehicles which each consecutive level corresponds to a higher level of automation with level 5 being a completely autonomous vehicle.

2.2. Sensing and Perception Technologies

Perception is an essential part of the intelligent transportation system (ITS) [12]. In the environment where the human being is in charge of the driving, the perception comes from human eyes, human ears, human nose, human skin, human brain, human decision-making, etc. Under the framework of AI, each of these tasks will be replaced by a system module (e.g. taking over the function of human eyes), and the purpose is to make the autonomous driving system emulate the human driver. The core character of this type of work is the use of machine learning techniques to accurately identify important target information from minute information. Its process includes multiple modules. When sensing the environment, the vehicle generally acquires environmental information through various sensors, and then through the target identification, the AI system makes a judgment and formulates a response policy towards the identified target.

The sensing and perception technologies are critical for the autonomous driving system. The main function of the perception module in an autonomous vehicle is to collect information about the outside world and make decisions about the surroundings, including such subsystems as environment recognition, mapping, localization, control, and motion decision, for clear autonomous decision making [13]. The perception of the autonomous driving system is realized through the continuous sensing of the surrounding environment by sensors such as LiDAR, camera, millimeter wave radar, GPS, IMU, ultrasonic radar, etc. All sensors are managed and controlled by a centralized controller (CC), as shown in Figure 1 [14]. In terms of architecture, the sensing and perception system, like the CDT (Environment Perception) and the DRCS (decision) are part of the AI backbone, where sensing, decision-making and other sub-modules are connected by a communication protocol.

3. Artificial Intelligence in Autonomous Vehicles

As shown by the above-mentioned historical evolution of driving policy models and the current AI workshop, the evolution of the prototypes of the above-mentioned driving policy models has been tested with the theory of stable spiral equilibria in mutually bonding driving, changing perception model ideas and theoretical theory of adaptivity to different operating conditions [15]. The main current research trends are: In the rebound-control-based lane change maneuver solution, artificial intelligence (AI) research (see, for example, Hinterseer et al. 2019 reads Schulze and Flemisch (2021)) supported by machine learning and reinforcement learning. The machine learning is an area, which provides the measures and possibilities for modeling, detection and prediction system performances, making it a crucial approach in the scope of AI within the context of today's software development. The PointNet segmentation network model is part of the point cloud feature learning explained in Qi et al. (2017).

· Recently, manoeuvre-based inference and control are trending; fortunately, supervised learning strategies focus on comfortable and safe driver-adaptive, smooth, and comfort-oriented motion. This paper distinguishes that ADS reactive control is naturally model-based due to the consistent interplay of the ADS and simulated human behaviors. In the last part, the paper didn’t provide a detailed discussion but identified the challenges in the safety validation of AI-powered ADSs, and the self-driving and highly automated driving levels are trending directions [16].

Due to the combination of artificial intelligence (AI), the internet of things (IoT), and fifth-generation (5G) communications, the automotive industry is in a challenging space of disruption [14]. This paper provides a comprehensive review including AI-powered ADS (advanced driver-assistance systems) inference, control, and safety validation in the context of the SAE International six levels of driving automation. ADS control includes the description of low-level adaptive cruise control (ACC) using Reinforcement Learning (RL) and imitation learning strategies, together with the description of mid-level lane keeping and lane change maneuvers using a model-free imitation learning algorithm. Finally, the research role and current progress in safety validation of AI-powered ADS are described.

3.1. Machine Learning Algorithms for Autonomous Driving

Simultaneously, in autonomous driving, the computer vision systems and traditional machine learning models will always have some respective limitations. The system capacity needs to be obtained, parallelism and real-time requirements can also be challenging. The utilization of a large amount of car accidents data is now known to be able to be used in the automotive design domain system instead of typical passive vehicles and road cameras. This can be effective for enhanced control of a vehicle motion analysis as active vehicle traffic can be considerably increased in current scenarios like machineries on a road. Also, adding a neural network to the Embedded part of the AI can be done for both preventing high concentration and congestion due to data retrieving/paper collisions and also handling a huge amount of simultaneous objects in a traffic flow. There are possible neural networks algorithms that are able to simultaneously address paths for evasion, and learning the distribution of the objects for planning in a garbage compartment routing and it is suggested that this PNG network can be an interesting potential candidate for future research for level 3-4 of autonomous driving. Also, there exists a need to make hard decision planes more separable, while allowing to condense easily and also increase the reaction time and width of the decision planes of the neural network [17].

In recent years, vision-based neural networks have become popular for perception in autonomous driving as they best interprets raw sensory data and provide detection, recognition and tracking of road agents in real time. Current focus is on GPUs to fit such networks to deploy on different types of sensors and different embedded controllers required for autonomous driving. The larger environment is tackled by a reinforcement learning (RL)-based approach, particularly kernel-based reinforcement learning (KBRL) technique, that is even more computationally efficient compared to classical RL [18]. Once the agent finds itself around a local minimum in the environment, this RL policy serves as a local reference. This technique is specifically focused around optimising some traffic scenario rather than lane-following task or any task in the environment with well-specified driving rules [19]. This work utilises a simple form of KBRL again using some statistical measures from poles tracking of a protected intersection. The joint probability distribution of any particular state-action pair provides with the exact KBRL policy. The upper large-scale simulator, the stochastic fluids trajectory generation algorithms used to realistically generate the intersection dynamics and the intersection-level KBRL policy joins these two components. This AI for traffic is observed to practically reduce traffic capacity at the intersection and produce a smoother flow and lower delays.

3.2. Deep Learning Applications in Autonomous Vehicles

The architecture of CNN is usually a pyramid, therefore it can extract image features in parallel. LSTM can effectively process moving objects at different speeds, similar to the process of the human visual system. RBM belongs to the category of unsupervised learning and is used in the field of autonomous driving for new event alerting of front vehicles. It can minimize data redundancy. Autoencoder can be used to batch process the data of the existing autonomous vehicle data set and alleviate the problem of data scarcity for autonomous driving. DCGAN is based on CNN but focuses on expressiveness and memory and can be used for stereo visual SLAM map creation. SAE is able to reflect the information interaction in different levels. ANN can perform the regression task by learning the behavior of a driver in a specific task. It has a dynamic online learning ability and can extract optimal continuous features, which is suitable to be used in a maneuver recognition system for autonomous vehicles. Each layer in a CNN has a specific enhancement in extracting visual features. The input data into the CNN are the camera images of autonomous vehicles. [9] For a traffic merging environment, the responsibility of predicting the routes of the merging vehicles is conducted by GRU with data from various vehicle sensors to construct the input data structure for the deep Q learning algorithm. The multi-sensor data fusion model combines the input data from the features extracted by these deep learning algorithms to shared layers, so that the autonomous vehicle can identify the surrounding traffic environment more comprehensively. The above algorithms are all used in the training phase of decision-making, trajectory planning and motion control functions. In addition, they are all mature algorithms and have been used by many teams around the world. In the navigation function of the M100 Smart car, the Internet of Vehicles (IoV) and V2X communication are used together to predict the intersection state of the traffic light and to calculate the corresponding trajectory decision in one block. To enhance the maximum sustainable throughput of automated vehicles and reduce the time-related aggregated delays of individual locally based adaptive cruise control (ACC) systems.

[20] [21] Deep learning (DL) is one of the most important and popular techniques in AI-driven technology for autonomous vehicle development. InThe CNN architecture is widely used in the field of visual perception and is used in autonomous vehicles, for example in object detection and recognition. The LSTM long and short-term memory architecture is able to process the temporal information from historical data and predict the future. The DenseNet consists of dense blocks and transition blocks and can be used to reduce the number of parameters. For multi-sensor fusion or sensor interference reduction in autonomous vehicles, the authors commonly deploy GAN algorithms or ReLU functions to preprocess the feature image extracted by the CNN algorithm, which improve the signal-to-noise ratio of data from different sensors and lay a foundation for later perception and prediction modules.

4. Traffic Flow Optimization

They can also communicate their route plots and current locations to higher levels of traffic regulation, such as road intersections. An AI-based intersection optimization control systems using connected vehicles can address problems caused by the current decentralized traffic signal control, such as ad hoc decisions that fail to solve the traffic congestion at intersections (Han and Zeng, 2010). In this paper, we present an AI model for advanced traffic light operation with the aid of AI autonomous driving-connected vehicles. This approach is used to address the traffic light control problem, with the ultimate aim of promoting an eco-friendly optimal solution to prevent negative impacts on the environment (Zaidi et al., 2016; Chen et al., 2018). Here we propose a novel system to support eco-friendly drivers: ARS with FOMAS (Tanmoy Maity Dibyendu Gorai and Nandlal Sahu et al, 2021).

Street management systems rely on various subcomponents (Pylar and Angarita, 2019). This includes real-time traffic light operation, predicting travel time and providing alternative routes based on congestion predictions and adapting to network state road traffic signals (Acosta et al. 2018; Garcia et al.2020, 2020) and promoting traffic flow optimization using smart traffic light systems deployed on roads (Odelbo et al. 2017). One potential use case to address the described problem of road traffic systems is autonomous connected vehicles (ACVs) (Mitseva et al. 2018;; Baranov, K. et al., 2021). The vehicles can act as moving sensors and could be taught to value traffic flow optimization according to the parameters of traffic congestion, travel time and fuel consumption (Wu, Ding, Feng, Ding & Wang, 2021). Moreover, they possess artificial intelligence (AI) algorithms that can use this information to set the best speed for the vehicles and adapt themselves to any potential stretching agent in the network (Chen et al., 2020; Tanmoy Maity Dibyendu Gorai Aritra Chatterjee Swarup Singh, 2021) so that a better traffic flow is achieved.

4.1. Traditional Traffic Control Systems

One of the main downsides of these adaptive signal control methods is their difficulty in scaling and extending the control to a large area. To respond to the problem of urban traffic congestion, much attention has been paid to improving traffic signal control methods with both connected vehicles and autonomous vehicles. Autonomous vehicles usually cover two basic ability levels: level 2, where vehicle deceleration and steering control are not required, and level 3, where the driving system manages the entire driving tasks if the driver does not intervene [22]. To make these vehicles more common, a more convenient and safe traffic signal should be able to work well. In addition, the signal of the intersection faced with the vehicles should be able to manage both the mixed traffic flow and the connected or autonomous vehicles. If the requirements of the intersection cannot be met, the safety and efficiency of the traffic signal control system will be reduced. By seeing the first two columns, it can be suggested that motivated by urban traffic congestion and the improvement of traffic signal control due to the extensive discussions of cooperative autonomous vehicles and connected vehicles, some reviews further emphasize the connection and autonomous leadership approach.

Traditional traffic control systems can be classified into three types: fixed timing, actuated, and adaptive. Fixed timing traffic signal controllers are usually used at low-density locations and make decisions on traffic signal control independently of dynamic traffic conditions. Actuated traffic signal controllers become widespread in practice due to their ability to better adapt to dynamic traffic conditions and make control decisions based on both real-time and predicted traffic demand [23]. Adaptive signal control systems are algorithm-activated and monitor traffic in dynamic conditions to optimize traffic flow in a real-time manner by continuously adjusting the cycle length, phase durations, and signal settings in an attempt to maximize travel time of vehicles in the network. However, in general, adaptive traffic signal control is generally conducted within a local scope and seldom considers how the traffic signals at different intersections are interrelated. Even though these schemes optimize the control in their own parts, there might be some factors which have negative impacts on the overall performance of the network [24].

4.2. AI-Driven Traffic Control Strategies

Heterogeneous vehicle traffic flow is a complex system with different types of vehicles, including autonomous vehicles. AI-driven path-planning and speed control of autonomous vehicles are considered in. Traffic flow stability in a well-controlled road traffic network should be robust in the presence of uncontrollable perturbations such as initial fluctuations. Traffic flow stability is studied in [25] in mixed lane traffic. In particular, we discuss control strategies for mixed movements and the impact of lane-changing rules. Results by computational experiments demonstrate the effectiveness of the control strategies. The results demonstrate that fixed-time control is only applicable to the integer lane algorithm. Our current model also only considers the scenario of the same road. Future work should extend the heterogeneous flow model to different branches. The dynamics of the flow controlled by the integer lane algorithm will also be our next focus.

Game theory is an effective way to model and solve non-cooperative situations by considering the conflicts of interest among participants. As an important traffic control parameter, vehicle speed can greatly influence traffic flow stability. By modeling the dynamic interaction of multiple vehicle entities that are competing for road resources and designing a suitable vehicle behavior selection mechanism in a smart traffic control system, it is possible to control the speed of vehicles in the system and optimize traffic flow [26]. In particular, control strategies for autonomous vehicles in smart traffic control systems based on game theory are a current research focus. In general, AI-driven traffic control strategies include network-informed traffic speed control, deep reinforcement learning for traffic speed control based on vehicle to vehicle (V2V) communications, deep transfer reinforcement learning traffic speed control, and traffic flow stability analysis.

5. Challenges and Opportunities

The capital of data if it is to be useful and the privacy preservation requirements associated with both data collection and release represent one of the most relevant challenges. Required communications and cooperation are increasing and, by maximizing the use of V2X, regulators are anticipating their benefits and proposing standard communications to help further build this future. Surrogate models are applied to preserve user privacy, but users reveal suffi- cient information about the environment for surrogates to work with enough quality to access traffic flow. Moreover, given the sensitive nature of XII, the communicational infrastructure will be subject to individualistic and coordinated DoS attacks. From a general point of view, the trust and transparency of the systems and autonomy of the vehicle simulation is essential to guarantee security, privacy, solidarity and social trust [3].

The design of AI-driven systems for AV traffic flow optimization and control in mixed traffic scenarios presents several challenges. Vehicle-to-everything (V2X) interactions need to be designed to optimize traffic flow and vehicle energy consumption at the highest level [27]. Low levels of infrastructure development and peer-to-peer vehicle autonomy imply that multiple layers of interactions and cooperation between vehicles are needed to maintain coordinated fluid traffic. AVs must also assess their energetic requirements and settle with reduced power macroscopic vehicle actuation to achieve infrastructure sustainability and unobtrusive interactions among human drivers-adjustable traffic signals, pedestrian detection, and road-condition prediction are all examples of how AVs can enhance traffic flow in a way that accommodates human driver needs while relying only on the raw conventional traffic control [28].

5.1. Ethical and Legal Implications

At this stage, AI developers require achievable, accessible, and understandable ethical guidelines to help them make informed decisions about the ethical implications of their AI application. For developers and AI decision makers in particular, ethical AI framework offer explicit instructions for trustworthy AI behavior within formal governance structures. While the framework leans heavily on Responsible AI (RAI) principles such as transparency, fairness, accountability, the ethical AI aspect is concerned with the more subtle ethical judgment about the behavior of autonomous AI systems. Addressing and correcting biases in data, algorithms, labels, and testing datasets is a difficult legal challenge for AVs and an obstacle for them to overcome to achieve real-world deployment. Therefore, to address this issue some engineering involved with the preparation, observation, and authentication of the data sets and of the system is needed, completed with reflect plan to resolve problems that occasionally to settle on future ifo behavior. Addressing the racial environment influence input or decision is becoming a legal issue for AV developers and AI scientists to assure behavior in extreme conditions and improve safety of beacons to level that does not have ethical concern, in which all legal and socially important answers about insurances, liabilities, and obligations may differ. While in the AI development and validation phase, vulnerability detection and correction is preferred, striking the appropriate balance is a significant legal challenge for AV nodes and a road to reaching barricade deployment in actual surroundings [29].

It is necessary to address the ethical, legal, and privacy implications associated with AI-driven AVTFOC systems [30]. AVTFOC systems that are driven by AI contain web-enabled and interconnected smart devices. AI-based ITS are expected to potentially support the development of Smart Cities, which are governed by a sustainable mobility vision [3]. As a result, these AI-driven systems will underpin several economic activities and societal services, and therefore their failings or misuse might have grave legal or ethical implications. For example, in France, numerous car manufacturers have tested cars with self-driving capabilities at the Centre d'Expérimentation et de Recherche des Industries de l'Automobile, and testing is set to continue in ESEO's French headquarters in Angers, and in numerous locations across Europe. These cohorts are being investigated by experts from EPITA's Laboratory of Electronics, Computer Science and Image in collaboration with Omron, a driverless vehicle guidance system supplier interested in AI-based an intelligent transportation system, with the aim of using AI in novel ways to assign paths and optimize vehicle traffic.

5.2. Future Directions in AI-Driven Traffic Management

Furthermore, when automating a network involving vehicles of different levels of automation, it will be useful to have traffic modelling approaches to correctly capture the dynamics of both human-driven and automated cars. Finally, when it will be possible to reach a situation where all road users are totally automated, the problem of traffic flow control can be seen as an optimization problem, where the optimization criterion, for instance, could be minimizing the travel times.

[3] The use of Artificial Intelligence (AI) for improving traffic management is significantly increasing. Recently, numerous AI-driven solutions have been proposed for advancing the state of the art for vehicle automation and traffic management [31]. This is achieved by operating and managing the Traffic Information System under an AI-based approach or by

introducing AI-driven automated management and decision-support systems and techniques for traffic regulation overall. AI solutions focus on addressing traffic flow optimization and propagation of traffic jams on urban networks, and it is being used to detect and attribute vehicle data, derive traffic information, predict traffic flows and detect/analyze traffic anomalies. Moreover, traffic prediction, trajectory forecasting and pattern recognition are three specific and relevant topics in driving data-processing and, more generally, in the telematic context. Various platforms are being developed to support travellers or traffic managers by using AI to decide about travelling behaviour, including road path planning for autonomous vehicles and traffic light control systems to support traffic flow on a selected network or at a single junction. A few AI systems are also able to forecast vehicle road paths for autonomous vehicles in urban network pedestrian conditions. The potential future directions of AI for autonomous vehicle traffic flow optimization and control are described, focusing on six major issues: AI-aided traffic micro-management, AI-empowered optimally connected automated mobility vehicles in dense urban environments,AI-powered demand-sensitive vehicle routing algorithms, state transition processes in AI-driven cell transmission model, AI-empowered traffic signal optimization with advanced urban consolidation strategies, and A new AI-empowered traffic management ontology to arrange a collective traffic standard.

6. Case Studies and Applications

A VANET-based Adaptive and Intelligent traffic management system (Smart ITM) for smart cities was presented. Ornate facilities to dynamically control traffic signal based on environmental, time, and road conditions were implemented using real-world sensors and collected data to expand a traffic management system. Implementation details of a variety of wireless communication protocols, such as a 3G based GPRS module for the central server, as well as IEEE 802.11p and IEEE 802.15.4 based WAVE module for traffic signals to ensure real-time data transmission, were given in this paper simulations behavior of all components, presence and absence of fire and accidents on road, inclement weather, and increased traffic were discussed. Data based on these simulated factors was collected, managed, and processed by IoT, and the results such as emergency vehicles being prioritized, traffic density being optimized, etc. in Smart City were observed, confirming the validity of deploying IoT devices in bright intersections [32].

An AI system for real-time optimization of grade-separated road intersections was created, using reinforcement learning with historical data [18]. The design of a model-based controller that considers learning from limited real-world vehicle platooning data was summarized. The AI architecture, as well as the simulations and optimization results, showed that the system efficiently controls vehicle platoons and simultaneously enhances fuel efficiency by 3.13%. Forecasting enabled by an AI-driven early warning system was discussed in the context of vehicle dynamics and slippery roads. An autonomous intelligent traffic management (ITM) system was proposed that intelligently predicts the duration for which the traffic signal should be green/red.

6.1. Real-World Implementations of AI in Traffic Control

Traffic signalized intersections are widely used in cities to direct vehicle and pedestrian movements. The traffic network requires a reliable and efficient signal control system to maintain smooth traffic flow. The control of the whole traffic network is split in a collection of local controls applied at each intersection with the objective to minimize the time and fuel consumption. Intelligent transportation systems (ITS) can provide better coordination mechanism between intersections, thus improving traffic efficacy. Traditional traffic controls adopt fixed programming sequence of green durations which yield to pollute the environment and degrade traffic fluidity. Traffic adaptative signal control (TASC) in the last two decades efficiently gain some advantages regarding the traffic flow, and thus reduces congestion in cities. Despite traffic signal controls can result in partial improvements in modern urban traffic, even with best and optimal traffic signal timings, still congestion is prevalent in most cities. Among several improvements, recent advancements of reinforcement learning and genetic algorithms (GAs) concepts can be an effective means for the betterment of traffic flow. There is an ease of controlling and learning about traffic systems using reinforcement learning agents and to locate the actual solution through GAs which makes traffic control adaptive and theoretically optimal [33]. Intelligent transportation systems (ITS) aim at enabling states, cities, and governments to improve road transportation while increasing air quality, saving energy, and ensuring road safety. Investigations based on assessment of road congestion indicate that a large part of energy consumption of transportation systems is due to the idleness of vehicles stuck in congestions and at signalized junctions. Thanks to the availability of big data, recent studies emerged in which intelligent agents for solving traffic flow optimization problems have been developed and tested on realistic scenarios. Although, for the needed of completeness, the development of specific formal model or information ecosistems can optimize the traffic even more. Traffic congestion, time waiting on road, time wasted until one travels from his origin to destinaiton is greatly minimized using the smart traffic light system. However, most of the previous related studies are done in specific geographic locations or simulations. Thus, they're neither optimized on general real scene nor tested in enough scenarios for different real environments. The experiments that are conducted in this study demonstrate that the proposed AI enhanced traffic optimization process is comparable or can even be better than corresponding non-enhanced optimizations. Severe congestion compared to minor congestion can affect the performance of the system, but it is not affected by real time constraints. Moreover, the Seattle traffic scenario it has been studied for is only one the many data sets of another dataset. A freely available synthetic data set generated by another open source simulator which can be considered as urban environment, developed and maintained by the Frankfurt Institute of Vehicles Systems and automotive technology. Systems can exploit extra time during which it is not busy with traffic to precompute a guess regarding the next signal plan to use as soon as a new request arrives after the buffer has been emptied [34].

7. Conclusion and Future Prospects

In future research, several optimization strategies can be applied together to achieve a more effective result regarding traffic flow. For instance, these systems can be coupled with big data and machine learning algorithms, to improve the safety and efficiency of future traffic flow in a network structure. The above suggestions indicate that for a given application one can choose from one of the considered scenarios or combine an ideal combination thereof to achieve the desired performance and satisfy the operational objectives of a given network. Additionally, other synchronization and pushing strategies dynamic road traffic with both connected and autonomous vehicles in multicellular scenarios can be developed. Nevertheless, the proposed strategies must be contrasted against these demands to refine and calibrate their model scenarios during real-world application and to improve if required their efficiency, especially in view of the operational environment and uncertainties that come with it [2].

[18] [27] This book chapter presents two AI-driven optimization and control strategies to enhance the safety and efficiency of future traffic management with traffic flow in a road area

shared by human-operated and autonomous vehicles considered. In the first decentralized autonomous vehicles control strategy, each autonomous vehicle makes its own decision of applying braking or acceleration control according to the sensed information. After that, the autonomous vehicles exchange their velocities in a V2V manner to avoid low flow oscillations. In addition, traffic lights are also optimized according to the fluctuating flow and stop-go waves at the intersections. In the second strategy, the traffic state detection, historical data learning, and the periodic or aperiodic real-time traffic control of autonomous vehicles and traffic lights at intersections are combined in a hierarchical manner for the road areas shared by human-operated and autonomous vehicles.

7.1. Summary of Key Findings

Local adaptation of the traffic light settings is realized through the application of advanced artificial intelligence methods (a standard module to produce optimal traffic junction signal phase scheduling plans has been constructed) [32]. The traffic phases plans were further adapted based on the traffic light subdomain log in real traffic observations being realized with the help of the infrastructure network chips/gateways installed in the traffic light 'lamps' placed in multiple different traffic light installations in the city area. A comprehensible model for real traffic light control system data localization process is developed as a neural image recognizing algorithm to measure parking lot usage. A demonstrated localization model for a parking lot space utilization method suggests the potential for predicting the local demand for public electric charging stations.

The development of requirements and proposals for the realization of autonomous vehicle traffic flow optimization and control with the help of artificial intelligence in cooperation with external intelligent transport systems (ITS) has been presented [3]. Results of the traffic flow traffic model adaptation with the transfer of real world observation data have been presented. Several detection and prediction methods in this area were devised and tested: models build on recurrent artificial neural networks (RNN—Long and Short-term Memory cells (LSTM Units)) as well as a mixture models. A theoretical model outperforming all other models in all practical measureable error characteristics is created. Additionally, incorporation of GPS, Bluetooth and WiFi as well as magnetometer data gathered in two different arrays and processed with real valued neural networks and clustering analysis was presented. More than 500 different signal phases were available per scenario in each situation. Individual traffic light controls can be adapted to autonomous traffic flow signals within microseconds at each car position if an instantaneous situation renders such reaction plausible.

7.2. Recommendations for Future Research

[6] From this work, several research directions have emerged, which could be part of the future research agenda. First, the intersection management problem with the introduction of active cues considered in this work, yet, similarly to related studies, entities such as pedestrians, cyclists and so forth have entirely been neglected. Thus, future efforts are warranted to address the problem with the inclusion of the Vulnerable Road Users (VRUs) of the transportation systems to develop a truly representative model. Furthermore, it's suggested to extend the problem space of AIM to larger systems, such as the urban road networks, where the objectives get more diverse and complex. Additionally, optimal scheduling and trajectory optimization are computationally highly demanding especially for a large number of vehicles and a broad study on managing real-time feasibility and scalability of the proposed frameworks is still open to future works.[4] The work has highlighted a number of key challenges and future research areas for AIM. Firstly, the limitations of agent-based approaches for producing globally optimal strategies. A potential fix could involve using an over-arching roadmap to guide agent strategies if we leverage information from a partially cooperative network. Secondly, the development of AV technology is of substantial importance to the success of AIM. Storage and computation cost are major limitations in practice which heavily limits pathway planning to offline simulation. Online generation of recommendations at scale (in constant time) with the ability to predict outcomes is crucial for the viability of the system. In addition, given that driver behaviour may change as a result of lighter (or perhaps almost non-existent) vehicle control, and the capacity for AVs to behave strategically, it's possible that we need to reconsider some of the current assumptions and characteristic modelling strategies .[35] The main focus of future work in this field should be on studying VRU behaviour in the presence of CAVs and developing strategies for sharing intersections with VRUs. Further, exploring coordinated routing and containment of CAVs in urban networks can research to a future research plan. Another avenue of future research is to develop domain adaptation methods for efficiently transferring learned criterion from one region of the city to other region. Additionally, AIM methods cannot be applicable to mixed traffic scenarios which include human driven vehicles. So developing AIM methods to handle mixed traffic CAV and Non-CAV Case is a challenging avenue for future research.

References:

1. [1] C. Wu, A. Kreidieh, K. Parvate, E. Vinitsky et al., "Flow: A Modular Learning Framework for Mixed Autonomy Traffic," 2017. [PDF]
2. [2] M. Vasirani and S. Ossowski, "A Market-Inspired Approach for Intersection Management in Urban Road Traffic Networks," 2014. [PDF]
3. [3] 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]
4. [4] Z. Qin, A. Ji, Z. Sun, G. Wu et al., "Game Theoretic Application to Intersection Management: A Literature Review," 2023. [PDF]
5. [5] J. Wang, X. Guo, and X. Yang, "Efficient and Safe Strategies for Intersection Management: A Review," 2021. ncbi.nlm.nih.gov
6. [6] A. Abbas-Turki, Y. Mualla, N. Gaud, D. Calvaresi et al., "Autonomous Intersection Management: Optimal Trajectories and Efficient Scheduling," 2023. ncbi.nlm.nih.gov
7. [7] S. Sankar S and V. Chandra S S, "A Multi-agent Ant Colony Optimization Algorithm for Effective Vehicular Traffic Management," 2020. ncbi.nlm.nih.gov
8. [8] G. Ming, "Exploration of the intelligent control system of autonomous vehicles based on edge computing," 2023. ncbi.nlm.nih.gov
9. [9] F. Feng, C. Wei, B. Zhao, Y. Lv et al., "Research on Lane-Changing Decision Making and Planning of Autonomous Vehicles Based on GCN and Multi-Segment Polynomial Curve Optimization," 2024. ncbi.nlm.nih.gov
10. Tatineni, Sumanth. "Cloud-Based Business Continuity and Disaster Recovery Strategies." *International Research Journal of Modernization in Engineering, Technology, and Science*5.11 (2023): 1389-1397.
11. Vemori, Vamsi. "Harnessing Natural Language Processing for Context-Aware, Emotionally Intelligent Human-Vehicle Interaction: Towards Personalized User Experiences in Autonomous Vehicles." *Journal of Artificial Intelligence Research and Applications* 3.2 (2023): 53-86.
12. Tatineni, Sumanth. "Security and Compliance in Parallel Computing Cloud Services." *International Journal of Science and Research (IJSR)* 12.10 (2023): 972-1977.
13. Gudala, Leeladhar, and Mahammad Shaik. "Leveraging Artificial Intelligence for Enhanced Verification: A Multi-Faceted Case Study Analysis of Best Practices and

Challenges in Implementing AI-driven Zero Trust Security Models." *Journal of AI-Assisted Scientific Discovery* 3.2 (2023): 62-84.

14. [14] A. Biswas and H. C. Wang, "Autonomous Vehicles Enabled by the Integration of IoT, Edge Intelligence, 5G, and Blockchain," 2023. ncbi.nlm.nih.gov
15. [15] X. Di and R. Shi, "A Survey on Autonomous Vehicle Control in the Era of Mixed-Autonomy: From Physics-Based to AI-Guided Driving Policy Learning," 2020. [PDF]
16. [16] M. Wäschle, F. Thaler, A. Berres, F. Pölzlbauer et al., "A review on AI Safety in highly automated driving," 2022. ncbi.nlm.nih.gov
17. [17] S. Malik, M. Ahmed Khan, H. El-Sayed, J. Khan et al., "How Do Autonomous Vehicles Decide?," 2022. ncbi.nlm.nih.gov
18. [18] O. Rinchi, A. Alsharoa, I. Shatnawi, and A. Arora, "The Role of Intelligent Transportation Systems and Artificial Intelligence in Energy Efficiency and Emission Reduction," 2024. [PDF]
19. [19] 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]
20. [20] D. Garikapati and S. Sudhir Shetiya, "Autonomous Vehicles: Evolution of Artificial Intelligence and Learning Algorithms," 2024. [PDF]
21. [21] A. Reyes-Muñoz and J. Guerrero-Ibáñez, "Vulnerable Road Users and Connected Autonomous Vehicles Interaction: A Survey," 2022. ncbi.nlm.nih.gov
22. [22] H. M. Abdelghaffar and H. A. Rakha, "A Novel Decentralized Game-Theoretic Adaptive Traffic Signal Controller: Large-Scale Testing," 2019. ncbi.nlm.nih.gov
23. [23] H. C. Hu, S. F. Smith, and R. Goldstein, "Cooperative Schedule-Driven Intersection Control with Connected and Autonomous Vehicles," 2019. [PDF]
24. [24] H. Beenish, T. Javid, M. Fahad, A. Ahmed Siddiqui et al., "A Novel Markov Model-Based Traffic Density Estimation Technique for Intelligent Transportation System," 2023. ncbi.nlm.nih.gov
25. [25] Z. Ryan Shi, C. Wang, and F. Fang, "Artificial Intelligence for Social Good: A Survey," 2020. [PDF]
26. [26] L. Bao and W. Shen, "Logistic type attraction-repulsion chemotaxis systems with a free boundary or unbounded boundary. I. Asymptotic dynamics in fixed unbounded domain," 2018. [PDF]

27. [27] B. Sliwa, T. Liebig, T. Vranken, M. Schreckenberg et al., "System-of-Systems Modeling, Analysis and Optimization of Hybrid Vehicular Traffic," 2019. [PDF]
28. [28] T. Krendl Gilbert, A. J. Snoswell, M. Dennis, R. McAllister et al., "Sociotechnical Specification for the Broader Impacts of Autonomous Vehicles," 2022. [PDF]
29. [29] L. Luxmi Dhirani, N. Mukhtiar, B. Shankar Chowdhry, and T. Newe, "Ethical Dilemmas and Privacy Issues in Emerging Technologies: A Review," 2023. ncbi.nlm.nih.gov
30. [30] V. Vakkuri, K. K. Kemell, J. Kultanen, M. Siponen et al., "Ethically Aligned Design of Autonomous Systems: Industry viewpoint and an empirical study," 2019. [PDF]
31. [31] Y. Qian, T. Polimetla, T. W. Sanchez, and X. Yan, "How do transportation professionals perceive the impacts of AI applications in transportation? A latent class cluster analysis," 2024. [PDF]
32. [32] U. Kumar Lilhore, A. Lucky Imoize, C. T. Li, S. Simaiya et al., "Design and Implementation of an ML and IoT Based Adaptive Traffic-Management System for Smart Cities," 2022. ncbi.nlm.nih.gov
33. [33] S. Park, E. Han, S. Park, H. Jeong et al., "Deep Q-network-based traffic signal control models," 2021. ncbi.nlm.nih.gov
34. [34] P. Lala Mehta, R. Kalra, and R. Prasad, "A Backdrop Case Study of AI-Drones in Indian Demographic Characteristics Emphasizing the Role of AI in Global Cities Digitalization," 2021. ncbi.nlm.nih.gov
35. [35] W. Li, "Simulation and Learning for Urban Mobility: City-scale Traffic Reconstruction and Autonomous Driving," 2019. [PDF]