AI-Driven Approaches for Autonomous Vehicle Fleet Coordination and Routing

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1. Introduction

The paper is mostly concerned with first understanding the large-scale population behavioural interactions in a system of car-shares of many different types—not necessarily from the same companies or with the same sizes or capabilities—all driven in concert with some other vehicles of various types and any amount of private cars. Only partly in competition with car-shares, we have a second fundamental source of artificial intelligence/autonomy-centric coordination: autonomous logistics. At the same time as car-shares and partners, autonomous logistics (e.g. droneHaulage—long distance and small parceled; droidDeliver small distance and localized) co-use shared AVs—either that are always AVs or that become AVs just for the last portion of each optimal whole journey—across scales from ways to streets to buildings. The principal uses of autonomous logistics vehicles require coordination too, although with quite different routing priorities, cost functions and penalty functions. Nonetheless, these are sufficiently similar in dynamic terms to consider simultaneously in one study different types of vehicles for goods carrying, and an additional type for worthy attention today with high technological readiness levels, for passengers, with no cargo but a bit of luggage maybe. They can share the schedule-able adaptive mobility and AV oscillation infrastructure and thus could be directly coordinated to nearly no extra work, although with necessary systematic complementarity and safety through all stages.

In the near future, the increasing use of autonomous vehicles (AVs) will need to be carefully managed as cities and highways clog up with inefficiency and wasted space. A complex network of many interconnected routes with a large number of moving units, all trying to find the route that is fastest for themselves, will be suboptimal for the network as a whole. Fleet management for a collection of AVs, as a form of intelligent transportation systems, will need to answer the challenge that shared AVs introduce. It is likely that we will want to use available AVs to form shared fleets that simultaneously deliver at all sorts of different points of demand. This paper proposes two principled, population-scaled, scalesensitive, context-sensitive strategies that address this mixed fleet cooperative vehicle routing problem by not treating it, as so much previous work does, in a decentralised, myopic, greedy manner. This work derives its results from first principles [1]. We see this as a mark of respect for the significant considerations that autonomous and joint behaviour-inciting heterogeneity present, rather than a limitation in the degree of further matching to harder reality in the here and now and for the near future. To do theoretical development that is more close to the here and now and perhaps to develop intuition about easier-tohold-in-mind features of theory, we focus mainly on car share usage here. Probably, we will have car-sharing and other shared autonomous fleets before we get to FULL UNIVERSAL autonomous with every singly owned vehicle being uniformly capable of being autonomously driven. Of course, the faster we get to the latter, the better. It goes without saying that we hope this to be soon.

This is the introduction section.

1.1. Background and Importance of Autonomous Vehicle Fleet Coordination

To this end, the core problem is that of how AVs can strategically bid for transport orders and how to coordinate AV fleets through dispatching decisions in near real-time so that the transportation demand, represented by transport orders, is fulfilled while AV drivers' private aims are maximally satisfied. In addition, the coordination problem is even more challenging if it is implemented in decentralized or distributed fashion, so that AV drivers with different profits or AVs that spatially located at different regions can dynamically, locally and asynchronously exchange information about the current coordination state with the intent of taking the appropriate local actions to progress towards a globally most (or, at least, more) preferred coordination state. In addition, AV coordination should be handled in a online or dynamic manner that adapts to the frequent changes in inventory supply (changes in number of AVs) and transport demand (changes in number or types of transport orders) in an AV fleet. Devising efficient and effective decentralized and distributed autonomous AV fleet coordination approaches to solve the aforementioned coordination and routing problems in a near real-time manner is the primary objective of this work [2].

[3] Autonomous vehicle (AV) fleets are expected to revolutionize the transportation industry by enabling new Mobility as a Service (MaaS) business models and providing efficient, inexpensive, and environmentally friendly transportation for the general public. Hence, developing efficient and effective coordination and routing algorithms for AV fleets is crucial for enhancing the benefits of AVs in transportation. More specifically, one requirement for achieving this goal is to develop approaches for coordinating the execution of orders among different AVs in an open transport market, where many vehicle drivers are potentially profit-driven independent service providers that autonomously bid for and execute orders without a centralized management approach [4].

1.2. Overview of AI in Autonomous Vehicles

Decades of research and development in the field of AI contributed to the state-of-the-art autonomous vehicles [5]. Traditional rule-based approaches have made way for more advanced smart transportation systems, where the relationships between different entities in transportation are determined, and behavior is coordinated by exploiting the capabilities and advantages of connected and cooperative systems. Behavior prediction and decision-making process models for cooperative AVs make full use of information such as environmental perception, planning and decision making. Hoteling and Wahde suggest the use of eleven up to date AI-driven methods to cooperatively solve AVs autonomous behavior. The need for efficiency in pre-processing sensors data emerges from this work due as scanning and updating a 3D map in the XY plane is of limited cost in term of computing resources [6]. In the first part of their article, Hoteling et al. try to have their local planner understand the behaviors and goals of neighboring AVs. To do so, they start proposing different methods to classify the capacities of these entities [7]. Although cooperative driving systems improve the safety and efficiency of transportation, coordination problems become more complicated in these systems from designing, implementation, and managing angles. Consequently, the complexity of design, management, and resource allocation increases.

2. Fundamentals of Autonomous Vehicle Fleet Coordination

To build the capabilities of each of these essential autonomous driving system components, key technologies need to be quantified and tested by interdisciplinary engineers. One automated solution to testing autonomous driving systems is the simulation environment, particularly for new environments or never-digitized paths or when evaluating the human driver's trainee performance. The emergence of algorithms such as Simultaneous Localization and Mapping, scans and builds digitized maps of the unknown path, and sex particles estimate the path's natural behavior of the driving data and the symbol on the established digital map. The Simultaneous Location and Mapping (SLAM) Algorithm is considered to be a fundamental technology for detecting foreign copies of autonomous robots working within an unfamiliar environment. In this scenario, machine learning is used for systematically reading the LIDAR sensor-scheme. In addition to algorithmic behaviors, developing a complete comprehensive functioning autonomous vehicle, we need to observe and balance a comprehensive set of sensors, fostering new business transmission applications in the automotive business.

75441924-5add-4355-a871-31d1fd64c8dd The four main components of an autonomous vehicle fleet coordination system are localization, modeling, planning/query, and path maneuvering. Localization and mapping identify the vehicle's state along with data on 3D indoor/outdoor environmental mapping. Understanding the surrounding environment through tasks such as object recognition, global-local localization updates, and 3D object detection provides comprehension information to a driverless car. Path determination involves finding the best route to a given destination, with collision-free computing for static and dynamic obstacles via continuous iterative processes. Finally, vehicle control involves generating an action plan for a specific route and ultimately controlling the subsystems by sending commands to the control vehicle for both the movement and stopping of a vehicle.

article_main_idea 205018d7-1293-46a0-9a9c-030412eb6ad8 Various approaches to autonomous vehicle fleet coordination and routing have been explored, such as autonomous intersection management, cooperative driving strategies for nonsignalized intersections, model predictive coordination, and velocity-based negotiation approaches. These approaches aim to optimize intersection crossing, conflict resolution, and platoon formation for efficient fleet coordination.

2.1. Basic Concepts and Terminology

Under the intelligent transportation system, vehicle accidents and side-on confusion time, future vehicle–vehicle communication environments, continuous trajectory planning, the general locomotive space–vessel trajectory planning can be tracked and the decision-making space and trajectory planning space of autonomous vehicles are established based on the method of artificial intelligence technology. By combining reinforcement learning of deep learning technology and inverse of vehicle control dynamics, then compare the planning displacement of the joint or trajectory planning obstacles of autonomous vehicles based on optimizing the target function, and finally complete the optimal decision-making of autonomous vehicles and rewrite the primitive trajectory planning of the model-recurrent learning by the driving state space. At last, a block diagram of the overall framework of this article is depicted.

Decision-making and trajectory planning algorithms, which are essential to the safety, efficiency, and law-comprehensiveness of autonomous driving systems, enable vehicles in complex environments to complete safe lane-change decisions and multi-region vehicle self-adaptive decision-making through intelligent fault-free planning in two different traffic scenes [8]. Non-data-driven and data-driven methods are more widely used for discrete decision-making and continuous tracking trajectory planning of autonomous vehicles. Discrete decision-making methods include finite state machine (FSM) [6], potential fields and game theory, while the data-driven decision-making methods in the continuous action decision-making space include deep learning, reinforcement learning, imitation learning, and model modulation. The research models for vehicle simulation trajectory planning include potential field, social force model, cubic polynomial model, matlab-Optimal control toolbox, dynamic programming algorithm, model predictive control, control neural network, natural policy gradient, graph neural network, and so on [9]. Especially, the trajectory planning method of the dynamic programming algorithm model for autonomous vehicle simulation has few limitations, lower environmental model requirements, and is more commonly used at present. Moreover, its temporal assistance learning and inferential learning need to be further researched.

2.2. Challenges and Opportunities

The simulator engine collects the actual data from different strategies and policies and translates the data into a preparable data structure, which is used for training the relevant policy and strategy learning module using the reinforcement learning (RL) algorithm [10]. The autonomous vehicle must be prepared to counter any situation that it might encounter with an RTU. Also, external factors can have a significant effect on the environment, enough to overwhelm the control limits of the vehicle. Simulations can help to solve these problems. All results in the current paper are validated via simulations, and not all related road traffic issues can be achieved from dissemination and experimental validation. The cost and utility of collecting and managing such data will be very expensive and will further delay the responsiveness and efficiency of the autonomous vehicle; however, this prevents large-scale rollout of connected vehicles. It may also be noted that even data collected through the link by companies may not cover all cases of the possible ad hoc and dynamic phenomena in the environment.

Autonomous vehicle technology has still got a long way to go before it can replace human operators in commercial-grade systems [4]. Nevertheless, the limited operational space for human drivers is still a major concern, which is usually addressed by applying a specific constraint on the system's speed in order to assure safe operation. Sensor limitations and computational restrictions can also lead to performance degradation and instabilities compared with human drivers [11]. These challenges hinder the exploitation of the full potential of the autonomous vehicle. However, the future four primary requirements can also be considered as providing a comprehensive learning scheme, including simulation-based learning, autonomous technologies especially in critical scenarios, interpretation and decision making, and the practically deployable technologies.

3. AI Techniques in Fleet Coordination

The article [9] concentrates the communication between AV and infrastructure by the fully controlled and communicated in AI based AV and partially controlled and communicated in partially controlled-case. In addition, relative position, relative heading, relative speed, and vehicle operation state information are acquired by the central controller in a period of 100ms after the communication initiation. Besides, the communication and control periodic time in both controllers are assumed to be 50 and 100ms, respectively, as per the simulation process. The research result shows that the AI based AV can track the lead vehicle in platoon more smoothly and safely than the PID controlled following vehicle in the partially controlled and communicated case. It is also reported that the vehicle tracking results in terms of lateral deviation, yaw rate, and control inputs have been improved by the proposed TPC strategy for autonomous platooning.

"AI-Driven Approaches for Autonomous Vehicle Fleet Coordination and Routing" is an article that refelcts heterogeneity of recent research area and organizes different challanges based on optimal reactive driving as well aspects fo fleet coordiantion in heterogeneous traffaic. It presents that AI can play significant role into orchestrating the operations of multiple autonomous vehicles (AVs) or fleet of AVs. A system hopping to coordinate autonomously it as well as fleet with the help of infrastructure in m ... [10]. In comparison direct communication of vehicles, AI based schemes are less prone to errors and secure from attacks. The intelligence of an AV can be perceived as acting in three layers. The basic layer is the vehicle control layer, which is responsible to ensure safety of autonomous driving. The top layer is a routing layer, where direction, route planning, and fleet coordination are performed. In between these two is learning and reasoning layer, designed to mitigate the uncertainty laden in the Control Layer and Software Layer.

3.1. Machine Learning Algorithms for Fleet Management

RL is a rule-based algorithm, and the principle of machine learning is learning rules from data to describe certain complex relations in different world. Therefore, we can extract the state rules of different driver patterns from the vitiated time series and put it in the rule pool. For the vehicle interaction, a SVM is adopted to fit the dot matrix obtained by FV and lane-decision to handle the new driver and the leader. Therefore, as shown in Fig. 3, the RL decision-making can be viewed as the search of optimal strategy from the context-state-action function and the state rule can reduce the 128 state to 4 by the basic rules. The RL itself will swing among RL values of eight states; however, the searching probability of wrong driver decisions will be significantly decreased by rules [12]

Local traffic control optimization using routing or scheduling algorithms in AVFMs may achieve suboptimal solutions if real-time herd moving and extended-continuous dynamics are not considered. In fact, the real-tie traffic environment is inherently dynamic performances are subjected to dynamic attributes and it is mot suitable to represent the interactions among platoons of different types to each other and to other traffic flow by introducing constraints and exogenous disturbances. As is shown in Fig. 1, a decentralized control method based on history-date and stability criterion is integrated with proposed routing and scheduling algorithms. The proposed extended-continuous flocking protocol flocks the forward movement of the AVs using LQGs feedback controller. The scheduling algorithm selects the optimal driver for platoon leading according to the length of the available route and the waiting time. The routing algorithm first analyzes the real-time herd moving using UDE VIPS and TMs. The traffic dynamics difference between the herd and the mixed traffic is calculated to perform the on-line planning. The proposed method is validated in different scenarios with/without control input uncertainties and prevailing traffic in an urban arterial road. [10]

3.2. Deep Learning Applications in Routing

Specifically, for routing applications, DRL seems to be an ideal candidate. A conventional Reinforcement Learning approach aims at finding the policy π : S → A, which is an approximate solution of the problem through a value function for each state Vπ(s), which estimates expected accumulated disutility incurred by the agent in environment when moving from s0 to t. DRL methods can tackle the limitations in large state-spaces search and function approximation such as a GPS application for vehicle routing services, and demonstrate better performance with a fragment of expert supplied sample for model evaluation. For instance, a DRL approach has been proposed to solve the issue of cruising space in a transportation network, DRL is treated to route vehicles and manage intersection flows effectively in a future transportation scenario; DDPG is utilized as an offline and online path planner for emergency vehicles to enforce the controllable population density along the emergency region. Enforcement of constraints in V2V' Cooperative Adaptive Cruise Control is also being investigated for DRL. The AI-assisted resource management is in heated demand since vehicles with compute and communication devices access to the other vehicles and edge computing resources for service requests, which creates new possibilities to explore decisive use cases of machine learning. These services are vital components of an intelligent connected vehicle stack. Deep RL comes out of the list that experts trust its suitability for online large system optimization communicate. The weight updating of the deep Q network (DQN) online offpolicysolution has shown its ability in tuning Q values with radio communication-related context.

Deep learning methods have seen significant success in various applications. This technology has attracted increasing interest in routing solutions for intelligent transportation systems (ITS). A CNN model is used to learn the traffic scene and make predictions more accurately and affordably [13]. Some initial work has been done to design data-driven multimedia traffic routing methods based on big data analytics, where a deep neural network is trained and used to predict the on-going traffic delay and reroute vehicles accordingly in VANETs. In addition, deep reinforcement learning (DRL) has shown an extraordinary ability to optimize complex navigation in skateboard trials and registrar, which enables it capable of tuning a vast parametric system for vehicular communication. Due to increasingly practices of autonomous driving, DL has been projected to be the decisive approach to achieve robust radio environment map for autonomous vehicles and handle high-resolution perception in vehicles.

4. Optimization Models for Fleet Routing

The last fleet routing models consider vehicle cooperative strategies. Unlike the centralized NF and SF methods, the decentralized coordination determine more permissive the traffic infras-structure affectation and, in different degrees, provide maneuver-padding-level coordination. Decentralized cooperation algorithms are schematized in Fig. 4. Overall, the vehicle coordination literature debate contributes to increased autonomy and to some discriminant high-scalability operational cost and CO_2 emissions-containment. Additionally, this future of coordination, based on a dozen of different studies, is considered. These different models are reviewed based on their mathematical structures including utilized algorithms and computation times, as well as evaluated by their performances on defined evaluation metrics with random instances and real-world road maps.

Various optimization models are identified for solving the fleet routing problem of Autonomous Vehicle (AV) and provide theoretical and computational insights for supporting related practice. The different types of models emphasize the importance of adding suitable driving dynamics to fleet routing models [14]. Different approaches have been proposed for tackling the fleet routing problem. Another first family of models consists of reformulating the fleet routing problem as a decentralized vehicle coordination and a fleet accelerated road infrastructures contention-presence decision process having predefined vehicle trajectories menus (road infrastructures batch [15]). The road infrastructure batch considers the available path continuities between all service points, so the predefined fleet trajectories are determined by associating periodically different permutations of test trajectories in the batch road infrastructures, for the asynchronous execution, in distributed context.

4.1. Mathematical Formulations for Routing Problems

Traffic navigation usually leads to a predefined route and timestamp, as a consequence, there may be a lot of vehicles using the same link at the same time, resulting in linked traffic jams. A route optimization method was utilized to avoid the situation where many vehicles used the same road with limited capacity at the same time. In their study the optimal control vehicle coordination N-point rendezvous problem that was applied in the autonomous vehicle routing and motion planning problem. The optimizing control vehicle coordination was solved for high performance trajectories. This method creates and solves a multi-point boundary value problem for n+1 or 2*n vehicle non-convex constraints, swapping through direct optimization and optimal control principles. The two rendezvous scenarios were compared, which were fully autonomous (no human driver) and partially autonomous (human driving legacy vehicles). The fully autonomous scenario was found to be more effective than the partially autonomous scenario. However, the single vehicle alone has lower fuel consumption and emissions than the fully autonomous scenarios. Tang et al. proposed a multi-vehcile routing optimization approach for hybrid electric vehicle (HEV) fleet management in urban areas [16]. The goal was to find the optimal operation path for the whole HEV fleet to operate the same optimization in energy consumption and unit dispatch time. All vehicles started at the same time, and the algorithm was used to adjust their arrival times after the results. The reasonable heuristic algorithm was proven in a 40-agent scenario regarding to 52-agent problem. The research also find that the energy consumption of the optimal path is not always the minimal. The results of congestion simulation also pointed out that the designed routing optimization strategy reduced the traffic delay in a highly congested case.

Traffic assignment problems for autonomous vehicles in congested areas should consider route optimization and vehicle routing in the process of fleet scheduling. Because autonomous vehicles can self-drive without human intervention, advanced vehicle dynamic route guidance or vehicle re-routing method should be considered for full autonomous vehicles which could have extra advantages in path planning. Igarashi and Rus published an article discussing a dynamic vehicle re-routing scheme implemented for a full autonomous vehicle without considering vehicle coordination [17]. This scheme was able to significantly reduce path travel time through minimizing congestion along travel paths of autonomous vehicles by providing a different travel path or departure time for the vehicle. Moreover, an Extra One-Pass re-edit method was proposed in this article to achieve low computational complexity in solving game dynamics based on Wardrop's first principle as well as to achieve small coordination overhead, compared to the benchmarked PLRre-route and REVOP methods. Matsubara et al. conducted a research for formulating the multi-agent path finding with continuous-time dynamics in the context of teamwork problems. Formulating time-dependent, continuous-time path planning problems in the context of multiagent systems is challenging due to simultaneously considering time-dependent path planning and physical vehicle dynamics. Real-world situations were discussed where multi-robot systems are required to plan continuous-time paths in order to minimize overall cost. A variety of application scenarios, including robotic swarms, search and rescue robots, and automated vehicles were discussed in this article.

4.2. Heuristic and Metaheuristic Algorithms

Several heuristic and metaheuristic algorithms were proposed in the literature to solve the problem of obtaining proper vehicle routes. Their advantages lie in their ability to find good solutions within an acceptable amount of time for large problem instances, but the main drawback is their tendency to get stuck in local optimal solutions. One of these models simulates a simple range-limited wireless sensor network that is divided into three-metric clustering and hierarchical structures. In the MDLVRP, the heuristic procedures aim to find the most effective and realizable routing plans. In the VRP, initial solutions consisting of incomplete routes are constructed by using cluster-first route-second policy, which integrates cluster-based and vehicle-based heuristics. The carriers for each cluster are chosen by onorder singleton carrier selection heuristics, respectively, with the minimum fuel consumption, cumulative arrival time, and waiting time criteria. The other clusters are gathered to the route of one selected cluster (closest/ farthest) in an appropriate depotbased sequence.

Common vehicles routing problems involve locating, sizing, and assigning a suitable number of depots, for instance, to minimize total distribution cost. A vehicle routing problem with time windows and heterogeneous fleets can be computed to simultaneously determine depots location, size, and capacity. The company's activities, vehicle routing, vehicle scheduling, and depot location are integrated in distributed vehicle routing problems with stationary multiple delivery locations already available in the literature [18]. In recent years, trends in the automotive industry reveal an increasing number of electrical vehicles on the roads. The primary solution to the problem is to integrate vehicles' recharging scheduling in the vehicle route planning problem to minimize the impact of multiple Depot-Location Vehicle Routing Problem (MDLVRP) to illustrate the relevance of the decision interdependence between strategic and operational levels [19].

5. Real-World Applications and Case Studies

In the urban scenario of this chapter, the solutions are based on discrete optimization problems and approaches, such as routing, scheduling, combinatorial optimization, and the related MILP, CPOP, TSP, VRP, etc. Recent results use BigData-based custom models (e.g., mathematical optimization + flow based machine learning algorithms), deep learning for strategies (e.g., routing + xGBoost), and hybrid/multilevel algorithms, in the A* search based on Genetic Algorithm to search for complex urban trajectories, VRP, and related kind of combinatorial optimization problems and algorithmic strategies, and Collective Motion optimization solutions for shared goals multi-objective optimization. On the other hand, in the highway scenario, the main focus has been on modeling decision-making problems by POMDP, reinforcement learning, and BTYPES in order to find a safe and executable vehicle trajectory. It is worth noting that in both urban and highway scenarios vehicle dynamics are not considered and vehicle policy issues. It is subject to future work and to the possible application of the urban and highway solutions developed in this chapter on different sectors of logistics and transport configurations other than those typical of the multiscale logistics logistics.

[20] Real-world routing problems require precise models encompassing uncertainty, timeliness, and limited resources. Usually, exact programming methods cannot handle all these properties, so holistic AI-driven approaches combining different techniques are needed. This chapter has reviewed and discussed several AI-driven approaches for the coordination of autonomous vehicle fleets, and their application over urban and highway logistics. Overall, these approaches add different degrees of intelligence into the decision-making process in the Autonomous Driving System, in order to handle the variety of usage scenarios and operational issues in the city and in the freeway.

5.1. Commercial Use Cases

The approaches proposed in this Chapter have the potential for application in a range of commercial enterprise settings, which can be inferred through use case studies, commercial projects, and design rationale. In principle, using a similar AI-driven coordination and routing capability enabled by fleet design and architecture considered here, organisations can enhance their agility to be adaptable to the market fears as time progresses [5]. The three key sectors in our design rationale and literature review of interest for fleet coordination and routing are autonomous mobility (AVs and drones), last mile logistics (through these autonomous systems), and AEC industry (construction companies)—forming a diversity of use cases and settings and domains that each positively piggy-back on progress in their peers [20]. For instance, the fast moving, developing, and resource intensive AV domain is impacted significantly by the progress in routing and logistics automation, even though the primary industrial logic of drones is the delivery efficiency (via resources such as distance). AI system architectures and interoperability structures and learning systems in urban logistics and transportation are also themes relevant for design, operational and procedural efficiency of construction and operation all large integrated mobility systems with a broader societal mission. For companies a better optimized working on construction sites and vast mobility networks could fundamentally operational and financially also reflect as driverless vehicles and commercial capacities for fast food tipping and medial foods and drugs outside local hospital systems also many other service robotic applications share operational and efficiency models important for any organization small or large with forward forwards mass-customisation [21].

5.2. Research Initiatives and Pilot Programs

Different algorithms to optimize CAVs' trajectories predictably managing intersections are comprehensively discussed, with central management, DQN, and joint control algorithms leading to significant commuting-time improvements vs. traditional CAV states. The future of AIM likely involves reducing reliance on forming parabolic approaches in favour of rigorous line optimization methods capable of near instantaneous computational communication abilities, capable of precise understanding of gimbaled human movements, as well as development of special communication hardware-ons (i.e., vehicle-vehicle/traffic signal-vehicle) permitting real-time feedforward decision-making capability. Additionally, many differences exist between the conditions in theoretical avenues in which AIM intersection required introduction and real-world operationalizing of operational intersections. [22] In recent years, numerous research initiatives and pilot programs are aiming to deploy connected and autonomous vehicle (CAV) fleets in several spaces and cities to validate the overall benefits that are expected once the transition to autonomous mobility is concluded. Over a few years, several projects have been carried out by Ford, Uber, Waymo, Argo, Aurora, and Cruise, bringing to market automation-driving-tir versión operations, which are currently in the testing phase in some U.S. downtowns and universally. They have subcruised the number of areas in the U.S. downtowns, in order to validate the system so that it is fully reliable, in spite of the huge dollars expenses for research and development. In the presence section a short review of several previous works and case studies on application of various AI techniques in the case of pilot initiatives, with CAV are presented, and, consequently, the main points to be developed to get more efficient and attractive, are also offered.

[8] Unlike rider, street maps, or Yuegui static evacuation route planning optimization dynamic response time is relatively short, a takes into account the dynamic state and structural constraints of the road network, and the dynamic coordination of a variety of scheduling conflicts and multi-technology, learning algorithm is found to be. This enables the routing system to automatically "learn" the optimal path when the surrounding dynamic streets and vehicles are connected. It is clear that modern geographical information systems (GIS) generally do not have optimization algorithm capabilities, and do not have coordination and scheduling optimization capabilities for spatially distributed and massive massive automation of cars on the cognitive or decision-making capabilities, in order to take the latter two function road network from the optimal reorganization of global mobility space within the calibration, navigation, integration into an organic whole, the initial realization and real-time route planning road closure and the urban road in view of the multi-technology adaptive dynamic complete linkages. Section 5.2 presents advances in autonomous vehicle intersection management. This approach involves the use of connected and autonomous vehicle intersections to coordinate routing and reduce congestion. Multiple scheduling algorithms to align intersection interaction with traffic flow priorities are discussed, potentially increasing roadside traffic management efficiency.

6. Ethical and Regulatory Considerations

Self-learning, autonomous ideas driven by navigation, parking paths, and EV?ecosystem integration might later line-up other dynamics. [23] These directions demonstrate where a more proactive role can be taken to focus, not only on the capacity and eciency implications of autonomous coordination strategies, but in an integrated manner also consider resource and energy implications. Hence, traf?c management is not only considering the bene?cial or at least diffusive welfare e?ect of a shift to shared mobility on the management of urban surface needs, but also other sectors very by the reduction of the request of automotive fuel and lubricants and of the following puri?cation of the environment from road transport pollutants, as well as favoring the energy and eciency of the transport e?t.

[24]Autonomous vehicles' (AVs) artificial intelligence (AI) solutions help to respond to the complex nature of large-scale fleet management. Although AI-driven fleet management can

mitigate a variety of pro?blems, the most ef?fective solutions might not provide the best outcome from an ethical perspective. Current AI models might struggle to respect ethical standards in traf?fic management. [25]Ethical decision-making for AVs involves several challenges, including the appropriate weighting of the priority of safety, balancing respect for the rule of law and potentially con?icting traf?c rules, as well as difficulties in balancing different groups' concerns in scenarios involving high potential injury.

6.1. Privacy and Data Security

Accessible onsite sensors may guide threat actors using island assaults toward human beings. For the recognition of pedestrians, human beings, and different non-motorized vehicles (bicycles, etc.), digital camera sensor can be put without delay to attack riders of different automobiles. This is difficult simply because the perception sensor (video, radar, light sensor) records various types of data. Like video, audio, and human-reading screen [26]. The physical model is to distribute attacks over a certain distance. If these attacks are stored on enormous websites, they will no doubt fall underneath the island attacks. For riders, it is essential to test whether or not or now not the transmitting information exhibits the singer's private privacy.

Autonomous vehicles with distributed architectures feature real-time decision-making capabilities and on-board sensors for perceiving the external environment. As AI-driven autonomous vehicles interact closely with surrounding vehicles and infrastructure elements, attackers may use various types of sensors to threaten riders, passengers, and pedestrians [27]. For the protection of autonomous vehicles from attacks, opportunities to contribute sensors and remote AI models need to be checked accurately without any revealing of personally identifiable data. This means undermining privacy and data issues, including security [28].

6.2. Compliance with Transportation Regulations

Ethical considerations of AVs have gained significant attention in recent years. Several studies have dealt with different ethical dilemmas arising mainly due to probable road crash scenarios. These ethical dilemmas have been addressed in different ways, such as collision avoidance strategy, trajectory planning under different scenarios, and ethical guidelines for autonomous vehicles. Moreover, all these have proposed decision criteria, or best actions, under the considered context of crash [29]. However, it has been argued in some of these studies that ethical considerations go far beyond deciding road crash scenarios. A well-documented examination of ethical dilemmas and privacy issues in emerging technologies is given by [30]. Developed by an interdisciplinary working group, the new ethical guidelines for intelligent technologies and systems focus on the ways these technologies might affect people and society.

Autonomous vehicles (AVs) have the potential to address road transportation challenges effectively. However, vehicle manufacturers will need to address certain issues in order to gain public acceptance and legal permission. One such important issue is the compliance of AVs with transportation rules. In this context, a broad classification of approaches and a robust evaluation framework for keeping track of transportation rules will need to be developed. Such compliance-based AVs will be able to inform other stakeholders about their actions and take necessary corrective measures in real time in case they are found to be in violation of any rules [31].

7. Future Directions and Emerging Trends

The global energy level of the fleet management module is reduced, and a flexible deep reinforcement learning model is proposed, which is designed to select the power of the vehicle and packing plan in order to use together with acceptable risk cost control. In the direction of the realization of car dispatch-sharing services, there is one of the main focuses on the planning of multi-distribution stations, multi-vehicle fleet dispatching control strategies, taking into account compensation for the distribution of the DMC and rider satisfaction, analysis of the routing challenge is a challenge course With dynamic changing's tension. According to Table 6 and, the completion of the mission plan is scheduled with insufficient seamless configuration among spatial-terrain conditions, and this is a multi-purpose topic is an important issue, where 10–20 approaches to the topic may be carried out by 2022. recognized. Scientists abandon the algory. research to complement the AI-based abstract awareness of edge network transportation demand, regulation strategies and optimal control development, in view of an integrated exposure monitoring methodological set, will be necessary for successful roadway traffic governance in urban edge clouds. random orientation at location. With respect to the fundamentals of the demand-based smart-edge AV deployment model through the showed, discussions and motivation involved in this solution. In general, the review paper covers big data.

The potential of AI technology in intelligent control systems for autonomous vehicles is continuously unlocking to solve the challenges encountered in practical applications [32]. In addition, the open research directions of artificial intelligence, cloud computing, and edge computing in the field of smart transportation intelligent algorithms are reviewed. As a significant extension of existing work, autonomous vehicle fleet management approaches and management algorithms are profoundly analyzed from the perspective of demand satisfaction, platform matching, and platform routing. It can be concluded that the optimization of autonomous vehicle fleet should take into account the user's individual demand, the dynamic matching between the resources of the platform, as well as the demand and the stage of the service, and the spatio-temporal multimode constraint in the platform routing. A large number of techniques and methods are proposed to avoid the congestion in the road transportation network, including the model prediction demand, forward-looking route planning, demand scheduling, and payload allocation. Most of the current planning algorithms do not consider the impact of the control strategies of different users to select different services, control the dispatch policies of different vehicle fleets, and compute the mode constraints between the initial and the final station in the plan service when designing smart-edge ride-sharing services.

7.1. Advancements in AI and Machine Learning

The impressive evolution of intelligent data mining requires the capability and prospects to handle complex tasks with a massively parallel and interconnected computing platform. This evolution inspires the necessity for large-scale autonomous vehicles by team coordination, fleet routing, large-scale pricing, and policy-making, i.e., to achieve maximally congestion-free and efficient traffic flow [33]. The above-explained robotic swarm and MPC systems will play an essential role in practice to solve problems like this. Moreover, the AI perspective facilitates decision-making, learning, time-delayed, software and hardware implementations, power consumption, and production during their design and development. Altogether, the blockchain-based coordination and routing systems, the practical planning and efficient implementation with grid blockchain, and future research directions were surveyed in this chapter. Please be attentive that in most of the cases, the MPC is very fast and its outcomes are interpretable and transparent; then if human-robot cooperation is important, we can integrate relevant reflections of the human through the different communication (audio, video...), supplementary robots working in the environment. Hence, we also introduced the research works of our dark warrior team, called AI2 with the corresponding URL links.

The evolution of Artificial Intelligence (AI) has brought significant advancements in autonomous vehicles, which facilitate intelligent robots with numerous applications across various industries. Over the past several years, this area has been further boosted based on the recent achievements in AI, machine learning (ML). A good example is the development of highly innovative robots, the autonomous vehicle industry. The road to achieving fully autonomous, driverless vehicles has reached a higher level than many people tend to think. In this age, autonomous vehicles make as many decisions in a few seconds as humans do. Although, transforming a 100-year-old modern transportation system into something revolutionary is not an easy task, and scientific innovation challenges appear nearly on a daily basis [8].

7.2. Integration of Autonomous Vehicles with Smart Cities

The coordination of autonomous vehicles and their behavior within a pervasive computing environment can take place at different levels and either be centralized or distributed. Indeed, the inclusion of intelligent technology such as interconnected road infrastructure brings to AVs the creation of an entire ecosystem of urban resources, into which AVs are resources and providers. An orchestration of the emerging technology directions termed IoT, 5G, AI, and blockchain, the merging of insecurities and privacy challenges, and the hard, overlapping, problem of compatibility between the technology is a technical challenge still to be tackled ([34]). Any coordination of future interactions of AVs within smart city networks need to consider it is topology, which may be static in the case of low cost deployments that are deployed once or set identically over a large area of the city, or dynamic in the case of variable deployment costs, which can work over parts of the city or change function in time to meet specific bandwidth requirements.

The development of autonomous vehicles (AVs) and smart cities can lead to better integration of the autonomous vehicle fleet with various building management systems ([7]). This will provide numerous ways to improve the quality of life for city residents as well as benefit the transportation industry and city services. The integration of AVs into wider city infrastructure can lead to improvements in mobility, city deliveries, and improvements in human lifestyle such as better parking and linkages to public transportation. This topic has hence just begun to be researched, and plenty of siloed research in these fields need to be linked together to lead to better properties for AV coordination and routing. The interactions between AVs and smart cities are as vast as the possible applications for smart cities themselves. A better provision of resources through conservative fuel rankings (COFRs), city bus timetables, taxi and Uber services, electric car charging and the myriad ways resources are transduced from energy suppliers. Better pollution control with threshold models of human emissions can be used to inform and control AVs on low carbon, low pollutant routes.

8. Conclusion

Today, optimal coordination policies should be more and more data driven by using a vast majority of traffic demand data and real-time traffic physical infrastructures monitoring data. Finally, the virtual and augmented reality systems, including gaming platforms and flight simulators, are helpful for preparing the AI easy and high-quality ways to preparations for the training of efficacy procedures for teaching of complex vehicle capabilities [35].

The technology advancements in AI promote the development of efficient and smart transport systems [36]. In particular, the increasing availability of data, including real-time data, has a significant impact on the dynamic characteristics of transport systems and allows traffic management, vehicle routing, and travelers' choices to be taken into account more thoroughly and effectively. In this context, the level of autonomy for level 5 fully automated vehicles becomes essential because they are actually capable of human-like driving everywhere and have no driver behind the steering wheel to take over the control in case of danger. AI, and in particular machine learning and planning technologies, allow fully autonomous vehicles to be able to understand dynamically the environment they perceive, and be able to interact with the real world and adapt to (unpredicted) changes [7]. AI developments are concerned by both the cooperation between vehicles forming convoys or fleets and the possible interactions between the autonomous vehicles and the traditional vehicles.

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