Machine Learning for Autonomous Vehicle Fleet Management and Optimization

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1. Introduction to Autonomous Vehicles

[1] A smart city integrates ICT and communication technologies into urban infrastructure to improve the quality of life for citizens. Autonomous cars are leading components of smart cities, and they represent the future of transportation. Urban fleet management is considered to be an efficient method for the deployment of autonomous vehicles in smart cities, including enterprise-level Fleet Management Systems (FMS) and consumer vehicle-sharing platforms. Such aspects show the potential of machine learning (ML) and artificial intelligence (AI) methods to dynamically optimize the operation of vehicles connected to the Internet of Things (IoT). It is the main challenge to coordinate the operations of autonomous vehicles participating in a fleet to achieve an optimal operation zone between picked up location and requested drop-off location, and meet the specific mobile metrics ($\forall i\ \lambda i(si, ti) < T$) related to passenger-related comfort levels for each passenger pick up etc.[2] This chapter represents a comprehensive review related to the use of ML and AI algorithms and systems developed for an autonomous driving system. In particular, the discussion in this chapter is also about researched developments in the deep learning domain for a vehicle driving scenario. Moreover, the discussion also includes research based on efficient switches and methods suggested to keep the performance optimal while keeping the route calculation energy efficient. In summary, in this chapter the authors discuss the future challenges and the proposed solutions, which are important for developing autonomous driving as well as smart transportation systems.

1.1. Definition and Types of Autonomous Vehicles

Automated driving systems work to have a nearly total absence of a human driver. The main goal of the highly automated vehicle (HAV) in east and advanced vehicle driver assistance systems (AVDAS) is to ensure the least human interference during emergency-driving situations. The researchers in some cases ignore features related to characteristics that are similar to a human driver in the engineering of self-driving or autonomously driven vehicles. However, the most important characteristic of human drivers in the decision-making process is determining whether the situation is predictable or not. Although it is difficult to determine the situation in most emergency-driving situations of the HAV due to the very low and static visual data types, optimization factors can be constructed for the decision-making process of the HAV. Such factors can be conveyed to the system in a decision-making process using a fuzzy inference system, making machine learning methods' processes much easier, faster, and providing retainment of the system as a black box system [3].

An autonomous vehicle makes decisions based on immediate information retrieved from its environment and long-term predictions or history. It follows a rule set and employs control aspects to arrive at a final decision. Because of the significant steps taken in the field of Machine Learning (ML) in recent years, it is gaining rapid attention in the field of autonomous vehicle control [4]. In particular, ML techniques are employed in handling the decision-making aspect focusing on two different aspects. The first formulates and solves the decision-making pipeline using ML capacity and the second involves the direct use of ML to make decisions. The former is employed when decision making depends on non-observable states, when the system under consideration is dynamic, and when sporadic outcomes occur. The latter is employed when observability is not a concern in the decision process and the machine learning-based decisions can directly influence the outcome of the decision-making process. Specific to autonomous vehicles, the engineering community has employed ML approaches as a significant solution technique that takes care of many hurdles in control.

1.2. Current State and Trends in Autonomous Vehicle Technology

In the past two years, the popularity and development of smartphones, mobile Internet and sharing economy have stimulated the rapid development of the online car-hailing industry, and the demand for intelligent driving brings an effective potential customer group to autonomous driving with its security and safety [5]. Hence, the development of autonomous driving and the commercial operation of autonomous vehicle fleets have been seriously researched by a lot of leading technology companies throughout the country. Base on the usage scenario and market demand of driverless cars, the researches are mainly focusing on the following aspects: the application of autonomous driving technology under the specific conditions of the Zijinshan Road and Harbor hospitals; The survey instrument for unmanned driving; Path planning algorithm for unmanned vehicles.

Autonomous driving technology has been available to the public since the early years of this millennium [4]. From the first fully autonomous vehicle in 2009 and the first grand autonomous driving of 2013, to Google's proposal, autonomous vehicles have gone through many rapid changes out of the public's sight. At present, when it comes to autonomous vehicles, the top few companies that come to mind include the atmapy brigade, Waymo, Baidu, Didi, and Tesla, which can be said to be the mainstream technology companies in the field of autonomous driving. Taking Waymo as an example, It proposed and built a completely unmanned taxi network as early as 2019, making Yosemite the first place in the world to formally launch a commercial autonomous vehicle operation.

2. Fleet Management Challenges

The complex dependency of the parameters of the fleet and regions makes the description of the problem difficult, what in turn influences its division into sub-tasks. Currently, there are no publications that would directly focus on the issue of fleet management using machine learning tools. To address this gap in the literature, we present a novel approach of fleet management using machine learning algorithms. We abstract the fleet management problem to data-driven decision making, to be implemented in the problem of autonomous vehicle fleet management and dispatching on the example of a car-sharing system. The chosen fleet management approach and vehicle operation constrained by regulation of a chosen city, allow us to bring together the vehicle's artificial intelligence decision making, vehicle routing problem and impact estimation of service policies on the decision-making strategies, ride-hailing at the customer's side, car parking, charging and vehicle maintenance.

Machine learning methods are widely applied in on-board vehicle control tasks in level 4 and 5 autonomous vehicles (AVs) [1], in command and control of AV fleet [6], and for an impact assessment of network composition elements on shared autonomous vehicles (SAVs) [7]. Generally, while the main focus is on managing traffic at the level of one vehicle, there are no significant publications on the use of machine learning for fleet management connected with the car rental. The main aim of this paper is to present a generic machine learning centric approach to fleet management and optimization.

2.1. Capacity Planning and Utilization

In the context of parking search, a model anticipates a driving agent who will need to find a suitable parking location [8]. Anticipating the spatial locations of spots they will accept allows a model to produce a distribution over driving agent behavior, where they choose actions bA at any spatial location of consideration, a distribution over plans pA(bA), that can be used in a model-based reinforcement learning paradigm to simulate possible behavior and calculate a set of expected values for navigation and parking completion at those locations. Initial investigations thus focus on situations where a driving agent is instructed where they will need to park (not necessarily where they will end up). These distributions can be created using a verified behavioral psychological model, in our case the model is based in part on the Corporate Average Fuel Economy (CAFE) 2017 survey of US driver parking habits and was verified on survey data and novel street interaction tasks in a previous work, or using k-means clustering on street parking availability dataset.

ML-based techniques for autonomous driving such as CNN models, LSTMs, and CPTs have been quite effective for vehicle detection, identification, localization, and tracking [9]. Recent research in federated learning, a tailored distributed machine learning paradigm, has shown promise in circumstances where models can be fit to a plurality of local datasets at edge nodes rather than centralized servers. While effective in its use-case, there are several opportunities to improve urban shared autonomous vehicle fleet management. The need exists to create efficient last-mile strategies, design parking search and information sharing strategies, and observe models in fleet management settings [10]. Particularly interesting is the need to better understand how individual behavior, either of other users or between individuals, may partially guide model results in both a parking search and a last-mile situation. This creates opportunities where partially supervised learning or conflicting reinforcement learning may be useful in describing anticipated behaviors in the simulation of parking navigation and choice of shared autonomous connections.

2.2. Route Optimization and Scheduling

This section deals with decision-support methods needed to effectively optimize the path of the vehicles from two perspectives – individual optimization, which focuses on the selection of the best path for a single vehicle, and joint optimization, which investigates how the path of each vehicle affects the overall traffic [11]. Consequently, these methodologies can improve the operational efficiency of the fleet of autonomous vehicles (route optimization, energy management, parking management) in the daily operational activities. Our survey can be divided approximately in three categories: (a) static and deterministic models with traditional heuristics and machine learning techniques; (b) static and deterministic models by using newer deep learning technique; and (c) dynamic and stochastic models realised using reinforcement learning algorithms.

Urban traffic generates several challenges, including congestion, increased travel times, high energy consumption, and carbon dioxide emissions. It is crucial to mitigate these issues through new urban mobility paradigms, such as ITS, VANET, electric vehicles, and Autonomous Vehicle technology [12]. These issues can be mitigated through the integration of intelligent transportation systems (ITS), future generation VANETs [13]. These challenges present a new and prominent research areas in advanced automation techniques (hybrid AI + Data-driven models, reinforcement learning, etc.) to support decision-making process of autonomous vehicles.

3. Machine Learning Basics

Machine Learning (ML) and AI algorithms are required to be implemented, tested, and evaluated on the basis of current and future extensive data coming from control units, sensors typical of autonomous vehicle technology, Internet of Things (IoT) devices, social networks and many other sources of data . Herein, the implementation, the commissioning, and the testing may be challenging since possible changes in vehicles performances connected to software driven performance failures shall be promptly recognized and corrected. Therefore, the final aim of this note is the introduction and description of the most recent and successful applications of AI and ML to automate a series of deceptive last several passengers of alerts stemming from a Vehicle Health Monitoring sub-system.

article_main_idea: There is a growing interest in developing and studying methods for Commercial Connected Automated Mobility (CCAM) concept, in which mobility services are provided by commercial companies possessing fully or partially connected automated vehicles . In , the authors introduced the multi-agent Discrete Event Systems based paradigm for “Connected Automated Vehicle Fleets”. In that model, a permanent bilateral information flow is established between the AV (A) and a remote Central Management (CM) unit, while the CM unit acts as an intermediate authority (total traffic manager) that directly supervises vehicles functionalities in terms of activation and deactivation of the automated level of the vehicles, handling of the car sharing and rental operations and performs safety supervising functions.

3.1. Supervised, Unsupervised, and Reinforcement Learning

The use of machine learning (ML) techniques in the development and optimization of autonomous vehicle-fleet management systems is gaining in popularity. A review of the recent state of the art indicates that a majority of the techniques abstraction levels range from preplanning (off-line) to online (perception and decision-making), which leads to a very centralized, monolithic, and myopic approach. Another trend observed in the review is that a large number of the perceivers are still—as of this review writing—handcrafted feature extractions or drivable area detection pipelines where deep learning based on segmentation (supervised or unsupervised) is the most popular approach, although some real-world autonomy platforms like Tesla's Autopilot [14], Waymo, Cruise, Aurora, Zoox, and Argo are also investing effort to convert perception problems into supervised machine learning by focusing on realistic high performance edge deployment with efficient online learning. However, in dealing with the challenges of optimising fleet management for ceteris paribus scenarios, such as demand forecasting, routing, and optimizing of dis/init low-planning practical resolutions, only simple models like linear regressions or based approaches on clustering (k-means, etc.) are applied. Furthermore, the existing review is not explicitly focussed on scalable, promising novel methods that are being applied to fleet management problems in the literature. The most popular deep learning techniques for automatic feature extraction and high-precision feature map labeling are supervised, unsupervised, and reinforcement learning. Convolutional neural network (CNN) based segmentation, like, U-Net, SegNet, and FCN, is the most popular implementations for supervised learning because they are robust and easily trained on large quantities of data. Recent advancement in unsupervised learning for scene understanding and neglecting manual pixel-level annotation in semantic segmentation, has led to a flood of techniques for simultaneous per-controlling slot operations of cameras in congested areas and to avoid infrastructure investments on optical sensors, such as lidar, by using passive sensor input like a monocular camera [15]. 'Reinforcement learning' can use data without any labeled ground truth data and train models through end-to-end control. However, there are some among researchers who postulate that there's little support for substantial benefits of integrated curriculum learning in autonomous driving [16]. Compared to other machine learning techniques, k- means, DBSCAN, hierarchical, and spectral clustering are less utilized for classification, regression and route-based discrete performance optimization problems. The reality is that these unsupervised learning algorithms are not always consistent when they are forced to segment sequential waypoint plan arrivals or large datasets and they are not implemented to seek minimum scalar benefit for fleet and demand satisfaction on metamer prickpea ata.

4. Machine Learning Applications in Fleet Management

Given continuous car usage and the spread of Internet of Things and wireless sensor networks, traffic congestion is a raising problem in many of today's major cities. Simultaneously, having efficient traffic load and distribution helps to extend battery lifetime of the cars and provides proper movement of urgent service vehicles such as ambulances and fire trucks. Many solutions are suggested to reduce the traffic congestion. Such solutions are either as simple as changing the traffic light duration or as complicated as routing vehicles by considering different traffic parameters in real time [2]. Developing Coordination protocols that react to the traffic condition in real time have also been proposed to better manage the traffic. Even more advanced solutions like utilizing flying cars have been suggested to reduce traffic congestion. However, there is one thing that all these solutions have in common. They all require precise information about the driver's environment to make clear decisions. This need for detailed information can be met by proper usage of machine learning methods that can help to predict future traffic patterns and to analyze vehicles routing history by taking into account different traffic parameters [17].

In the last several decades, intelligent transportation systems (ITS) have been focused on mitigating the negative effects of transportation on the environment. Given the importance of energy consumption, many approaches have been adopted to improve-traffic operation, such as flying cars [18]. These cars have proven to cause fewer accidents and reduce latency in city modernization. Moreover, several routing algorithms have been proposed in order to reduce the consumption and emissions of cars in dynamic environments.

4.1. Demand Prediction and Forecasting

[19] Autonomous vehicle fleet management and optimization requires accurate demand forecasting. To optimize consumer interests and asset utilization, and to reduce operating

costs, fleet service providers need accurate forecasts of passenger demand. The purpose of Demand Forecasting is to predict consumer ride requests in the upcoming period for different fleet areas, levels of traffic congestion, and time of the day. Based on the predicted future and current consumer demand and incomplete information, the planning strategy for fleet vehicles in the next period can be optimized, and the results can be used for deployment of fleets and optimal use of the available vehicle-sharing pool.[20] Demand prediction and forecasting is an important part of vehicle dispatching. Through the demand prediction and forecasting of the fleet service area, the future demand of passengers can be effectively predicted, and the passenger demand situation of the entire service area in the future can be better understood, and the efficiency and quality of the dispatch of the fleet can be greatly improved. A variety of demand prediction and forecasting methods have been used in fleet dispatch management. Traditional traffic forecasts are mainly based on classical time series analysis and regression methods. However, these methods may need to consider more influential factors, and it is not easy to adapt to various changes. This area is relatively large, so many researchers have proposed to use machine learning or deep learning forecasting methods to improve the efficiency and accuracy of demand forecasting and dispatching of fleet management models.

4.2. Dynamic Pricing Strategies

In smart cities, autonomous or self-driving vehicle fleets will introduce a fleet management problem in the supply chain, which can be handled in different ways as an optimization problem, for example, by controlling the locations and movements of vehicles. In this paper, a machine learning method is integrated in a fleet management decision-making model, where the objective is to provide the most convenient autonomous vehicle fleet for customers and for the service provider. This paper will provide a machine learning optimization tool for private and shared self-driving transportation. For private self-driving cars, a system for mobility on demand, with users leaving their self-driving car wherever they like, will be developed. For shared self-driving vehicles, where passengers share a car, an earnest passenger-first approach will be implemented. This paper describes the functioning of an autonomous robotic vehicle, built from a Mobile-Robot K3. It provides tools for developing a dedicated decisional model specifically designed for that application. We describe an architecture based on finite state machines (FSM) concepts. Different scenarios in decision theory can be distinguished. They differ by the objective, the domain on which the decision is made and the decision makers involved. The selected decision-making model is often ruled by technical constraints of the robotics systems. In the model proposed in this paper, a hierarchical FSM decision model has been used. The first step in this model aims at classifying the contextual scenario. The next steps consist in identifying the "best" action in the given scenario, according to one or more strategies associated to the current behavior.

5. Optimization Techniques

Prediction-based learning allows us to minimize prediction error, characteristic-based learning allows preventive schedule changes, and exploiting the model to optimize is model-based learning. The learning models we describe in this section are the most commonly used and more popular among other models in literature. [21] The predictionbased learning, mainly used to model relations between energy consumption and speed information, are various machine learning models, such as simple linear regression, multivariate kernel regression, and Gaussian process regression. Data-driven clustering has been applied to classify the service areas according to the conditional probability distribution of the future customer requests (classification-based learning). A model estimating energy cost and the battery charge probability was developed using reinforcement learning, which then optimized the driving policy of electric vehicles. Algorithms were proposed in the two-stage scenario: a machine learning model predicts the weather-based energy costs, and then this result is integrated in the optimization formulation. [22] In the multi-crieria optimization branch, there is simultaneous reversal between the prediction and optimization problems, where regression-based learning is the most used one among others. The machine learning tools applied to the location routing problem in intuition and augmented multi-objective optimization include the elastic net, least angle regression, ridge regression, and t-distributed stochastic neighbor embedding (t-SNE). Constraint handling techniques that exploit the correlation between the objectives and constraints coordinated with binary classification, binary relevance, and binary relevance weighted with a margin scaling model are used to implicitly predict and optimize simultaneously. The complex scheduling problem is modeled as a set of regression, classification, and ranking problems. Epsilon support vector regression, ordinal regression, Gaussian process regression, and the support vector data description are popular among the optimization-based learning methods. Providing a disappointingly meager understanding of the combined effect of all the criteria on the world may unlock new insights.

resulting optimization problem comprises coordination and scheduling over all vehicles based on the future predictions. The challenge is to maintain some reserve capacity in resource management to satisfy a certain performance level in the presence of uncertainties. Regridding and recalculating accurately is not possible in a "real time" or "on the fly" optimization environment. However, an adequate structure equipped with learningbased methods can provide flexibility in prediction and optimization. While there are learning techniques that are predictions-based, characteristic-based, or model-based learning, we develop models that combine various approaches where applicable.

[23] Optimization is essential for efficient autonomous vehicle fleet management. It includes tasks such as predicting future states and customer requests with high precision. The

5.1. Linear and Integer Programming

These predictions are fed into an IP-based vehicle routing problem (VRP) model, typically solving it real-time. When solving IPs for real-time AV decisions, it is crucial to tailor the ILP model to the considered application— the classic ILP fundamentals are insufficient. Some AV ILP strategies : directly model the RL problem as a MIP. However, usually we include tight training-time generated upper bounds on the maximal number of passengers to serve and vehicles to use, since the MIP is prone to degenerate solutions that result in slow solution times and extensive iterations . Acknowledging the LP relaxation of the MIP, another key development here is that reinforcement learning can guide policy improvement in this relaxation, by biasing LP variable bounds and therefore the decomposition's subnet structures.

A linear program (LP) aims to optimize a linear objective function over a constraint set that can be naturally represented using matrices of constants and variables. Integer programming (IP) extends LP to optimize over not just reals, but also integers. Therefore, IPs can represent all combinatorial optimization problems up to some imprecisions [24]. Hence, IPs have broad applications in urban traffic management and MAFM of goods, services, and people [25]. Yet their only-memory approach to linearize nonlinear and disjunctive constraints can be quite conservative and prune a large fraction of feasible and potentially high-quality solutions. With growing availability of data and computing resources, tailored algorithms that leverage this to optimize IP solutions are desirable, notably in the context of AVs. Within this context, random forests and machine learning (ML) models feature prominently in the recent literature [23]. For instance, they are used to predict future vehicle uses.

5.2. Genetic Algorithms and Simulated Annealing

\newline The implementation of a ride-hailing solution with Genetic Algorithms (GAs) and Simulated Annealing (SA) is already discussed in this section. A ride-hailing service like Uber in a city with huge number of Autonomous Vehicles (AVs) would be seen in the future. Therefore, fleet management, which needs the scheduling of vehicle tasks and their trajectory control, is particularly significant for the system to achieve riding quality and high efficiency at the same time. [26] Beyond traditional methods, researchers should also explore deep learning-based strategies and low-latency real-time optimization methods, including applying the methods highlighted in this section.

[27] The solution to the routing problems of managing ride-hailing vehicles or autonomous vehicle (AV) fleets is called the vehicle rerouting problem. Genetic algorithms (GAs) can be used to fix vehicle trajectories at the departure times of passengers to maintain an optimized plan while Simulated Annealing (SA) calculates a probabilistic turn probability for rerouting. GAs and SA, MAS, Reinforcement Learning, meta-heuristic & traditional methods considered for solving ride-hailing vehicle management regarding minimizing Distance Traveled, Frustration, and Number of Passenger Requests Refused problems.

6. Simulation and Testing

Before modeling the autonomous control/control strategies of an entity, the entities themselves (henceforth, vehicles) should be modeled in a straightforwardly observable way, and connected to the rest of the vehicle-control infrastructure using standard vehicle- control interfaces. This ensures that control strategies developed using only high-level abstract inputs (like “desired throttle position” for a passenger vehicle under cruise control) can be directly deployed to the real entity. This is because it is common that a software control strategy outperforms the original goals of that entity. For example, a dynamic traffic management system allows passengers to substantially increase their willingness to accept longer trip times if they know that the vehicles they are in are operated by akin dynamic management strategies. Such a transition in vehicle operation can only take place if the developers of the dynamic management strategy can show that the new strategy doesn’t exacerbate the gap between the desired behavior of the controlled vehicle (for example, surge speed) and the as-built or the as-driven vehicle. The damage control can take the form of additional controlled entities modeling layer as has been modeled through careful choice of constrained control inputs managed by a particular ECU modeling the acquired constraints for critical entities and the use of zero-shot imitation learning via zero-shot action-conditional RNN for non-critical entities [28].

[29] [30]Simulating autonomous vehicles in the real world is costly and can be unsafe. Simulations are a safer and run under more controlled conditions than real-world testing~\cite{DBLP:journals/corr/abs-2008-11335}. Open-source software like Microsoft AirSim, Ford's CARLA, and even NASA World Wind with Gazebo can model both the environment in which the vehicle drives and the subsequent vehicle behavior. This modeling ranges from modeling the physics and vehicle controls to modeling every individual pedestrian in the environment. The simulator can also introduce multiple types of noise, distractions, and other driving hindrances to provide more robust testing than real-world testing can. As a result, current research and development in autonomous vehicle technology emphasize a testing-first approach.

6.1. Virtual Environments and Simulators

Open-source traffic simulation packages, by focusing on quick manual data visualization and explicit user dynamic interactions, typically offer real-time, easily adjustable, interactive traffic scenarios. They require only limited physical domain knowledge or programming skills and are aimed towards the development of a large, loosely coupled scientific community. When it comes to reversible planning, model training and data validation are needed. The control problems with an AD and with an AV fleet require an extensive amount of data and extensive real-world testing and validation. This is due to the diversity of essentially random and chaotic traffic interactions which involve many entities with different behaviors and control capabilities. In these situations, the safe, easy to repeat and controllable scenarios provided by V&E&S are potentially a perfect training, validation, exploration and AI traffic engineering choice.

The machine learning approach necessitates extensive training and validation data coming from real traffic flows, which are oftentimes not readily available, are difficult to collect, and introduce safety and privacy constraints [31]. Virtual environments and simulators (V&E&S)

feature the role of fully transparent, adjustable, and re-creatable traffic system representations useful for safe artificial intelligence (AI) algorithm training and for controlled AV-FM (autonomous vehicle fleet management) scenario testing, also denoted as off-line and on-line training and validation scenarios [28]. Simulators allow for complete control over all entities of the simulated environment, which opens up and provides the feasibility of strictly targeted model exploration and performance evaluation, in bounded and unbounded AD (autonomous driving) and AV-FM training and validation scenarios. Most of the ensemble-based, open-source simulators personalize either physics-based simulations engine, traffic flow and congestion complexity, API (application programming interfaces), or the ease of use, but in most cases they offer only limited user interactions [30].

7. Case Studies and Real-World Applications

In this paper, we propose a novel effective model, called LaSSLSTM, in order to better predict other agents' behavior in realtime. It is crucial for any autonomous driving agent to be able to predict what will happen next on a road in the near future. Curb weight, vehicle's movements, and vehicle's existence on the road could be obtained from raw data by applying initial feature extraction. Then, the trajectories representing the future path of agents are determined by using predictions. In order to understand that LaSS-LSTM is better in end-to-end highway driving scenarios than lane-aware LSTM and plain LSTM, LaSS-LSTM should be analyzed and compared in terms of prediction success, following traffic rules, staying in its lanes, and differentiating vulnerable users.

[16] Machine learning is playing a critical role in helping autonomous and connected vehicles react to other road users, traffic, and infrastructure. This paper summarized our efforts with advanced machine learning technologies for autonomous applications, including vehicle trajectory prediction, autonomous navigation, and autonomous fleet management and optimization, which are critical for the focal field. Overall, the knowledge on vehicular data analysis with machine and deep learning in this paper implements a system that records, analyses, and provides real-time feedback. This system uses machine and deep learning models, which are trained with driving behavior data using 18 different features such as speed, acceleration, etc. for each driver segment using supervised learning. After model training, by using the physical hardware setup, the driving behavior of a driver can be evaluated based on the incoming data. Furthermore, this system uses ML models to find

driving changes of the drivers and allows to interact with an environment's dynamic components like other cars, cyclists, and pedestrians. This system aims to generate immediate safety and eco-friendly behavioral warnings for drivers regardless of the restriction.[32] Autonomous vehicles running in the real world will sooner or later need reliable driving models on other road users, including the vehicles to predict the position and behavior of surrounding vehicles in the near future. To this end, we proposed a novel predictor called lane stream attention-based LSTM (LaSSLSTM), which effectively leverages road information to improve prediction. Our proposal builds on the assumption that public driving datasets are generally collected under the similar lane configurations and prioritize stream information from the lanes to improve the accuracy of trajectory prediction in challenging scenarios. In highway settings, we proposed a method that can improve the prediction capability of trajectory prediction models when there are not enough historical data.

7.1. Uber and Lyft: Dynamic Pricing and Route Optimization

In the following, I present some online dynamic routing and pricing strategies. presents a selection of algorithms that efficiently and successfully control the car routing and fleet management in the context of autonomous electric vehicle on-demand ride-sharing services with substantial battery recharging constraints, demonstrating an average gain in number of served customers per day up to 40% or more in our experiments. leans on carpooling transportation features through a hierarchical multi-agent approach which enables effective fleet operation and provides sustainable transportation alternatives ensuring convenient, cost-effective, and demand-responsive rides. The flexibility and control of the entire ride tours respecting the market conditions of carpooling allows stakeholders to partially shape their desired travel pattern over time and space, while the adoption of a reinforcement learning algorithm provides an efficient probabilistic approximation to the TAR pool demand function in situations where the space of states and demand pattern are unknown and/or large.

[33] [34]Operational and decision-making strategies to manage fleets of autonomous vehicles require considering dynamic routing and vehicle dispatching, as well as the real-time decisions to take, such as dynamic pricing and trip matching. This section aims at reviewing the strategic and operational challenges faced by ride-hailing companies' fleet optimization systems. As to be expected, Lyft and Uber are two of the most requested and well-known mobility service platforms within urban areas. Lyft and Uber's systems operate in a similar

yet different operational model which is further described below. This section analyzes both companies with the dual aim of identifying strategic and operational differences and providing an overview of the state-of-the-art methods needed to address their issues.

8. Ethical and Legal Considerations

Considering the whole range of challenges that we are facing, including technical, operational and people's behavior challenges this research in particular: 1) focused on the development and validation of Machines Learning (ML) algorithms for covering both the short and long term multimodal predictive optimization of autonomous vehicles fleet management features, 2) definitions the application of ML-based approaches for Ethical and Legal considerations in the manage and operations of AVMs. Indeed, the significant upgrade in AV safety capabilities that the Industry 4.0 new approach to risk analysis, reduction and management should actively manage the Ethical & Legal issues related to the new risk factor must be properly considered. Adopting the above mentioned parallel approach to the evitable reduction in the residual risk (namely by the inclusion of new safety appropriate hardware and/or performing on-road extensive verification and validation tests), proper the serious of ethical and legal accidents avoidance system on on of these vehicles can provide a form of very well welcomed warranty to the public. [35]

Enabling technologies and spiking consumer interest have become the force driver for the Smart Mobility/Transportation Services, including the burgeoning deployment of Autonomous Vehicles (AV). Autonomous vehicle (AV) will transform transportation by doing their work more efficiently, saving lives, and mitigating negative environmental impacts [36]. The future of AV remains undefined as concerns exist amongst the public and regulators with the potential harmful consequences. As pointed out by Massaro and Taddia, the development and deployment of fully automated vehicles raises ethical concerns, especially in extreme traffic situations ('trolley problem') where they may need to make challenging ethical choices [37]. In today's AV market however, ethical concern is a marginal issue, solving different technological, legal, or technical barriers is rather the focus of the industry. However, these challenges deserve addressing by including ethical and legal criteria in the development of mobility solutions, both in the software or hardware system and regulatory fields.

8.1. Data Privacy and Security

Guideline 6!seudo-logical approaches are becoming a goal driven venue for machine learning approaches to be implemented. Therefore the requirement of verification and validation must be ensured that the model is safety, dependable and has been built through a security risk modeling life cycle development and testing. This means that foundational dumb data AI, deep learning AI and safety and security AI models should be trained on dirty and confounding datasets. Dirty data to ensure the baselines are the minimums for ML/AI models in associated self-driving cars sensors and map localization understanding. Confounding data to further train deeper models that are more effective in a larger set of tasks.leta models like SWAGEN or Adversarial NLG outperforms foundation AI models for generating multi turn dialogues and Class discriminative models. In case we require foundation models with higher granularity, then AGPT-4 can be utilized to convert model from AGPT-2B model to AGPT-3B model by either using the transformer knowledge or distilled model method.

Predictable action has been achieved in implementing Single Net classifiers, where a data generating model is trained to generate favorable trajectories and replayed to train a single policy network. On the other dimension, Reinforcement Learning (Sutton 1998) technique, has also been shown to perform even better while training the learning model to take multiple number of steps in the future for each training data. Once a physical network has been trained, it can be discretized to be used in shorter distance prediction or other experimental use-cases. Deep learning (LeCun et al. 2015, Goodfellow 2016, He et al. 2015) can be a good choice in many industry-level data-driven production systems, machine vision, and natural language processing especially when the input data is images or a high figure representation language like natural language. Though other type of neural networking would suit good, the deep learning however with the associated convolution neural network (CNN) has outperformed in many learning models performance especially in image recognition and object detection. Nevertheless, it should be noted that machine learning model of autonomous vehicle has entered into a state, where acting technically without causing risk.

Several limitations: static and dynamic placement optimization models for MECs are scientific preliminary research; much effort should be devoted to confronting the NP-hard nature of the problem and developing effective heuristic or meta-heuristic algorithms; real-world data from autonomous vehicles is hard to collect and are often confidential. autonomou driving data can be available through simulators. The bulk of computing must be performed at the MEC on a real-time basis. The need to carefully manage distributed data processing must be integrated into autonomous driving strategies. This is the driving force behind the use of emergent technologies such as edge computing, federated learning, and true hybrid learning with machine, distributed ETL and Mec. Model explainability in autonomous driving system also plays a critical role to solve a following challenge. An explainable model shows the certain evidence or explanations to the reason behind the prediction result. Ran' lot "" has shown that a lot of theoretical relation and techniques would be mentioned if a machine learning model is selected for an Autonomous Vehicle (AV). These machine learning models in essence is a function that takes the input state of the surrounding neighborhood and predicts the good maneuver in order to transit from the current state to a desirable state.

Managing autonomous vehicle fleets from a central server requires real-time data stream synchronization including PALD (passenger autonomous driving) data and OAD (online autonomous driving) training data. Model explainability requires that experiments be designed and analyzed so that performance can be understood in the context of the underlying physics. For the components of AMoD, the CCN model with graph-convolutional networks is promising. Foundation models such as LLMs/VLMs may have potential performance and accuracy advantages, but they have challenges that can make them worse than the best current approaches when used as previously proposed.

9. Conclusion and Future Directions

The benefits of using machine learning for predicting the Electric Vehicles activity beyond the capabilities may become organising smarter and more efficient public transport systems and in this work the first results obtained combining machine learning clustering model and queuing are represented in a closed-loop city route scenario. The effective urgency of obtaining real-world data and creating prediction models has not allowed justifying the real achievement of effective and perceptible benefits on transit service performances. Now, the future applications in which the here represented predictive model can find application are exemplified by the real-world problems already solved by neural network prediction driven solution. This last part provides several real-world analogous application areas already tackled by neural network based prediction foundational improvement, to possibly anticipate at which kind of problems currently faced by existing shuttle services the proposed model could be efficiently and effectively used in a near-future perspective.

[19], [32] The work presented in this chapter aims to demonstrate the potential of combined machine learning and queueing theory models for fleet management optimization of autonomous electric vehicles operating in mixed fleet, closed-loop shuttle circuit scenarios within an urban environment. This computational approach is designed to provide dynamic and optimal deployment and operation strategies, based on real-time vehicle localisation data, electric vehicle state-of-charge data, and queueing theory based demand forecast, to suffering transit service operators to transit agencies, with the target of enhancing the daily services provided to the passengers while enhancing the fuel and the duration of battery provided by operating electric autonomous vehicles that may have impacts on the entity's environmental performances [36].

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