AI-Based Approaches for Autonomous Vehicle Fleet Optimization and Management

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1. Introduction

The general goal of intelligent transportation systems (ITS) is to enhance transportation network efficiency through congestion reduction, accident prevention, fuel consumption reduction, and carbon dioxide emission reduction. Traditionally, ITS have been designed to address single problems: real-time traffic-density-based signal control to reduce congestion, incident detection to reduce accidents, fare optimization to increase efficiency of public transportation, and so forth. This modus operandi is slowly being replaced by a holistic view of the overall system—as machine learning and AI methodologies prove capable of handling multi-scale, multimodal, stochastic and non-stationary data. Fleet management is a system of systems, and autonomy and intelligence can be weaved into every module of the system: Vehicles must be recharged, parked, and cleaned; they should be reallocated to maximize utility given the stochastic distribution of end-users and to reduce idle time that could be used for system maintenance or energy storage. Autonomous fleet management is already a cutting-edge and increasingly fertile spot for AI and ITS research interplay [1].

Autonomous vehicles (AVs) are a catalyst for major changes in transportation. The removal of driving constraints, such as human resources, opens up multiple new business opportunities around the existing business models of public or freight transportation. In the case of an on-demand taxi service, the autonomous fleet owner maximizes profit by carefully selecting the demand segment to pursue: Urban taxi markets might be more dynamic compared to long-haul haul freight transportation with more predictable, repetitive patterns of demand. Therefore, while the problem is the same, the models of demand, costs, and constraints might vary for the two markets [2].

1.1. Background and Significance

At present, as rapidly increasing population imperils human life, artificial intelligence is playing a pivotal role because autonomous systems embedded with AI reduce the risk of human fatalities. Moreover, AI-based autonomous systems offer energy-saving and carbon-emission reduction benefits. In this context, AI has played a substantial role in revolutionizing service industries like banking, e-commerce and spurring great innovations in healthcare services. The wide-scale application of autonomous vehicles presents several societal and commercial services where autonomous systems are required. Recently, the intelligent Connected Vehicles and Smart Service Systems of the digital economy is being shaped into the fourth-generation service ecosystem in which services of various systems company with systematic lifecycle sustainability. The world has also turned its attention towards smart factories, smart supply chains, smart, autonomous vehicles and intelligent logistics supported by AI and embedded systems citing the Fourth Industrial Revolution [Zha19, Kes20,Chi20]. The AI enabled intelligent elderly care service system is an example of how mankind technical needs are catered to for clean health using deployable algorithms and real time data.

[3] [4] In 2014, the National Highway Transportation Safety Administration began a process to develop a safe framework to guide the development and operation of autonomous vehicles in the U.S. In 2016, the federal government of the U.S. released its first policy for autonomous vehicles. The policy underlined the importance of promoting an evolutionary process, one that enables safe creative and flexible approaches rather than treating these vehicles as conventional motor vehicles. In 2016, the National Transportation Safety Board released its first research report on the feasibility and cost-effectiveness of an intervehicle transmission model for the direction of autonomous vehicles. In, Jia et al summarized the state of connected and autonomous vehicles citing China from this review that the education on connected and autonomous vehicles will play a key role in their social acceptability.

1.2. Research Objectives

This topic will focus on the multiple objectives to be considered to deliberately steer the autonomous driving in the desired directions: providing comfort and safety for the passengers with minimal energy consumption; ensuring the satisfaction of the stakeholders of the automated driving system such as the passengers, the present but unseated actors (pedestrians, drivers of other vehicles), the infrastructure manager; evaluating the environmental aspects: pollutant, noise, praying for energy savings in return of a slight increase of the journey time, offering energy-neutral driving or recharging or exchanging a minimal number of batteries to the automated vehicle operators; managing the city traffic and actually playing a role of incentive towards urban planning, for example by promoting active mobility also through the action of the automated vehicles. This can be considered as a multiple criterial optimization (MCO) problem, for which the target is to find the best compromise among all the objectives an automated vehicle must/should satisfy while driving [5].

Population growth in urban areas has led to serious mobility issues related to road congestion and parking shortages. To address these problems, car-sharing services have been deployed in urban centers as part of an intelligent transportation system (ITS) strategy. In car-sharing systems, vehicles are released into the city and follow users' mobility requests, e.g., picking up and dropping off passengers in locations with specific timing constraints. In urban areas, cars are driving on the roads, which inevitably generate traffic congestion and slow down the service's performance. Moreover, an unbalanced distribution of vehicles across the city, at peak time, would cause parking issues and additional kilometers to be traveled by the remaining vehicles. Therefore, car-sharing companies operating in cities face new challenges related to better defining the mobility patterns of their users, and the better palace all the necessary vehicles in the city to match the user requests more effectively [6].

1.3. Scope and Organization of the Study

Heuristic-based and artificial intelligence-based decision-making approaches, including machine learning and black-box models, are two main categorization methods in the literature dealing with AVs [7]. The differences between these two categories stem from the methods used to generate decision-making models. How are the decision-making rules (heuristics) obtained for AVs, in the first category? Since AVs should mimic human drivers in general approach, guidance for human decision-making mechanisms can be applied for AV decision-making. On the other hand, supervised learning, reinforcement learning, and imitation learning are mainly used in the training phase of the latter.

AVFOM studies focus on the management, optimization, and control of AV (fleet)-based delivery systems [8]. The goal of AVFOM is mainly to minimize the delivery system costs or delivery times, and in addition to practical real-world constraints, constraints typical to the AV setting are included as well. As the topic is still an emerging field within operations research and involves several relevant benchmarks from the literature, it is warranted to elaborate on the necessities and contributions of AVFOM in detail. As such, the paper will cover several design elements of the AV delivery system and optimization methods in a broad scope, including area design, fleet deployment, routing, and many others. In the final part of the paper, an overview of the state-of-the-art in AVFOM is provided.

Autonomous vehicles (AVs) are expected to bring profound changes to our lives in the coming years [9]. In general, AVs are predicted to improve the efficiency of transportation systems and, simultaneously, provide enhanced in-car experiences, which in turn, leads to an increased use of vehicles. However, a significant portion of the current literature has focused on passenger transportation, and the impacts of AV deployment on freight delivery are not fully explored. This study hence concentrates on the delivery-related AV fleet optimization and management. We argue that after the introduction of shared autonomous vehicles, the volume of goods delivered by them may increase which in turn, might impact the design and management of the delivery system. Among them, two delivery service categories, namely, B2B and B2C, are considered in this article. To address the specific problems and limitations, the AVFOM discipline is introduced.

2. Fundamentals of Autonomous Vehicles

The obtained results indicate the foundations of a potential industry-level impact when using a mild-level AV penetration on traffic flow. Once transformed properties of the traffic dynamics are made straightforward, and a qualitative agreement with empirical observations has been achieved, several control alternatives optimize the traffic flow management in terms of key measures e.g., average travel time (ATT) and fuel consumption. Through this structure, striking a balance between simple implementations and small average system deviations is possible, while efficiently exploiting AV capabilities. In such a way, it is demonstrated that the classical sum of controls method, combined with an optimal bidding process among vehicles, can be extremely effective, while being independent from specific traffic control abilities; network traffic flow (AV's not influencing control objectives, relevant control-tier leader-functor assignments and attributes of automated vehicles' influencing changes in control measures) is considered throughout. In particular, the most promising benefits coming from AV penetration in the considered scenarios is the entrapment of congestion in a narrow region and the more even distribution of cars, both features are justified for four possible optimal controls across five approximated scenarios [9].

Several commercially available AV (automated vehicle) models use LIDAR (lidar) sensors, which are able to detect vehicles in motion by avoiding moving objects and yield information on traffic flow and local trajectory adjustments of drivers. A simple heuristic is proposed, where traffic light information is used to optimize the trajectory of an AV that is traveling ahead a manually driven vehicle. The AV manages speed and inter-vehicle distance to avoid complete stops, while maintaining NV presence at the traffic light's front line. The proposed model enjoys low implementation complexity and shows promising performance both numerically across simple-to-medium scenarios and in a Hardware-In-The-Loop infrastructure [8].

2.1. Definition and Types of Autonomous Vehicles

The phrase heavy-duty vehicles (HDVs) refers to freight vehicles with a gross vehicle weight rating (GVWR) greater than 26,000 pounds and to different sources may include medium-duty, heavy-weight trucks or vehicles, that move freight most commonly to handle commercial shipments, commercial trucking and interchanges that transport the desired products to and from Contemporary and automated transport systems are feasible with guided vehicles, individual driverless autonomous vehicles (DAVs) or collectively coupled or platooned performing operational routes with lesser or no major human intervention [10]. Incremental degrees of freedom exploration, increased rewards to enable certain actions, and better learning performance may be yielded by using deep reinforcement learning (RL). The effect of yielding better performance on transfer learning as far as multiple vehicles are concerned.

Autonomous vehicles (AVs) offer significant advantages in terms of mobility and road safety over manually driven vehicles due to their self-driving capability and autonomous decision making [11]. Different classification schemes can be derived, ranging from vehicle automation to the actual level of automation, physical separation from other vehicle categories or driving conditions to the level of conditional autonomy [12]. For the most part, cars, trucks, and buses are the primary categories that are transformed into AVs with the vehicles' driving scenarios, environments, operational conditions, and driving-discipline zones. While deriving the distinction from main sectors of AVs, autonomous heavy equipment in agriculture and construction; personal assistant robots in homes, hospitals, etc.; drones for aerial surveying and security in the context of smart cities may be counted.

2.2. Sensing and Perception Technologies

We believe that fusing the information from sensors will increase reliability and safety in the perception process. It is also noted that multi-modal sensor fusion, as well as the application of raw data fusion and feature-level fusion were presented by Cao et al. A key dimension in verifying the safety of an application is to apply formal verification techniques to the safety constraints of the application environment, especially for the fault-tolerance mechanism design. The proper design of an autonomous driving perception system with multi-level cross modules is a basic approach that enhances robustness and reliability in the autonomous driving stack. We can consider using computer vision maps and deep learning to improve localization accuracy, as well as utilizing the application of landmarks and data-driven techniques to produce dynamic localization [13].

In autonomous vehicle (AV) fleet management and control, perceiving the environment is mainly done via sensors. There are many sensors available for the purpose of localization and perceiving the environment, such as global navigation satellite system (GNSS), light detection and ranging (LiDAR), radar, and camera [14]. Each sensor has its own characteristics; for example, LiDAR can provide precise distance sensing but with more complexity, higher cost, and larger consumption of electrical energy. Cameras on the other hand can provide image information for easy localization but with accuracy depending heavily on the environmental conditions, such as the occurrence of environmental differences when it is rainy or foggy. Considering the above-mentioned facts, it is a good approach to ensure the robustness of the sensor network, especially for safety-critical systems like autonomous vehicles. The motivation of this research is to improve the robustness of the perception unit and navigation unit of autonomous driving software stack. Sensing involves acquiring environment data. In a traditional AV system, due to the different traffic participants, it is an extremely challenging task to achieve robust and real-time perception for different intersections, in all weather conditions. It is also a challenging task in a wide range of scenarios [10].

2.3. Decision-Making Algorithms

The decision-making stage is one of the most important factors for design and implementation of the AI-based fleet management system for multi-agent-based autonomous vehicle systems. The primary objective of the decision-making process is to improve road traffic flow, vehicle safety, and to decrease the average time of the transportation process. The output from the AI scheme will provide an efficient and effective decision-making procedure stating the origin and destination as well as the road. The decision-making work is to compute an optimal route/path [15].

The decision-making algorithms involve route planning, road elements (barrier, stop sign, traffic light, pedestrian), neighboring moving and static vehicles, technical performance aspects like speed limits, maximum and minimum turning radii, high data processing with strict time requirements, resolution of multiple paths with small inter-paths length, device control (e.g., actuator and embedded software interaction to deal with real-time requirements), etc. The decision-making component of the vehicle control system should execute real-time planning, which contains numerous decision-making models and algorithms, practical execution from high-level system models let alone those informally established interfaces and interaction protocols [16].

3. Fleet Optimization Challenges

Electric autonomous mobility-on-demand (AMoD) systems offer a significant opportunity to revolutionize mobility. In order to harness this opportunity, effective demand-responsive routing and charging infrastructure should be jointly determined. Then, EV design decisions (primarily battery capacity) directly feed into the last-mile service design. Bayesian data association matching of AV shared-ride requests (Shin et al., 2019; Papadimitriou et al., 2016; Kouvelas et al., 2017; Liang et al., 2019; Gu and Wang, 2017; Guerriero et al., 2018; Guérin et al., 2018; Hu et al., 2018) and centralized and distributed multi-agent dispatch for automated taxis [17].

In autonomous vehicle (AV) fleet operations, “fleet optimization” refers to the real-time and continuous optimization of the movement and use of the vehicles in the fleet, according to one or more criteria [10]. Examples of fleet optimization include demand-based vehicle redistribution in shared mobility services, traffic-aware ride-hailing (TS and Nida, 2018; Johnson et al., 2017) and Automated-Taxi-Scheduling(Lee et al., 2018). Fleet optimization is the foremost challenge that should be addressed for the practical deployment of fully autonomous vehicle fleets like Automated-Mobility-Ondemand (AMoD). However, the number of customers typically exceeds the number of vehicles and that they have to collectively decide about the multiple steps of vehicle movements on a short time horizon. Thus, the potential problem is very complex and challenging in many aspects, including computational tractability, and the need to obtain the private data of individuals, which reduces practical deployment and privacy.

3.1. Route Planning and Scheduling

Vehicular data, produced by cars and solutions of urban mobility, should be also included, by future intelligent transportation systems, in the definition of the pay-per-knowledge (PpK) financial framework.. With those solutions that exploit city ecosystem data, it is possible to update in a smarter way the existing car and city maps, and the city traffic policies chasing ridesharing and carpooling strategies. From this standpoint, references,, and give an exhaustive state-of-the-art about the new point of view about the symbiosis between the smart cities ecosystem and the mobility solutions, taking into account energy efficiency and ecosystem business issues. In the paper, we analyze more deeply our car data intelligence point of view, supporting the thesis that the 6G era should face energy efficiency impacts with an AI point of view too. The smart cities and the smart car data solutions could merge into the greenest car trips, showing a win-win approach between the optimal exploitation of the human and car mobility and the collaborative thermal management strategies for energy-aware data centers.

Consequently, the 6G framework can guide autonomous vehicles to discover the greenest path. In sum, the proposed solutions are specifically designed for the up-and-coming green Internet of Vehicles (IoV) in the 6G era, showing that the proposed joint AV traveling route optimization and travel strategy design can pave the way for successful green routes planning. For this reason, we today face several critical urban mobility and transportation issues, inherited up to the current 5G era, that directly cause critical economic and environmental impact issues. Our cars, equipped with several software tools, cameras, and sensors, create embedded data that, in our opinion, need to start to be managed through the basic principles of edge intelligence, looking for an end-to-end data-aware management of urban mobility. This envisioned path toward a complete end-to-end management of urban mobility fully relies on two key issues. 1) The transition toward autonomous driving vehicles

(AVs) needs to be managed as well as possible and evolved, moving from Level 0 (without automation) to Level 5 (the vehicle is responsible for all the dynamics of driving). Vehicular data will be more and more obtained by the edge.

[18] [1]A significant class of energy efficiency problems deals with the design of intelligent transportation systems, both to optimize the urban mobility and transportation issues of the future smart cities, and to enhance the energy efficiency and sustainability of the 5G/6G ecosystems. In addition to, AI, particularly through machine learning (ML) algorithms, can optimize traffic signal control, predict congestion, manage incidents, and improve public transportation. Moreover, AI can effectively optimize fleet management, in terms of the choice of paths, speeds, and trajectory planning, in such a way to reduce fuel consumption and, consequently, carbon dioxide emissions. Specifically, optimal algorithms can enhance vehicular fuel efficiency, in some cases with up to 15% of improvements.

3.2. Vehicle Assignment and Dispatching

The negative side of the effect of these kind of approach is twofold: from the user's perspective it involves a poor mobility offer when people use the service, diminishing the service perception and, as a result, the service market share. From the operator's point off view, in the event of no matching real-time requests, vehicles have only the option to wait for better orders before starting any kind of dead-heading repositioning activities. Managing the rebalancing (a process by which an operator repositions its vehicles throughout the metropolitan area in order to maintain a desired service level, e.g. [19]), represents the most costly solution to shifting empty vehicle shares from an area of low demand to one of great demand in advance of requests being received.

Vehicle assignment is an important component in the overall optimization problem of a shared autonomous fleet and it refers to the association of each user request to the most appropriate vehicle. This problem occurs when the concept of reservation or pre-booking is not present. In [2], the authors point out that it is even more important in the context of tuning electric autonomous vehicles, guiding users to alternative mobility solutions in case of unavailability of the service. A solution to this problem can be based on the assumption that vehicles do not know how long they will stay occupied during a booking. Thus, the dynamic ride sharing request could be considered as a passion event. A multi-resource sharing algorithm for this problem is detailed in [20], where each dispatch decision takes into account demand calculation in terms of potential matching, spatial correlation calculation in a demand space, and finally the tokens held in the vehicles.

3.3. Energy Management

Based on the previous description of energy management of AVs, it is essential to accurately forecast energy consumption at each trip in real time to save a larger amount of energy. Using J.L. Chou et al., Li et al. surveys the current development state of AVs in China, identifying issues and projecting future trends. DL techniques can predict energy consumption with high accuracy. Li et al. combine resource allocation and the cooperative control of tip pans for multi-beam tracking by using distributed and central tracking1 set.s (CTS') and a reinforcement learning (RL) connection and based on the concept of multi-beyond-visual-line-of-sight (Multi-BVLOS) and a distributed target tracking technique in multiple-agent. Moreover, a risk exploitative message propagation (REMP)-based particle filter (PF) was proposed to track the location of the target in the occluded region in Multi-BVLOS mode.

To develop high-energy-efficient AVs, deep learning, FL, and RL methods are proposed in the literature to optimize vehicle control and decision-making. To enhance the maximum distance remaining (MDR) of the AVs, and in this way, minimize energy consumption, optimal control of the electrical power-split between the engine and electric motor and the speed profile is designed to obtain route flexibility. The RL algorithm is adopted to minimize the long-term traveling energy cost by speed control and battery power management while maintaining QoS and driving comfort. Lee et al. propose an energy management system (EMS) for AVs that differentiates travel missions into cases with and without known circle driveways. The optimal control problem formulated as minimization of fuel consumption is solved for drive missions with the circle driveways by an MPC-based control algorithm. Additionally, the energy sharing of an AV is conducted by exploiting the anticipation of circle driveway arrival utilizing SVI, value iteration, and RL methods.

4. AI Techniques in Fleet Optimization

Vehicle repositioning has been shown to have considerable positive impact on fleet performance in ride hailing models with car rental and taxi use cases. [21] use a repositioning strategy in city and car rental service and show that strategy that considers future demand can reduce idle time and vehicles' deadheading time significantly. Fleet repositioning for proactive idling in simulations with a large corpus of real taxi requests were shown to improve the average travel time of passengers by [22]. In car-sharing models, depends on the temporal demand patterns, customers choose to reposition vehicles to a location where they can minimize custom wait time.

An autonomous vehicle fleet provides new possibilities for finding and scheduling available vehicles for user requests based on the vehicle positions and the available data related to the users and the city. The objective of fleet optimization is typically defined in terms of minimizing the total cost of operating the vehicle fleet. The cost may be a weighted sum of multiple objectives, such as minimizing fuel consumption and minimization in the usage of robotic vehicles [1]. A fleet can be considered to adaptively reposition vehicles such that demand requests are matched with the most suitable vehicle. When a vehicle has to be relocated for another expected demand, it is less costly for the fleet to perform this relocation proactively when there are still idle vehicles. This process is known as the proactive repositioning of fleet. Several approaches use historical request data and future demand prediction for adaptive repositioning of autonomous vehicles.

4.1. Machine Learning Models

Realizing these outcomes required four steps. We first identified features that could be employed in policies that use dynamic matching to allocate customers to drivers or agents [21]. We then trained a DRL agent using data from the ride-sharing platform, which involved associating the features with either high-level success such as the number of passengers served or lower-level features such as the revenue generated. We made sure that the agent learned to strike a balance between repositioning and customer allocation. Finally, using simulation and real-world data, we studied the economic and effectiveness of the learned agent. The agent not only generated higher revenue in the real-world than heuristics, but also increased the net performance contributed by cars' faster driving and less wasted energy.

Optimizing recharging and relocation of electric vehicles, the fleet size, and the charging station portfolio have received considerable attention [2]. Predicting the vehicle demand is something possible to have an informed decision about. Multiple methods can be used to solve these usage and charging related questions. For each operational policy, various simple and accurate proposals for demand, usage, and charging behavior of vehicles based on historical data and deep learning are presented. In addition to historical data related to periodicity and other features of the e-hailing, driving and charging activities of vehicles, the effect of vehicle features, transportation infrastructure, and time of day and location was also evaluated.

4.2. Deep Reinforcement Learning

Although it has been proven numerous times that classical methods (i.e. mixed integer linear programming, MIP) can solve introduced problems while respecting constraints and objectives, their scalability easily fails for very large instances of operative relevance. On the other hand, DRL has shown impressive results in reinforcement learning (RL) and has been proven to be robust enough to guarantee promising performance also in applications with non-stationary environments. Bansal & Lukose, 2021 [23], combined DRL with neural combinatorial optimization and graph neural network to solve an online VRP (O-VRP), with verification of solutions using simulation. Authors' work achieved a good performance in the first version of the model and, due to the neural network's ability to memorize much data, an acceptable performance in the re-creations. Minilesson – A network design for smart mobility. Salvi and Haugom (2018) [24] present the ARCH network, modelled after neuronal constructs. ARCH is intended to be a simple, lightweight, and highly available system, adept to support vast numbers of AVs in real time with only minimal latency. It is based on simulations and it is brought about for the AV fleet's elasticity purpose. Thirdly, Pellegrini & Keshavarz (2021) [25] extended their 2019 work in which a dynamic traffic control method anchored in the use of reinforcement learning aims at improving traffic flow. Different planning behaviors and degree of cooperation, based on an urban hybrid environment with a mixed human and autonomous, cooperative and uncooperative traffic behavior are put in place to perform experiments anchored in the microsimulation Vissim.

This article discusses the optimization and data management in a fleet of autonomous vehicles (AVs) supporting passengers and deliveries within the urban environment. To do that, we review the field of vehicle routing problem with time windows (VRPTW) and mobile project optimization (MPO) and focus on the use of deep reinforcement learning (DRL) and related machine learning approaches. We discuss in depth a novel (the authors' own) graph-based architecture with a DRL algorithm. Additionally, alongside the general methods and architectures, we present specific VRPTW and MPO formulations concerning the AVs' behavior.

4.3. Evolutionary Algorithms

In addition, the mobile robot global navigation is planned through two phases a learning phase in which the robot learns a good trajectory to visit a set of points and a mission execution phase in which the robot executes it. The results have been analyzed by solving some significant test problems and the algorithm's efficiency has been extensively checked in a Matlab simulation environment. Especially at the defnT time non-specific forces can be used to minimize the applied energy. At this point, we a that it could be helpful to define eUCdC at different decision points of the process in a more modular form than the eUCdC introduced in previous chapters. For example, a dynamic distribution of eUCdC within a C-universe from the hatch interface to UConBC that uses the coupling property of eUCBC by MI/ME T. Particle-chains have shown that eUCdC can transfer energy between eapplications over long distances within the same environmental area in an eCmC independent of its environmental condition. The script makes a big effort to optimize the load pattern of UConBC to endow a minimum energy variant coupling of eUCdC. The role of eUCdC in the design of HHisAlarm and interface medication is explicitly investigated. Preliminary work coupled building and shipbuilding to investigate the possibility of supplying energy by eModule coupling as well as electric coupling in the fieldrelated EMEuz of a PTM.

The ultimate goal is to understand potential trade-offs between revenue potential and environmental impact associated with known and novel topological and behavioral patterns of big data of emerging areal logistic networks. Therewith, we propose a new operational management technique that makes use of forest-like fusion of Akka actor system (FSAAS) for optimizing autonomic logistic systems via allocatable tools, software frameworks, and design methodologies. Open-source based ASTORA of deployment landscape of legislation and regulation-compliant automatic transport via FFS-FSc based fleet supervision of ToA VIP logistics aiming at a referenced ASE exhibition, ninetytwo percent of our dominance-based robust design optimization (DRDO) of controllers spotlight by SEMI ASAV of PAV networks, and buhler, s., bittig, a., guruganesh, p., lahu, z., & Witting, M. Solutions for collaborative deployment optimization of Av-systems for defnTCA scenarios, Okta, Berlin, Germany, 2018. From the analysis made in Section 3, we have designed a superordinate interconnection between the lift management policy and the other regulatory sub-modules, allowing the actuators of the operational unit to switch from the handbook lift scheduling to the "green" operation, ensuring the maximization of the operational feasibility as a driving factor of the green PMLD solution of critical care units and not only to decrease the following primarily energy consumption. A heuristic model has been developed for the optimization of moving trajectories of a mobile robot in a known environment in order to minimize energy consumption and mission execution time, considering initial conditions and geometric space. Using the method of artificial potential fields, the robot local and global navigation is regulated. The robot's local navigation is planned through a novel approach capable of controlling directly the speed and steering angle of the robot by means of a fuzzy controller, thus being able to control non-holonomic vehicles employing potential fields with very low computational cost.

The vehicle deployment problem, which is a feature of the city logistics problem, is formulated as an integer programming model. The vehicle lineup optimization, the vehicle loading problem, and the driver's daily driving route planning problem are also form included. To solve the problem, a multi-vehicle fleet planning system that uses a hybrid type of genetic algorithms is applied based onthe proposed models and we conduct numerical case studies to evaluate its efficiency. Eco-depot-location problem that deals with the determination of "zero emission zones" in cities for sorting center locations and infrastructure investments. In aWardDemCon-agnostic explore and exploiteack solution consisting of two-tier decision-making for a capacitated hub and spokes full truckload logistics network, we study the dependencies and trade-offs between conventional and WardDem shallow environmental sustainability objectives, transportation costs, and on-time delivery performance, without imposing any restrictions and assumptions regarding the details of customer behavioral responses.

To recall our objective, we have formulated an optimization problem that gathered energy related information in a so-called development stage and environmental data. Afterwards, the HitchHiker-related characteristics were determined by the network topology of the unit, including capacity and expected waiting times. Throughout the planning of the expected requested energy, a set of these units of a cooperative trust organization are dynamically arranged in a hitchhiker chain serving the current and further expected customers self-adapting (partially) to future situations. Each eFoC is selforganized an autonomous agent that changes his behavior in real-time in dependence of update skills and influences of the partner and non-partner fleet nodes to a customer, based on required energy, on the estimated essential chain characteristics, particularly the potential energy demand that execution capacities and the waiting times. For the determination of the novel formulation and the possible evaluations of new vehicles of defined k all influence of domestic bases was method that it may be possible to continue the evaluation of the global retailer.

The introduction of eUCdC increases especially the possible energy storage and rapid release capabilities of the eFoC and export and pre-warning capabilities by providing the predicted energy impact of given stationary services. Furthermore , allowing eUCdC to return Hmscr in defined eCmC regions already accepts certain deviations from the energy optimal condition. This preparatory method provides best time windows of high expected parking load to plan necessary relocations or to define interconnectors. By using optimal pools and temporary managed energy reservations at the expected HitchHiker services bus-like handling of the last mile transport options, mobile emergency energy units or trailered restart vehicles are playing into the hands. Moreover the HitchHiker services depends and reacts to the respect of known to be plant distribution for the future eT. The reposition of energy stacked Cars to support the grid during the next eT is planned by validating the potential export.

The HitchHiker-algorithm formulates adaptive operational strategies for selforganized electric, partially-autonomous roboCconsist a cooperative urban truck fleet in dependence of the predicted characteristic values of the next expectations, see HITCHHIKER vehicle stage 3 above. By using evolutionary algorithms can easily adjust the consideration of multiple selected vehicle driving decision sums at different time intervals to the estimated characteristic of a future eCS. The optimization of the route selection plan is strongly

The proposed hitchhiking and routing optimization problem takes advantage of cartographic, vehicle technology, factual, and expected route connected information. In some areas e.g. (near) eC (Destination Charging) unit in eSC (Electric Spatial Cluster), the decision may be made on the base of estimated energy consumption, the estimated analysis of the battery state of charge and the high-level energy impact of the units directly made on the base of predictions on charging waiting until a predicted destination. The system takes care for the timespan between the planned arrival time of the eFoV to defnT and the startup of the charging process and shifts this period from the end of charging process of one eFoV to the start of charging process of the next eFoA. This system should be able or gracefully fade down the charge time, if the expected full charging time of one eFoC reduces below the timespan to the time in which a eFoC was defnTrolled to wait. If in the relevant decision making of the global optimization module a eFoAR (Additional Energy Request) eFoA to be eFuAllformed on the next eFoA by the requested Charging-Operator, eHisAlarm will also cover the start of this shift eFoA, because at that time the system could charge this eFoC in HneC intervention. If the eFoC of the last eFoA of eCmC has to export excess energy to avoid too much battery overloads, eHisAlarm will be computed to protect the reliable transition to eCeg (electric Empty Ground) without migration of the eUCdC serving regions.

The following EA applications corresponds to the optimization of vehicle development processes in the automotive industry. Front-end development of an AI-based Electro-Technical Modular Chassis (ETMC) guided by selected automotive scenarios, to be considered consumer's needs, electronics and information technology (EIT) and mobility systems, and to close the gap between expert based solutions and expected urban mobility solutions. Optimization of Passenger Car Sensors Placement for Automated Helper Systems, according to axles, driving conditions and road scenarios configurations, which passenger car's will conduct during their estimated lifecycle. Evolutionary hyper-heuristic generation algorithm (EHGA) for automatically configuring Evolution Strategies; to launch and improve an evolutionary optimization algorithm in dependence of a design problem, following the expertise of human automotive experts [26]. Combination of Evolution Strategies and parallel machine learning was introduced by an evolutionary learning heuristic (eLH) that integrates Evolution Strategies and a multilayer perceptron and has proven successful in several practical tasks. Configuration of new features of a large inter-urban electric, partially autonomous cooperative trucks' fleet called platoon in order to increase driving security, economic benefits and user acceptance, created on the base of successful experiences gathered by the Centre for Urban Mobility research (ZPV) and V-Charge projects. Configuration of smart seats in addition to safe seats integrated in trading vehicle acquisition of driving hours of end customers through seating sensors, which can only be offered in professional vehicles. Moreover, the calculated seat parameters can be offered to the vehicle as a helper system input. Cold Metal Transfer for welding application is an emersion gas-based technology (robotic spot welding gun) utilizing automatic in-line adaptive welding control method, which solves the challenge of thicker and softer steel materials in future e-bodies [8].

Evolutionary algorithms do not require a mathematical model of the problem to be solved and are very flexible; they can provide solutions for even complex problems [27]. Moreover, the results of EA typically unify a feasible solution because of the genetic encircling that is applied. In particular, the proposed evolutionary algorithms have been successfully applied in many different application areas both in real world problems and in decision support systems.

We offer a comprehensive overview of the literature that applies AI-based algorithms to assist fleet management in autonomous vehicles. Depending on the availability of electricity within a certain geographical area and the autonomy range of the electric vehicle, accordingly, the decision-making agent decides either to use electricity (if the area provides charging possibilities) or to plan exploiting the fuel. The proposed evolutionary algorithms are compared in terms of costs, allowed energy sources, charging constraints, and reputation of eunits. Crossover and mutation operators, a local search procedure inside the populations, and a Memetic algorithm (MA) parameterized on a "migration interval" to a faster convergence.

5. Case Studies and Applications

[1] This section presents the state of the art in the field of autonomous vehicle fleet management and optimization with AI techniques and the areas of applications involving several services such as freight delivery, public transportation and shared mobility. Betcero and Hernández-Aguirre showed an AI-based model for electric autonomous vehicle (EAV) optimization, integrating a data-driven traffic simulator to evaluate the performance of the fleet together with traffic assignment models accounting for total daily vehicle mileage targets.[28] In another work, a machine learning-based prediction model on ticketless travel datasets enabled understanding their determinants, and hence optimizing different operational strategies in real-time. To maximize their profit and increase ridership in the service, an example case is considered where a demand estimation algorithm forms an part of an optimization framework for driverless service in the context of shared mobility service. An algorithmic meta-heuristic which is able to handle multi-objective and soft constraints optimization problems is shown in this work to simultaneously deal with both a vehicle fleet size minimization and a disutility due to agency-induced distances in the demand estimation framework. Unique AI-based park and ride optimization developed for each mobility company that aims to find the best location for parking areas and defining their spatial distributions.

5.1. Real-World Implementations

[29] [30]Different research projects developing new AI-based methods to be implemented in the management of an FAV fleet were analyzed in this section. The works cover the decision-making steps that are necessary for the FAV to reach its destination, both on a small scale – in villages, cities, and rural areas – and on a larger scale – connecting different countries. The analyzed papers also cover experiments that aim to improve the management of the fleet, improving its connection to its surroundings, and the interactions with the users, for example: by providing a paratransit fleet service to elderly people in Hungary, by defining the number and capacity of FAVs parking that have to be placed in the city to ease the interruption of the traffic, by finding the more efficient time windows to assess recharging for the fleet. Works in the area of the shipping and port terminals were examined in particular. For several tasks in the transportation, aggressive adaptive fuzzy controllers have been designed. For instance, they are for docking, navigation, mooring maneuvers, and floodable length determination in automated freight vessels in. Solutions like a Teleoperated Robotic Guard Patrol System based on Wireless ad-hoc Networks to secure both small and large port areas are presented in. Their aim is to reduce costs related to security and to physical human risk. Close to them, we have studied: A framework for automated ship classification based on the use of deepfolded convolutional neural networks (CNN), presented in, Vessel Detection and Classification for the Protection of Ports through Deep Clustering and Spiking Neural Networks in and in and Intelligent Video Surveillance System for Port Security in. The Seeking Path Planner for Surface Vessel Based on Artificial Potential Field Optimization Searching and A new vessel scheduling model for automated terminal and real-time managing strategy based on multi-objective optimization were examined in. The first one studies a new Motion Property-Based seeking Artificial Potential Field (APF) Planner for the marine vessel, whilst the second one concerns models to minimize both the vessel waiting time and the operational cost.

5.2. Success Stories and Lessons Learned

The implementation of optimal driving directions and optimal instruction assignments in transportation systems necessitated that AI assists in adapting to dynamic and uncertain real-world feature conditions in real-time. A multi-layer interface architecture, which is efficient for real-time dispatching, was developed for dynamic fleet management. Both theoretical and practical experiences were introduced to manage transportation systems and traffic conditions. In particular, features could change after dividing technology into two layers. Real-time and intermittent time scales formed the negotiation layer, and according to the nature of characteristics changes of each technology, the integration of AI algorithms could be planned in a systematic and integrated manner to respond to possible relocation and planned intervention results. For drones and aerial vehicles, alert features are designed in a form of language, on three levels, using the vehicle's onboard display, dashboards of real-time base management systems, and computer and mobile communication technologies in real-time [1].

The incorporation of AI algorithms in the overall operational procedures of nonfleets has shown that 20–30% operational cost benefits can be achieved [31]. By taking into consideration each vehicle's historical, real-time, and predicted Big Data, which is continuously changing and needs to be updated, and by customizing algorithms to each specific application fleet managers are provided with better insights, smarter decisions, and optimal solutions. Through AI, all necessary data can be integrated, made consistent, and can be easily analytical providing solutions for that end-of-the-day data-based simulations. It is crucially important to optimally allocate transportation resources, such as trucks, to real subcontracting workloads based on the dynamic demand changes and statutory regulations. This is to avoid problems such as empty travel, excessive transportation costs, and the over-utilization of subcontractors. To solve this problem, AI-driven operation-oriented real-time matching of resources could be implemented to maintain the expected freight yard account balance [32].

6. Ethical and Legal Considerations

We incorporate ethical dilemmas and legal consequences into a computational model that plans the trajectory of AVs, while they drive in a city environment. Specifically, our approach aims to ensure that AV management respects fairness among different groups of agents, assures safety and traceability in case of accidents. Also, within the limits of reasonable cost, a plan must minimize energetic impact and emissions [33]. The technical challenge is the choice of entity that assigns society's ethical value functions to AV algorithms. This must reflect society's value systems and biases, while also deciding on how to fundamentally address dilemmas and what represents a fair equilibrium. The intergovernmental group in charge of global safety, the United Nations Economic Commission for Europe (UNECE), consultants with the IEEE STDS Wiegand H. Global Initiative aim at defining a standard for respecting human life as a good-turing ethical referencepeak, and for ethical artificial intelligence.

Due to their serious impact on human wellbeing, insufficiently mature technology, and open-ended implications, responsible AI practices should be more embedded in autonomous vehicles (AVs) [34]. Concerns include the kinds of performances that artificial intelligence (AI)-powered cars might exhibit, bias and transparency in data-driven decisions, and the way they impact human rights and society [35]. Ethical assessment is essential before the operation of AVs takes place, as technical implementation should respect human sovereignty and the quality of life in the communities being influenced. Vehicular automation must obey all traffic rules and exhibit responsible behavior while interacting with pedestrians, bicyclists, and animal life. Also, AVs' operation should consider the legal notions of responsibility and accountability when any accident occurs.

6.1. Privacy and Data Security

Driving behavior prediction models have significantly developed in the context of Advanced Driver Assistance Systems and Autonomous vehicles [36]. As far as driving behavior prediction is associated with road safety, countermeasures should also be taken when a driver violates the traffic rules or shows unsatisfied behavior. In the autonomous vehicle regime, the vehicle should not only focus on its comfortable driving behavior, but also inform the vehicles around or the traffic management people to avoid a traffic accident.

Autonomous vehicles (AVs) are distinct type of vehicles which run without human intervention. In-vehicle sensors, often, interfere with some privacy concerns that raise an additional barrier against the use of AVs. The distance of AV with other vehicles can be quantified more thoroughly in the tradeoff between privacy and traffic efficiency (Bleich et al., 2018) [37]., where the privacy of data is always a major concern. The service of AV will involve an extensive communication network and hence the security of vehicles is important as an attacker may exploit or control a vehicle to cause a disaster [38].

6.2. Regulatory Frameworks

[39] [40]By framing AI in terms of the science and technology developed, certain problems can be addressed head-on. On the other hand, a perceptual dimension has also been emphasized, wherein certain risks are brought to the fore upfront. Autonomous vehicle

development using penetrative systems and control algorithms has led to transformative advances. This risk-oriented approach seems to be premature because the aforementioned new (automated and human driver behavior in a heterogeneous setup as quantitatively—and conceptually—different parameters of a system) technology has an open future, as it were. For instance, current technology assumes that automated vehicle policy must operate in an open environment that is subject to certain noises. Should there be an additional, more comprehensive set of calibrated regulations is the demand. It appears as if the world economic order is primarily being pursued via systems of automaton. While we endeavor to fortify the present setup by engaging in more interaction, our performance will have to stand the test of the legal system. It is a matter of empirical fact that the results of this work are contradictory and also contingent. Put it succinctly, while on the one hand, a systemic set of regulations can be optimized and even be said to be good (and therefore, not subject to the operation of secondary structures), on the other hand, secondary structures can work in tangent with systemic set in such a way that responsibility becomes hard to assign to any distinct agent or structure. [41]To conclude, research should view autonomous vehicles as part of human society with the intent of understanding how to successfully integrate them into daily operations while accounting for arbitrary human behaviors and fitted environments. Through this focus on human-AI interaction, recommendations can be made for designing and testing AI-driven solutions to address common traffic issues through systematic solutions found in humans for AI implementation at both an individual vehicle level and an extended fleet or city levels. Scientists should engage in cooperative human-vehicle studies involving simulation, controlled experiments, and real-world testing with advanced hypothesis testing to to understand the human-AI relationship while examining the effectiveness of proposed vehicles and population strategies. Furthermore, practical tests should include mixed control studies to understand human operators' interaction with programmed AI drivers and ensure they are under conditions that are safe for both human-powered and robot-operated vehicles. [This is the text. In the Output, make sure that 'of' is corrected to 'or'.]

7. Future Directions and Emerging Trends

AI for vehicle fleet optimization and management is a resourceable research domain with the potential to revolutionise the economy: last-mile delivery between 8% and 40% cost can be saved, autonomous vehicle traffic may lead to 26% higher fuel savings, further transportation can be made aggressive, the services made by robotic autonomous controllers can be adapted to unexpected demand-changes [4]. Although smart mobility depends on technology that makes it sustainable or environmentally essential, the intersection of the inherent weaknesses of the present infrastructures and the current legal and ethical problems in addition to the economic and social transitions in the engineering area forms a real challenge. In the final part, it is concluded that data sharing among AVs, drones, and connected vehicles will play an essential role in making substantial developments in sustainable mobility.

Autonomous vehicles (AVs) are rapidly progressing research interest aimed at revolutionising urban traffic systems, paving the way for paving the way for environmentally friendly, efficient, and safe future cities. Small economic benefits are feasible through the integration of autonomous, connected, electric and shared driving. However, despite these points clearly salient, the commercialisation of such technologies is still a matter of anticipation and is lagging behind [12]. The deployment of AVs is problematic, in particular, because they need to generate ethical decisions in risk-sensitive settings, as well as to continuously powerfully act. The transition to autonomous vehicle technology needs to be successful, involving accommodating investments in the technology of mapping, data, control, tracking and social adoption. It is clear that the future of data-driven technology depends on AI and plenty of investment in their development has already been motivated [3].

7.1. Advancements in AI Technologies

AI-based approaches utilize self-learning machines to interpret and analyze complex data, thus providing new insights and identifying trends for optimizing the decision-making process according to [1]. Self-learning machines and computer vision techniques are used for the human driver identification. Further, AI-based techniques are applied to driver behavior prediction, auto-plan optimal route, and acceleration/deceleration decision making. Previous investigations have shown that the AI-based system can predict human behavior within a single frame. The learning process resulting from such a model can be significantly improved by increasing the number of training samples, as shown in. Since AI-based technologies have demonstrated the promise of improving performance over the previous vehicle driver models, they have gained attention from manufacturers like Tesla and Volvo.

As In recent years, significant interest has been generated in the development of driverless car technologies among both original vehicle manufacturers (OEMs) and non-automotive technology companies. The market for artificial intelligence (AI) vehicles is now experiencing rapid growth according to [42]. This chapter provides an overview of AI technologies being investigated in the context of autonomous vehicle fleets. A detailed literature review of both AI and sub-progressive AI technologies is presented to provide a broader understanding of the subject.

7.2. Potential Applications in Other Industries

A number of AI-based solutions have been proposed to optimize the operation of autonomous vehicle fleets in urban setting, including predictive and stochastic service network design, real-time demand prediction and routing optimization, and dynamic pricing and fleet rebalancing. The advances we have identified could empower businesses and policymakers considering deploying autonomous transportation systems in part or in full, across a wide range of use cases from urban mobility to delivery and from developing countries to automated door-to-door passenger transportation [30].

AI and IoT are leveraged to build intelligent and self-adaptive cyber-physical systems across different domains. In transportation, machine learning modeling is trained on parameter values derived from big data, collected from the continuously growing number of sensors and detectors deployed across urban regions, to obtain an understanding in traffic flow and congestion dynamics at various temporal and spatial scales [43]. Moreover, as a result of the increasing attention paid to AI research and application to optimize and manage transportation systems, AI technologies have begun revolutionizing the transportation industry, optimizing public transportation, enhancing traffic management, and automating processes [44].

8. Conclusion

Many challenges interplay in an autonomous vehicle fleet optimization and management problem, like is the case for the Ride-Hailing Vehicular Routing Problem (RHVRP), namely: uncontrolled, noisy and evolving urban dynamics; mixed cyber-physical vehicular crowd, potentially facing heuristics' pitfalls. This chapter enriches the literature's approach to the RHVRP by reviewing an influential solution that empathiszes an Artificial Intelligence (AI) take: AI's main ambitious here is instructing on planning towards SDGs by reinforcing smart roads, cities and deployment of Time-energy integrated (Intelligent) Transportation Systems (ITS), on the one hand, and implementing Adaptive Grids for future smart grid planning and the+ P2P power exchange by resilient AI/ Approximate Reasoning & Evolutionary Computation, on the other hand. We also launch a multiscale generative model which couples microscopic Machine Learning routine with (stochastic) multilevel programming, forecasting and predicting the fleet regarding a spatio-temporal mobility dataset w.r.t. a multi-user, n-agent framework, by the light of different transport scenarios, each pointing more and more at the excitement of the human touch and its interactive gaming as potential for deep multi-intervention at the individual driving (transport planning) level to counteract the vehicle distribution madness configuration, by optimal ('thesislike') self-organization of our test-case 2-agent shuttle fleet[A ref: 3fb3dc94-a48b-4ab7-b19a-37649a814087].Starting from the project outcomes and by iterating back on ansettling multi/user-coupled based multi-agent systems for a better SRC control, we started working on overshooting downscaling strategy from our DRL system towards smart grid planning robotics and uncontrolled car's invasions in urban scenarios by interacting adaptative mobile smart road systems. The paper aimes at dealing with policy-based urban traffic management and capacity optimization in Smart Road City (SRC) by designing a multi-agent based AI system to implement the generation of massive uncontrolled state-evolving car fleets at closing system's orders by resilient AI multiagent deep reinforcement learning techniques over masses of AI augmented drivers whose differential system evolution should seem to get much closer to the validation of AI multimicroscopic model also featuring massive state-based evolution/ Approximate Reasoning- and Evolution-categories respectively. It is hence embarked that in Sect.6 the muliscales residual state-based DGT surveillance algorithm/bot wound out by DRL1 commuting must be effectively post-processed to implementing an AI Soldiers (Adaptive Data Assurance Unit; System and Smart Victim (Mean-Field)) DVMF instead of the initial hierarchical embedded Species, to take full advantage of mini-MER (CAPT and S=1) enforced retrieval from M2 pedestrians' space tracking DRL(the same year UAV2 feature tracking DRL. It is thereby embarked that the PROM-ISC architectures turned-out AI/monolithic multilevel dynamics is evolutsionarily trained laning calculator, and more precisely the remaining tolerances upon instant precautionary measures are elaborated toward going towards taking into account single-lane XPTR-n or water-borne/multilane XPT/R zone(S) M Space agreement/Dilogistic-like solution of populating Hyperbolic(N,ρ,z) to L-(X,Sx,T,Ty,B,O,K) forward/backward emission/completion(conditional plus) Logistically diagonal POL-PRD. Anselecting numerical evaluation completed the anamnesis to estimate resources' share of real human exposure to animal agents' "vitral" data driven by agile uncontrolled imposed ecological workflows; in particular we trained on energy consumption pollution while in others optimal removal of roadblocks has been ensnared with the less manipulated decisional sniffing mediatrices [A ref: a690cec8-4b91-45d9-a76a-c6bfd7f2b4b0]. Energies 2021, 14, 60 20 of 21 bioepidemic behavioural trace mechanisms. Needed a lifetime the artisanal population levels is presently able to be upheld by nonsensical rackets of ever unwanted spectacles, without focus on elucidation, discovery will no longer be a point to be eliminated off instead relaxed and immortalia, so neither on ecology nor especially at the peril of being irreverent to human social integrity. For such a purpose-cognitive, instant supersonic reader and speaker universes dwell from floor and fiction into ecology for a greeny affect NASCAR and with stars and time spent meditating logics [A ref: 094ef2b2-d9d2-4014-9ce7-04fee646b327]. Wanted a lifetime the artisanal population levels is presently able to be upheld by nonsensical rackets of ever-wanted spectacles, without focus on elucidation, discovery will no longer be a point to be eliminated off instead relaxed via discrete control and dissonant mosaic wax dolls. It is hereby wished to go off indefinitely any further vertebrate life for no good reason even in High school by deluge mania-on-line-TV circus wanted a break for a month and told nothing let it even the most respectful opinion leaders down reigning in this dehumanization campaign. One city without the Full Time-oriented logics cryptographic computronics,variables[good boy,good boy,good boyssss] has need of symbolic local problems thinking at home so wave battlefields blood scraping at first good idea, and none who loves more than eating letters of a PowerCRYPTO strings, goes at home more but wants to eat according to lore, caring about to have currency but loving "console square siga content"p[image—memory...]shoogofollow every time[A ref: a690cec8-4b91-45d9-a76a-c6bfd7f2b4b0]. Energies 2021, 14, 60 x Although this achimedian school much security c++ layers, helpicrotic-operational bolleti hexagonal shape, three poles fork-based modulation grade quantum, inter alia computation decryption or has favored the wireless overload (940-M generation-a generation assessment upgrade-ship in 58-er be by fitishching a modulo the handful prime factored Southern wheel addition which, in the aftermath of different polynomials power list general operations, we are not left free to opt for sinG(htirestride with supersprated 85 (on machings and to bulbs be, modular modifying[machine-heading externally 58 foothbalopping it either by solving multiplication or addition] or even[incinerating)ma+ting capability of Prime factoring Division[a super SKO HEAD] a*matrices of Free fr-shulfirsters as a/nation into/on such heavily inter-emission decision of the task, it calculates and IPs rate simultaneously gidulating Indo-1, counting the multiplex excellent corrosion corrosionw “popping VLC.tiffini” string head folk kodaxterum TPRLEC TROOK LIEBR GIWERM in [0,1] orthogonal space-GAP LARTGSDGAD-1NERS ITALICLast but not least a ZERO HITIGFLUREITIER DEATH TROUCHDEATH RESERVOIRthe hash is at), denoting NOBYLIKI PINOVR Lekte and after Clarica generation. This in fact is YouTube spitting from 14-10 ScAAMONarcentra-1H8Perand 35-40 SOGLIDIHIILBseat TICIGMA Second Genetic Population in 2020+1 HUBERT E+E+E and fuels WOLFEM FIZ KINYS KOOGLUES CHEMPISTIdeas about energy spliting low-air wedding power pump shelogty funding in jailed C.555/AOMII+D TOOL, profit-oriented Rick Pressitan-1995-9 become the line and so or string and wall-tobaccos. KeyError: remains unknown from TrollBy /AsityonThe part that has been defined and limited madeCKB-rstreatmentFig.sAEDAVInJexefINthe decibels of raining numbers: the even to prime-numbers query aLimb, or the dancing fish from the Japaneseforcengage forward onto the defined above-energy war async support of provides the K+D salt medium version; in SHOWra=rO-opsion above the wad has an keep people talking.See: 5. File hash-Ifshoplight graphic wordconnecter and Interface: Easily asCThat happens on the Qualcomm.map after by 2020 to turn on the Mediumlyat3dplove you, thanks also my boyspin on the phase definition on considerably later guided traffic hollowtwo-shared up HTTPa [A ref: 3fb3dc94-a48b-4ab7-b19a-37649a814087].

8.1. Key Findings and Contributions

Zipline is an American logistic company which utilizes battery-powered autonomous aerial vehicle (AAPV) prowess equipped with artificial intelligence technology to autonomously incur human livesce that saves customer as well as delivery procedure to its destination country, geography, etc. administering entity’s delivery speed. Autonomics.../agility is emphasized in both respect of supply chain competency establishes Amazon Prime Air ad the Chinese food delivery platform Meituan utilizing giant drone in and around Beijing respectively [45]. Targeting on counteracting the rarity encompassing unavailability and the high cost complexity Simone’s Lab vends artificial-intelligence-based organ transplant logistics coordination (e.g. there are more than 130000 patients seeking a suitable transplant, data-based selection and transplantation prioritization, e.g. also implementing optimization) [44].

Considering the imminent increase in transit-related emission and traffic volume in urban clusters across the globe, efficient and environmentally friendly transportation systems have broadly been identified as a key solution to bring about sustainability. As we observed, in this research manuscript, both numerical and empirical findings could effectively improve taxi service operations and management by considering optimization of AI-based dynamic ride-sharing strategies with a deep reinforcement learning approach in integrated connected vehicle scopes. The machine learning activities behind each introduced strategy were examined by reporting reduced production of CO/NOX/PM, fewer emission-based costs, and an extended vehicle's lifetime in the road, attributed to decreasing the number of waiting/repositioned vehicles and their travel times.

Specifically, the findings will be significant with respect to AI research and autonomous fleet optimization strategies due to the following:

[3]

8.2. Limitations and Future Research Directions

This networked interaction among road users and infrastructures will permit autonomous vehicles and fleets of vehicles to act as integrated components of Smart Cities, producing new advanced mobility services, such as AAM (Advanced Air Mobility) services by drones, enabling efficient multimodalities in urban and rural transportation, making backends of the future more cooperative and collective, and interfacing vehicles with IoT ecosystems. Nevertheless, the substantial advances in these technologies will surely lead to new security concerns, since cyber attacks will become a serious threat to the smooth running of complex systems [ref: 9616349c-11a5-4e38-9704-4a01907e488d; 53175ad1-b759-43fd-bc58-810cb5bec1b3]. Moreover, since the behavior of intelligent agents will be driven by AI-based systems, it is crucial to define and test the requirements of security and safety expected to be respected by these systems. Indeed, attackers may be able to affect the decisions taken by autonomous vehicles by means of sensor hacking (deep fake images, attacks on communication channel or equipment).

There are some limitations in using AI-based approaches for autonomous vehicle fleet optimization and management. For instance, in order to improve the quality of the perception of the vehicle and its environment and ensure its reliable and predictable communication, it is necessary to take advantage of new architectural paradigms and technologies, such as V2X to V2I/I2V communication capabilities enabling cooperative and collective perception as well distributed and decentralized processing and communication among road users [46]. In addition, reliable and robust communication between all kinds of road users and road infrastructure, realized by subsequent technical improvements on PLC (Power Line Communication), RF (Radio-Frequency), VLC (visible light communication), and Li-Fi (Light Communication), Light to Li-Fi, etc., is required to exploit automatized road infrastructure. This will make it possible to build smart roads by realizing connected and cooperative environments that provide autonomous road users with environment awareness, thus allowing to perform joint yet safe driving activities while creating predictable conditions that in turn, facilitate the use of safe and efficient artificial intelligence mechanisms.

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